Evaluating Norway's electric vehicle incentives

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ABSTRACT

Since the advent of Electric Vehicles (EVs), policymakers worldwide have implemented a wide array of policy tools to stimulate their adoption. Our aim is to assess the effectiveness of these tools and explore their associated trade-offs. Norway, with its strong incentive framework and substantial EV market share, provides an ideal study setting. Using new car registration data from 2000 to 2021, we evaluate Norway's taxes on fossil fuels, EV purchase tax exemption, and other incentives like road toll discounts. Our results show that purchase tax incentives are particularly effective in promoting EV adoption: removing the EV exemption from purchase taxes would reduce the EV market share to 25 percent from the 66 percent observed in 2021, increase CO_2 emissions of new cars sold by 170 percent, reduce their total weight by 22 percent, and reduce the number of new cars sold by 10 percent. Furthermore, in anticipation of the projected phaseout of Internal Combustion Engine Vehicles (ICEVs) by major economies, we conduct a forward-looking analysis comparing this scenario to potential levels of differentiated purchase taxes. Findings show that, accounting for all relevant trade-offs, leveraging taxes to influence EV adoption may be a more desirable strategy than implementing an outright ban.

Keywords: Environmental taxes, automobiles

JEL classification: H23, L62, Q58

1 Introduction

The transition from internal combustion engine (ICE) to electric vehicles (EV) is widely considered a key component of emissions reduction strategies. By some estimates, road transport accounts for 15 percent of world carbon dioxide (CO_2) emissions, compared with

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about 2.5 percent from aviation.[1] Major economies are planning a complete phaseout of ICE vehicles, with California and the EU envisaging bans on their sale by 2035.[2]

The electrification of the vehicle fleet in Norway has been faster than in most countries. EVs comprised 66 percent of new car sales in 2021, against 3 percent in the US and 9 percent in the EU.[3] After Norway, the European countries with the highest EV share in new car sales are Iceland (28 percent), the Netherlands and Sweden (both 20 percent), and Germany and Denmark (both 14 percent).

An important factor in driving EV uptake has been the dramatic improvement in the range and quality of electric cars marketed. In 2010, only two car brands offered EVs in the Norwegian market, while in 2021, 33 out of 42 brands did. Sales-weighted mean motor power for EVs was more than four times higher in 2021 than in 2010. This increase in EV quality and variety explains why the EV market share in Norway was much higher in 2021. But since the improvement in EV quality and product range is a global phenomenon, we must turn to national policies to explain the high electric market share in Norway.

In this paper, we quantify the effects of different policy instruments on the EV market share in Norway. The most noticeable feature of the Norwegian electrification policies is the favourable treatment of EVs in car puchase taxes. They are exempt from value-added tax, which is otherwise 25 percent of pre-tax price, and the CO_2- and weight-based *registration tax*, which is on average 45 percent of the pre-tax price for ICE vehicles in 2021.[4] A second factor is the substantially lower energy cost of driving an EV, which is partly due to taxes on fossil fuels. A final set of incentives includes bus lane access, exemption from or discounts on road tolls, car ferry fares, and parking charges.

Our main aim is to assess the role that each of these three types of policy levers has played in EV uptake. We do this by using sales and price data for the period 2000 to 2021 to estimate how the demand for different products responds to changes in the energy cost of driving and in price or purchase taxes.[5] Because our data do not include variation in toll road discounts, bus lane access, etc., we cannot identify the separate effects of each of these factors. Instead, they are subsumed in an estimated EV-specific effect.

To assess the three groups of EV incentives, we look at counterfactual experiments where

[1] https://ourworldindata.org/co2-emissions-from-transport

[2] https://www.gov.ca.gov/2022/08/25/california-enacts-world-leading-plan-to-achieve-100-percent-zero-emission-vehicles-by-2035-cut-pollution/ ; https://www.reuters.com/markets/europe/eu-approves-effective-ban-new-fossil-fuel-cars-2035-2022-10-27/.

[3] Hybrids are 22 percent of sales in Norway, 6 percent in the US and 9 percent in the EU. For US and EU numbers, see https://www.bts.gov/content/gasoline-hybrid-and-electric-vehicle-sales ; https://www.eea.europa.eu/ims/new-registrations-of-electric-vehicles.

[4] Hybrids are not exempt, but pay a lower rate because of low official CO_2 emissions and a weight discount in the tax calculation.

[5] We use the term 'purchase taxes' to encompass both value-added tax and the registration tax.

(a) there is no energy cost differential between ICE vehicles and EVs, (b) EVs and hybrids pay the same taxes as similar ICE vehicles, and (c) the EV preference effect corresponding to a catch-all for "all other reasons to prefer an EV" is set equal to the average effect for non-EVs, or alternatively set to zero. We find that (a) reduces EV market share from 66 percent to 55 percent, (b) to 25 percent, (c) to between 41 percent (when the EV effect is set to zero) and 60 percent (when the EV effect is set to the non-EV average), and the combination of all three reduces the EV market share to 14 percent. Because of substitution to ICE vehicles, the total number of new cars sold falls by a relatively moderate 10 percent even in the combined counterfactual.

In a demand function, price is likely to be correlated with unobserved demand shocks. To deal with this we use the registration tax as an instrumental variable for price.[6] The tax is a convex increasing function of product characteristics and therefore partially correlated with price after controlling for the linear effect of product characteristics. Our exclusion restriction is that the tax is irrelevant for consumer choices after controlling for price, observable product characteristics and product fixed effects. We discuss some limitations of linear models in this context, and the importance of modelling substitution patterns in a realistic way.

A second goal of the paper is to quantify some of the tradeoffs involved when designing EV incentives. EVs are heavier than ICE vehicles, and consequently have higher non-exhaust particulate matter emissions from tire, brake, and road surface wear and resuspension of road dust. Our results show that equal tax treatment of all vehicles (counterfactual (b)) reduces the total weight of vehicles sold by 22 percent relative to the current EV-friendly tax regime. On the other hand, it triples the sales-weighted mean CO_2 emissions of new vehicles from 32 to 95 g/km, while the total emissions increase by slightly less (170 percent) because the number of new cars sold is lower.

In a partial equilibrium welfare analysis, counterfactual (b) obviously raises tax revenue, but reduces consumer and producer surplus. The sum of these effects is a reduction in total surplus per new car sold in 2021 of 25,000 NOK (Norwegian kroner; approximately 2900 USD)[7] or 5.6 percent of the average sales price. That is, even without counting the value of emissions reductions, the tax exemption is welfare enhancing.[8]

[6]Sales taxes are used as an instrument for price in the cable TV market in Goolsbee and Petrin (2004) and in the car market in Thomassen (2017).

[7]Throughout the paper we the Norwegian currency unit *kroner*, abbreviated NOK, for all monetary values. For ease of interpretation, we also provide US dollar equivalents, using the average exchange rate for 2021, 8.6 NOK/USD provided by Norges Bank at `https://www.norges-bank.no/en/topics/Statistics/exchange_rates/?tab=currency&id=USD`. Note that the NOK/USD exchange rate has varied from about 5 in 2008 to over 11 in 2023, so that USD numbers should not be taken too literally.

[8]Distributional effects – welfare improvement accrues disportionately to relatively high-income buyers of new EVs – is an interesting topic for research, but outside the scope of this paper. Valuing emissions reductions is made more difficult by the fact that while EVs have zero on-the-spot CO_2 emissions, they

The Norwegian EV tax incentives are often labelled 'subsidies' and considered a luxury policy that is feasible only because "Norway's fossil fuel heritage (...) helped to cushion the loss of tax revenues".[9] But since most countries have much lower car purchase taxes than Norway, a country that wished to copy the Norwegian system would do so by raising taxes on ICE vehicles, not by subsidizing EVs. Norway's high purchase taxes on ICE vehicles might appear politically infeasible in the US and elsewhere. However, given that an outright ban on non-EVs has emerged as a serious policy option, differentiated purchase taxes may be an attractive alternative.

In a final and more forward-looking analysis, which anticipates the issue of too many (and too heavy) EVs, we assess the relative merits of differentiated purchase taxes and a ban on non-EVs. We do this with a set of three counterfactuals where EVs pay a tax rate similar to that currently paid for ICE vehicles, and where ICE vehicles and hybrids (d) pay twice this rate, (e) four times this rate, or (f) are removed from the consumers' choice set – corresponding to a ban. While counterfactual (f) necessarily yields a 100 percent market share for EVs, heavy taxation can achieve a similar outcome, with counterfactuals (d) and (e) resulting in EV market shares of 76 and 95 percent, respectively. Without accounting for the value of emissions reductions, counterfactuals (d), (e) and (f) give total welfare losses per vehicle sold in 2021 of, respectively, 86,000 NOK, 135,000, and 156,000 (or 19, 30, and 35 percent, respectively, of the mean sales price) relative to the current tax regime. In return for this loss, counterfactuals (d), (e) and (f) reduce CO_2 emissions from new cars by 21, 85, and 100 percent, respectively, relative to the current tax regime.

We present results from a linear demand model as well as from a structural demand model on the lines of the seminal studies of Bresnahan (1987), Berry et al. (1995), Petrin (2002). Using automobile data, these papers introduce a methodology that integrates heterogeneity in consumer valuation of product attributes into substitution patterns.
Numerous studies employ structural model estimation to examine the implications of subsidy design in the automobile sector. Most of these studies diverge from our approach in terms of the specific incentives being examined. Linn (2023) and Armitage and Pinter (2021) examine the welfare and distributional effects of standards imposed on the firm side. Linn (2022) and Xing et al. (2021) analyze the impact of income-based tax credits in the US. In contrast to these studies, our analysis encompasses the full range of consumer-side incentives in Norway.

increase electric power consumption, which on the margin in the connected European grid is arguably met by coal or gas power (but in the longer term possibly by wind and solar power).

[9] "The electric car future is finally taking off", Financial Times, 12 January 2021; https://www.ft.com/content/f6e9ea18-acf6-46d9-ba2b-2920495db8f3. Also see "Reality of subsidies drives Norway's electric car dream", Financial Times, 14 June 2017. https://www.ft.com/content/84e54440-3bc4-11e7-821a-6027b8a20f23, https://www.wsj.com/articles/electric-car-shift-drains-fuel-taxes-in-some-countries-11632407063

This allows for a comprehensive understanding of the effects of incentives, and importantly, enables us to disentangle the share of EV demand arising from each incentive.

More similarly to our study, Springel (2021) and Johansen and Munk-Nielsen (2022) investigate Norwegian EV incentives. Springel (2021) uses Norwegian registry data spanning from 2010 to 2015 to focus on the interaction between the two sides of the EV market: consumers and charging stations. Specifically, the study estimates the relative impact of reducing purchase costs for consumers through subsidies versus lowering entry costs for charging stations through incentives. Our paper has a narrower scope compared to Springel (2021), as we do not delve into considerations of the charging stations side of the market. However, a notable strength of our study lies in its examination of a mature EV market, rather than the behavior of early adopters. Also, the extended time span of our analysis, 2000 to 2021, allows us to capture large variations in EV market shares, reflecting the different phases of the EV market development.

Johansen and Munk-Nielsen (2022) explores how synergies within household car portfolios affect the impact of EV incentives in Norway. Here, the discrete choice of purchasing a car depends on the expected utility derived from driving, with portfolio complementarities explicitly tied to driving as well. Our study takes a different approach as it does not incorporate driving patterns. Additionally, the paper aggregates cars into 20 types by averaging across products, which differs from our approach. A contribution of our study lies in generating more realistic substitution patterns through the preservation of granularity in product attributes. We define products using a combination of various attributes, resulting in 10,349 year/product combinations from a dataset of 2,681,853 vehicles sold. This approach allows us to capture a broader spectrum of variation crucial for understanding consumer preferences accurately and reflecting realistic substitution patterns.

