Quality Choice and Diffusion of Electric Vehicles

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Abstract

How do firms adjust the price and quality of products in response to subsidies and marginal cost changes? Knowing the answer is essential for designing electric vehicle subsidies. I show that the answer to this question is ambiguous in a monopoly model of quality provision. I then build an equilibrium model of competition in the new car market where firms can adjust the quality of electric vehicles. I estimate the model using data from Germany and find that the marginal cost of quality provision dropped by 39% between 2012 and 2018. Firms passed on this lower cost of quality provision by increasing quality, leading to higher prices. On the contrary, I find that firms passed on a subsidy introduced in Germany in 2016 by reducing price more than one-to-one, leading to lower quality. Incentivizing quality provision with a subsidy leads to higher quality at the expense of diffusion, leaving policymakers with a tradeoff between quality and quantity.

1 Introduction

How do firms adjust prices and quality in response to a subsidy and lower marginal cost? The answer to this question is crucial for designing electric vehicle subsidies. Electric vehicles play an integral role in reducing carbon dioxide emissions of the transportation sector. Numerous countries around the world have introduced subsidy schemes to boost the diffusion of electric vehicles. Simultaneously, falling lithium-ion cell prices, an essential input for an electric car's battery pack, have led to lower marginal costs. However, there exists little evidence on how subsidies and lower marginal cost have affected the price and quality of electric vehicles.

My paper explains how firms adjust the price and quality of electric vehicles in response to subsidies and lower marginal costs. I do so in two steps: I first build a model of quality provision by a monopolist. The model allows me to study the mechanisms at play when the monopolist re-adjusts price and quality in response to a subsidy or a change in marginal cost. I then build a data set of new car transactions in Germany and use it to estimate a structural model of demand and supply with endogenous quality choice. This application allows me to study the introduction of a subsidy on electric vehicles in 2016. It also allows me to quantify the effect of lower input prices on the marginal cost of providing quality. Finally, I can extend the comparative statics obtained from the monopoly model to the multiproduct oligopoly case to verify and quantify the theoretical model's predictions.

My framework connects the literatures on quality choice and price pass-through to help understand how firms decide whether to pass on subsidies or lower cost to price or quality.[1] In the monopoly case, lowering price will attract more price-sensitive consumers but decrease margins. Increasing quality will attract more quality-sensitive consumers but is costly. In differentiated product markets, cannibalization effects on other own-firm products and the strategic impact on rival products complicate the picture. I study how these effects drive the equilibrium price and quality levels in the presence of subsidies and cost changes. To the best of my knowledge, this paper is the first attempt to study pass-through to quality in differentiated product markets.

I exploit a subsidy scheme imposed in the German new car market as a setting to study how these effects play out empirically. In doing so, I contribute to a recent but growing literature evaluating subsidy schemes for electric vehicles. (Beresteanu and Li, 2011; Springel, 2019; Xing, Leard, and Li, 2019) This literature has focused on the demand side and charging stations, abstracting away from car supply or only allowing firms to adjust prices. My framework

[1] The literature on quality provision has mainly focused on how firms with market power choose their products' price and quality and its welfare implications (Spence, 1975; Sheshinski, 1976; Mussa and Rosen, 1978; Crawford, Shcherbakov, and Shum, 2019). The literature on pass-through has studied how firms pass on taxes or cost changes via price (Bulow and Pfleiderer, 1983; Kim and Cotterill, 2008; Weyl and Fabinger, 2013)

incorporates a direct channel for quality pass-through, allowing me to predict the effect of subsidies not only on price but also on quality. Also, I contribute to the literature by shedding light on the impact of falling marginal costs that characterize the industry.

My theoretical model considers a single-product monopolist choosing price and quality. The model allows me to derive testable predictions regarding the effect of a subsidy on price and quality. The model can also be adapted to obtain similar predictions regarding pass-through of marginal cost changes. I am also able to extend it to the case of a multiproduct oligopoly, giving me testable predictions regarding the effect of subsidies and marginal cost changes on price and quality.

My empirical model is based closely on Berry, Levinsohn, and Pakes (1995) and Crawford et al. (2019). On the demand side, consumers choose between cars with different engine types and exhibit preferences over price, quality, and other observed and unobserved characteristics. On the supply side, firms compete in price and quality. Estimation is carried out via the Generalized Method of Moments, using approximations to optimal instruments (Chamberlain, 1987) proposed by Gandhi and Houde (2019) as well as cost shifters.

I find that a subsidy can lead to three outcomes: higher quality and lower prices, higher quality and higher prices, or lower quality and lower prices. Which result occurs depends on the relative price- and quality elasticities, as well as the marginal cost of providing quality, making it an empirical question. I obtain a similar result when analyzing a change in the marginal cost of providing quality. In the market for electric cars in Germany, I find that the marginal cost of providing quality decreased by around 39% between 2012 and 2018. Firms used the lower marginal cost of quality provision to increase quality and prices. Firms used quality pass-through more than one-to-one and compensated by rising prices as well.

I also find that the subsidy introduced in 2016 decreased prices and qualities for all subsidized products. Firms passed through the subsidy to price more than one-to-one and compensated by reducing quality, the opposite of the effect found in the analysis of the marginal cost decrease. Together, this suggests upward pressure on price and quality due to the falling marginal cost of quality provision and downward pressure on price and quality due to the subsidy. I find that the upward pressure on quality was more substantial throughout the sample period. For the price, the upward pressure dominated initially before the downward pressure became dominant.

To compare the flat subsidy scheme introduced in Germany to alternative designs, I evaluate subsidy schemes that put incentives on quality. I find that a policymaker subsidizing electric vehicles faces a trade-off between quantity and quality. These findings have important implications for designing electric vehicle subsidies that achieve their stated goal. Rather than obtaining a "one size fits all" result, my findings suggest that policymakers need to carefully study price-and quality elasticities, firms' cost structures and their implications on firms' incentives to adjust price and quality.

The framework that I use applies to other markets with endogenous product characteristics. It can predict the effect of taxes on prices and endogenous characteristics. The extended theoretical framework nests several more specific cases, such as single-product firms or duopolies. It also nests cases utilizing functional forms for demand or cost that may yield unique predictions, such as in Battaggion and Vaglio (2018) who study newspaper subsidies. The general implications of this paper are also salient for markets in which quality may respond to subsidies such as the access to basic infrastructure in developing countries that governments often subsidize, which may have adverse effects on quality (McRae, 2015).

Related literature. My paper relates to several strands of literature. It builds on a long literature studying quality provision, both from a theoretical and empirical perspective. Seminal contributions are Spence (1975) and Sheshinski (1976) who study quality provision of a monopolist and its welfare implications. They show that a monopolist may over- or under-provide quality depending on the inverse demand curve's shape. A related literature on screening (Mussa and Rosen, 1978; Maskin and Riley, 1984) shows that a monopolist tends to degrade quality for consumers with low willingness to pay. Crawford et al. (2019) test the predictions of these strands of literature and find that quality is over-provided in cable TV markets. In a similar vein, my paper is also connected to a long literature studying pass-through of taxes or cost changes to price (Bulow and Pfleiderer, 1983; Stern, 1987; Kim and Cotterill, 2008; Weyl and Fabinger, 2013). This literature studies how factors like market power and the demand curve's shape affect the pass-through rate. The literature on international trade also studies pass-through extensively (Feenstra, 1989; Chen and Juvenal, 2016). The main focus is on tariff pass-through and how it differs across the quality spectrum. Quality stays endogenous in most studies except for Ludema and Yu (2016) who study how firms adjust quality in response to tariff decreases.

My paper also contributes to a literature evaluating subsidies for low-emission vehicles and regulations aimed at reducing the emissions of the transport sector. Knittel (2011) studies the technological progress in the automobile sector since the 1980s. Klier and Linn (2012) study the medium-run effects of fuel economy standards in the US and find that a fuel tax reduces fuel consumption at less cost. Similarly, Grigolon, Reynaert, and Verboven (2018) find that fuel taxes also out-perform fuel economy-based attribute taxes. Durrmeyer and Samano (2018) show that feebate schemes outperform fuel economy standards as well. Reynaert (Forthcoming) finds that manufacturers adapt to emission standards through a mix of technology adoption but also gaming. Reynaert and Sallee (Forthcoming) show that gaming fuel economy standards was indeed widespread but that buyers profited as the cost savings from gaming were passed through to lower prices. A recent but quickly growing sub-strand of this literature studies the effects of subsidies and other regulatory changes on electric vehicles. Beresteanu and Li (2011) find that tax incentives and rising fuel prices were the main drivers in increased hybrid car adoption. Pavan (2017) and Springel (2019) show that there exist important feedback loops between purchase subsidies on cars and subsidies for charging points of alternative fuel cars. Li (2019) finds that a compatibility standard for charging stations would have important welfare effects and increase electric vehicle sales. Xing et al. (2019) show that better targeting subsidies to low-income households would be more cost-effective and less regressive. Yan (2019) shows that Tesla's decision of making their R&D on electric cars open-source had a positive impact on technological progress.

Finally, my paper is related to a growing literature studying equilibrium outcomes when firms can adjust one or more product characteristics or their whole product portfolio. Fan (2013) studies a merger between newspapers and shows that ignoring adjustment in product characteristics leads to substantially different predictions. Wollmann (2018) examines the government bailout of US truck manufacturers in 2009 and shows the importance of allowing product offerings to adjust. The paper closest to mine in methodology is Crawford et al. (2019) who allow firms to choose both price and quality of their products.

2 A model of quality provision

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.

Set-up

Let us consider a monopolist who chooses price (p) and quality (q) of a single product sold to final consumers.[2] 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.

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

Quality choice

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

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

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

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

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

$$c_q = \frac{\partial s(p,q)/\partial q}{|\partial s(p,q)/\partial p|}, \tag{1}$$

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 (1), 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. To find the effect of the subsidy on the equilibrium price and quality levels, we can differentiate the system of FOCs with respect to λ. Doing so leads to the following result:

Result Suppose price and quality are strategic complements (meaning $\pi_{pq} > 0$).[3] Let s_p and s_q denote the price and quality semi-elasticities. Then, for a given marginal cost of providing quality,

[3] A case where price and quality are strategic substitutes can occur when consumers like higher prices. This special case does not fit the market for cars that I study.

- price and quality decrease for large values of $\frac{|s_p|}{s_q}$,
- price and quality increase for small values of $\frac{|s_p|}{s_q}$ and
- price decreases and quality increases for intermediate values of $\frac{|s_p|}{s_q}$.

