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

Kevin Remmy

A Additional Tables

Table A1: Summary statistics

Mean values of key characteristics

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

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

Table A2: Charging station entry

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Charging stations										
Total	1,169	1,461	2,104	3,326	5,638	9,560	17,509	27,098	36,439	42,373
Level 2	1,162	1,454	2,077	3,170	5,141	8,421	15,331	23,756	31,614	36,900
Level 3	7	7	27	156	497	1,139	2,178	3,342	4,825	5,473
Pct Level 2	0.994	0.995	0.987	0.953	0.912	0.881	0.876	0.877	0.868	0.871

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

Table A3: First Stage Estimates

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

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

Table A4: Demand and marginal cost estimates

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

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

Table A5: Station entry estimation: Robustness checks

	OLS	IV	IV	IV	IV	IV
Log(EV base)	0.593	0.491	0.589	0.704	0.706	0.707
	(0.079)	(0.177)	(0.22)	(1.508)	(0.191)	(0.191)
Subsidies national	0.122	0.141	0.123	0.113	0.116	0.116
	(0.025)	(0.022)	(0.033)	(0.061)	(0.021)	(0.021)
Subsidies local	0.004	0.026	0.004	-0.016	0.022	0.022
	(0.042)	(0.059)	(0.063)	(0.043)	(0.030)	(0.030)
R-quared	0.926	0.924	0.926	0.924	0.859	0.859
First stage						
F-stat		23.811	24.239	417.561	124.797	111.219
p-value		0	0	0	0	0
R-squared		0.840	0.833	0.990	0.917	0.917
Instruments						
Gas station density		X	X	X		X
Gas prices		X		X	X	X
Road network		X	X	X	X	X
Controls						
County FE	X	X	X	X		
Time trend				X	X	X
State controls					X	X

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

Table A6: Station entry: First Stage

	Dependent variable:	
	Log(EV Base)	
Subsidies national	−0.037	(0.021)
Subsidies local	0.018	(0.022)
Gas station density	−0.030	(0.588)
Road network length	2.725	(0.500)
Gasoline price	0.804	(0.196)
Observations	112	
R^2	0.917	
F Statistic	111.219	

Note:
This table reports the first stage for the specification used in the paper (last column of Table A5.

Table A7: Station entry estimation: Using lagged station density

	OLS	IV	IV	IV	IV	IV
Log(EV base)	0.593	0.462	0.519	-0.274	0.706	0.707
	(0.079)	(0.167)	(0.20)	(0.983)	(0.192)	(0.192)
Subsidies national	0.122	0.146	0.136	0.077	0.116	0.116
	(0.025)	(0.027)	(0.034)	(0.046)	(0.021)	(0.021)
Subsidies local	0.004	0.032	0.02	-0.018	0.022	0.022
	(0.042)	(0.057)	(0.062)	(0.043)	(0.03)	(0.03)
R-quared	0.926	0.923	0.925	0.939	0.859	0.859
First stage						
F-stat		24.999	25.313	427.436	123.261	109.864
p-value		0	0	0	0	0
R-squared		0.846	0.839	0.991	0.916	0.916
Instruments						
Lagged gas station density		X	X	X		X
Gas prices		X		X	X	X
Road network		X	X	X	X	X
Controls						
County FE	X	X	X	X		
Time trend				X	X	X
State controls					X	X

Table A8: International sales numbers for BEVs in 2018

Model	Germany	Total Europe	Share Europe	Rank Germany	Austria	Belgium	Bulgaria	Czech Republic	Denmark	Finland	France	Hungary	Iceland	Ireland	Italy	Netherlands	Norway	Poland	Portugal	Romania	Slovakia	Slovenia	Spain	Sweden	UK
Ampera	384	2,152	0.178	3	5	0	0	0	0	0	0	0	0	0	0	0	0	860	0	0	0	0	0	0	903
B-Klasse	80	122	0.656	1	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*
C-Zero	102	1,247	0.082	1	64	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	*
Golf	5,722	24,521	0.233	2	3,672	411	9	260	34	274	254	637	1,403	414	75	162	113	2,361	40	56	7	1,212	74	16	7,238
IONIQ	1,694	7,115	0.238	2	1,027	4	0	43	22	124	177	63	91	104	0	52	0	0	4	18	3	1,074	70	18	2,523
Kona	371	4,035	0.092	7	584	1	10	4	0	444	34	652	444	0	0	0	47	551	1	0	0	14	16	12	842
Leaf	2,380	49,036	0.049	7	1,964	0	0	0	0	2	486	9,368	10,650	1,216	0	0	0	3,369	0	3,160	0	3,840	200	42	12,303
Model S	1,247	13,095	0.095	4	572	0	0	0	0	0	236	0	0	20	0	0	0	5,633	0	0	0	1,744	10	0	3,633
Soul	3,289	5,430	0.606	1	158	0	0	0	0	0	24	0	0	16	0	0	0	0	0	0	0	456	18	0	1,469
Zoe	6,361	32,781	0.194	2	1,485	119	0	4	432	1,042	57	13,728	1,792	67	1	0	287	426	14	942	15	2,570	111	2	3,141
e-Niro	18	1,706	0.011	5	34	0	0	0	0	0	0	410	0	0	0	0	0	0	0	0	0	198	0	0	1,046
forfour	3,654	4,860	0.752	1	38	0	0	0	0	728	0	266	138	20	0	0	0	0	0	0	0	2	10	4	*
fortwo	3,045	4,481	0.680	1	92	0	0	0	0	48	0	946	316	26	0	0	0	0	0	0	0	2	0	6	*
i3	5,088	23,481	0.217	3	1,938	144	80	0	0	950	98	0	5,428	270	0	0	0	1,602	0	524	0	1,484	164	0	5,687
iOn	147	211	0.697	1	56	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	4	0	*
up!	1,011	3,284	0.308	1	324	32	86	47	19	533	8	358	33	298	0	5	54	59	1	14	83	154	46	36	*
Focus	17	17	1.000	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*
i-MiEV	19	23	0.826	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	*