More broadly, our paper connects to the literature that has examined the impact of purchase-related incentives (Muehlegger and Rapson (2022); Clinton and Steinberg (2019); Yan and Eskeland (2018); Chandra et al. (2010)) as well as usage-related incentives on EV adoption, such as toll charges and bus lane access (Isaksen and Johansen (2021); Halse et al. (2023); Jenn et al. (2018); DeShazo et al. (2017); Mersky et al. (2016); Bento et al. (2014)), access to low-emission zones (Barahona et al. (2020); Wolff (2014)), and charging infrastructure (Schulz and Rode (2022); Li (2019)). Our paper also broadly relates to a literature that explores how factors beyond incentives contribute to EV adoption. Notably, Borenstein and Davis (2016) investigate the influence of household income, while Tebbe (2023) explores the impact of peer effects.

In addition to purchase and usage incentives, we investigate the impact of energy costs incurred when driving, which are substantially lower for EVs than for ICEVs. In 2021, the cost of driving an EV is approximately one-third that of an ICEV. We observe that even with an increase in electricity prices to match fuel prices, there is only a modest reduction in sales, with the EV market share decreasing by 10%. In this sense, our paper is related to a large body of literature that investigates the effectiveness of fuel taxes and standards. The literature reveals contrasting evidence regarding buyers' sensitivity to driving costs. In the context of conventional cars, Sallee et al. (2016) find that consumers fully value fuel economy, and studies from Busse et al. (2013), Grigolon et al. (2018), and Allcott and Wozny (2014) find little evidence of consumer undervaluation of fuel costs. On the contrary, Gillingham et al. (2021), Leard et al. (2023), and Leard et al. (2019) show that consumers exhibit myopic behavior, reflected in low valuation parameters of fuel costs. Another question addressed in the literature is whether consumers are equally influenced by electricity prices and fuel prices. Ito (2014) finds that consumers poorly understand the marginal electricity price they face. Bushnell et al. (2022) present evidence that consumers are more responsive to gasoline prices than electricity prices. The authors argue that gasoline prices have a more significant impact on the demand for electric vehicles than electricity prices.

The next section describes key features of the market for new cars and the policy environment in Norway. Section 3 discusses results from linear demand models. Section 4 sets out the structural model and our strategy for estimating its parameters. Section 5 presents estimates from the structural model, and Section 6 presents the counterfactuals. The final section concludes.

2 Description of the data and market

2.1 Data sources

Our main data sources are annual new car registrations at the product level for the years 2000–2021, and price lists for the same years, both from the national industry association OFV.[10] Variables included in both data sets are year, brand, model (nameplate), fuel type (petrol/diesel/hybrid/electric), engine displacement, engine (motor) power, body style, transmission (automatic/manual), and drive wheels (2WD/4WD). In addition, the registration data contain the number of units sold, while the price list has price, length, weight, fuel consumption, CO_2 and NO_x emissions. We collect data on energy consumption for EVs and hybrids from the websites fueleconomy.gov, evcompare.io, elbil.no, ev-database.org. Historical corporate ownership of car brands is obtained from the Wikipedia entries on each brand. The rules for calculating the registration tax ("engangsavgiften") are available at a

[10] Opplysningsrådet for veitrafikken ("Information council for road traffic"), https://ofv.no/.

government website for recent years.[11] For the early years of our data tax rules were collected from the websites of the Norwegian Customs and the Norwegian Tax Administration.[12] Annual average sales prices of and taxes on petrol, diesel and electricity, as well as the annual consumer price index (CPI) are obtained from Statistics Norway's website. All prices and taxes are converted to 2021 NOK using the CPI.

Throughout the paper and in each year of the data, we define a product as a combination of the variables brand, model, fuel type, drive wheels, transmission, body style, with the baseline engine power and the corresponding price, length, weight, fuel consumption, and CO_2 emissions. This results in a total of 10,349 year/product combinations. The total number of vehicles sold in the data set is 2,681,853.

2.2 Taxes on new cars

The purchase taxes on new cars, paid upon first-time registration in Norway, include a value-added tax of 25 percent of the pre-tax price, and a registration tax. The registration tax is a piecewise linear, increasing, and convex function of vehicle characteristics. Until 2006, the tax was based on weight, cylinder volume, and engine power, from 2007 to 2016 on weight, engine power and CO_2, and from 2017 on weight and CO_2 only.[13] Electric vehicles are exempt from both value-added tax and registration tax. Hybrid vehicles pay both taxes, but get a 23 percent deduction in the weight component used to calculate the registration tax.

We now explain how the CO_2 component of the tax is calculated under 2021 rules. It is based on the vehicle's CO_2 emissions measured in g/km. For the first 87 g/km there is no tax. Vehicles with emissions of X g/km, where X<87 g/km get a deduction of (87-X)820.70 NOK. In addition, vehicles with emissions of X g/km, where X<50 g/km get a deduction of (50-X)965.57 NOK. Such vehicles therefore end up with a negative tax contribution from the CO_2 component. The tax is 801 NOK per g/km in the range 88–118 g/km. For the range 119–155, the rate is 898 NOK per g/km. It then increases sharply to 2352 NOK per g/km in the range 156–225, and to 3752 NOK per g/km from 226 g/km. The weight component is calculated with the same kind of increasing, piecewise linear function. As an illustration, the 2021 Porsche Cayenne petrol with reported CO_2 emissions of 309 g/km ends up with 539,737 NOK (62,760 USD) from the CO_2 component of the registration tax alone. Its weight of

[11] https://www.regjeringen.no/no/tema/okonomi-og-budsjett/skatter-og-avgifter/avgiftssatser-2022/id2873933/

[12] These were collected for an earlier project. Some now appear to be unavailable on the internet, but can be obtained from the authors on request.

[13] In addition, NO_x emission has been a component of the tax since 2014, but its contribution to the total tax is minimal compared to the other components.

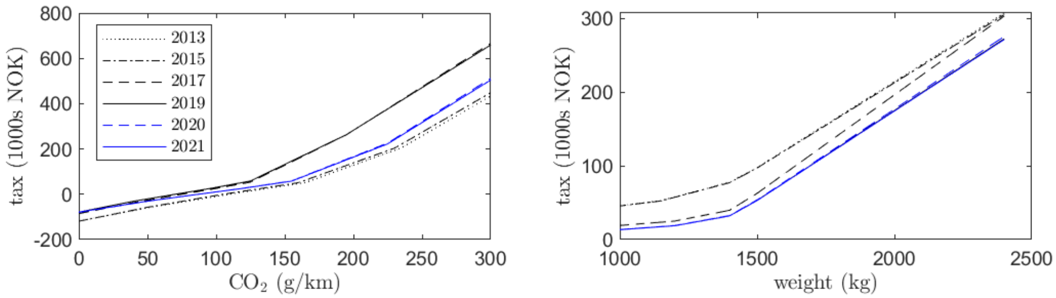

Figure 1. Tax schedules for selected years, CO_2 and weight components.

2183 kg earns it a weight tax of 218,725 NOK. For comparison, the sales-weighted average emissions for ICE vehicles in 2021 is 151 g/km and average weight is 1453 kg. Figure 1 shows the CPI-adjusted tax schedule for the CO_2 and weight component for selected years in our sample.

2.3 Other EV incentives

Other than the purchase tax exemptions, major EV incentives relate to toll roads, car ferries, parking, and bus lane access. EVs paid no charges on toll roads until 2017, at most half of full charge on toll roads in 2018–2021, no fare on car ferries until 2017, and at most half of full ferry fares from 2018. Municipal parking was free for EVs until 2017, and in many places still free or discounted after that. EVs had unlimited access to bus lanes until 2016. From 2017 local authorities could limit bus lane access to only include EVs that carry one or more passengers. In addition to exemptions from VAT and registration tax, EVs were exempt from the annual road tax of about 2800 NOK (326 USD) until 2020 and paid a reduced rate in 2021.

A final incentive to choose electric is the tax on fossil fuels: in 2021 it was 6.4 NOK (0.7 USD) per litre for petrol and 5.2 NOK (0.6 USD) per litre for diesel. These taxes did not undergo significant changes during our sample period.

2.4 Trends in sales and vehicle characteristics

Table 1 shows summary statistics for the new car market in each year of our data. Columns 2, 4 and 5 show the number of brands, models and products (as defined in section 2.1) on offer in each year. There is some variation across years, but no dramatic changes. The next column shows, in thousands, the number of units sold. Here there is a clear upward trend, presumably explained at least in part by Norway's remarkable population growth in our sample period, from 4.48 million in 2000 to 5.39 million in 2021. From the column

year	brands	brands EV	models	products	units (1000s)	price (1000 NOK)	price EV (1000 NOK)	reg.tax (1000 NOK)	VAT paid (1000 NOK)	dcost (NOK / 10 km)	power (kW)	power EV (kW)	length (m)	weight (1000 kg)	CO_2 (g/km)
2000	37	0	161	369	91	398		112	57	9.5	82		4.29	1.21	
2001	37	0	170	386	87	403		138	53	7.6	83		4.33	1.25	
2002	36	0	166	386	83	412		151	52	8	85		4.36	1.27	
2003	37	0	177	388	86	423		161	52	7.7	88		4.37	1.3	
2004	36	0	184	438	114	441		170	54	8.2	90		4.4	1.33	
2005	39	0	195	457	106	434		166	53	8.6	88		4.4	1.34	169
2006	37	0	201	483	106	469		187	56	9.9	94		4.43	1.4	178
2007	36	0	193	449	125	442		154	58	9.6	91		4.42	1.4	160
2008	35	0	198	469	107	438		162	55	8.6	94		4.45	1.41	158
2009	35	0	190	464	95	437		156	56	8.7	92		4.43	1.41	151
2010	38	2	197	463	122	420	284	142	55	9.2	91	40	4.41	1.39	145
2011	36	4	186	469	132	421	266	140	56	8.9	92	54	4.43	1.4	136
2012	35	5	200	522	131	432	291	139	57	8.9	96	70	4.42	1.4	133
2013	32	7	207	536	135	412	402	125	53	8.8	97	78	4.42	1.39	126
2014	31	10	197	536	135	423	401	118	52	7.7	100	85	4.43	1.42	117
2015	30	11	194	552	143	415	348	104	50	6.7	102	87	4.43	1.43	103
2016	33	13	209	565	146	445	332	102	58	7.3	115	91	4.46	1.48	96
2017	35	14	221	586	150	485	399	97	61	7.6	123	93	4.51	1.55	90
2018	34	16	221	534	141	460	363	79	53	7.3	123	93	4.48	1.56	77
2019	34	18	223	493	138	445	380	61	44	6.3	147	156	4.51	1.64	62
2020	39	29	214	434	137	474	421	33	42	5.1	160	162	4.49	1.72	46
2021	42	33	214	370	172	450	411	22	32	6.4	168	169	4.48	1.78	33

Table 1. Choice and choice set descriptives.

marked 'price' onwards, numbers are sales-weighted means for each year. Prices, which are in thousands of 2021 NOK, adjusted by the CPI, have changed little, while power (kW), length (metres) and weight (1000s of kg) exhibit strong upward trends. Energy costs (in NOK per 10 km driven), 'dcost', remained fairly stable during the first two thirds of our sample period, and then fell towards the end. This is the product of several factors: ICE vehicles have become more fuel efficient, but consumers buy bigger cars, while petrol and diesel prices have remained fairly stable. The fall towards the end reflects the lower energy costs for EVs.