The derivation of this result is in Appendix A.1. The effect of a subsidy on quality and price depends crucially 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. For now, let's focus on the semi-elasticities: If $\frac{|s_p|}{s_q}$ is large, consumers care more about price than quality. The firm then decreases price by more than the amount of the subsidy and compensates by decreasing quality as well to keep their margins from thinning. If $\frac{|s_p|}{s_q}$ is small, consumers care more about quality than price. The firm passes through the subsidy by increasing quality. Since doing so is costly, prices will rise as well. In the intermediate case, firms use a mix of price- and quality pass-through by lowering the former and increasing the latter. In all three cases, the marginal cost of providing quality will affect the range at which different levels of $\frac{|s_p|}{s_q}$ lead to the different sub-cases. The larger the marginal cost of providing quality, the larger the range of values at which $\frac{|s_p|}{s_q}$ leads to lower price and lower quality, for instance.

The "Spence condition" and subsidies

Instead of letting the monopolist choose price and quality, Spence (1975) studies a monopolist choosing quality and quantity who faces an inverse demand function $P(s, q)$. He then finds that the monopolist over-provides quality compared to what a social planner would choose if the cross-derivative of the inverse demand function P_{sq} is larger than zero and under-provides quality if $P_{sq} < 0$. How does this result translate into the findings of the previous paragraphs? Using the implicit function theorem gives us $P_{sq} = \frac{-s_{pq}}{s_p^2}$. As the denominator is positive, the cross-derivative sign depends on the sign of s_{pq}. The sign of s_{pq} cannot uniquely predict the effect of a flat subsidy on price and quality, meaning there exists no one-to-one relationship between the "Spence condition" and the price- and quality effects of a flat subsidy. What can be said is that over-provision can occur both when price and quality are strategic complements, and when they are strategic substitutes. Under-provision can, however, only occur when price and quality are strategic complements. See Appendix A.2 for details.

Accommodating marginal cost shocks

The model can also accommodate the effects of a shock to marginal cost. In this case, we can no longer directly link the impact of such a cost shock to the semi-elasticities of price and

quality. However, what goes through is that if price and quality are strategic complements, the effect of a shock to the marginal cost of providing quality is ambiguous. See Appendix A.3 for computational details using a specific functional form for marginal cost.
To summarize, the model shows that if price and quality are strategic complements, the effect of a subsidy on either has an ambiguous sign. It depends on the relative magnitudes of the price-and quality semi-elasticities and the marginal cost of providing quality. The "Spence condition" does not help in predicting the direction of the effect. Consequently, the impact of a subsidy on price and quality is an empirical question. The same holds true for the effect of a shock to the marginal cost of providing quality.

Extension to multiproduct oligopoly

In Appendix B, I extend the model presented above to the multiproduct oligopoly case. There are two further complicating factors in this case: The first is that cannibalization effects exist. Firms take into account the effect of changing the price or the quality of one product on all the other products in their portfolio. Similarly, there are strategic effects due to the oligopoly structure. However, I can show that performing comparative statics on the system of first order conditions yields testable predictions.

3 Industry Description and Data

In my empirical application, I consider the new car market in Germany. The dominance of combustion engine cars using gasoline or diesel as fuel has characterized this market over the past decades. Simultaneously, sales of electric vehicles have increased more than 20 times between 2012 and 2018. I estimate both consumer demand for new cars and competition in price and quality of 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 vehicles 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 the electric engine to an external source. Over the past decades, two new technologies have emerged: One is the plug-in hybrid electric vehicle (PHEV) that combines a fuel engine with an electric battery pack with the possibility of plugging it to an external power source. The other is a pure battery electric vehicle (BEV) whose powertrain unit only consists of a battery pack (throughout the remainder of the text, "BEV" will be used synonymously with "battery electric vehicle", "PHEV" synonymously with "plug-in hybrid electric vehicle" and "EV" means both "BEV" and "PHEV"). Electric vehicles have been singled out by policymakers and firms alike as key technologies to decarbonize the transportation sector as part of the goal to contain the rise of global temperatures to below 2°. To buttress diffusion, governments around the world have introduced subsidies and tax incentives on electric vehicles. The scope and design of subsidies varies considerably across and sometimes even within countries, with some countries using flat subsidies and others making subsidies depend on characteristics like the driving range or battery size.[4]

Another feature of electric vehicles 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: LIC price estimates (USD per kWh)

Source: Hsieh et al. (2019)

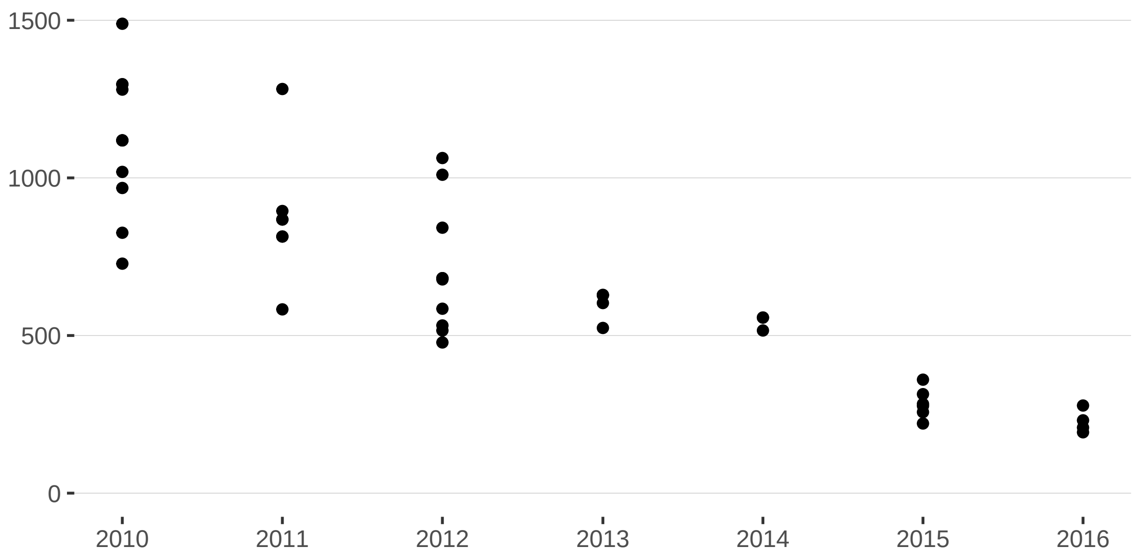


Figure 1 shows different approximations of the evolution of lithium-ion cell prices. Although there is considerable variation in the estimates, there is a clear downward trend. This trend suggests that providing driving range has become considerably cheaper over the past decade. This feature is closely related to the main barriers of mass adoption of electric vehicles: They tend to be more expensive and have lower driving range than combustion engine cars. In consumer surveys, these two factors repeatedly show up as the most critical determinants of whether or not 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;

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

Rezvani, Jansson, and Bodin 2015).

The German car market. The automobile sector is a key industry sector in Germany, accounting for 4.7% of gross value added and employing around 880,000 people with another 900,000 jobs heavily depending on the sector, accounting for 4% of total employment.[5] Germany is home to three of the largest 15 car manufacturers in the world as measured in sales and is the fourth-largest country in the world in terms of motor vehicle production.[6]. The German car industry also saw a major corporate scandal in the past decade when in 2015, Volkswagen admitted to having cheated emission standard tests in the US using a defeat device. Research suggests that the scandal hurt German car producers as a whole (Bachmann, Ehrlich, Fan, and Ruzic, 2019). Moreover, the market share of diesel cars among new registrations fell from around 48% in 2015 to approximately 32% in 2018.[7]

Electric vehicle incentives in Germany. Over the past decade, the German government has undertaken measures to boost sales of electric vehicles. One such measure was the Government Program for Electric Mobility in 2016. Part of this program was a support scheme that gives a subsidy of €2,000 for battery electric vehicles and a subsidy of €1,500 for plug-in hybrid electric vehicles. The list price of the car needs to be below €60,000 to be eligible for the subsidy. Also, carmakers pledged to give a rebate equal to the amount of the government subsidy. The program's total funding was capped at €1.2 billion, with the government and carmakers each footing 50% of the bill. The program also provided funding for new charging stations and various tax benefits from buying, using, and charging electric vehicles.[8] The plan reinforced the government's goal to have 1 million electric cars on the streets by 2020 and 6 million by 2030.[9] The budget was forecasted to be sufficient to give subsidies until 2019. However, by June 2017, only around 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 sales. These lackluster sales numbers were why the government stepped up its efforts in 2019 and passed a federal climate protection act. This act increased the government subsidy for battery electric vehicles to up to €3,000 depending on the list price, with car producers increasing their rebate to the same amount. The pact also increased tax incentives for electric vehicles and decided to introduce a price on CO_2 of €10 per ton 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

[5] https://www.destatis.de/EN/Press/2019/04/PE19_139_811.html;jsessionid=BE75B79E28D4051C4893AF740C378364.internet8711

[6] https://en.wikipedia.org/wiki/List_of_manufacturers_by_motor_vehicle_production and https://en.wikipedia.org/wiki/List_of_countries_by_motor_vehicle_production

[7] https://www.kba.de/DE/Statistik/Fahrzeuge/Neuzulassungen/Umwelt/fz_n_umwelt_archiv/2019/n_umwelt_z.html?nn=2601598

[8] https://www.bmwi.de/Redaktion/EN/Artikel/Industry/regulatory-environment-and-incentives-for-using-electric-vehicles.html

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

doubled the subsidies to up 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 contains yearly new registrations on the state level for every model. A firm-and-trim identifier ("HSN/TSN") defined on a very granular level identifies a model. It differs by car class, body type, engine type, kw, weight, and the number of doors. I follow the previous literature on demand estimation of 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 consists of the list price of cars that I use in the estimation as the transaction price, again following the literature on demand estimation of car markets. The ADAC data also contains the HSN/TSN identifier, allowing me to match the two data sets relatively easily except for some observations requiring manual matching.

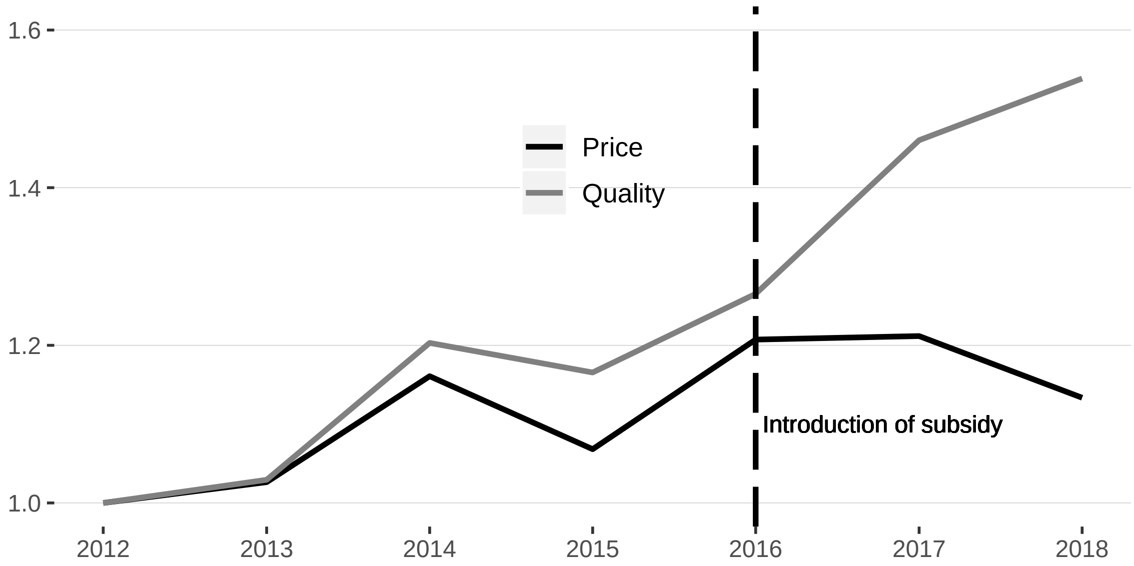
Charging Stations. I obtain the number of charging stations for electric car batteries from a publicly available data set listing all public charging stations from the Federal Network Agency (BNetzA). The data set contains each station's opening date and its location.