Note: This table shows total sales for all BEVs available in Germany in 2018 across Europe. It also shows the share of European sales that Germany accounts for and where Germany ranks in sales for each model in Europe. Note that * means sales data was not available for this model.

B Additional Figures

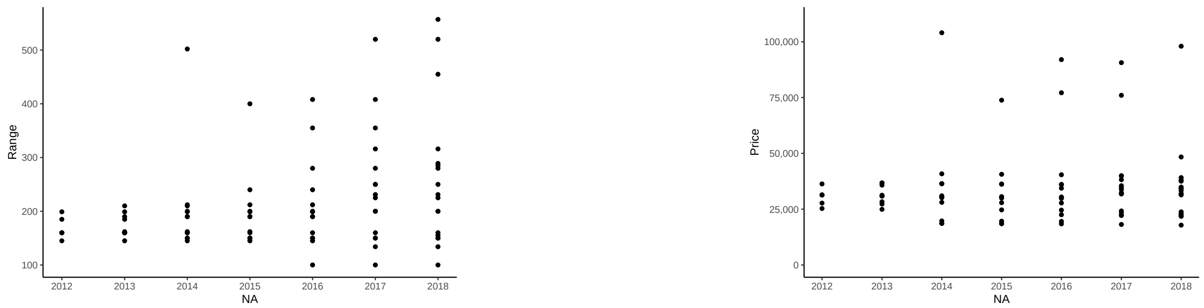

Figure B1: Price and range evolution over time

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

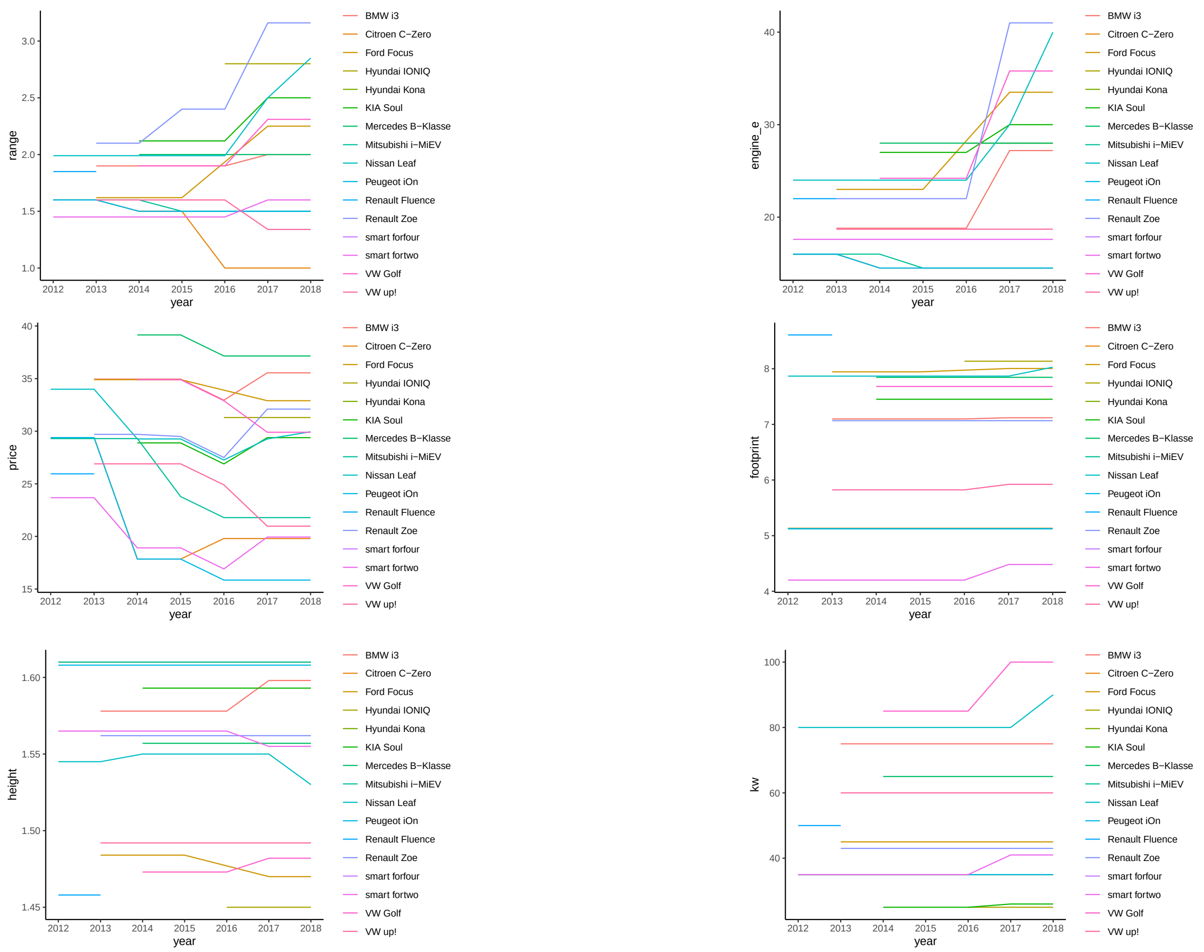

Figure B2: Evolution of selected attributes over time

Note that the Ford Focus was not offered in 2016

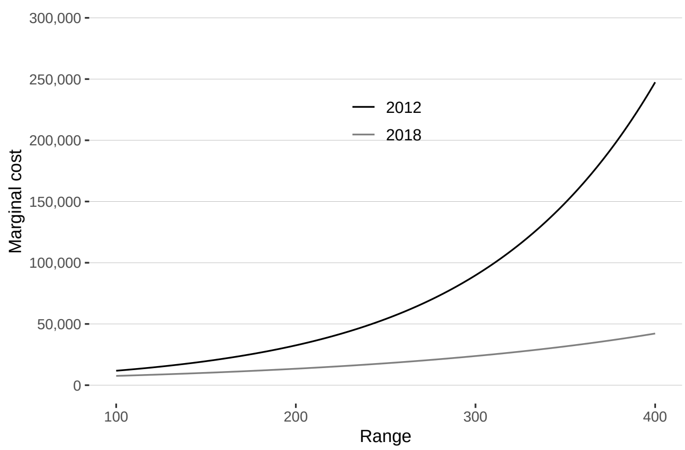

Figure B3: Estimated marginal cost functions for 2012 and 2018

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

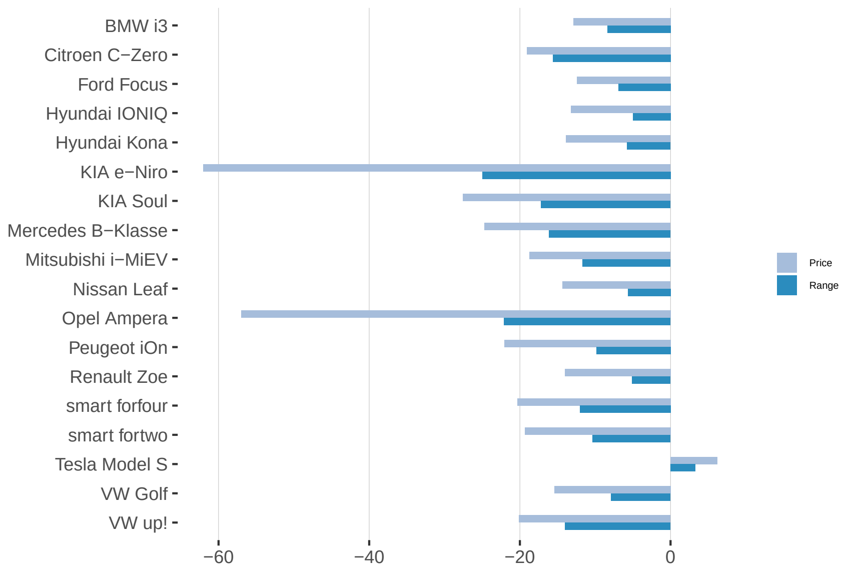

Figure B4: Percentage changes of price and range due to introduction of subsidy

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

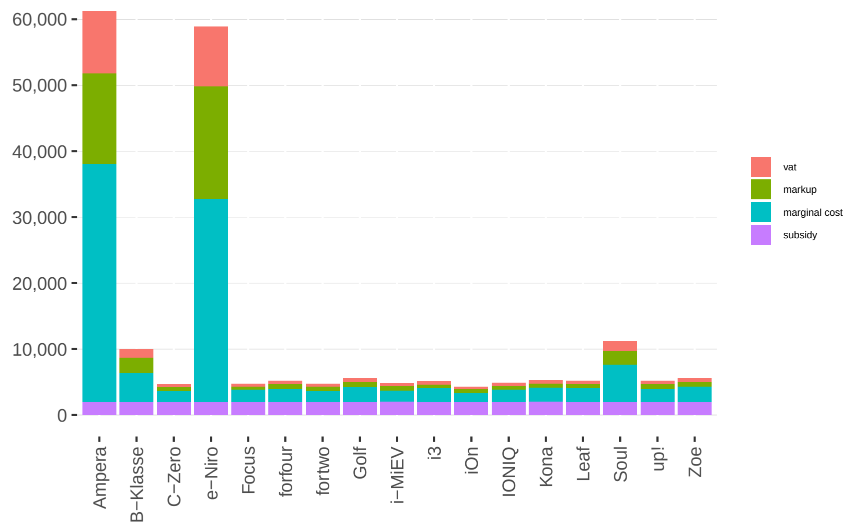

Figure B5: Decomposition of price changes in response to the purchase subsidy.

C Estimation details

C.1 Zero market shares

Approximately 4% of my observations are products with strictly positive national-level sales but zero state-level sales. Zero sales pose a problem in random coefficient demand models, as the estimation procedure is not well defined when zero sales are present. Deleting observations with zero sales from the sample is problematic because it alters the market structure and makes these products unavailable in counterfactual analyses. There exist approaches in the literature to accommodate zero sales in random coefficient demand models.[1] I follow Xavier D'Haultfœuille, Isis Durrmeyer and Philippe Février (2019) and use a simple correction of state-level market shares:

$$s_{jm}^{c} = \frac{q_{jm}^{obs} + 0.5}{\mathcal{M}_m},$$

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