We next turn to some numbers that are particularly pertinent to the rise of EVs. Column 3, 'brands EV', of Table 1, shows the number of brands that offer EVs. In the early years of EV sales (from 2010) very few brands offered electric options. Furthermore, the columns marked 'price EV' and 'kW EV' (which give sales-weighted means for EVs only) show that these were small-engine, relatively cheap cars. By contrast, in the later years of our sample period most brands (33 of 42 in 2021) offer EVs, and electric cars are powerful and almost as expensive as other cars in spite of their tax exemption. The columns 'reg.tax' and 'VAT paid' show that the sales-weighted mean tax paid (in thousands of 2021 NOK) has fallen dramatically. Since there has been no strong trend in tax rates, this is entirely due to the shift in consumption towards tax-exempt EVs (and lower-tax hybrids).

3 Linear demand model

We now turn to the question of how various incentives have contributed to the increasing market share of electric vehicles. In this section we report results from a simple linear demand model, and discuss some limitations of this approach.[14] Let j denote a product and t year. We are interested in the causal relationship

$$\ln(Q_{jt}) \quad = \quad \alpha p_{jt} + \gamma_1 dcost_{jt} + \gamma_2 EV_j + x_{jt}\beta + w_{jt} \tag{1}$$

where Q_{jt} is the number of units sold, p_{jt} is price, $dcost_{jt}$ is the energy or fuel cost of driving one km, EV_j is an EV dummy, x_{jt} is a vector of other product characteristics, including model dummies and year dummies, and w_{jt} is an error term that contains all other determinants of Q_{jt}. The parameters α, γ_1 and γ_2 determine the effects of EV incentives: changing the price of electricity or taxes on fossil fuel affects demand through $\gamma_1 dcost_{jt}$; changing purchase taxes affects demand through αp_{jt}; and changing other EV incentives affects demand through $\gamma_2 EV_j$.

Estimating the parameters of (1) is challenging for the classical reason that any unobserved demand shock, which enters the error term w_{jt}, is likely to influence the observed equilibrium price p_{jt}. We deal with this problem in two ways, both of which make use of the registration tax.

First, we estimate an equation similar to (1) but with the difference that the regressor p_{jt} is replaced by the registration tax paid for product j in t, τ_{jt}.[15] Given that our main interest is in the effect of the tax on demand, this is a more direct approach. The registration tax is an exogenously given function of observable product characteristics, and therefore not affected by product-specific unobserved demand shocks.[16] The nonlinearity of the tax function ensures that τ_{jt} is not collinear with product characteristics.

The second approach is to estimate (1) with two-stage least squares, using the registration tax τ_{jt} as an instrumental variable for p_{jt}. The previous paragraph set out an argument for the independence between the tax and demand shocks. Since we control for price and other product characteristics, the tax should be excluded from the demand function. Because the

[14] The model is inspired by Klier and Linn (2015) and Yan and Eskeland (2018), although their models are richer than ours. We intend this as a first-pass approach to complement our structural analysis.

[15] Klier and Linn (2015) and Yan and Eskeland (2018) use tax as their main explanatory variable.

[16] This assumes the other product characteristics are uncorrelated with demand shocks; see Section 4.3 for further discussion.

Variable	Mean	Std Dev	Min	Max
Registration tax (1000 NOK)	195	172	0	1579
Price (1000 NOK)	556	371	129	3626
Energy cost (dcost) (NOK/km)	0.93	0.29	0.10	2.38
Engine power (100 kW)	1.16	0.56	0.40	4.04
Car weight (1000 kg)	1.46	0.30	0.66	2.47
Car length (m)	4.46	0.36	3.41	5.33
CO_2 emissions (100 g/km)	1.09	0.77	0.00	3.25

Table 2. Description of regression variables.

tax is a component of price, and a nonlinear function of product characteristics, it is partially correlated with price after controlling for product characteristics.

Table 2 gives descriptive statistics for the main variables used in the regressions. The first column in Table 3 shows results from the regression where tax, not price, is the main explanatory variable of interest.[17] The coefficient on registration tax is an estimate of the semi-elasticity of the demand for j with respect to the registration tax. Tax is measured in thousands of NOK, so that a 10,000 NOK (1163 USD) increase in the registration tax is estimated to reduce demand by 2.7 percent. In 2021, the sales-weighted mean price paid is 450,000 NOK, which gives an implied elasticity of demand for j with respect to price, based on the estimated sensitivity to the registration tax (and assuming tax is fully passed on to consumers), of $-0.0027 \times 450 = -1.2$. This is somewhat lower than existing estimates of individual product demand elasticities (see discussion in Section 5.2). We next discuss a possible explanation for this.

The OLS estimates are based on the premise that everything else (than tax and the other regressors) remains constant on average when the tax changes. And in an ideal controlled experiment, we would change the tax for one product at a time, holding the tax of all other products fixed. But in the data, when tax changes (whether through a shift in the tax schedule over time or in product attributes in a cross-sectional comparison), the relevant substitute products also pay a different tax. The observed change in demand is therefore a composite of two opposite effects: a higher tax reduces demand for j, but the fact that relevant substitutes also pay a higher tax increases demand for j. This inherent failure to hold substitutes fixed means that the magnitude of the estimated effect is likely to have a downward bias (relative to the true causal effect of changing the tax for one product while holding everything else fixed).[18] The OLS results are of course informative about how log

[17]In the early years of the data, CO_2 emissions are not reported. Our regressions therefore include a dummy for observations where CO_2 emissions are not observed, to distinguish them from EVs with zero emissions.

[18]Klier and Linn (2015) (p. 231) state "(. . .) we interpret the tax coefficient as the effect of a vehicle's tax on its own registrations, accounting for the effects of taxes for other vehicles. An alternative is to control directly for the taxes of the other vehicles, in which case we interpret the tax coefficient as the effect of the

Dependent Variables:	log(units)	price	log(units)
IV stages		First	Second
Model:	(1)	(2)	(3)
Variables			
registration tax	-0.0027***	0.9319***	
	(0.0005)	(0.0487)	
price			-0.0029***
			(0.0006)
dcost	-0.8197***	23.36	-0.7529***
	(0.2338)	(20.32)	(0.2507)
power	-0.3544***	183.9***	0.1712
	(0.1118)	(22.39)	(0.1984)
weight	-0.800*	82.69**	-0.564
	(0.409)	(32.21)	(0.451)
CO_2	-0.0090	-0.3211	-0.0100
	(0.0765)	(4.726)	(0.0764)
length	0.9678***	74.93***	1.182***
	(0.2930)	(18.80)	(0.3209)
CO_2 not observed	-0.5613*	83.00***	-0.3241
	(0.2960)	(12.68)	(0.2888)
electric	1.625***	28.30	1.706***
	(0.3976)	(22.17)	(0.4171)
diesel	0.0568	31.66***	0.1473
	(0.1198)	(9.346)	(0.1308)
hybrid	1.995***	48.51***	2.133***
	(0.1828)	(14.62)	(0.1794)
4WD	0.2224**	-4.311	0.2101**
	(0.0894)	(6.336)	(0.0975)
automatic	-0.0038	15.11***	0.0394
	(0.0417)	(2.304)	(0.0437)
Fixed-effects			
car model	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	10,349	10,349	10,349
R^2	0.41627	0.97461	0.40405
Within R^2	0.13657	0.80637	0.11849

Clustered (car model) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3. Linear demand model.

quantity tends to vary with taxes in the data, since it is always a consistent estimator of the linear projection (of log quantities on the regressors). But to evaluate counterfactual changes, we need to estimate the causal effect. We will get back to this issue in Section 4.

The last two columns of Table 3 report results from the two-stage least squares estimates of (1). The middle column is the first-stage regression of the endogenous variable, price, on the instrumental variable, tax, and the other explanatory variables. The t-statistic for tax is 19.14 (F-statistic 366), so the instrument is not weak. The 2SLS estimates in the last column have a coefficient on price that is very similar to the coefficient on tax in the first column. This is not too surprising, given that consumers presumably do not care whether a price increase is due to tax or something else. It should also be noted that the possible correlation between registration tax and unobserved demand shocks, discussed in the previous paragraph, would make the tax an invalid instrument. The estimate on *dcost*, the energy cost in NOK of driving one km, is -0.753. This implies that a one standard deviation (see Table 2) increase in energy costs reduces demand by 21.8 percent. Otherwise we note that all parameters have the expected sign, but that engine power is not significant.

We next turn to the counterfactuals, which are all based on the 2SLS results in the last column of Table 3. Section 6 sets out the counterfactual experiments in detail, so we describe them only briefly here. First we double the electricity price and set the taxes on petrol and diesel to zero. This makes the energy costs of EVs and ICE vehicles similar on average. Second, we remove the favourable tax treatment of EVs and hybrids by imposing an imputed registration tax similar to that paid by ICE vehicles of the same length, engine power, body style and drive wheels, and by imposing the standard 25 percent VAT on EVs.[19] In the third counterfactual, we change the EV effect from the estimated 1.706 to the (unweighted) average of the petrol (0; normalized), diesel (0.147), and hybrid (2.133) effects, which is 0.76. This is meant to undo all the things that make EVs systematically different from non-EVs and instead set this component equal to the average for non-EVs. Ideally we would like to remove only bus-lane access, and parking, toll road and ferry discounts. In reality the EV effect will also capture anything else that makes EVs different on average from non-EVs. Therefore this third counterfactual should be interpreted with caution. We do a second version of this counterfactual, where instead we set the EV effect to zero.

To simplify the notation somewhat, let the estimated equation be $\ln(Q_{jt}) = Z_{jt}\hat{\beta} + \hat{w}_{jt}$. The first (energy costs) and second (imputed tax) counterfactuals involve changing one of

tax holding fixed the taxes of other vehicles. We tend to estimate larger coefficients when controlling for other vehicles' taxes, but the results depend on how we measure other vehicles' taxes (not reported)."

[19] We assume 100 percent pass-through of taxes to prices. This is partly justified by the similarity of the coefficients on tax and price in the two regressions in Table 3. In our structural model we solve for equilibrium pass-through.

the regressors at a time. The predicted sales are then

$$\tilde{Q}_{jt} = \exp(\tilde{Z}_{jt}\hat{\beta} + \hat{w}_{jt}),$$

where $\tilde{Z}_{jt}$ is the modified vector of regressors. Both versions of the final counterfactual (EV effect set to the non-EV average and to zero, respectively), involve changing a component of the coefficient vector $\hat{\beta}$. We write $\tilde{\beta}$ for the modified coefficients vector and obtain the predicted sales as:

$$\tilde{Q}_{jt} = \exp(Z_{jt}\tilde{\beta} + \hat{w}_{jt}).$$

Figure 2 shows the predicted market shares of EVs, ICE vehicles, and hybrids for each counterfactual. The last two panels show the sales-weighted average vehicle weight and CO_2 emissions for each counterfactual. The first panel shows that undoing the favourable tax treatment of EVs (and hybrids) is the counterfactual with the smallest effect on EV market share, reducing it from 66 percent to 56 percent. This effect is surprisingly small, which we conjecture is caused by a downward bias in the estimated price sensitivity, as discussed above. Changing energy costs gives an estimated EV market share of 52 percent, while undoing "other incentives" results in an EV share of 42 percent (setting the EV effect equal to that of non-EVs) or 25 percent (setting the EV effect to zero). Finally, the combined counterfactual gives a reduction in the EV market share in 2021 from 66 percent to 23 percent in 2021. Furthermore, undoing EV incentives reduce sales-weighted mean vehicle weight and increases CO_2 emissions significantly.