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 from Federal Reserve Economic Data. I build a measure of fuel cost in €/100km using yearly average gas price data from ADAC and electricity cost data from the German Economics Ministry.[10]

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 one for tractability. The "correct" answer to this trade-off may differ according to what the researcher wants to study in particular. In my final data set, I define a product on the firm/model/engine type-level, allowing the engine type to vary between combustion engine (ICE), plug-in hybrid (PHEV), and battery electric (BEV) (p.e. VW Golf ICE vs. Renault Zoe BEV). In aggregating up to this product definition, I keep the price and characteristics of the most sold variant nationally.

[10] `https://www.adac.de/verkehr/tanken-kraftstoff-antrieb/deutschland/kraftstoffpreisentwicklung/` and `https://www.bmwi.de/Redaktion/DE/Infografiken/Energie/strompreisbestandteile.html`

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



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 at one-quarter of the number of households.[11] In total, the data consists of 28,288 year-state-product observations.

Figure 2 shows how the average price and quality of battery electric vehicles developed during the sample period. Prices slightly increased, and quality rose by almost 60%. It is unclear from this picture to what extend falling LIC prices, and subsidies drove these trends. Detailed summary statistics can be found in Table 6 of Appendix C.

4 Empirical Model

Set-up

To quantify the effects of falling LIC costs and subsidies on electric vehicles' prices and qualities, I build a structural model of a new car market following Berry et al. (1995) and Crawford et al. (2019). Consumers choose the product maximizing their indirect utility and exhibit heterogeneous preferences over price and product characteristics on the demand side. The supply side allows firms to compete in price and quality.

I assume that the driving range of a car determines its quality. Further, I assume that consumers only care 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 the anecdotal evidence on purchase behavior and consumer preferences regarding battery electric vehicles.

[11] This implies that households decide whether to buy a new car or not every four years.

Several consumer surveys have found that driving range is the most critical determinant for considering an electric vehicle next to the price and charging station availability.[12]. Also, the driving range of combustion engine cars is sufficiently high, and the network of gas stations is sufficiently dense. Hence it does not play a role in consumer purchase decisions nor firms' profit maximization problems.

I further assume that firms choose prices and qualities simultaneously on 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 size dimensions of the car. A battery pack is made up of a large number of lithium-ion cells, giving firms flexibility to scale up or down the size of the battery pack. Also, firms choose prices and qualities at the national level because list prices and characteristics do not vary across states. Finally, I assume that firms only choose their battery electric vehicles' quality. This assumption is partly a consequence of the fact that I assume consumers not to have preferences for the quality of combustion engine cars. Besides, I assume that firms do not choose the quality of plug-in hybrid electric vehicles. I do so first because the driving range has not moved much over the sample period and second because of the different technology of PHEVs.[13]

Demand

A state m observed in a year t defines a market.[14] 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 the consumer buys a used car or doesn't buy a car at all. Choosing one of the "inside" products means buying a new car. Consumers can only purchase in their own market. The utility consumer i enjoys from purchasing one of the products $j = 1, \ldots, J$ is

$$u_{ijmt} = q_{jt}\beta^q - \alpha\frac{p_{jt}}{y_{imt}} + x_{jt}\beta_i^x + \xi_{jmt} + \varepsilon_{ijmt}, \tag{2}$$

[12]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.

[13]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 range since the combustion engine provides enough range. On the other hand, it is also more difficult to increase it given that there are more space constraints.

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

where q_{jt} is quality of product j, p_{jt} it's price, y_{imt} the income of consumer i and x_{jt} 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 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 the standard deviation of preferences. The parameter β^q captures preferences for quality and α captures price sensitivity. Remember that consumers only care about the quality of electric vehicles. In the model, this translates into setting $q_{jt} = 0$ for products with a combustion engine. Finally, the utility from purchasing the outside option is normalized to be $u_{i0mt} = \varepsilon_{i0mt}$.

A consumer i in market mt chooses the alternative $j = 0, \dots J$ that maximizes her utility. Each consumer is characterized by her income y_i and her vector of idiosyncratic preferences ν_i. Income y_i follows a log-normal distribution whose parameters I estimate based on draws from the observed income distribution. Remember that ε_{ijmt} follows a type I extreme value distribution. This assumption enables me to derive the probability that product j procures the highest utility across all possible alternatives by integrating over the individual-specific valuations for characteristics:

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

where $F(\cdot)$ is the joint CDF of the unobserved taste shocks and $G(\cdot)$ denotes the distribution of income. Further, δ_{jmt} is the mean utility holding all terms from (2) that do not vary across individuals and $\mu_{ijmt} = -\alpha \frac{p_{jt}}{y_{imt}} + \sum_k \sigma^k \nu_i^k x_{jmt}^k$ holds the individual deviations from the mean utility. Finally, defining the observed market share as $s_{jmt} = \frac{q_{jmt}}{\mathcal{M}_{mt}}$ and stacking observed and predicted market shares into a vector, we get the system of equations $s_{mt} = s_{mt}(p, q, x, \xi; \sigma)$ for each market mt.

Supply

I model the profit-maximizing price and quality decisions of F multi-product firms for each year t. I assume the product portfolio of firms to be given. I also assume that firms have already chosen all product characteristics except for the quality of BEVs. Remember that the measure of quality is the BEV's driving range. Firms then maximize profits by setting the price of all products in their portfolio, as well as setting the quality of their BEVs, on 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:

$$\max_{p,q} \pi_{ft} \equiv \sum_m \phi_{mt} \sum_{j\in J_{ft}} \Big(p_{jt} - mc_{jt}(q_{jt}, w_{jt}; \theta_s)\Big) s_{jmt}(p, q, x, \xi; \sigma)\mathcal{M}_{mt}, \tag{3}$$

where $\phi_{mt} = \frac{\mathcal{M}_{mt}}{\sum_{m'} \mathcal{M}_{m't}}$ is the weight of state m, J_{ft} is the product portfolio of firm j, $mc(\cdot)$ 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 quality are then given by

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

$$\frac{\partial \pi_{ft}}{\partial q_{jt}} = \sum_m \phi_{mt} \Big\{ - \frac{\partial mc_{kt}}{\partial q_{jt}} s_{jmt} + \sum_{k\in J_{ft}} \Big(p_{kt} - mc_{kt}\Big) \frac{\partial s_{kmt}}{\partial q_{jt}} \Big\} = 0 \tag{5}$$

Equation (4) 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 firm f offers. We can rewrite (5) as

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

When choosing quality, firm f trades off the decrease in the markup from providing more quality (intensive margin) against the higher demand from providing more quality (extensive margin) as well as the cannibalization effect on the other products in firm f's portfolio. Loosely speaking, equilibrium quality will decrease with a higher marginal cost of providing it (which squeezes the markup) and increase with larger values of the demand semi-elasticity with respect to quality (which increases the extensive margin).

The first order conditions in (4) and (5) can be expressed in matrix form. I use the index B for battery electric vehicles and I for other vehicles. I let J_B, J_I denote the set of either type of vehicle, and also the number of either kind of vehicle in the market. I then define the following matrices:

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

$$\Delta_q^B: \ J_B\text{x}J_B \text{ matrix with entry } k,l = \begin{cases} \sum_m \phi_{mt} \frac{\partial s_{lmt}}{\partial q_{kt}} \text{ if } k,l \in J_f \text{ and } k,l \in J_B \\ 0 \text{ otherwise} \end{cases}$$

$$\Delta_q^I: \ J_B \text{x} J_I \text{ matrix with entry } k,l = \begin{cases} \sum_m \phi_{mt} \frac{\partial s_{lmt}}{\partial q_{kt}} \text{ if } k,l \in J_f, \ l \in J_I \text{ and } k \in J_B \\ 0 \text{ otherwise} \end{cases}$$

The system of first order conditions can then be expressed as

$$\mathbf{s} + (\mathbf{p} - \mathbf{mc})\Delta_p = 0 \tag{6}$$

$$-\frac{\partial \mathbf{mc}^B}{\partial \mathbf{q}^B}\mathbf{s} + \Delta_q^B(\mathbf{p}^B - \mathbf{mc}^B) + \Delta_q^I(\mathbf{p}^I - \mathbf{mc}^I) = 0, \tag{7}$$

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

Marginal cost specification

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

$$\log(mc_{jt}(q_{jt}, w_{jt}; \theta_s)) = \underbrace{w_{jt}\psi + \omega_{jt}}_{\substack{\text{baseline} \\ \text{marginal cost}}} + \underbrace{(\gamma_0 + \gamma_1 t + \eta_{jt})q_{jt}}_{\substack{\text{marginal cost of} \\ \text{providing quality}}}, \tag{8}$$

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 quality-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 (8) is zero for products that are not battery electric vehicles since I do not model their quality choices. In the case of BEVs, I assume that the marginal cost of providing quality depends on an intercept term, a linear time trend allowing for less costly quality provision over time, and an unobserved, product-specific part. The exponential nature of fixed costs is in line with the technology facing firms: Increasing quality is analogous to increasing the driving range, possibly by increasing the size of the battery. Providing more quality becomes more costly at higher levels of quality. One reason is that the car's dimension restricts the size of the battery and adds more weight.