C.2 Estimation of the car demand side

On the demand side, the vector of parameters to be estimated is given by $\theta_d \equiv (\beta_i^x, \beta^r, \alpha)$. I allow for random coefficients on characteristics for which I believe consumer heterogeneity matters: the driving range, an *EV* dummy for battery- and plug-in hybrid vehicles and *Fuel Cost*, measured in €/100 km. The random coefficient on range allows for flexible substitution patterns between EVs with different range levels. The random coefficient on the *EV* dummy allows for flexible substitution between electric cars and combustion engine cars. Obtaining such flexible substitution patterns is crucial for studying the market outcomes of subsidy schemes, as substitution between EVs with different range levels and across engine types drives these outcomes. The random coefficient on *Fuel Cost* allows consumers to have idiosyncratic preferences for a characteristic that proxies the usage cost of cars. Additionally, substantial differences across engine types exist in the fuel cost per 100 km, which renders the substitution

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

patterns between cars of different engine types more flexible. I include a trend in the mean taste for range, possibly capturing taste changes for range over time. In addition, I add several characteristics for which I only estimate the mean taste, including the number of public charging stations per 10,000 inhabitants, fuel cost, footprint, doors, dummies for electric vehicles, a linear time trend, and a dummy if the firm has its headquarters in the state considered.[2] I also add brand, class, body, and state–fixed effects. All remaining unexplained variation is then collected in ξ_{jmt}, which is interacted with the instruments described in the previous section to build moment conditions of the form $E[z^d_{jmt}\xi_{jmt}] = 0$, with z^d_{jmt} as an instrument. Stacking ξ_{jmt} across products and markets into a column vector ξ, I obtain the GMM objective function to be minimized:

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

where Z^d contains the instruments and W^d is a positive definite weighting matrix. I use the two-step efficient GMM estimator, where I use an approximation of the optimal weighting matrix based on an initial set of estimates to recover the final estimated vector of parameters. The estimation algorithm that I use is described in detail in Steven Berry, James Levinsohn and Ariel Pakes (1995) and Aviv Nevo (2001). In the estimation, I account for various numerical issues that recent literature has drawn attention to (Jean-Pierre Dubé, Jeremy T Fox and Che-Lin Su (2012), Christopher R Knittel and Konstantinos Metaxoglou (2014), Daniel Brunner, Florian Heiss, André Romahn and Constantin Weiser (2025), Christopher Conlon and Jeff Gortmaker (2020)). First, I approximate the market share integral with 1,000 draws using modified Latin hypercube sampling. Stephane Hess, Kenneth E Train and John W Polak (2006) and Brunner et al. (2025) show that this method performs very well in random coefficient logit models and provides better coverage than the more frequently used Halton sequences. Second, I set the tolerance level in the contraction mapping of the inner loop to 1e-14 to solve for the demand-side unobservables. A tight tolerance prevents numerical errors from the inner loop from propagating to the outer loop. Third, I use the low-storage BFGS algorithm of NLOPT. Fourth, I initialize the optimization routine from many different starting values to search for a global minimum. Finally, I check first- and second-order conditions at the obtained minimum to ensure the optimizer did not get stuck at a saddle point.