4 Structural model

Some limitation of the linear models in the previous section are that: (i) they restrict demand responses to be the same for all products; (ii) they do not give estimates of equilibrium price responses and tax pass-through, or changes in profit and consumer surplus; and (iii) product-specific taxes may not be valid instruments for price. The remainder of our analysis relaxes these restrictions. We start by discussing the third point, first raised in Section 3, and formally relate it to our structural demand model.

Let ξ_{jt} denote a product- and time-specific shock to unobserved quality, reflecting features such as marketing, prestige, quality, fashion, etc., which are not observed by the researcher, but known to consumers and firms. Clearly ξ_{jt} enters the error term w_{jt} in (1). But demand for j is also affected by how attractive consumers find other, competing products. Let ρ_{jt} denote the sum of these effects, where closer substitutes matter more. We can then write $w_{jt} = \xi_{jt} + \rho_{jt}$. The presence of demand shifters for substitute products in w_{jt} poses a

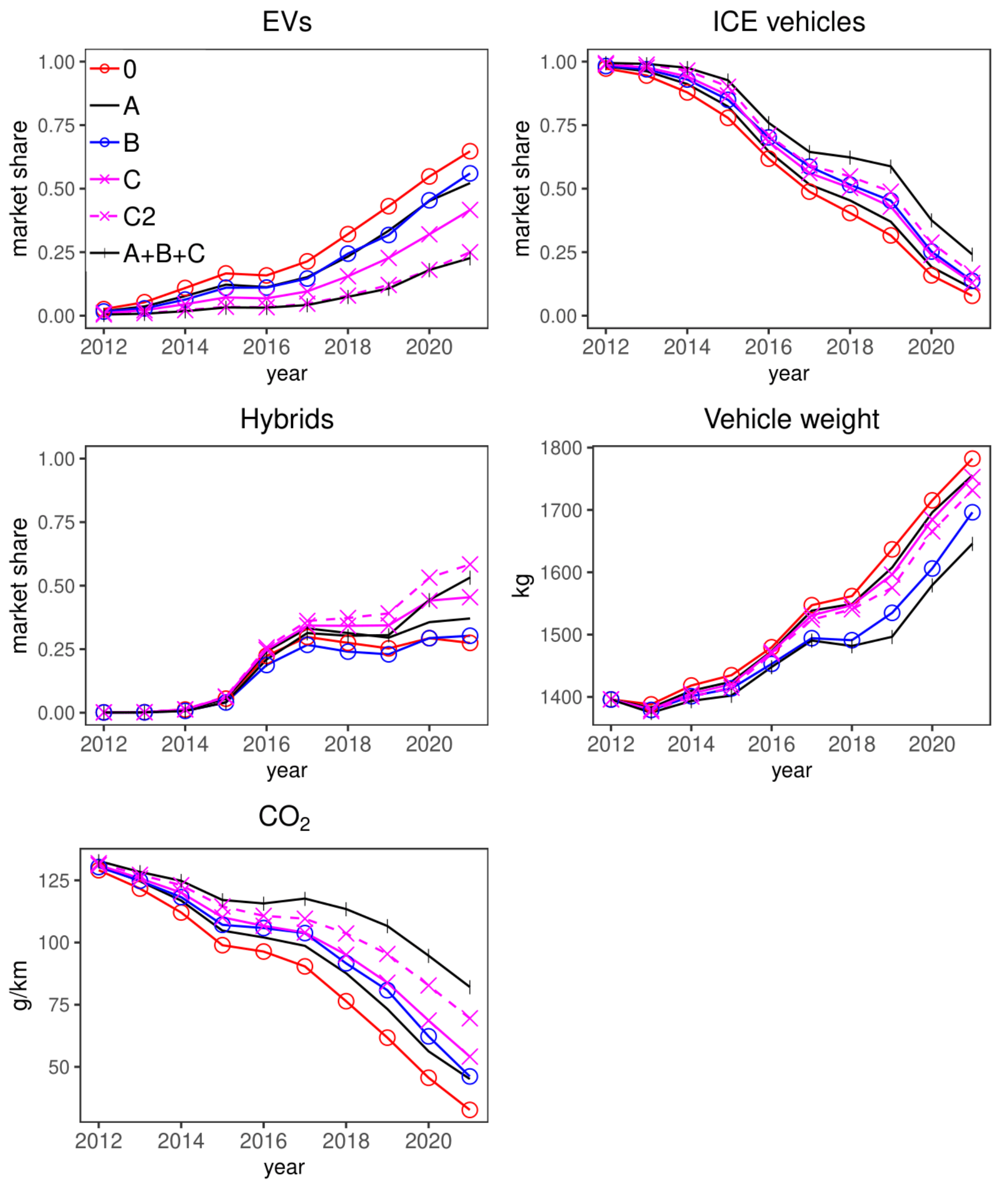

Figure 2. Counterfactuals, linear demand model. Market shares by fuel type, and sales-weighted average weight and CO_2 emissions actual (0) and counterfactuals: equalized energy costs (A), imputed taxes (B), EV effect set to non-electric average (C), EV effect set to zero (C2), and A-C combined (A+B+C).

challenge to the use of the registration tax as an instrumental variable for price. When tax increases for one product, the tax will typically be higher for other similar products too, shifting their prices in turn.[20] This affects demand for the first product through the ρ_{jt} term. Unless the demand model controls for the prices of all products, registration tax τ_{jt} is likely to be correlated with the error term w_{jt}.

The obvious way to control for all prices is simply to write log quantity as a linear function of own price and other prices, with a separate equation for every product.[21] This approach has the drawback that the number of estimated semi-elasticities (price coefficients) is very large. It it is also unclear whether semi-elasticities can reasonably be assumed to remain constant when we vary taxes, fuel costs and EV preferences, like we do in our counterfactuals. Finally, we cannot use this model to quantify changes in consumer surplus. For these reasons, we prefer a discrete-choice model along the lines of Berry et al. (1995). In the industrial organization literature this is the standard approach for estimating demand systems for differentiated products. The remainder of this section sets out the details of the model.

4.1 Demand

Suppose consumer i derives indirect utility from buying vehicle j at time t of

$$U_{ijt} = x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \varepsilon_{ijt} \tag{2}$$

where x_{jt} is a $1 \times l$ vector of product characteristics, and p_{jt} price. The scalar ξ_{jt} is the jt-specific shock discussed above. The outside option $j = 0$ of not buying a new car has indirect utility normalized to $U_{i0t} = \varepsilon_{i0t}$. The idiosyncratic taste term ε_{ijt} is assumed to be i.i.d. standard Gumbel (type-I extreme value). Let J_t denote the set of all inside options in t, or, when it is evident from the context, the number of elements in this set.

If the coefficients on x_{jt} and p_{jt} are the same for all consumers, $\beta_i = \beta$ and $\alpha_i = \alpha$, we have a multinomial logit model where the market shares of $j > 0$ and $j = 0$ are

$$s_{jt} = \frac{\exp(x_{jt}\beta - \alpha p_{jt} + \xi_{jt})}{1 + \sum_{k \in J_t} \exp(x_{kt}\beta - \alpha p_{kt} + \xi_{kt})}, \quad s_{0t} = \frac{1}{1 + \sum_{k \in J_t} \exp(x_{kt}\beta - \alpha p_{kt} + \xi_{kt})}. \tag{3}$$

This model has the advantage of making explicit how the demand for j depends on other

[20] If the tax increase comes from an shift in the tax schedule, this is obvious. If it comes from a cross-sectional comparison, the consumers who are likely to buy the higher-tax product have a higher willingness to pay for engine power, and so substitutes with larger engines have a higher weight in ρ_{jt}, and these substitutes also have a higher tax.

[21] That is, estimating $\ln(Q_{jt}) = \beta_0 + \alpha_j^j p_{jt} + \sum_{k \neq j} \alpha_k^j p_{kt} + \gamma_1 dcost_{jt} + \gamma_2 EV_j + x_{jt}\beta + w_{jt}$, where a_k^j is now the cross-price semi-elasticity of the demand for j with respect to the price of k.

goods, whereas in (1) this dependence was relegated to the component ρ_{jt} of the error term w_{it}. In fact, a simple transformation of (3) now gives a demand function where ρ_{jt} is no longer in the error term:

$$\ln(s_{jt}) - \ln(s_{0t}) \quad = \quad x_{jt}\beta - \alpha p_{jt} + \xi_{jt}. \tag{4}$$

If the model is correct, the registration tax is now a valid instrument for price, unlike in (1), since the error term only contains the jt-specific demand shock. However, it is well known that the simple logit model imposes strong restrictions on substitution patterns. In particular, there is no sense of close or less close substitutes, and cross-price derivatives of demand are simply determined by market shares.[22] To control for the effect of substitute products on demand we need a realistic model of substitution that relaxes these restrictions.

We do this by estimating a standard random-coefficients discrete-choice model, where consumers are heterogeneous in terms of their willingness to pay and their marginal utility of product attributes. Let $\beta_i = \beta + \Sigma\nu_i^\beta$, $\nu_i^\beta \sim N(0, I_l)$ and $\alpha_i = \exp(\alpha_0 + \alpha_1\nu_i^\alpha)$, $\nu_i^\alpha \sim N(0,1)$, where the estimated parameters are the $l \times 1$ vector β, the main diagonal of the $l \times l$ diagonal matrix Σ, and the scalars α_0 and α_1. To limit the number of parameters we estimate only a subset of the diagonal elements of Σ, while the others are set to zero. The matrix I_l is the $l \times l$ identity matrix.

To simplify the notation, let $\nu_i = (\nu_i^\beta, \nu_i^\alpha)$, $p_t = (p_{jt})_{j\in J_t}$, $\delta_t = (\delta_{jt})_{j\in J_t}$, and $\theta = (\alpha_0, \alpha_1, \beta, \Sigma)$. Also define

$$\delta_{jt} \quad = \quad x_{jt}\beta + \xi_{jt} \tag{5}$$

$$\mu_{ijt} \quad = \quad x_{jt}\Sigma\nu_i^\beta - \alpha_i p_{jt}. \tag{6}$$

We then get the choice probabilities

$$s_{jt}(p_t, \delta_t, \theta) \quad = \quad \int \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k\in J_t}\exp(\delta_{lt} + \mu_{ilt})} f(\nu_i) d\nu_i, \tag{7}$$

where f denotes the pdf of ν_i.