Having a functional form for marginal costs allows me to express the equilibrium levels of price and quality 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 quality levels are

$$\mathbf{p} = \mathbf{mc} + \Delta_p^{-1}\mathbf{s} \tag{9}$$

$$\mathbf{q} = \frac{1}{\mathbf{c_1}} \log\left(\frac{\Delta_q^B(\mathbf{p}^B - \mathbf{mc}^B) + \Delta_q^I(\mathbf{p}^I - \mathbf{mc}^I)}{\mathbf{s}^B\mathbf{c}_1}\right) - \frac{\mathbf{c}_0}{\mathbf{c}_1} \tag{10}$$

We get the usual result of the price being equal to marginal cost plus a markup. The expression for quality again makes apparent the trade-off between increasing 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 the ones 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

$$\max_{p,q} \pi_{ft} \equiv \sum_{m} \phi_{mt} \sum_{j \in J_{ft}} \Big(p_{jt} + \lambda_{jt} - mc_{jt}(q_{jt}, w_{jt}; \theta_s)\Big) s_{jmt}(p, q, x, \xi; \sigma)\mathcal{M}_{mt}, \tag{11}$$

and the system of first order conditions is now given by

$$\mathbf{s} + (\mathbf{p} + \boldsymbol{\lambda} - \mathbf{mc})\Delta_p = 0 \tag{12}$$

$$-\frac{\partial \mathbf{mc}}{\partial \mathbf{q}}\mathbf{s} + \Delta_q^B(\mathbf{p}^B + \boldsymbol{\lambda}^B - \mathbf{mc}^B) + \Delta_q^I(\mathbf{p}^I + \boldsymbol{\lambda}^I - \mathbf{mc}^I) = 0, \tag{13}$$

where $\boldsymbol{\lambda}$ is the vector of subsidies.

5 Estimation

Instrumental Variables

Demand side

Estimation of the demand side parameters presents the well-known endogeneity issue related to price and here also to quality: As the demand- and supply-side shocks realize before the price and quality choices, price and quality 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 likely to depend itself on the electric vehicle base, creating an endogeneity issue (Springel, 2019; Li, 2019; Pavan, 2017). Instruments are needed to account for this endogeneity issue. At the same time, instruments also help in identifying 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 the optimal instruments of Chamberlain (1987). In my estimation, I use 'differentiation IVs' introduced by Gandhi and Houde (2019). The idea is to describe the relative position of each product in the characteristics space. I build two variants of differentiation IVs. A *local* variant that counts products close in characteristic space and a *quadratic* variant that sums squared differences between product characteristics:

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

where $|d_{jrt}^{k}|$ is the absolute value of 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, ICE) and one considering rival-firm products of the same engine type. For discrete characteristics, I construct a *discrete* variant counting the number of own-and rival products sharing the same discrete characteristic, respectively.

I build the local and quadratic variants for all the continuous characteristics and the discrete variant for all the discrete characteristics. I also create local and quadratic variants for a price index obtained by regressing the observed price on demand- and cost shifters. Since the range of battery electric vehicles is endogenous, I build the local variant for the quality of plug-in hybrid vehicles and for battery efficiency (measured in kWh/100km), which I assume to be exogenous. I use a subset of all these instruments I create. Further, I use an estimate for the cost of lithium-ion cells. This cost shifter helps to correct for the endogeneity of the driving range. I account for the endogeneity of the charging station network by including subsidies as instruments.

Supply side

On the supply side, quality may be correlated with the unobserved cost shocks due to quality being endogenously chosen. I account for this endogeneity issue by differentiation IVs built on the exogenous characteristics entering the marginal cost function. In addition I include the observed exogenous characteristics entering the baseline marginal cost as these characteristics were chosen before the quality, guaranteeing their exogeneity with respect to the unobserved quality cost shock. Like on the demand side, I use a subset of the instruments I create.

Identification

Using the set of instruments described above allows me to pin down the estimated parameters. The parameters in the mean utility β and the cost parameters ϕ can be recovered through a linear projection. β is then identified by variation in market shares and observed characteristics. The demand side parameters coupled with an assumption on firm behavior allow me to back out implied marginal costs. The vector of marginal cost parameters ϕ is then identified by changes in the implied marginal cost and observed cost shifters. Much of this variation comes within markets as well as across time. Market shares also exhibit considerable variation across states (the m part of the market index), whereas product characteristics do not vary across states in a given year (with the exception of the endogenous charging station variable). Next to using the instruments described above, identification of σ is also aided by variation in the observed characteristics. Similarly, the price coefficient α is identified using variation in market shares, prices as well as consumer income. 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 providing quality are identified from variation in observed quality as well as in 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

Around 4% of my observations are products with strictly positive national-level sales but zero state-level sales. Zero sales pose a problem in random coefficient demand models as the estimation procedure is not well-defined when zero sales are present. Deleting observations with zero sales from the sample is problematic because it alters the market structure and makes these products unavailable in counterfactual analyses. There exist approaches in the literature to accommodate zero sales in random coefficient demand models.[15] I follow Durrmeyer and Samano (2018) and 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

[15] 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.

parameters can be consistently estimated. D'Haultfœuille et al. (2019) provide an interesting and detailed discussion on this.[16]

Estimation of the demand side

On the demand side, the vector of parameters to be estimated is given by $\theta_d \equiv (\beta_i^x, \beta^q, \alpha)$. I allow for random coefficients on characteristics where I believe consumer heterogeneity to matter: a *EV* dummy for battery- and plug-in hybrid vehicles and *acceleration*, measured as horsepower divided by weight. The random coefficient on the *EV* dummy allows for flexible substitution between electric cars and combustion engine cars. The random coefficient on *acceleration* allows consumers to have idiosyncratic preferences for a characteristic describing the engine performance of their car. I allow for a trend in the mean taste for quality, possibly capturing changes in taste for quality over time. Besides, I add several characteristics for which I only estimate the mean taste, including the number of charging stations, 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.[17] 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} some 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 is holds 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 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 been drawing 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, 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 Halton sequences used

[16]The zero sales problem is rather small in my sample, given that it only affects around 4% of my observations. In fact, my results are robust to different corrections (such as replacing $q_j = 0$ with $q_j = 1$), which I see as evidence that my demand parameters are indeed consistently estimated and leads me to believe that the correction I use is sufficient.

[17]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 regulation or to sell these cars at a discount later. Not accounting for this may introduce a bias especially for products with small market shares.

frequently. Second, I set the tolerance level in the contraction mapping of the inner loop to 1e-14 to solve for the demand-side unobservables to prevent numerical errors from the inner loop to propagate 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 make sure the optimizer didn't 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 providing quality consists of an intercept and a linear time trend, aimed to capture the decreasing cost of lithium-ion cells that are a crucial determinant of range. Any unobserved, product-specific cost of providing quality is then captured by η_{jt}.

The first order conditions in (6) and (7) 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:

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

where Z^s holds the instruments and W^s is a positive definite GMM weighting matrix. The baseline marginal cost parameters ψ can be concentrated out of the minimzation routine, much like the linear mean tastes in the utility function. Note that the number of observations differs on the demand-and supply side. I assume price and quality to be chosen nationally, meaning that on the supply side, I have one national market per year t and not m state-level markets per year t.

I take account of subsidies as outlined in (12)-(13). I do not take account of the 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.[18] 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.

6 Estimation 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 D. Table 7 in Appendix C 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			**Quality Provision**		
Quality	1.944	(0.259)	Intercept	0.903	(0.027)
Quality x Trend	-0.134	(0.032)	Trend	-0.081	(0.006)
Charging Stations	2.363	(0.505)			
BEV	-12.548	(2.737)			
PHEV	-9.943	(2.618)			
Acceleration	0.320	(0.029)			
Interactions					
Price / Income	-4.802	(0.480)			
Standard Dev.					
EV	4.110	(1.024)			
Acceleration	0.036	(0.047)			
Statistics					
Mean own-price elasticity	-3.262				
Mean own-quality elasticity (BEVs)	3.059				
Mean markup (€ 1,000)	10.773				

Note: Prices are deflated and in EUR 1,000. Vehicle class-, Body-, Firm- and State Fixed Effects included. See Appendix D for the full estimates.

Consumers like higher quality, all else equal. The quality-specific trend is negative, meaning consumer preferences for quality become less intense throughout the sample period. One explanation for this could be that range anxiety has decreased over time due to consumers learning more about electric vehicles. This learning may come from their own experience, that

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

of peers, or simply more information being available 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 around 50 miles per day on average. Another explanation may be that faster battery charging has made consumers less worried about range. 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, 2019). The mean quality elasticity is equal to 3.059.

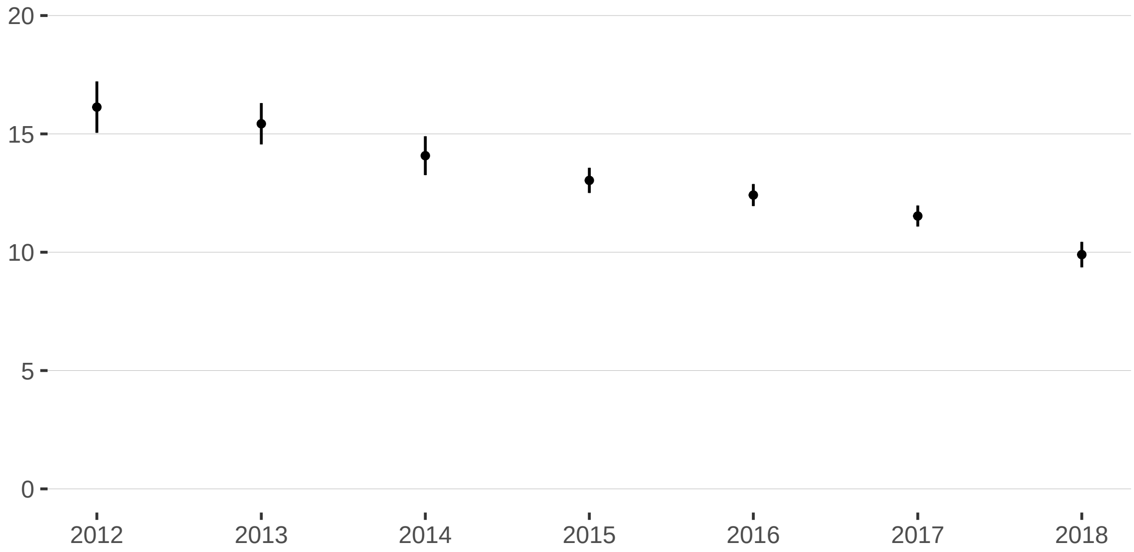
The negative and significant coefficient on price over income translates into a mean price elasticity of -3.262, within the range of figures found in the long literature on demand estimation of new car markets. Table 11 in Appendix F shows how my estimated price elasticity compares to those found in other papers. Unlike for quality, price sensitivity barely changes over the sample period. Due to slightly larger and slightly more dispersed household income, the mean price sensitivity dropped slightly from 2012 to 2018, with the variance increasing slightly. Graphical evidence of the findings is provided in Figure 8 in Appendix C. The relative stability of the price sensitivity together with the finding of lower valuation for quality over time suggest that towards the end of the sample period, consumers value price more relative to quality 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 prefers electric cars over those with a combustion engine. Consumers also prefer higher performance cars, as evidenced by the positive sign on the mean taste of *Acceleration*. The estimated standard deviation of taste for *Acceleration* is small and statistically insignificant, suggesting that there does not exist much heterogeneity in the valuation if this characteristic.

On the marginal cost side, I find that quality is costly to provide. Quality provision has become 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 quality of around 39% 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 that they may not directly benefit from price drops due to long-term contracts, it seems plausible that the fall in the marginal cost of providing quality follows the lithium-ion cell price decrease less than one-to-one.