C.3 Estimation of the car supply side

With demand estimates in hand, I can derive implied markups and marginal costs. The vector of parameters to be estimated is $\theta_s = (\psi, \gamma_0, \gamma_1)$. I let the baseline marginal cost depend on several observed characteristics, such as the product's weight, footprint, fuel efficiency, and

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

engine power measured in kilowatts. I also include year, firm, class, and body-fixed effects. All remaining unobserved marginal cost-shifters are then collected in ω_{jt}.

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

The first-order conditions in (1) and (2) can be solved for the pair of supply-side unobservable vectors ω and η. I then interact them with the instruments described in the previous section to build moment conditions of the form $E[z^s_{jt}\omega_{jt}] = 0$ and $E[z^s_{jt}\eta_{jt}] = 0$. Letting ρ_{jt} = (ω_{jt}, η_{jt}) and stacking across products and markets, I then obtain the GMM objective function to be minimized:

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

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

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

C.4 Estimation of the charging station entry side

The estimation of the charging station side is straightforward. Once I obtain equation (8), I estimate υ using two-stage least squares. In the estimation, I include national-level subsidies and state-level subsidies. I set the national-level subsidies equal to € 8,000. The vast majority of stations (around 86.7%) in my sample received a subsidy of up to € 3,000 for the installation and of up to € 5,000 for the connection to the grid. In the preferred specification, I also include a linear time trend and state-level controls. In particular, I use the population density (which varies across time) and the surface area of the state (which does not vary across time). I allow the time trend to be different for the states of Berlin, Hamburg, and Bremen. These three states are city-states in which the development of the EV market is likely to be very different

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

from other, less dense states. I also include a city–state dummy to control for unobserved differences between these states and the other states. I also run an alternative specification in which I replace these state-level controls with a state fixed effect, which I report along with other robustness checks in Appendix Table A5. I use data from 2015 to 2021 to estimate the station entry side. The reason for this choice is twofold. First, adding later years to the data set offers more cross-sectional and temporal variation in state subsidies and the EV base. Second, I only have information on gasoline and diesel prices starting in late 2014, so I cannot build the gas price instrument for 2012 to 2014.

D Results under simultaneous moves

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

Table D1: Results under simultaneous moves

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

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

Table D1 holds the estimation results. As outlined in Section IV, elasticities and markups change. Also, the supply-side results change, even though we can see that they do so only slightly. We still recover the drop in the marginal cost of providing range. Table D2 holds the results for the grid search under simultaneous moves. Akin to Table 6, I report the subsidy schemes that optimize different policy objectives, along with the observed scheme and the case in which there are no subsidies. Table D2 suggests that the results are robust to using this alternative timing assumption. Results in the simultaneous move game are similar to the ones found in Section V.B. The exact amounts of the subsidies, as well as the effects on range, prices, and policy objectives, only change slightly. Overall, the conclusions we could draw from Section V.B go through.

Table D2: Comparison of subsidy schemes (simultaneous moves)

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

E Supply side: details

E.1 Matrix form

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

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

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

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

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

$$\begin{cases} \mathbf{s} + (\mathbf{p} + \boldsymbol{\lambda} - \mathbf{mc})\Delta_p = 0 & (1) \\ -\dfrac{\partial \mathbf{mc}^B}{\partial \mathbf{r}^B}\mathbf{s}^B + \Delta_r^B(\mathbf{p}^B + \boldsymbol{\lambda}^B - \mathbf{mc}^B) + \Delta_r^I(\mathbf{p}^I + \boldsymbol{\lambda}^I - \mathbf{mc}^I) = 0, & (2) \end{cases}$$

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

E.2 Marginal cost specification

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

$$\log(mc_{jt}(q_{jt}, w_{jt}; \theta_s)) = \underbrace{w_{jt}\psi + \omega_{jt}}_{\substack{\text{baseline}\\ \text{marginal cost}}} + \underbrace{(\gamma_0 + \gamma_1 t + \eta_{jt})r_{jt}}_{\substack{\text{marginal cost of}\\ \text{providing range}}}, \tag{3}$$

where w_{jt} is a vector of observed cost-shifters, ω_{jt} is a cost shock observed by firms but unobserved by the researcher, t is a linear time trend, η_{jt} is a range-specific marginal cost shock observed by firms but unobserved by the researcher, and $\theta_s \equiv (\psi, \gamma_0, \gamma_1)$ is a vector of parameters to be estimated. Note that the second part of (3) is zero since I do not model their range choices for products that are not battery electric vehicles since I do not model their range choices. In the case of BEVs, I assume that the marginal cost of providing range depends on an intercept term, a linear time trend allowing for less costly range provision over time, and an unobserved, product-specific component. The exponential nature of fixed costs is in line with the technology facing firms: Increasing range may be achieved by increasing the size of the battery. A kilometer of range becomes more costly at higher range levels. One reason is that the car's dimensions restrict the size of the battery. Additionally, other ways of increasing range, such as achieving a higher energy density of batteries, may also be constrained by technological factors and make range provision costlier at higher range levels.