4.2 Supply side

In each market t, let J_{ft} be the set of products owned by firm f, so that $\cup_f J_{ft} = J_t \setminus \{0\}$. We assume the marginal unit cost of production c_{jt} is constant over the relevant range of output. Let τ_{jt} be the amount paid in registration tax for product j at time t, and let v_{jt}

[22] $\partial s_{jt}/\partial p_{kt} = \alpha s_{jt} s_{kt}$ for any two products $j \neq k$.

be the value added tax rate paid for j (some j are exempt from VAT). VAT is paid on the price net of the registration tax. For each unit sold of product j, the seller receives $p^*_{jt} = (p_{jt} - \tau_{jt})/(1 + v_{jt})$. The sales price p_{jt} can then be decomposed as follows:

$$p_{jt} = \underbrace{p^*_{jt} - c_{jt}}_{\text{margin}} + \underbrace{c_{jt}}_{\text{marg. cost}} + \underbrace{\tau_{jt}}_{\text{reg.tax}} + \underbrace{v_{jt} p^*_{jt}}_{\text{VAT paid}}. \tag{8}$$

We assume that dealerships, importers and manufacturers engage in optimal vertical contracting that maximizes their joint surplus, to avoid double marginalization. The marginal unit cost c_{jt} then includes marginal costs related to retailing and shipping as well as manufacturing. Firm f chooses sales prices p_{jt} of its products to maximize variable profit $\sum_{j \in J_{ft}} (p^*_{jt} - c_{jt}) Q_{jt}$. Letting M_t be the total number of consumers in t, $Q_{jt} = s_{jt} M_t$, where s_{jt} is given by (7).[23] The firm solves the problem

$$\max_{\{p_{jt}: j \in J_{ft}\}} \sum_{j \in J_{ft}} \left(\frac{p_{jt} - \tau_{jt}}{1 + v_t} - c_{jt} \right) s_{jt}(p_t, \delta_t, \theta) M_t,$$

which has first-order conditions

$$\frac{1}{1 + v_t} s_{jt}(p_t, \delta_t, \theta) + \sum_{k \in J_{ft}} \left(\frac{p_{kt} - \tau_{kt}}{1 + v_t} - c_{kt} \right) \frac{\partial s_{kt}(p_t, \delta_t, \theta)}{\partial p_{jt}} = 0, \; j \in J_{ft}.$$

To put this system of equations on matrix form, define the $J_t \times J_t$ matrix $\Delta_t(p_t)$ with entries

$$\Delta_t(p_t)[j,k] = \begin{cases} \frac{\partial s_{kt}(p_t, \delta_t, \theta)}{\partial p_{jt}} & \text{if } j \in J_{ft} \text{ and } k \in J_{ft} \text{ for some } f \\ 0 & \text{otherwise.} \end{cases}$$

The vectors c_t, τ_t and $s_t(p_t, \delta_t, \theta)$ stack marginal cost, registration tax and market shares, and φ_t stacks $\varphi_{jt} = 1/(1 + v_{jt})$ for all $j \in J_t$. The first-order conditions for all firms can then be written as follows, where $*$ denotes pairwise, or element-by-element, multiplication of two vectors:

$$\varphi_t * s_t(p_t, \delta_t, \theta) + \Delta_t(p_t)[\varphi_t * (p_t - \tau_t) - c_t] = 0. \tag{9}$$

We use (9) to i) find the value of c_t implied by demand estimates at observed prices and taxes, and ii) find the equilibrium value of p_t implied by counterfactual tax regimes, which change s_t and Δ_t. We use the fixed point method proposed by Morrow and Skerlos (2011)

[23] Let the maximum (over the years of our data) share of the population purchasing a new car be $\bar{s} = \max_{2000 \leq t \leq 2021}(Q_t/pop_t)$, where Q_t is the total number of new cars sold and pop_t the population of Norway in t. We define the potential market size as $M_t = 1.5 \cdot \bar{s} \cdot pop_t$. Here we follow Miller and Weinberg (2017).

to solve for equilibrium prices and quantities, and report the results in Section 6.

4.3 Estimation and empirical strategy

Let S_{jt} be the observed market share of product j in year t. Berry et al. (1995) provide a fixed point algorithm for obtaining, in each market t and for any parameter value θ, the unique vector δ_t that satisfies

$$S_{jt} \quad = \quad s_{jt}(p_t, \delta_t, \theta), \; j \in J_t, \tag{10}$$

where the right-hand side is given by (7). Since (10) defines $\delta_{jt}(\theta)$ as an implicit function of θ (for given S_t and p_t), we can also write, by rearranging (5), $\xi_{jt}(\theta) = \delta_{jt}(\theta) - x_{jt}\beta$. We form moment conditions involving the econometric error term $\xi_{jt}(\theta)$, and estimate the model's parameters with GMM. Our moment conditions are based on the assumption that for the true parameter value θ_0,[24]

$$\mathbb{E}[\xi_{jt}(\theta_0)|x_{1t}, \ldots, x_{J_t t}, \tau_{1t}, \ldots, \tau_{J_t t}] \quad = \quad 0. \tag{11}$$

The standard assumption used to justify (11), which we also maintain, is that observable product characteristics x_{jt} are determined without taking the realization of ξ_{jt} into account. One reason for this may be that the long-term product design process that sets x_{jt} takes place before ξ_{jt} is fully revealed to car manufacturers (see Gandhi and Nevo (2021) for a discussion). The vector of product characteristics x_{jt} includes car model dummies. The error term ξ_{jt} therefore does not contain the effect of the general design, quality, prestige, etc. of a model, but only the product/year-specific deviation from this average effect. Since these deviations are presumably in large part specific to the Norwegian market, while x_{jt} are set for a global market (of which the Norwegian market is a negligible part), the condition (11) is more likely to be satisfied in our setting than for larger markets. Business cycles and other factors that affect the overall attractiveness of new cars are absorbed by year dummies.

The mean independence condition (11) implies a set of orthogonality conditions whose sample analogs serve to estimate the parameters in our model. We discuss these in turn, and group them according to which parameters we believe the specific moment condition will be particularly helpful in estimating.

Linear preference parameters, β. Estimation of the coefficients β is based on the orthogonality condition $\mathbb{E}[x_{jt}\xi_{jt}(\theta_0)] = 0$. The intuition for these moments is similar to in a linear

[24]Since the registration tax is a function of product characteristics, $\tau_{jt} = \tau(x_{jt})$ for some function $\tau(\cdot)$, it is not strictly necessary to condition on the τ_{jt} (as long as $\tau(\cdot)$ is exogenously given) but we do so to make the mean-independence relationship explicit.

model: to estimate the effect of x_{jt} on market shares we require that the model should fully account for the relationship between x_{jt} and market shares, and that, correspondingly, the error term ξ_{jt} should play no role in explaining this relationship. For instance, if cars with lower energy costs have higher market shares, this cannot be rationalized by systematically assigning larger values of ξ_{jt} to such products. Instead the model is forced to generate this outcome with a negative coefficient on energy costs in the utility function.

Random coefficients, Σ. To estimate the random coefficients spread parameters Σ we use instruments intended to capture the market position of product-year jt: how similar is j to its competitors in market t? This is the idea behind the instruments in Berry et al. (1995). We use the "differentiation" version of these instruments, proposed by Gandhi and Houde (2020) and discussed in Gandhi and Nevo (2021). In our setting the instruments are functions of length, power, fuel cost, CO_2 emissions, and registration tax. They include the average squared distance between product j and other products along each dimension (product characteristic), and interactions of these distances across dimensions.[25] These instruments can be thought of as indices of product j's extent of differentiation from its competitors (in terms of observed product attributes). Denoting the vector of differentiation instruments by z_{jt}, (11) implies

$$\mathbb{E}[z_{jt}\xi_{jt}(\theta_0)] \quad = \quad 0. \tag{12}$$

We next discuss the intuition for why this moment condition is informative about the parameters Σ. At one extreme, when $\Sigma = 0$ consumers distribute across products j based only on their realization of the idiosyncratic shock ε_{ijt}, since everyone has the same preferences for observed product attributes x_{jt}. It follows that the index of differentiation z_{jt} exhibits no systematic relationship with market shares. In contrast, if Σ is large, consumers will primarily choose products based on the bundles of attributes (x_{jt}) they represent. A less differentiated product will now have lower market share, because it loses customers to nearby competitors, while a more differentiated product will have a higher market share. Other than a high value of Σ, there is one other moving part in the model that could conceivably generate such a pattern: systematically higher ξ_{jt} for products that have a higher index of differentiation (z_{jt}). The moment condition (12) acts precisely to rule out this alternative explanation. It says that Σ fully accounts for any systematic relationship between the index of differentiation (z_{jt}) and market shares, and that none of that relationship should be accounted for by error term ξ_{jt}.

Price parameters, α_0, α_1. The parameters α_0 and α_1 together determine the mean

[25]The interactions capture the covariance between the extent of differentiation in different dimensions.

and spread of the price coefficient α_i. The moment condition $\mathbb{E}[\tau_{jt}\xi_{jt}(\theta_0)] = 0$ provides one moment restriction to pin down the mean effect of the price coefficient, in the same way as the conditions discussed above for β. To estimate the spread of the price coefficient, we rely on the moment conditions discussed above for other random coefficients. Our "differentiation" instruments include registration tax as one of the dimensions of differentiation, which should be particularly helpful for estimating the spread of the price coefficient.

Estimator. In light of this discussion, and the combined population moment condition $\mathbb{E}[Z_{jt}\xi_{jt}(\theta_0)] = 0$, where $Z_{jt} = (x_{jt}, z_{jt}, \tau_{jt})'$, we define the GMM estimator $\hat{\theta} = \arg\min_\theta \, [Z_{jt}\xi_{jt}(\theta)]'W[Z_{jt}\xi_{jt}(\theta)]$.[26]

5 Results

5.1 Demand estimates

Table 4 shows parameter estimates for the discrete-choice models. The first two columns give results from the simple logit model in (4), and the last column from the mixed (random-coefficients) logit model in (7). Both models include dummies for year, car model, and body style. The scale of the variables is like in Table 1, except price, which is now in million NOK.

In column (1) price is used as an instrument for itself. We believe price to be positively correlated with unobserved demand shocks, so that the magnitude of the estimated price coefficient will be biased downwards. Instrumenting for price should therefore increase the magnitude of the estimated price coefficient. Column (2) is like (1) except we now use the registration tax as an instrument for price. As expected, the magnitude of the estimated price coefficient, -2.413, is larger than that in column (1), -0.707. The other parameter estimates in (2) have the expected signs: *dcost*, the energy cost per kilometre driven, has a negative coefficient, engine power (measured in hundreds of kW) has a positive coefficient but is not significant, weight (measured in metric tonnes or thousands of kg) has a negative coefficient, CO_2 (measured in hundreds of grams per km) has a negative coefficient, and car length (measured in metres) a positive coefficient.

For the random-coefficients model in column (3) we use the instruments discussed in Subsection 4.3. In the remainder of the paper all results are based on the results in column (3). The mean implied price coefficient is -16.04,[27] which is substantially larger in magnitude than the simple logit estimates. In light of the discussion at the beginning of Section 4, if

[26] Here W is the standard GMM weighting matrix $\{\sum_{jt}[Z_{jt}\xi_{jt}(\tilde{\theta})][Z_{jt}\xi_{jt}(\tilde{\theta})]'\}^{-1}$, where $\tilde{\theta}$ are first-stage estimates obtained with the same estimator but with $[\sum_{jt} Z_{jt}Z'_{jt}]^{-1}$ as a weighting matrix. We use 2500 simulation draws per year to simulate the integral in (7).

[27] If X is lognormally distributed with parameters μ and σ^2, then $\mathbb{E}(X) = \exp(\mu + \sigma^2/2)$.

only the random-coefficients model accurately accounts for the role of other products in the demand for product j, the instrument might not be exogenous in the other specification. For instance, if j has a powerful engine, when tax goes up for high-power cars, it reduces demand for close competitors, which shows up in the error term ξ_{jt} unless this effect is accounted for elsewhere in the model. Because of its restricted substitution patterns, the simple logit model does not capture the fact that this effect is particularly strong for other high-power cars.

The spread parameters on length and power (kW) are precisely estimated. The estimated coefficient on *dcost*, the energy costs in NOK of driving 1 km, is -0.698, which when divided by the mean price coefficient (price is measured in million NOK) implies that increasing energy costs per km by 0.7 NOK (the difference between the means for EVs and ICE vehicles in 2021), reduces the value of a car to the average consumer by 30,460 NOK.[28] This equals the additional cost (with a discount rate of zero) of driving 43,514 kilometres when energy costs per km rise by 0.70 NOK, or 3.2 years of average driving.[29] The coefficients on dummies for EV, hybrid and diesel imply average valuation advantages relative to petrol vehicles of, 69,700, 134,790, and 22,380 NOK, respectively, while the mean coefficients on engine power and length imply an average valuation of 6290 NOK for 10 kW additional engine power, and 4250 NOK for an additional 10 cm of length (the mean parameter is not significant, however).[30]

5.2 Substitution patterns and pricing

Substitution between products and to the outside option are important determinants of the effects of the incentives addressed in this paper. To assess the substitution patterns implied by our demand estimates, in Table 5 we split all products on the market in 2021 into quarters according to price. We look at the substitution behaviour that results from marginally increasing the price of one product at a time. As a proportion of consumers who substitute away from the product, we record how many end up in each of the four price quarters, as well as in the outside option of not buying a new car. For each row, numbers are the average proportion of lost consumers for products in that price quarter that end up in a product in each of the column price quarters. The groups are exclusive and exhaustive, so the entries in each row sum to one.