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, respectively. Battery electric vehicles are cheaper to produce all else equal, which is reasonable given that

Figure 3: Estimated yearly mean marginal cost of quality (€1,000, vertical lines are 95%-CI)



apart from the costly quality provision, there are many parts (gearbox, exhaust pipe, starter, injection system) not necessary in the production of a BEV. The supply-side results suggest that quality provision accounts for around 62% of the marginal cost of producing a BEV, on average. This is in line with recent engineering cost estimates (Lutsey and Nicholas, 2019).

7 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. Doing so allows me to disentangle the evolution of price and quality to quantify the contributions of marginal cost changes and subsidies. I can also see how the predictions from the monopoly model presented in Section 2 generalize to a multiproduct oligopoly setting. In the monopoly case, the sign of the effect of both a marginal cost shock and a subsidy on price and quality is ambiguous if price and quality are strategic complements. In the multiproduct oligopoly case, there are two more complicating factors: The first is that cannibalization effects exist because firms have to consider the impact of their price and quality choices of one product on the other products in their portfolio. The second is that strategic effects exist as firms compete in prices and quality with their competitors. Taken together, this makes the effect of either marginal cost changes and subsidies on the price and quality of products an empirical question.

Procedure

Having estimates of price- and quality semi-elasticities, a system of first order conditions for prices and qualities, and an estimate for the marginal cost of providing quality, I can compute the new equilibrium vectors of price and qualities. I employ an iterative algorithm to find the new equilibrium vector of prices and qualities $(\mathbf{p}, \mathbf{q})$. I proceed as follows: At iteration h,

1. Use the price FOCs to compute $\mathbf{p}^{h+1} = \mathbf{mc}(\mathbf{q}^h) + \Delta_p^{-1}\mathbf{s}(\mathbf{p}^h, \mathbf{q}^h) - \boldsymbol{\lambda}$
2. Update market shares and elasticities using $\mathbf{p}^{h+1}, \mathbf{q}^h$
3. Use the quality FOCs to compute $\mathbf{q}^{h+1} = f(\mathbf{q}^h, \mathbf{p}^{h+1})$, where $f(\cdot)$ is the expression of quality from (10).
4. Update market shares and elasticities using $\mathbf{p}^{h+1}, \mathbf{q}^{h+1}$
5. Let $d_{max} = \max(d_p^h, d_q^h)$, where $d_p^h = \max|\mathbf{p}^{h+1} - \mathbf{p}^h|$ and $d_q^h = \max|\mathbf{q}^{h+1} - \mathbf{q}^h|$
6. If $d_{max} \geq \epsilon^c$ with ϵ^c some convergence criterion, go back to step 1. If $d_{max} < \epsilon^c$, extract $(\mathbf{p}^{h+1}, \mathbf{q}^{h+1})$ to be the new equilibrium vector of prices and qualities.

I adapt the algorithm for counterfactuals in which only price or only quality is allowed to be re-adjusted simply by only using the respective FOCs. I find this procedure to converge to the same vector of prices and qualities even when starting 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 quality 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 quality and repeating both iterations until the "outer loop" converges. These alternative procedures give me confidence that the counterfactual results I find are robust to the specific algorithm and starting values chosen. I perform all counterfactuals for 2018.

Lower marginal cost increases price and quality

On the supply side of my model, I found that the marginal cost of quality provision has decreased by around 39% 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.,

Table 2: Market outcomes with lower marginal cost of quality

	With subsidy	**Without subsidy**		
	Base	Price, quality adjust	Only price adjusts	Only quality adjusts
Price	31,482	742 (600, 1,015)	-334 (-463, -242)	0
Quality	259	8 (6, 10)	0	3 (3, 3)
MC	23,569	923 (816, 1,123)	-286 (-386, -211)	52 (49, 56)
Markup	7,913	-181 (-300, -79)	-48 (-77, -31)	-52 (-56, -49)
Sales	34,761	523 (328, 787)	871 (616, 1,198)	924 (727, 1,168)

The table gives mean differences from observed outcomes with 90% C.I. in parentheses.

2019; Nykvist and Nilsson, 2015; Green, Armstrong, Ben-Akiva, Heywood, Knittel, Paltsev, Reimer, Vaishnav, Zhao, Gross et al., 2019).

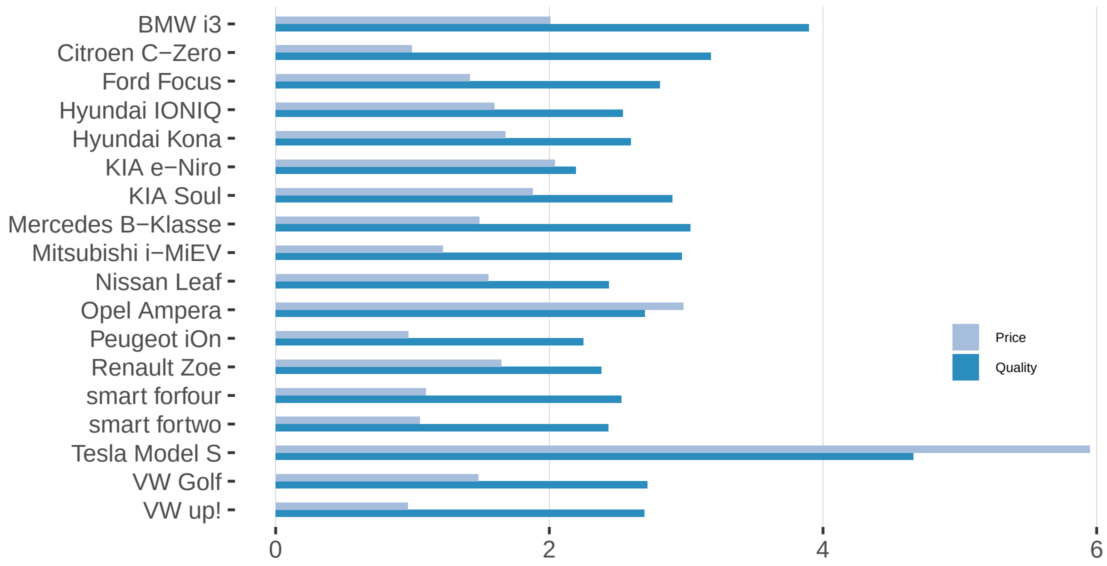
In principle, firms can pass through lower marginal costs to price or quality. The pass-through rates are given by $\frac{dp}{dc_1}, \frac{dq}{dc_1}$, where c_1 denotes the marginal cost of providing quality. The signs and magnitudes of the rates are determined by the relative price- and quality semi-elasticities, the marginal cost of providing quality, cannibalization effects, and the strategic effect of their 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 quality drops by 1%.
I perform this counterfactual under three scenarios. In scenario 1, I allow firms to adjust prices and qualities. In scenarios 2 and 3, I restrict firms to only adjusting price and only adjusting quality, respectively. The results are 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 quality decreases by 1%, and both price and quality can adjust. 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 quality. Firms now sell a more expensive, higher-quality product. In the last line of Table 2, we see that sales also increase, by around 1.5%. Figure 4 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 quality can adjust, respectively. In the case of pure price adjustment, the average price decreases by around €334 or 1.06%, meaning there is a slight over-shifting of the marginal cost drop. In the case of pure quality adjustment, the average driving range increases by 3km or 1.15%, also suggesting over-shifting. We can also observe that when firms can only adjust a single variable, the markup decreases less compared to the case where both quality and price are free to change.

This section provides an answer to the question of how a marginal cost shock affects the price and quality of battery electric vehicles: A negative marginal cost shock increases both prices and qualities, leading to more expensive, higher-quality products. We also see that the markup decreases in all three scenarios.

Figure 4: Percentage changes of price and quality due to lower marginal cost of quality



Subsidies reduce price and quality

The German government introduced a subsidy on 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 qualities of battery electric vehicles. In a first step, I use an extension of the monopoly model from Section 2 to predict the signs of the effects. In the second step, I perform counterfactual exercises to quantify them.

Using comparative statics to predict the effects

In Section 2, I derived the effects of a subsidy on prices and qualities using comparative statics for the monopoly case. In Appendix B, I extend the derivation of comparative statics to the multi-product oligopoly case. The resulting system (in 14) enables me to predict the effects of a subsidy on prices and quantities. I can also compute the sign of $\pi_{fp_jq_j}$ for all battery electric vehicles in the sample. Remember that the sign of this cross-derivative determines whether or not price and quality are strategic complements. The results are in Table 3.

Table 3: Effects of subsidy on price and quality

Model	Subsidized	π_{pq}	sign($\frac{dp}{d\lambda}$)	sign($\frac{dq}{d\lambda}$)
BMW i3	Yes	> 0	$-$	$-$
Mercedes B-Klasse	Yes	> 0	$-$	$-$
smart forfour	Yes	> 0	$-$	$-$
smart fortwo	Yes	> 0	$-$	$-$
Ford Focus	Yes	> 0	$-$	$-$
Hyundai IONIQ	Yes	> 0	$-$	$-$
Hyundai Kona	Yes	> 0	$-$	$-$
KIA e-Niro	Yes	> 0	$-$	$-$
KIA Soul	Yes	> 0	$-$	$-$
Citroen C-Zero	Yes	> 0	$-$	$-$
Opel Ampera	Yes	> 0	$-$	$-$
Peugeot iOn	Yes	> 0	$-$	$-$
Mitsubishi i-MiEV	Yes	> 0	$-$	$-$
Nissan Leaf	Yes	> 0	$-$	$-$
Renault Zoe	Yes	> 0	$-$	$-$
Tesla Model S	No	> 0	$+$	$+$
VW Golf	Yes	> 0	$-$	$-$
VW up!	Yes	> 0	$-$	$-$

We can see that π_{pq} is positive for *all* battery electric vehicles in 2018, meaning price and quality are strategic complements for every product. In the monopoly case, a positive sign of π_{pq} means that the effect of a subsidy on price and quality is ambiguous and an empirical question. Table 3 provides the answer to this question in the case of battery electric vehicles, showing that increasing the subsidy has a negative effect on both the price and quality of all subsidized models. The only non-subsidized model in my sample is the Tesla Model S, whose price and quality increase when the other products' subsidy rises. The intuition behind these results is a combination of two factors described in Section 2: On the demand side, consumers value lower prices relatively more than higher quality, so the subsidy decreases both prices and quality. On the supply side, the marginal cost of providing quality is too high for firms to increase quality in response to an increase in the subsidy. These factors lead firms to pass through the subsidy to price more than one-to-one. To keep margins from shrinking too much, firms compensate by also decreasing quality.

Note that these results also hold in the opposite direction: A decrease of the subsidy or a counterfactual world in which the subsidy didn't exist would lead to both higher prices and higher quality of the subsidized products.

Using counterfactuals to quantify the effects

In this section, I quantify the effects found using comparative statics by performing these counterfactuals. Table 4 shows the results from three counterfactuals. Column 3 shows outcomes when both price and quality are allowed to adjust. Columns 4 and 5 show outcomes where only price and only quality are allowed to adjust, respectively.