E.3 Equilibrium price and range levels

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

$$\begin{cases} \mathbf{p} = \mathbf{mc} + \Delta_p^{-1}\mathbf{s} & (4) \\ \mathbf{r} = \dfrac{1}{\mathbf{c_1}} \log\left(\dfrac{\Delta_r^B(\mathbf{p}^B - \mathbf{mc}^B) + \Delta_r^I(\mathbf{p}^I - \mathbf{mc}^I)}{\mathbf{s}^B\mathbf{c}_1}\right) - \dfrac{\mathbf{c}_0}{\mathbf{c}_1} & (5) \end{cases}$$

F Counterfactual details

F.1 Procedure

This section presents details on the counterfactual procedure.

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

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

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

   (a) Compute a new price vector using the price FOC given by equation (4). Take a small step towards the simulated price vector: $\boldsymbol{p}^{h+1} = \alpha \boldsymbol{p}^* + (1-\alpha)\boldsymbol{p}^h$, with α small.

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

   (c) Compute a new range vector using the range FOCs given by equation (5). Take a small step towards the simulated range vector: $\boldsymbol{r}^{h+1} = \alpha \boldsymbol{r}^* + (1-\alpha)\boldsymbol{r}^h$, with α small.

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

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

3. Update charging stations by iterating on equation (7) until convergence. Extract the new charging station vector $\boldsymbol{d}^{l+1}$.

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

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

F.2 Details on grid search

To find the budget-equivalent values for $\boldsymbol{\lambda}$, I use the following procedure: At a given budget B, I search for values of $\boldsymbol{\lambda}$ that satisfy the budget constraint. I employ a grid search where at each candidate value $\tilde{\boldsymbol{\lambda}}$, I solve for the counterfactual equilibrium vector of prices and ranges as outlined in Appendix F and compute the total cost of the scheme. If the cost is either above or below B, I discard the candidate value, and if the cost is equal to B (up to a small tolerance), I keep it. For each candidate point, I compute the mean price and range of BEVs, the quantity sold of BEVs, consumer surplus[4], and fleet emissions. To calculate fleet emissions, I rely on data that gives me the average distance driven by fuel type coming from a survey conducted by the German Federal Highway Research Institute (Marcus Bäumer, Heinz Hautzinger, Manfred Pfeiffer, Wilfried Stock, Barbara Lenz, Tobias Kuhnimhof and Katja Köhler, 2017).[5]

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

G The role of internalizing spillovers on price and range choices

In the estimation of the model, I find that ignoring indirect network effects leads to markups that are 19% higher on average and that BEVs act as complements in both price and range. In the first set of counterfactuals that I perform, I take a closer look at the relationship between indirect network effects and firms' price and range choices. In particular, I am interested in how the complementarity between BEVs affects market outcomes. I consider two scenarios. In the first scenario, I assume firms do not internalize the effect of their price and range choices on any other EV, not even the EVs in their product portfolio. This scenario amounts to modifying the matrices Δ_p and Δ_r^B in equations (1) and (2). Specifically, I set each entry $(j, k),\ j \neq k$ in (1) and (2) to zero if row j and row k correspond to an EV. Note that doing so is different from

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

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

assuming single-product firms, as firms still internalize diverted sales towards their own firm's combustion cars. In the second scenario, I assume firms internalize the effects of their price and range decisions on all other EVs in the market. This scenario also amounts to modifying the matrices Δ_p and Δ_r^B in equations (1) and (2). Specifically, I set each entry (j, k) in (1) and (2) to one if row j and row k correspond to an EV. Note that doing so is different from assuming a complete merger to monopoly in the car market as firms still only internalize diverted sales towards own-firm combustion cars and not towards combustion cars produced by other firms. Given that the vast majority of new car sales still come from combustion cars in 2018, assuming a full merger to monopoly would likely entail large coordinated effects that would pollute the effect of merely assuming full internalization on rival firm EVs.