The table shows that consumers substitute disproportionately to products in or near their

[28] $0.7 \cdot 0.698/16.04 = 0.03046$ million NOK.

[29] Average annual driving distance for cars that are 0-4 years old is 13,564 km. See `https://www.ssb.no/en/statbank/table/12575/`.

[30] The calculations are, in million NOK, 1.118, 2.162, and 0.359 all divided by 16.04, and $0.1 \cdot 1.01/16.04$ and $0.1 \cdot 0.682/16.04$, respectively.

	simple logit		mixed logit
	(1)	(2)	(3)
instruments:	price	tax	tax + GH
price (α)	0.707	2.413	
	(0.15)	(0.313)	
price (α_0)			2.544
			(0.145)
price (α_1)			0.68
			(0.065)
RC length (Σ)			1.913
			(0.765)
RC kW (Σ)			0.584
			(0.242)
dcost	-0.892	-0.733	-0.698
	(0.154)	(0.28)	(0.169)
kW	-0.408	0.089	1.01
	(0.079)	(0.117)	(0.207)
weight	-0.986	-0.623	0.565
	(0.247)	(0.267)	(0.358)
CO2	-0.422	-0.193	0.266
	(0.083)	(0.111)	(0.102)
length	1.031	1.245	0.682
	(0.25)	(0.266)	(0.752)
electric	1.435	1.566	1.118
	(0.257)	(0.27)	(0.286)
hybrid	2.075	2.015	2.162
	(0.134)	(0.143)	(0.143)
diesel	0.034	0.124	0.359
	(0.054)	(0.08)	(0.062)
4WD	0.257	0.231	0.511
	(0.05)	(0.052)	(0.054)
automatic	0.007	0.036	0.283
	(0.028)	(0.028)	(0.037)
CO2 not observed	-0.842	-0.449	0.245
	(0.144)	(0.181)	(0.171)
constant	-9.647	-11.378	-3.852
	(1.389)	(1.499)	(4.339)
observations	10349	10349	10349

Table 4. Estimates from discrete-choice models. Standard errors assume clusters at the product level. Tax instrument is registration tax. Gandhi-Houde (GH) instruments are "differentiation instruments" based on length, power, fuel cost, CO_2 emissions, and registration tax.

	Q1 price	Q2 price	Q3 price	Q4 price	outside good
Q1 price	0.46	0.36	0.06	0.01	0.11
Q2 price	0.3	0.49	0.13	0.03	0.05
Q3 price	0.19	0.5	0.21	0.08	0.03
Q4 price	0.09	0.39	0.28	0.23	0.02

Table 5. Diversion ratios 2021. When the price increases for a product in a row group, the numbers in the row give the proportion of those who substitute away from the product that end up in each of the column groups, where the outside good is choosing not to buy a new car.

own group. For instance, for cars in the bottom quartile by price, 46 percent of consumers lost (as a result of a marginal increase in price) end up buying another bottom-quarter car, while only 6 percent end up in the third quarter, and 1 percent in the fourth quarter. For the second quarter, 49 percent of consumers lost end up buying another second-quarter car. There is limited substitution to the outside option of not buying a new car. In particular, for products in the fourth quarter, only 2 percent of lost customers end up not buying a new car at all. For the bottom quarter, on the other hand, this number is 11 percent. This pattern of disproportionate substitution towards similar and to inside goods (rather than to the outside good), is peculiar to the mixed logit model, since diversion ratios in the simple logit model are a function of market shares only.[31]

Table 6 summarizes features of the estimated demand functions and pricing implications for each year of our sample. The second column, 'own', shows sales-weighted mean own-price elasticities of demand. These are very similar to the -5.06 sales-weighted average reported by Grieco et al. (2023). Berry et al. (1995) report own-price elasticities ranging from -3.09 to -6.76 for a sample of products.

Given the estimated demand function, we can use the first-order conditions for profit maximization in (9) to infer the margins and unit costs implied by the observed product ownership, prices and taxes. In the last four columns of Table 6 we use the decomposition in (8), divided by retail price, to obtain the share of retail price accounted for by the manufacturer's margin, cost, registration tax, and VAT, so that the four components sum to one:

$$1 = \frac{p_{jt}}{p_{jt}} = \underbrace{\frac{p^*_{jt} - c_{jt}}{p_{jt}}}_{\text{margin/price}} + \underbrace{\frac{c_{jt}}{p_{jt}}}_{\text{cost/price}} + \underbrace{\frac{\tau_{jt}}{p_{jt}}}_{\text{reg.tax/price}} + \underbrace{\frac{v_{jt} p^*_{jt}}{p_{jt}}}_{\text{VAT/price}}, \tag{13}$$

where p_{jt} is retail price and p^*_{jt} is the pre-tax price received by the seller, and which VAT is

[31]The diversion ratio from k to j in the simple logit model is $\frac{\partial s_{jt}/\partial p_{kt}}{-\partial s_{kt}/\partial p_{kt}} = \frac{\alpha s_{kt} s_{jt}}{\alpha s_{kt}(1-s_{kt})} = \frac{s_{jt}}{1-s_{kt}}$.

	own	single prod.	margin/price	cost/price	reg.tax/price	VAT/price
2000	-4.26	0.19	0.21	0.37	0.28	0.14
2001	-4.39	0.18	0.21	0.32	0.34	0.13
2002	-4.38	0.18	0.21	0.31	0.36	0.13
2003	-4.42	0.18	0.2	0.3	0.37	0.13
2004	-4.85	0.17	0.19	0.31	0.38	0.12
2005	-4.8	0.17	0.19	0.31	0.38	0.12
2006	-4.99	0.16	0.18	0.31	0.39	0.12
2007	-5.05	0.16	0.18	0.35	0.33	0.13
2008	-4.65	0.17	0.2	0.32	0.35	0.13
2009	-4.59	0.17	0.2	0.33	0.33	0.13
2010	-4.59	0.17	0.2	0.35	0.31	0.14
2011	-4.7	0.17	0.2	0.36	0.31	0.14
2012	-4.79	0.17	0.19	0.37	0.3	0.14
2013	-4.54	0.18	0.2	0.38	0.28	0.13
2014	-4.69	0.18	0.2	0.41	0.26	0.13
2015	-4.66	0.18	0.21	0.44	0.23	0.12
2016	-4.82	0.17	0.2	0.47	0.21	0.13
2017	-5.08	0.17	0.19	0.5	0.19	0.12
2018	-4.63	0.19	0.21	0.52	0.16	0.1
2019	-4.69	0.19	0.21	0.58	0.12	0.09
2020	-4.92	0.19	0.21	0.66	0.06	0.08
2021	-4.99	0.19	0.21	0.69	0.04	0.06

Table 6. Market and own-price elasticities; decomposition of price in to margin, cost, reg. tax and VAT.

based on (v_{jt} is the applicable VAT rate). The table shows sales-weighted means for each year of the data. Margins have been more or less constant around 0.20 throughout our period. For comparison, Grieco et al. (2023), find that sales-weighted mean margins in the US market decrease from 0.42 in 1980 to 0.22 in 2018. The main change observed in our sample period is that as zero-tax, high-marginal-cost EVs enter the market from the early 2010s, tax revenues fall rapidly, while the share of retail price accounted for by unit costs increases fast enough that the sum of taxes and cost, and therefore margins, remain roughly constant.

The third column of Table 6, 'single prod.', shows the same calculation as 'margin/price', but under the alternative assumption that each product is sold by a separate profit-maximizing unit, so that manufacturers do not internalize cross-product substitution when setting prices. The difference between the 'margin/price' and 'single prod.' columns is therefore an estimate of the contribution of the portfolio effect (of owning multiple substitute products) to car manufacturer margins. This portfolio effect typically accounts for about 2 percentage points of the 20 percent margins, so ten percent of margins can be explained by portfolio effects.

Consider the highest-selling Tesla products, Model 3 and Model Y, in 2021. Their retail prices are 400,000 NOK and 450,000 NOK, while the implied margins from our model are 85,000 NOK and 124,000 NOK, and implied marginal unit costs 315,000 NOK and 326,000

NOK, respectively. Note that marginal cost includes all incremental costs incurred in manufacturing, shipping, transport, selling at a dealership, expected warranty fulfillment, and free service, of one additional unit sold in Norway. For a simple external check on our cost estimates, an engineering estimate from 2018 puts the unit production cost of Tesla Model 3 at 28,000 USD, or 241,000 NOK.[32] Tesla's cost of goods sold per vehicle (cost of the materials and labor directly used to create the good) is reported as 36,000 USD, or 309,600 NOK in Tesla's 2021Q4 income statement (shareholder deck). In January 2023 Tesla cut the sales price of its Model Y by 120,000 NOK, which implies cutting margins essentially to zero according to our estimates.[33]

6 Counterfactuals

The dramatic reversal of observed EV and ICE market shares since 2012 cannot be explained by any corresponding change in taxes or other policies. Instead, it must be attributed to the expansion of the range of electric cars on offer and their quality improvements, as discussed in section 2.4. This expansion in range and quality is an international trend. Yet other countries have not had the same increase in the EV share. This suggests that it is the combination of choice set improvements and incentives that has resulted in the high observed EV share in the last few years of our sample period. In this section we turn to the counterfactual experiments, which are designed to disentangle the respective contributions of these incentives.

A change in taxes or other market primitives affects consumer choices, but also firms' pricing decisions. When looking at counterfactual changes to energy costs, car taxes, and other factors, we therefore compute profit-maximizing price responses that take into account the product portfolios of car manufacturers as well as consumer substitution behaviour. Using the estimated demand system, for each counterfactual experiment, we find the price vector p_t in each market t that satisfies the first-order conditions for profit maximization (9). We first set out the details of how we change market primitives in our counterfactual experiments, and then present the results.

[32] See https://qz.com/1294282/the-tesla-model-3-cost-28000-to-build-german-engineers-say-and-it-still-may-not-be-profitable.

[33] https://www.motor.no/aktuelt/tror-teslas-nye-priser-gir-kollaps-i-bruktmarkedet/240764.

6.1 Counterfactual changes in market primitives

The first factor we look at is the energy costs incurred when driving, which are substantially lower for EVs than for ICE vehicles. In 2021 the energy cost of driving 10 kilometres had a sales-weighted average of 10.6 NOK (approximately 1.23 USD) for ICE vehicles and 3.5 NOK (0.41 USD) for EVs. This cost differential is partly due to taxes on fossil fuels. Without these taxes, the cost for ICE vehicles would be reduced to 7.0 NOK. For our first counterfactual, we set petrol and diesel taxes to zero, and double the electricity price in each year.[34] The left panel of Figure 3 shows the average energy cost of driving 10 km, by year and by fuel type (see legend in the right-hand panel), where the average is across products marketed in that year and not weighted by sales. The black lines are observed energy costs. Variation over time is driven by changes in the set of products offered and by changes in energy prices. The red lines are averages in our counterfactual, where in each year the electricity price has been doubled and the fossil fuel taxes removed. The red lines are closer together than the black lines, corresponding to an approximate equalization of energy costs.