Table 4: Difference in market outcomes without subsidy

	With subsidy	**Without subsidy**		
	Base	Price, quality adjust	Only price adjusts	Only quality adjusts
Price	31,482	3,075 (2,776, 3,606)	2,076 (2,011, 2,172)	0
Quality	259	10 (7, 15)	0	-14 (-20, -9)
MC	23,569	858 (640, 1,197)	0	-1234 (-1,296, -1,149)
Markup	9733	397 (292, 592)	256 (191, 352)	-586 (-672, -524)
Sales	34,761	-5,892 (-7,182, -4,706)	-5,475 (-6,587, -4,459)	-4,091 (-4,699, -3,437)

Table gives differences from observed outcomes with 90% C.I. in parentheses.

We can see in column 3 that the predictions drawn from the comparative statics are validated. Without the subsidy, both prices and qualities would have been higher on average. The results suggest that, on average, price pass-through was more than 100% (the subsidy was €1,927 in 2016 €). Firms compensated this overshifting by lowering quality. Markups also fell in response to the subsidy, meaning that firms sold cheaper, lower-quality products on which they collected a smaller markup. Column 4 suggests overshifting of the subsidy in the case where firms are only allowed to adjust prices. Column 5 indicates that if firms had only been able to change quality, the subsidy would have led to an increase in quality. In the last line of Table 4 we can see that the subsidy increased sales by 5,892 units or around 20%. We also see that not accounting for quality adjustment leads to a slight under-prediction of the effect the subsidy had on sales. In either case, we can conclude that the subsidy is far from generating the diffusion needed to have a stock of electric vehicles reaching 1 million by 2020.

Figure 5: Percentage changes of price and quality due to introduction of subsidy

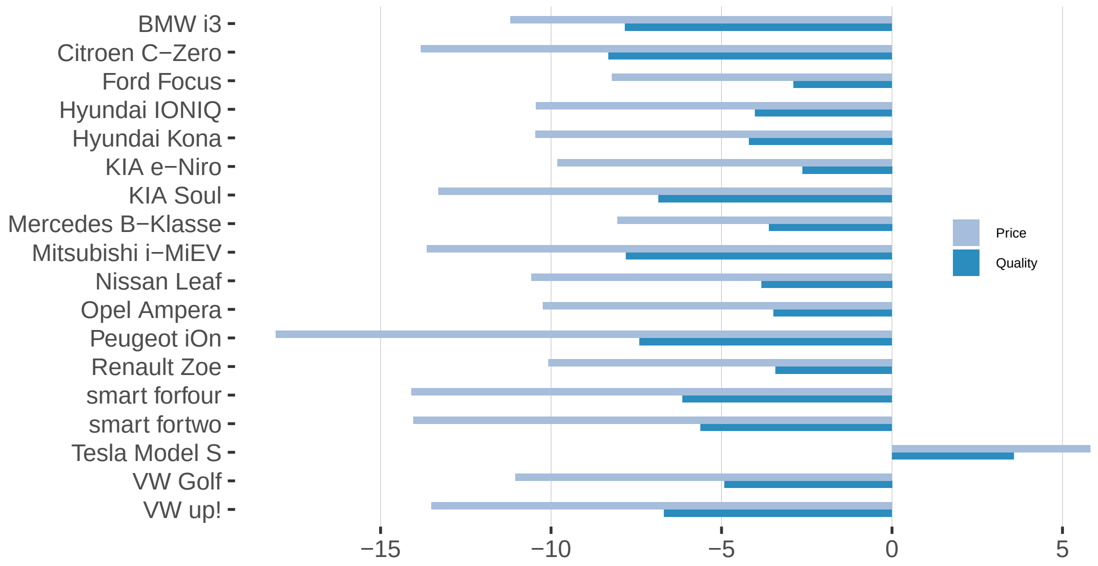


Figure 5 shows the product-level effects of the subsidy. We can see that the predictions from Table 3 hold: Firms decreased the price and quality of all subsidized products, and the lone non-subsidized BEV increased both price and quality.

These results raise questions for policymakers regarding subsidy design. The findings suggest that a possibly unintended side effect of flat purchase subsidies is lower quality. On the one hand, using the support scheme to offer lower-quality, lower-price products may be desirable for very price-sensitive consumers and allow firms to increase sales. On the other hand, this strategy is unlikely to close the quality gap between battery electric vehicles and combustion cars. However, closing this gap is crucial for electric cars to replace combustion cars in the near future.

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, quality, and margins. On the other hand, the downward trend in the cost of providing quality puts upward pressure on prices, qualities, and margins. The total effect will depend on the amount of the subsidy, the magnitude of the marginal cost decrease, as well as consumer preferences, and the current price and quality levels. Depending on these factors, the total effect can be either positive or negative for price and quality.

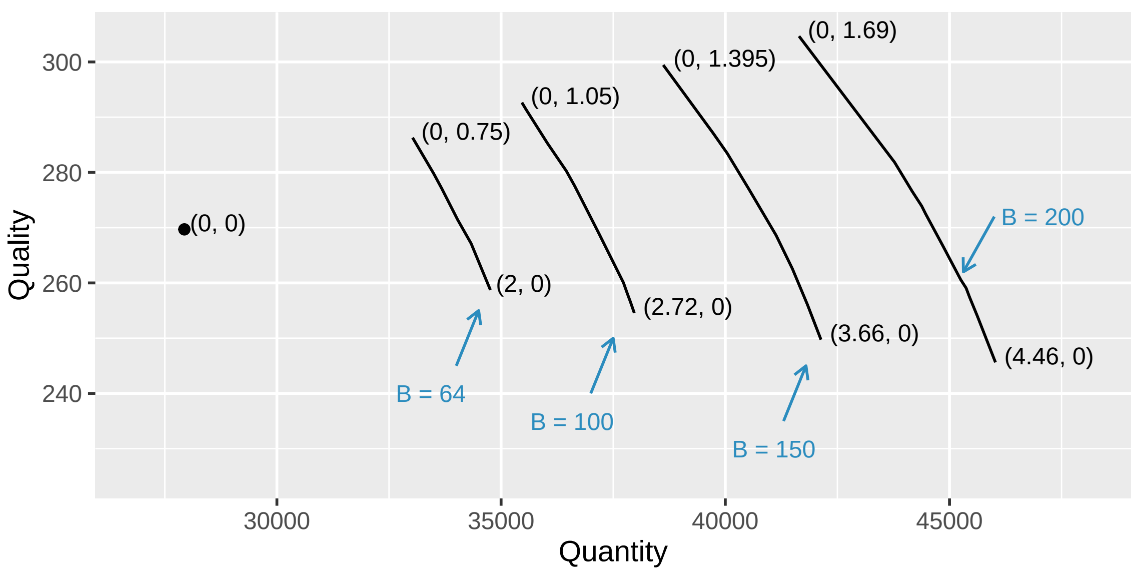
These countervailing effects can also explain the evolution of price and quality over the sample period (see p.e. Figure 2): Until including 2015, there was no subsidy in place, meaning that there only was upward pressure on prices and qualities, explaining the increasing slopes of both curves. Starting with the introduction of the subsidy in 2016, we see that prices first plateau and then come down, suggesting that the subsidy's negative price effect dominated the marginal cost drop's positive price effect. The net impact on quality stays positive, even though the increase seems to slow down.

Incentive-based subsidies

One way to prevent the downward pressure of subsidies on quality is to put incentives on quality. Policymakers in California and China do so by making the total subsidy amount a function of the driving range (Rokadiya and Yang, 2019). In this section, I consider a simple version of such incentive-based subsidy schemes. In particular, I evaluate subsidies of the form $\lambda_j = \lambda_0 + \lambda_1 q_j$. Note that while simple, this scheme nests both the flat subsidy and the marginal cost decrease. 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 quality. This case is equivalent to a decrease in the marginal cost of providing quality, while 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: It can treat it as quality becoming cheaper, using it to increase quality, or treat it as the product becoming cheaper overall, using it to decrease prices. On the other hand, a pure quality-based subsidy forces firms to treat the subsidy as a decrease in the marginal cost of providing quality. One can interpret the intermediate cases where both λ_0 and λ_1 are non-zero as putting weights on a general and a quality-specific marginal cost decrease.

Figure 6: Quality-quantity trade-off at different subsidy schemes (λ_0, λ_1) and budgets

Subsidy in €1,000, budget in € milliom



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 $(\tilde{\lambda_0}, \tilde{\lambda_1})$, I solve for the counterfactual equilibrium vector of prices and qualities and compute the total cost of the scheme. If the cost is either above or below B, I discard the candidate; if the cost is equal to B (up to a small tolerance), I keep the candidate. I perform this search for different values of B: In the first search, I set B equal to the observed subsidy scheme's cost in 2018 and then increase B subsequently in further searches.

Figure 6 shows the results. I plot the quantity- and quality-maximizing values for (λ_0, λ_1) at each budget, as well as the "initial point" without subsidies from Table 4. We can see that with incentive-based subsidy schemes, there exists a clear trade-off between increasing diffusion of battery electric vehicles and increasing their quality. We also see that the pure incentive-based scheme *always* maximizes quality, and the flat scheme *always* maximizes quantity with the other minimized in each case. Intermediate values of (λ_0, λ_1) lead to intermediate outcomes in terms of quality and quantity. The slope of the iso-budget lines gives the marginal rate of substitution between quality and quantity. The steeper the absolute value of the iso budget line's slope, the weaker the quality-quantity trade-off. Table 5 shows the market outcomes of the flat schemes and the pure incentive-based schemes at the different budgets. When the budget is set to €200 million, for instance, the flat subsidy ($\lambda_1 = 0$) leads to a 23km, 9%, decrease in quality and a 59% increase in quantity, 17,158 cars in absolute terms. A pure incentive-based subsidy ($\lambda_0 = 0$), on the other hand, leads to a 36km, or 13%, increase in quality but only a 44% increase in quantity, 12,775 cars in absolute terms. In other words, an extra 4383 units "costs" the policymaker 59km of quality (59km are equal to around 22% of the average quality in 2018).

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

	No subsidy	**Budget = 64 million**		**Budget = 100 million**		**Budget = 150 million**		**Budget = 200 million**	
		Inc.	Flat	Inc.	Flat	Inc.	Flat	Inc.	Flat
Sales	28,869	4,157	5,892	6,596	9,102	9,747	13,266	12,775	17,158
Quality	268.9	17	-10	24	-14	31	-19	36	-23
Price	34,557	616	-3,075	927	-4,326	1,276	-5,776	1,414	-6,993
λ_0	0	0	2,000	0	2,720	0	3,660	0	4,460
λ_1	0	750	0	1,050	0	1,395	0	1,690	0

"Inc." denotes subsidy with full incentives on quality.