Table G1: Market outcomes with different market structures

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

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

The results are in Table G1. We can see that in the scenario in which firms do not internalize the effect of their price and range choices on any other EV (column "No internalization"), BEVs would, on average, be more expensive and have a higher range. Sales of BEVs would be lower and fewer charging stations would enter. These results suggest that complementarities in price and range choices lead to BEVs that are cheaper but also have a slightly lower range. These cheaper, lower-range BEVs generate a large number of extra sales and also spur charging station entry. On the other hand, we can see in the last column that when firms internalize the effect of their price and range choices on all other EVs in the market, BEVs are, on average, substantially cheaper and have a much lower range. However, these inexpensive, low-range BEVs generate large additional sales and strong charging station entry. Overall, consumer surplus would increase by around €200 million in this case. However, much of the increase in consumer surplus comes from increased substitution from the outside option. The rest of the consumer surplus increase comes from the fact that EVs become substantially cheaper, and the fact that there are more charging stations available. Interestingly, firms have an incentive to reduce the range of their cars when internalizing indirect network effects. One reason for this may be that consumers have a relatively low willingness to pay for range. Another reason is the indirect network effects at play: Reducing the price of BEVs induces more charging station entry. This increase in charging stations makes it possible for firms to reduce range and generate additional sales by further reducing the price. The indirect network effects strengthen the incentives of firms to reduce price and range.

H Alternative model with range-charging station interaction

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

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

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

The estimation results in Table H1 suggest that range and charging stations are substitutes, with the valuation of range being a decreasing function of the number of charging stations and vice versa. Introducing the log of charging stations has implications for the first-order conditions and the estimates of c_1, the term pre-multiplying range in the marginal cost function, because the level of range is now measured in kilometers instead of 100 kilometers. However, I obtain similar estimates of the marginal cost of providing range.

In Table H2, we see that the trade-off between maximizing EV sales, maximizing consumer and total surplus, and minimizing CO2 emissions persists. There are slight changes to the type of subsidy schemes that optimize different policy goals. Instead of focusing on subsidizing charging station entry, consumers now prefer a scheme that balances incentivizing charging station entry and incentivizing range provision. The EV sales-maximizing scheme looks very similar to the one in the main specification, with the policymaker having an incentive to focus most of the spending on flat purchase subsidies. To minimize CO2 emissions, policymakers

Table H1: Estimation results with interaction

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

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

Table H2: Comparison of subsidy schemes: range-station interaction

Scheme	Price	Range	Sales	Stations	CO2	CS	TS
(0, 0, 0)	36,147	277	25,686	9,570	5,196,955	43,198	64,523
(2, 0, 8)	-3,365	-19	+9,075	+7,939	-4,750	+87	+135
(3.15, 0, 4)	-4,470	-16	+14,685	+1,850	-7,348	+107	+169
(3.25, 0, 2.85)	-4,501	-14	+15,109	+797	-7,529	+107	+168
(3.25, 0, 2.85)	-4,501	-14	+15,109	+797	-7,529	+107	+168

should increase the flat part of the purchase subsidy and decrease the charging station subsidy. Again, this scheme looks very similar to before. Overall, price and range adjustments are less substantial compared to the model in the main part of the paper. This is because shifting spending to purchase subsidies reduces charging station entry, which increases consumers' willingness to pay for range and hence increases firms' incentives to provide it, limiting the scope for large range reductions and accompanying price reductions.

I Robustness to alternative corrections

Table I1 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, Durrmeyer and Février (2019). The second column (*Laplace*) uses a correction based on Laplace's rule of succession that is used in Amit Gandhi, Zhentong Lu and Xiaoxia Shi (2013). It consists of replacing market shares by $s_{jmt}^{\sim} = \frac{\mathcal{M}_{mt}s_{jmt}+1}{\mathcal{M}_{mt}s_{jmt}+J_{mt}+1}$, with J_{mt} the number of products in market mt. Finally, column 3

(*Naive*) uses a naive correction where quantities of zero sales observations are assumed to be 1. We can see that the estimates barely differ across the different corrections, leading me to conclude that the prevalence of zero sales does not pose a serious threat in my estimation.

Table I1: Estimates of key parameters under alternative corrections for zero market shares

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

Note: Standard errors in parentheses.

J Estimated price elasticities in selected papers

Table J1 presents estimates of price elasticities from several papers using a similar structural model of demand to mine.

K A model of quality provision

K.1 Monopoly

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

Table J1: Estimated price elasticities of selected papers

Author(s)	Price elasticity
Arie Beresteanu and Shanjun Li (2011)	-10.91
Berry, Levinsohn and Pakes (1995)[1]	-3.928
Berry, Levinsohn and Pakes (1995)[2]	-3.461
Li (2023)	-2.732
Thomas Klier and Joshua Linn (2012)	-2.6
Giulia Pavan (2017)	-2.85
Mathias Reynaert and James Sallee (2021)	-5.45
Katalin Springel (2021)[3]	[-1, -1.5]
Jeff Thurk (2018)	-3.6
Paul LE Grieco, Charles Murry and Ali Yurukoglu (2024)[4]	-5.36

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

Set-up

Let us consider a monopolist who chooses price (p) and quality (q) of a single product sold to final consumers.[6] In my application, q would be the driving range of a car. The demand function $s(p, q)$ is increasing in quality, decreasing in price, and is twice differentiable. Cost is an increasing function of quality and is denoted $c(q)s(p, q)$. A social planner subsidizes the product with a subsidy denoted by λ, possibly to increase the diffusion of the product. This scheme mirrors the type of subsidy for electric vehicles employed in countries such as Germany.