In our second counterfactual, we undo the favourable tax treatment of electric and hybrid vehicles. For VAT, we make EV buyers pay the same 25 percent rate as buyers of other products. The registration tax is based on CO_2 emissions and weight, which are respectively zero and unusually high for EVs. To make EV buyers pay the same tax as buyers of similar non-electric cars, we impute a registration tax for EVs and hybrids based on dimensions in which they are comparable to ICE vehicles. Concretely, for ICE vehicles only and separately for each year of data, we regress registration tax paid on length, engine power, their squares and interaction, as well as dummies for 4WD and body styles. We then use the estimated coefficients to impute the tax for EVs and hybrids, based on the same characteristics. The right panel of Figure 3 shows average observed registration tax (in black) by year and fuel type. Note that for EVs the tax is identically zero throughout. The red lines show the imputed taxes for EVs and hybrids. For petrol and diesel cars the registration tax remains unchanged in the counterfactual. The imputed tax for hybrids is high for most of the period, because the hybrids on the market had powerful engines from early on, while EVs became more powerful only at the end of our period.[35]

In our final counterfactual change of market primitives, we want to explore the effect of

[34] There is no subsidy for electric power sold to households in our sample period (although a subsidy was introduced in mid-December 2021 in response to unusually high electricity prices). Therefore our counterfactual change of electricity prices is not strictly speaking a case of undoing an EV incentive. However, we are interested in how much of EV uptake can be explained by lower energy costs of driving, and therefore look at an approximate equalization.

[35] Hybrids had an unweighted average engine power just over 190 kW in every year from 2015 to 2021. Electric/petrol/diesel cars had averages of 82/121/110 kW in 2015, and 169/174/135 in 2021.

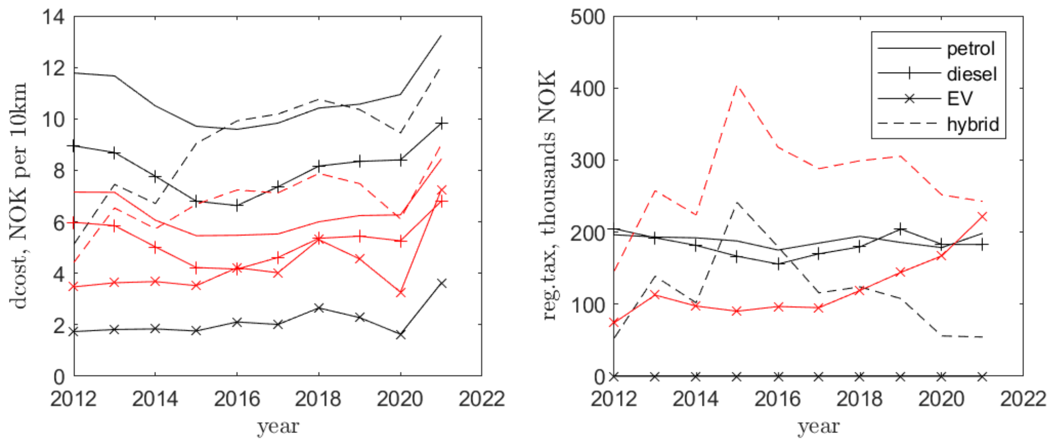

Figure 3. Mean (not sales weighted) energy costs of driving (NOK per 10 km) and registration tax (in thousands of NOK); observed (black) and counterfactual (red).

"other EV incentives", such as bus lane access and reduced road toll fees. In our demand model, these incentives are absorbed in the estimated EV effect (1.118 for the mixed logit model). However, this estimate also captures other features of EVs that shift the average utility that consumers derive from them relative to the baseline of petrol cars (whose fuel type effect is normalized to zero). Switching off the EV effect would mean changing it to the petrol car level. We do this in a second version of this counterfactual, but in our preferred version we set the EV effect to the average for non-electric vehicles (petrol, diesel and hybrid), which do not benefit from bus lane access, reduced toll road fees, etc. That is, for the counterfactual we change the coefficient on the EV dummy from 1.118 to $(0 + 2.162 + 0.359)/3 = 0.84$. Since the difference in fixed effects between EVs and other vehicles could also be due to other factors (which might in sum be either positive or negative) than the EV incentives we mention, the results from this third counterfactual should be interpreted with caution.

6.2 Counterfactual outcomes

The first three panels of Figure 4 show observed and counterfactual market shares for EVs, ICE vehicles, and hybrids, respectively, for each year from 2012 to 2021. In the upper left panel, we see that the combined counterfactual (equalized energy costs and taxes, and EV effect set to non-electric average) results in an EV market share that grows more slowly and reaches 14 percent in the last year of data. This outcome broadly corresponds to the evolution seen in countries without strong EV incentives.

Looking at each set of incentives in turn, we see that equalizing energy costs (counterfactual A in the figure) has a moderate effect on the electric market share, reducing it by

10 percentage points in 2021. This suggests that the large reduction of EV market share in the combined counterfactual comes mainly from equalizing taxes and removing other incentives such as bus lane access etc. Undoing the favourable treatment of EVs in purchase taxes (counterfactual B in the figure) is the counterfactual with by far the largest effect, reducing the EV share to 25 percent in 2021. The third counterfactual attempts to undo "other incentives" such a toll road discounts. The two versions of are shown in the figure as counterfactuals C (setting the EV effect equal to the effect of non-EVs) and C2 (setting the EV effect to zero). The former has only a moderate effect, reducing the EV market share from 66 to 60 percent in 2021. The second version reduces the EV market share to 41 percent in 2021.

From the panels for ICE vehicles and hybrids, we see that equalizing taxes has a strong positive effect on ICE vehicles, while for most years it reduces the sale of hybrid vehicles. The reason is that the tax counterfactual increases the tax paid by buyers of hybrids (although by less than for EVs), making them less attractive relative to ICE vehicles. For ICE vehicles on the other hand, the tax is unchanged in the counterfactual, leaving them unequivocally more attractive (relative to EVs and hybrids). The fact that both EVs and hybrids become less desirable for consumers, means that the total number of vehicles falls, as can be seen in the fourth panel.

The favourable tax treatment of EVs and (to a lesser extent) hybrids is the most distinctive part of the Norwegian incentive scheme. In light of this, it is interesting to note that undoing the tax exemptions still leaves the predicted EV share at 25 percent in 2021 — a significant reduction from the observed outcome, but still a high EV share by international standards.

We turn next to quantifying some of the tradeoffs involved when designing EV incentives. EVs are heavier than ICE vehicles, and consequently have higher non-exhaust particulate matter emissions, from tyre wear, brake wear, road surface wear and resuspension of road dust. As stricter emissions standards for ICE vehicles have reduced exhaust emissions, non-exhaust emissions constitute a large and rising share of total particulate matter emissions. Timmers and Achten (2016) estimate a non-exhaust share of as much as 85–90 percent of the total, and find that non-exhaust emissions have a strong positive relationship with vehicle weight. Figure 5 shows how mean sales weighted CO_2 emissions and vehicle weight in the counterfactual scenarios, as well as observed values.

The combined counterfactual results in a dramatic increase in sales weighted mean CO_2 emissions per km and a large reduction in sales weighted mean vehicle weight. Undoing the EV and hybrid tax advantage is the counterfactual with by far the largest effect.

While Figure 5 gives sales-weighted means, Table 7 shows, for 2021 only, the percentage

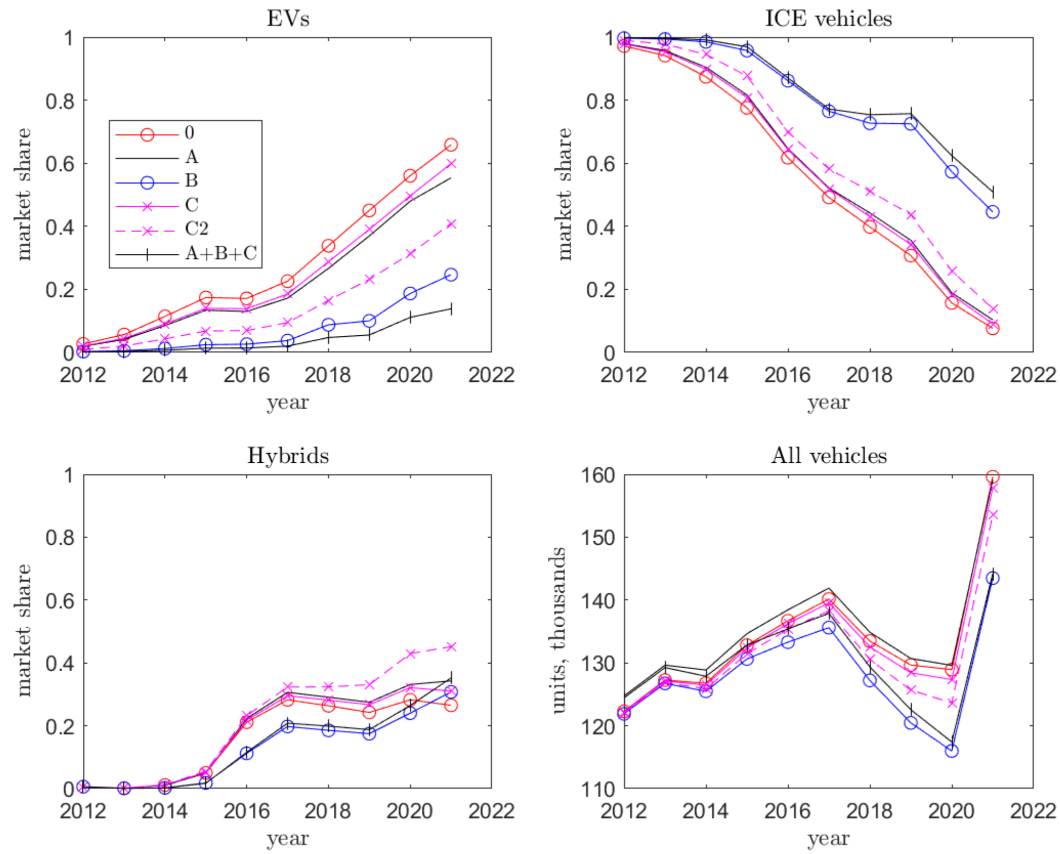

Figure 4. Units sold by year, observed (0), and counterfactuals: modified energy costs (A), equal tax treatment (B), EV effect set to non-electric average (C), EV effect set to zero (C2), and A-C combined (A+B+C).

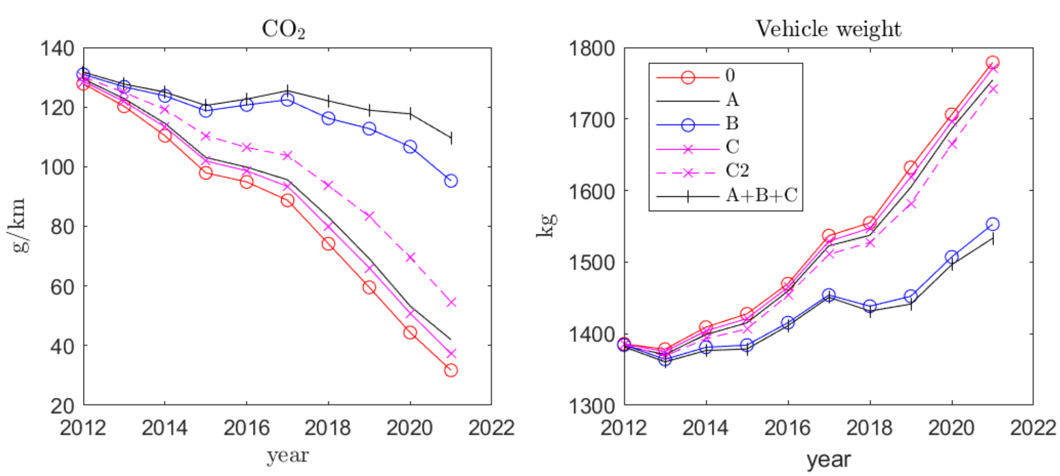

Figure 5. Attributes, sales-weighted means. Observed (0), and counterfactuals: modified energy costs (A), equal tax treatment (B), EV effect set to non-electric average (C), EV effect set to zero (C2), and A-C combined (A+B+C).