Discussion These results suggest that at the observed levels of price, quality and marginal cost in 2018, a policymaker interested in maximizing diffusion merely needs to introduce flat subsidy schemes. The rationale behind this result is that consumers value lower prices relatively more than higher quality. For firms, this means that the extensive margin (increasing sales) is more important than the intensive margin (increasing the markup on existing sales). Letting firms free to choose how to pass on the subsidy will then lead to the sales-maximizing outcome where firms overshift the subsidy and decrease quality. By putting incentives on quality, the policymaker makes a part of the subsidy equivalent to a decrease in the marginal cost of range provision and forces firms to increase the quality. When subsidies are purely quality-based, firms' profit-maximizing strategy is to pass on the subsidy by improving quality. In that case, the intensive margin becomes more important than the extensive margin, leading firms to overshift by increasing quality and price.

Policy implications Taken together, the counterfactuals suggest that policymakers face a trade-off between increasing diffusion with downward pressure on quality and increasing quality with downward pressure on diffusion. A strategy aimed at maximizing diffusion may then lead to unintended side-effects in the form of lower quality. The downward trend in the marginal cost of providing quality alleviates- and can even flip- the negative effect on quality. Note that the sign of these effects depends on the levels of prices and qualities and the marginal cost of providing quality. They are thus subject to change at different levels of these variables. For the German market studied here, the results suggest that flat subsidies were indeed diffusion maximizing, albeit with a moderate overall effect. What holds regardless of the level of prices, qualities, and marginal quality provision cost is that a policymaker intending to maximize diffusion with a subsidy should be mindful of the impact of price and quality on firms' intensive and extensive margins. A subsidy aimed at maximizing diffusion should incentivize the firm to adopt a strategy that prioritizes the extensive margin. In the case of battery electric vehicles in Germany, a flat subsidy achieves maximal diffusion. Because firms' optimal reaction to the subsidy coincides with the diffusion -maximizing outcome, firms' incentives and the policymaker's incentives are aligned. Furthermore, as long as quality provision continues to become cheaper, a flat subsidy's adverse quality effects are likely to be mitigated or even dominated by a quality-enhancing effect of cheaper quality provision. The findings also suggest 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 amount of the subsidy.

This section's findings are also relevant for other markets: Policymakers often subsidize access to basic infrastructures like 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 their impact on firms' intensive and extensive margins. As we have seen in Section 2, this is an empirical exercise that needs to be carried out on a case-by-case basis.

8 Conclusion

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

I first build a simple monopoly model of quality provision to understand the mechanisms that determine how firms choose price and quality. I find that the effect of a subsidy and a decrease in the marginal cost of quality provision on price and quality is ambiguous. It depends on the relative magnitude of the price- and quality elasticities as well as the marginal cost of quality provision, making it an empirical question to find the sign of the effects on price and quality.

I then develop a structural model of demand and supply for new cars in which consumers can choose between cars of different engine types, and firms compete in prices and can set the quality of their battery electric vehicles (BEVs). I find that the marginal cost of providing quality has decreased by around 39& over the sample period. I use the estimated model to analyze how firms adjust price and quality in response to cheaper quality provision and subsidies. I find that while the cheaper quality provision led to an increase in both price and quality of BEVs, the subsidy reduced both prices and quality of BEVs. I compare the flat subsidy scheme introduced in Germany in 2016 to alternative designs that put incentives on quality provision and find that there exists a trade-off between increasing quantity and increasing quality.

The results have implications for policymakers who are interested in maximizing the diffusion of electric vehicles. It is crucial to know relative preferences for price and quality, as well as the cost of quality provision to properly design subsidies that achieve their stated goal. These insights generalize to other markets in which firms are able to adjust quality in response to subsidies. The findings suggest that the subsidy introduced in Germany increased sales by around 20% in 2018, far below the governments' goals.

My paper leaves scope for future work. First, I do not 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 important in understanding 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 quality add an additional angle to quality provision as firms may distort price and quality within their menu.

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A Monopoly model of quality provision

A.1 Proof of Proposition 2

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 $\pi_{q\lambda} > 0$. It is then straightforward to see that if $\pi_{pq} < 0$, meaning price and quality are strategic substitutes, we have $\frac{dp}{d\lambda} < 0$ and $\frac{dq}{d\lambda} > 0$.
In the case where $\pi_{pq} > 0$, things become more ambiguous. Note that we can write

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

It is straightforward to see that

- if $\frac{|s_p|}{s_q}$ is sufficiently large, we get $\pi_{p\lambda} < 0$ and $\pi_{q\lambda} < 0$,
- if $\frac{|s_p|}{s_q}$ is sufficiently small, we get $\pi_{p\lambda} > 0$ and $\pi_{q\lambda} > 0$ and
- for intermediate cases, we get $\pi_{p\lambda} < 0$ and $\pi_{q\lambda} > 0$.

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.

A.2 Link to Spence (1975)

The demand function can be written as $S = s(p, q)$, where S is quantity demanded and $s(p, q)$ is the demand function. In order to find p_{sq}, we can make use of the implicit function theorem: First, define $F(s, p, q) \equiv S - s(p, q)$. We have that $\frac{\partial p}{\partial s} = -\frac{F_s}{F_p}$ and subsequently $\frac{\partial^2 p}{\partial s \partial q} = -\frac{F_{sq}F_p - F_s F_{pq}}{F_p^2}$. Plugging in the expressions yields

$$\frac{\partial^2 p}{\partial s \partial q} = \frac{-s_{pq}}{s_p^2}$$

The denominator is positive, so the sign is determined by the sign of s_{pq}. We can distinguish the following cases, making a connection to the sign of π_{pq}:

1. $s_{pq} < 0$ **overprovision of quality**
   (a) $\pi_{pq} < 0$
      - $\frac{\partial p}{\partial \lambda} < 0, \frac{\partial q}{\partial \lambda} > 0$

   (b) $\pi_{pq} > 0$
      - Signs of $\frac{\partial p}{\partial \lambda}, \frac{\partial q}{\partial \lambda}$ ambiguous
2. $s_{pq} > 0$ **underprovision of quality**
   - $\pi_{pq} > 0$ unambiguously
   - Signs of $\frac{\partial p}{\partial \lambda}, \frac{\partial q}{\partial \lambda}$ ambiguous

There is no one-to-one relationship between the "Spence condition" of under- or overprovision of quality and the effect of a subsidy on price and quality.

A.3 Marginal cost shock

The model can also be adapted to accommodate the effects of a shock to marginal cost: Let $c(q) = \exp(\gamma q)$, with $\gamma > 0$ a parameter scaling the marginal cost of providing quality that is given by $\frac{\partial c(q)}{\partial q} = \gamma \exp(\gamma q)$. We can then interpret a shock to the marginal cost of providing quality as a change in γ. To find the effect of such a cost shock on price and quality, we can again differentiate the system of FOCs, this time with respect to γ. This gives us

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

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

$$\begin{aligned}
\pi_{pp} &= 2s_p + s_{pp}(p + \gamma - c) \\
\pi_{qq} &= -\gamma^2 \exp(\gamma q)s - 2\gamma \exp(\gamma q)s_q + s_{qq}(p + \lambda - \exp(\gamma q)) \\
\pi_{pq} &= s_q + (p + \lambda - \exp(\gamma q))s_{pq} - \gamma \exp(\gamma q)s_p \\
\pi_{p\gamma} &= -\gamma \exp(\gamma q)s_p \\
\pi_{q\gamma} &= -q \exp(\gamma q)s_q - \exp(\gamma q)(1 + \gamma q)s.
\end{aligned}$$

This gives

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

where $\Delta \equiv \pi_{pp}\pi_{qq} - \pi_{pq}^2 > 0$ from the second order conditions of having a global maximum. We can see that if price and quality are strategic substitutes (meaning $\pi_{pq} < 0$), $\frac{dp}{d\gamma} > 0$ and $\frac{dq}{d\gamma} < 0$ unambiguously. On the other hand, if price and quality are strategic complements, the effect of a marginal cost shock on price and quality is ambiguous.

B Subsidies in a 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 $j \in \mathcal{I}$.[19] The social planner puts a subsidy on products in $\mathcal{B}$ but not on those in $\mathcal{I}$. Let us look at the firm f's profit maximization problem:

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

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

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

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

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

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

[19] 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.

meaning that the general results from Proposition 2 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.

C Additional Figures and Tables

Table 6: Summary statistics

Mean values of key characteristics

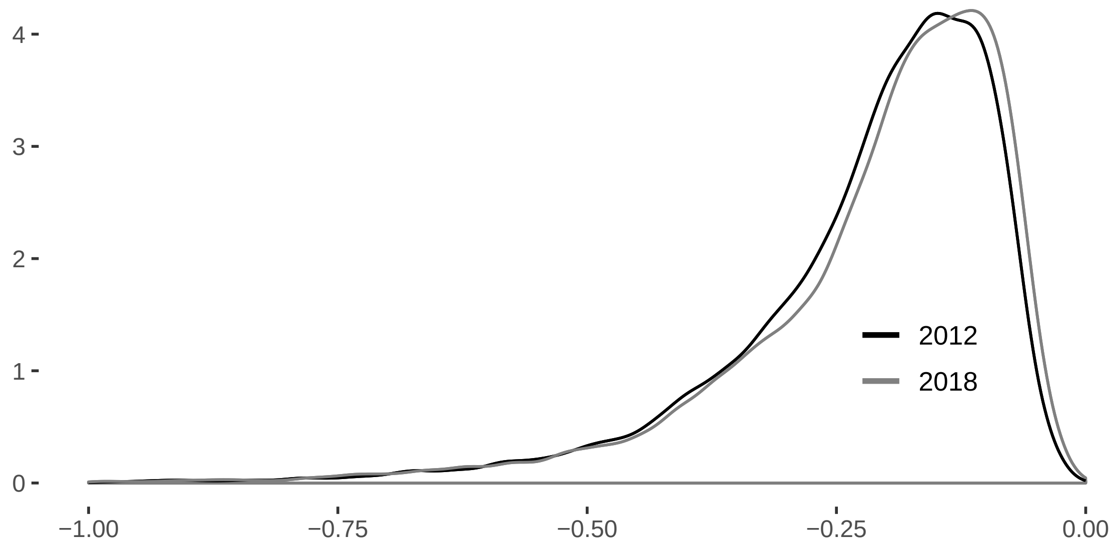
Variable	2012	2013	2014	2015	2016	2017	2018
BEV							
Price	29,380	30,156	34,104	31,384	31,774	31,925	29,555
Quality (Range in km)	168	173	202	196	213	246	259
Fuel Cost	3.77	4.14	4.2	4.04	4.1	4.21	4.21
Acceleration	2.8	2.98	3.19	2.96	3.31	3.26	2.94
Weight	1,581	1,662	1,797	1,797	1,867	1,902	1,841
Footprint	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	41,713	46,708	42,655	53,969	52,402	49,721	52,157
Quality (Range in km)	54	53	52	44	40	45	45
Fuel Cost	4.97	5.38	5.54	5.56	5.39	5.48	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	31,397	31,677	32,680	32,648	33,392	32,444	32,427
Quality (Range in km)	995	1,018	1,039	1,057	1,063	1,023	997
Fuel Cost	9.44	8.88	8.29	7.32	6.76	7.34	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 7: First Stage Estimates