Quality choice

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

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

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

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

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

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

$$c_q = \frac{\partial s(p,q)/\partial q}{|\partial s(p,q)/\partial p|}, \tag{6}$$

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 (6), 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 extent of this pass-through depends on the curvature of the demand curve. The more elastic the demand curve, the higher the amount of pass-through. If both the price and quality can adjust, there is no clear-cut answer to how the monopolist will react. Differentiating the system of first–order conditions gives

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

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

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

This gives

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

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

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

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

We can then conclude that

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

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

K.2 Multi-product oligopoly

In this section, I show how the main insights obtained in the monopoly case generalize to a multi-product oligopoly setting. The fact that there are cannibalization effects within a firm's product portfolio and the fact that products are differentiated within and across the product portfolio will influence the effect of a subsidy on price and quality but not alter the main conclusions. To see why, let us consider the following setting: There are $j = 1, \dots J$ products in a market. Consumers care about the quality of a subset of products $j \in \mathcal{B}$ and do not have any preferences over the quality of the remaining products $j \in \mathcal{I}$.[7] 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 are the price and quality vectors of all firms in the market, and J_f is the portfolio of firm-f products.

[7]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 strategic decisions.

The FOCs for product one are then given by

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

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

Increase of subsidy for a single product

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

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

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

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

Things become more complicated when we consider an increase in 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

$$\begin{bmatrix} \frac{dp_1}{d\lambda} \\ \vdots \\ \frac{dp_J}{d\lambda} \\ \frac{dq_1}{d\lambda} \\ \vdots \\ \frac{dq_{J_\mathcal{B}}}{d\lambda} \end{bmatrix} = \begin{bmatrix} \pi_{f(1)p_1p_1} & \cdots & \pi_{f(J)p_Jp_1} & \pi_{f(1)q_1p_1} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}p_1} \\ \vdots & \vdots & \vdots & \vdots & & \\ \pi_{f(1)p_1p_J} & \cdots & \pi_{f(J)p_Jp_J} & \pi_{f(1)q_1p_J} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}p_J} \\ \pi_{f(1)p_1q_1} & \cdots & \pi_{f(J)p_Jq_1} & \pi_{f(1)q_1q_1} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}q_1} \\ \vdots & \vdots & \vdots & \vdots & & \\ \pi_{f(1)p_1q_{J_\mathcal{B}}} & \cdots & \pi_{f(J)p_Jq_{J_\mathcal{B}}} & \pi_{f(1)q_1q_{J_\mathcal{B}}} & \cdots & \pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}q_{J_\mathcal{B}}} \end{bmatrix}^{-1} \begin{bmatrix} -\pi_{f(1)p_1\lambda} \\ \vdots \\ -\pi_{f(J)p_J\lambda} \\ -\pi_{f(1)q_1\lambda} \\ \vdots \\ -\pi_{f(J_\mathcal{B})q_{J_\mathcal{B}}\lambda} \end{bmatrix}, \tag{7}$$

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 7 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 7, 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 the 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, one can use this framework to analyze 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 the pass-through of a shock to the marginal cost of providing quality.

References

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

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

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

Brunner, Daniel, Florian Heiss, André Romahn, and Constantin Weiser. 2025. "Simulation error and numerical instability in estimating random coefficient logit demand models." *Journal of Econometrics*, 247: 105953.

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

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

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

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

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

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

Grieco, Paul LE, Charles Murry, and Ali Yurukoglu. 2024. "The evolution of market power in the us automobile industry." *The Quarterly Journal of Economics*, 139(2): 1201–1253.

Hess, Stephane, Kenneth E Train, and John W Polak. 2006. "On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit model for vehicle choice." *Transportation Research Part B: Methodological*, 40(2): 147–163.

Klier, Thomas, and Joshua Linn. 2012. "New-vehicle characteristics and the cost of the Corporate Average Fuel Economy standard." *The RAND Journal of Economics*, 43(1): 186–213.

Knittel, Christopher R, and Konstantinos Metaxoglou. 2014. "Estimation of random-coefficient demand models: two empiricists' perspective." *Review of Economics and Statistics*, 96(1): 34–59.

Li, Jing. 2023. "Compatibility and investment in the us electric vehicle market." *Working Paper*.

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

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

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

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

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

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

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