	% change from observed outcome		
	total kg	total CO2	total units
(A) changed energy costs	-1.7	32.0	-0.3
(B) imp. tax on EVs and hybrids	-21.5	169.9	-10.1
(C) EV effect to non-EV avg.	-1.6	16.1	-1.1
(C2) EV effect to zero	-5.8	65.8	-3.8
(A+B+C)	-22.1	212.3	-9.7

Table 7. Counterfactual percentage changes relative to actual tax regime: total weight, total CO_2 per km, and total units of new cars sold in 2021

changes in total weight and total emissions per km. Since the respective counterfactual experiments differ in terms of their effect on the total number of vehicles sold, these totals are perhaps more relevant from a policy perspective. We see that undoing the tax advantages for EVs and hybrids reduces total weight of new vehicles sold by about one fifth, while the total CO_2 emissions (assuming no changes to the distance driven) increases by 170 percent.

6.3 Additional counterfactuals: tax vs. ban on non-electric vehicles

Major economies have announced a complete phaseout of ICE vehicles, with California and the EU planning effective bans on their sale by 2035.[36] But taxing non-EVs may be more efficient than banning them: in isolation, a non-EV purchase tax equal to the incremental negative externality of an additional non-electric vehicle allows ICE or hybrid buyers with a willingness to pay that exceeds the externality to obtain a positive surplus. With a ban, this surplus is lost. However, when taking into account substitution between EVs and non-EVs, and other factors, the tradeoffs are less clear.

In a final set of counterfactuals, we attempt to assess the relative merits of differentiated purchase taxes and a ban on ICE and hybrid vehicles. Given the congestion and non-exhaust particle emission consequences of having a large number of EVs, we think it will eventually be desirable to tax EVs too, but without inducing too much of a switch back to ICE vehicles. Therefore, in this last set of counterfactuals EVs are no longer tax-exempt, but pay the imputed tax (like in counterfactual B above) similar to that paid by ICE vehicles in the current tax regime. In three different counterfactual experiments, ICE vehicles and hybrids pay twice this rate, four times this rate, or are removed from the consumers' choice set (corresponding to a ban), respectively. Figure 6 shows market shares for EVs, ICE and hybrid vehicles, as well as total number of units sold, in the three counterfactual experiments, together with the observed outcomes, which are the same as in Figure 4. With sufficiently

[36] https://www.gov.ca.gov/2022/08/25/california-enacts-world-leading-plan-to-achieve-100-percent-zero-emission-vehicles-by-2035-cut-pollution/ ; https://www.reuters.com/markets/europe/eu-approves-effective-ban-new-fossil-fuel-cars-2035-2022-10-27/.

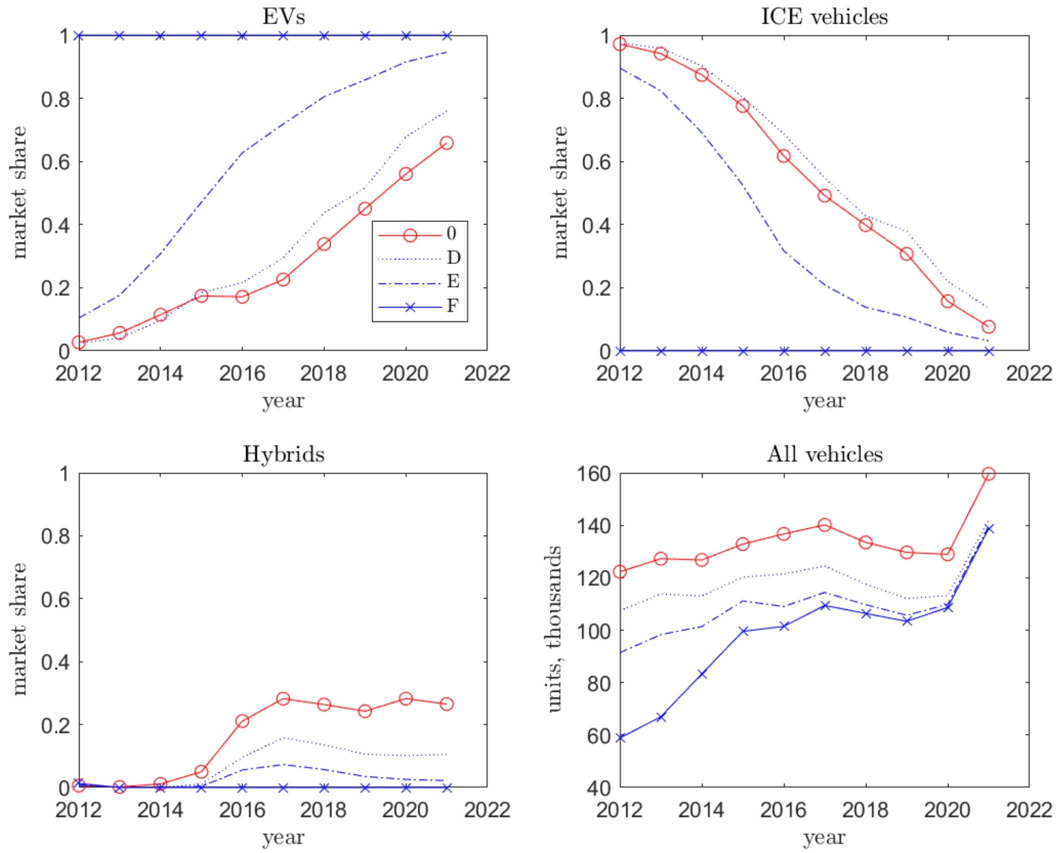

Figure 6. Market shares by fuel type and units sold by year, for actual taxes (0), imputed taxes for EVs and hybrids, and 2× tax for ICE and hybrid vehicles (D), 4× tax for ICE and hybrid vehicles (E), and ban on ICE and hybrid vehicles (F).

high taxes on non-EVs, we see that the EV market share can be driven to 95 percent in the last year of our data. But note how the EV share in this (high-tax) counterfactual increases sharply over time, suggesting that as EV quality and product range continues to improve, the non-EV tax penalty required to make their market share negligible will decline. Table 8 shows that all three counterfactuals reduce the total weight of new cars sold significantly, and by more than the reduction in the number of units, implying that cars sold are on average lighter in the counterfactual. The reduction in CO_2 emissions in the high-tax counterfactual E is 85 percent, only slightly less than the 100 percent reduction from banning ICE and hybrid vehicles.

	% change from observed outcome		
	total kg	total CO2	total units
(D) 2xTax non-EVs, imp. tax on EVs	-18.0	-20.8	-11.0
(E) 4xTax non-EVs, imp. tax on EVs	-17.0	-85.3	-12.5
(F) remove non-EVs, imp. tax on EVs	-16.5	-100	-13.1

Table 8. Counterfactual percentage changes relative to actual tax regime: total weight, total CO_2 per km, and total units of new cars sold in 2021

6.4 Variable profit, consumer surplus, and tax revenue

In each counterfactual we obtain equilibrium prices and quantities demanded for each product. It is then straightforward to find total tax revenues from VAT and the registration tax. Given the marginal unit cost estimates, discussed in Section 5.2, variable profit is also easily obtained. Consumer surplus is given by the expected utility of the optimal choice, expressed in money terms, which follows from the demand estimates.[37] Table 9 shows changes in variable profit, tax revenue, consumer surplus, and the sum of the three, denoted total surplus, for each of our counterfactuals, relative to the observed outcome. For ease of interpretation all numbers are expressed per new car actually sold in 2021, as a percentage of average price.

Consider counterfactual B, which involves undoing the tax benefits of EVs and hybrids by imputing a similar tax to that levied on ICE vehicles. The counterfactual gives a large increase in tax revenues, but an even larger drop in consumer surplus. Combined with a fall in variable profits, this results in a total surplus loss per new car (actually) sold of 5.6 percent of its price. The first four rows of the table correspond to our initial set of counterfactuals, which all increase CO_2 emissions (cf. Figure 5). The total welfare loss is therefore greater than reported in the table, since it also includes the welfare loss caused by higher emissions. Put differently, the current Norwegian tax exemption for EVs (and tax reduction for hybrids) is welfare-enhancing even without counting the welfare gain from emissions reductions. However, it should be noted that the surplus generated is not evenly distributed: the loss in tax revenue affects everyone, while the gain in consumer surplus accrues to relatively high-income households that buy new EVs.

In contrast, the last three rows of the table correspond to counterfactuals that reduce CO_2 emissions relative to the observed outcome. Here there is a trade-off in that each policy change reduces the sum of consumer surplus, variable profit and tax revenue. In 2021, high taxes for non-EVs (counterfactual E) gives a total surplus (not counting emissions) that is higher than that from a ban on non-EVs (counterfactual F) by an amount that equals 5.8 percent of the average price per new vehicle sold in 2021.

[37] $CS_t = M_t \cdot \int (1/|a_i|) \left\{1 + \sum_{k\in J_t} \exp(\delta_{lt} + \mu_{ilt})\right\} f(\nu_i) d\nu_i$, where M_t is the market size (see Section 4.2).

	change, per new car sold in 2021, % of price			
	total surplus	var. profit	tax rev.	cons. surpl
(A) changed energy costs	2.2	-0.6	3.2	-0.4
(B) imp. tax on EVs and hybrids	-5.6	-3.0	28.4	-31.1
(C) EV effect to non-EV avg.	-2.2	-0.5	1.7	-3.5
(C2) EV effect to zero	-6.1	-1.6	7.0	-11.5
(A+B+C)	-3.3	-2.8	29.0	-29.6
(D) 2xTax non-EVs, imp. tax on EVs	-19.1	-0.3	18.1	-36.9
(E) 4xTax non-EVs, imp. tax on EVs	-29.9	0.5	12.6	-43.0
(F) remove non-EVs, imp. tax on EVs	-34.7	0.7	9.7	-45.1

Table 9. Counterfactuals summary, 2021, changes relative to observed outcome, per new car sold (observed quantities) in 2021, in percent of avg. price. The change in tax revenue includes registration tax and VAT from new cars, but not from taxes on fossil fuels.

7 Conclusion

The global transition from ICE to electric vehicles is critical for reducing emissions. Norway has been particularly successful in electrifying its fleet, with EVs making up 66 percent of new cars sold in 2021. Our study examines the effectiveness of Norwegian EV incentives in changing the composition of the vehicle fleet. EVs are exempt from value-added tax and CO2- and weight-based registration tax, which together make up about 70 percent of the pre-tax price of ICE cars. We find that these tax exemptions are the most effective lever in driving EV adoption. Without them, EV market share would drop to 25 percent. Taxation of EVs may be necessary in the future to address road congestion and non-exhaust particle emissions generated by these vehicles. We examine several scenarios where EVs are no longer tax-exempt, and ICE vehicles are either taxed more heavily or completely banned. Results indicate that heavy taxation could achieve similar outcomes to a ban, for instance, EVs would reach 95% market share if ICE cars were taxed four times their EV counterparts. Important aspects of EV incentives that are outside the scope of this paper are distributional effects and the detailed analysis of incentives like bus lane access and discounts on road tolls, parking charges, and car ferry fares, as well as the access to charging stations outside the home.

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