	Price		Range		Range x Trend		Stations	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Exogenous Charac.								
Fuel Cost	-0.592	(0.023)	-0.001	(0.000)	0.005	(0.002)	0.001	(0.001)
Footprint	5.234	(0.134)	0.050	(0.003)	0.193	(0.018)	0.001	(0.004)
Acceleration	2.639	(0.043)	-0.021	(0.002)	-0.100	(0.010)	-0.001	(0.002)
Doors	0.954	(0.063)	-0.039	(0.002)	-0.185	(0.011)	0.000	(0.002)
BEV	0.111	(0.557)	1.804	(0.023)	10.389	(0.138)	0.524	(0.041)
PHEV	2.507	(0.640)	0.107	(0.033)	5.682	(0.257)	0.486	(0.062)
Own State	0.000	(0.234)	0.000	(0.009)	0.000	(0.055)	0.061	(0.018)
Trend	-0.400	(0.016)	-0.010	(0.001)	-0.034	(0.004)	0.002	(0.001)
PHEV								
Range x PHEV	-0.058	(0.010)	0.007	(0.001)	0.061	(0.007)	-0.002	(0.001)
Range x Trend x PHEV	1.138	(0.170)	-0.108	(0.013)	-2.447	(0.113)	0.056	(0.028)
Cost shifters								
LIC Price	0.910	(0.069)	-0.022	(0.004)	-1.040	(0.020)	-0.048	(0.004)
Station Subsidies	0.037	(0.015)	0.018	(0.002)	0.243	(0.011)	0.027	(0.002)
Differentiation IVs								
Price-local-own	-6.509	(0.151)	-0.160	(0.015)	-0.820	(0.089)	-0.002	(0.007)
Fuel cost-quadratic-own	0.399	(0.043)	-0.003	(0.001)	-0.015	(0.004)	0.001	(0.001)
Fuel cost-quadratic-own nest	-0.364	(0.136)	0.002	(0.002)	0.028	(0.011)	0.005	(0.002)
Acceleration-quadratic-rival	2.423	(0.105)	0.085	(0.007)	0.343	(0.047)	-0.004	(0.010)
Acceleration-quadratic-rival nest	-2.497	(0.125)	-0.094	(0.007)	-0.380	(0.051)	0.004	(0.011)
EV efficiency-quadratic-own	0.507	(0.057)	0.043	(0.008)	0.192	(0.043)	0.002	(0.007)
EV efficiency-quadratic-own nest	6.345	(0.677)	-0.122	(0.046)	-1.940	(0.353)	-0.036	(0.124)
PHEV-count-own	-10.816	(0.920)	-0.228	(0.038)	-4.159	(0.368)	0.066	(0.201)
Footprint-local-own	33.699	(1.257)	1.571	(0.102)	7.727	(0.584)	0.058	(0.056)
Footprint-local-rival	-5.930	(0.161)	0.035	(0.003)	0.127	(0.017)	-0.002	(0.004)
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	238.757		211.046		72.994		33.492	
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 8: Kernel density estimation of price sensitivity



D Full demand and supply estimates

Table 9: Full demand and marginal cost estimates

Utility			Marginal Cost		
	Coefficient	SE		Coefficient	SE
Mean Utility			**Quality Provision**		
(Intercept)	-9.508	(0.296)	Intercept	0.903	(0.027)
Quality	1.944	(0.259)	Trend	-0.081	(0.006)
Stations	2.363	(0.505)	**Baseline Marginal Cost**		
Quality x Trend	-0.134	(0.032)	Intercept	1.426	(0.140)
Fuel Cost	-0.197	(0.008)	Weight	0.301	(0.043)
Footprint	0.548	(0.055)	Fuel Efficiency	-0.048	(0.006)
Acceleration	0.320	(0.029)	KW	0.005	(0.00)
Doors	-0.226	(0.027)	Footprint	0.098	(0.020)
BEV	-12.548	(2.737)	BEV	-0.574	(0.049)
PHEV	-9.943	(2.618)	PHEV	0.190	(0.026)
Own State	1.034	(0.086)	2013	-0.023	(0.015)
Trend	-0.114	(0.008)	2014	-0.027	(0.014)
Audi	2.814	(0.089)	2015	-0.045	(0.014)
BMW	3.209	(0.096)	2016	-0.033	(0.015)
Chevrolet	0.485	(0.123)	2017	-0.069	(0.015)

Table 9: Demand and marginal cost estimates *(continued)*

	Coefficient	SE		Coefficient	SE
Citroen	0.340	(0.089)	2018	-0.099	(0.015)
Dacia	0.983	(0.148)	Audi	-0.111	(0.054)
Daihatsu	-0.432	(0.196)	BMW	-0.002	(0.055)
Dodge	-3.196	(0.306)	Chevrolet	-0.315	(0.070)
Fiat	-0.052	(0.103)	Citroen	-0.167	(0.058)
Ford	1.722	(0.093)	Dacia	-0.891	(0.068)
Honda	1.533	(0.095)	Daihatsu	-0.245	(0.052)
Hyundai	1.608	(0.094)	Dodge	-0.331	(0.078)
Jeep	0.641	(0.107)	Fiat	-0.236	(0.055)
KIA	1.115	(0.090)	Ford	-0.250	(0.057)
Lada	-0.187	(0.153)	Honda	-0.109	(0.058)
Lancia	-1.334	(0.125)	Hyundai	-0.214	(0.056)
Land Rover	1.607	(0.115)	Jeep	-0.162	(0.057)
Mazda	2.215	(0.084)	KIA	-0.244	(0.054)
Mercedes	3.137	(0.100)	Lada	-0.610	(0.068)
MINI	1.918	(0.255)	Lancia	-0.194	(0.057)
Mitsubishi	1.188	(0.107)	Land Rover	-0.160	(0.055)
Nissan	1.282	(0.098)	Mazda	-0.150	(0.055)
Opel	1.654	(0.095)	Mercedes	-0.080	(0.055)
Peugeot	0.863	(0.089)	MINI	-0.033	(0.064)
Renault	1.483	(0.091)	Mitsubishi	-0.212	(0.063)
SEAT	1.945	(0.099)	Nissan	-0.296	(0.060)
Skoda	2.785	(0.096)	Opel	-0.237	(0.054)
smart	3.207	(0.176)	Peugeot	-0.186	(0.054)
Subaru	0.243	(0.092)	Renault	-0.272	(0.056)
Suzuki	1.059	(0.093)	SEAT	-0.336	(0.054)
Tesla	1.902	(0.511)	Skoda	-0.314	(0.056)
Toyota	1.224	(0.090)	smart	-0.056	(0.098)
Volvo	1.460	(0.092)	Subaru	-0.037	(0.058)
VW	3.015	(0.089)	Suzuki	-0.208	(0.059)
Compact Executive	0.248	(0.093)	Tesla	-0.398	(0.108)
Executive	0.615	(0.146)	Toyota	-0.025	(0.055)
Luxury	1.784	(0.208)	Volvo	-0.098	(0.054)
Mid-size	0.077	(0.047)	VW	-0.232	(0.056)
Coupe	-1.392	(0.139)	Compact Executive	0.288	(0.030)

Table 9: Demand and marginal cost estimates *(continued)*

	Coefficient	SE		Coefficient	SE
Station wagon	1.437	(0.134)	Executive	0.275	(0.042)
Roadster	-1.116	(0.137)	Luxury	0.482	(0.051)
Hatchback	1.443	(0.130)	Mid-size	0.175	(0.018)
Sedan	-0.670	(0.130)	Coupe	-0.194	(0.030)
SUV	1.812	(0.121)	Station wagon	-0.258	(0.025)
Van	1.454	(0.127)	Roadster	0.063	(0.043)
ber	-0.895	(0.096)	Hatchback	-0.322	(0.025)
bra	-0.129	(0.092)	Sedan	-0.275	(0.030)
bre	0.084	(0.093)	SUV	-0.157	(0.026)
bwt	-0.496	(0.089)	Van	-0.226	(0.027)
ham	1.057	(0.113)			
hes	0.733	(0.093)			
mvp	-0.173	(0.095)			
nie	-0.281	(0.076)			
nrw	-0.590	(0.077)			
rlp	-0.264	(0.097)			
sac	-0.080	(0.084)			
san	-0.169	(0.086)			
sar	0.407	(0.098)			
swh	-0.397	(0.100)			
thr	0.151	(0.093)			
Interactions					
Price / Income	-4.802	(0.480)			
Standard Dev.					
EV	4.110	(1.024)			
Acceleration	0.036	(0.047)			

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

E Robustness to alternative corrections

Table 10 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) and Durrmeyer (2018). The second column

Table 10: Estimates of key parameters under alternative corrections for zero market shares

	Min bias	**Laplace**	**Naive**
Mean Utility			
Quality	1.944	1.852	1.960
	(0.259)	(0.248)	(0.259)
Quality x Trend	-0.134	-0.128	-0.133
	(0.032)	(0.031)	(0.033)
Charging Stations	2.363	2.317	2.482
	(0.505)	(0.486)	(0.512)
BEV	-12.548	-12.462	-13.278
	(2.737)	(2.618)	(2.759)
PHEV	-9.943	-9.996	-10.676
	(2.618)	(2.509)	(2.638)
Acceleration	0.320	0.301	0.324
	(0.029)	(0.028)	(0.029)
Interactions			
Price / Income	-4.802	-4.519	-4.887
	(0.480)	(0.450)	(0.474)
Standard Dev.			
EV	4.11	4.17	4.383
	(1.024)	(0.976)	(1.015)
Acceleration	0.036	0.052	0.037
	(0.047)	(0.032)	(0.045)

Note: Standard errors in parentheses.

(*Laplace*) uses a correction based on Laplace's rule of succession that is used in Gandhi, Lu, and Shi (2013). It consists of replacing market shares by $\tilde{s_{jmt}} = \frac{\mathcal{M}_{mt}s_{jmt}+1}{\mathcal{M}_{mt}s_{jmt}+J_{mt}+1}$, with J_{mt} the number of products in market mt. Finally, column 3 (*Naive*) uses a naive correction where quantities of zero sales observations are assumed to be 1. We can see that the estimates do not change much across the different corrections.

F Estimated price elasticities in selected papers

Table 11 presents estimates of price elasticities from several papers using a similar structural model of demand to mine.

Table 11: 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 (2019)[3]	[-1, -1.5]
Thurk (2018)	-3.6

Own estimated price elasticity: -3.262
[1] Conlon and Gortmaker (Forthcoming) replication
[2] Conlon and Gortmaker (Forthcoming) own procedure
[3] Range of elasticities for EVs