Would you like to super-size your car? The effect of environmental subsidies on emissions

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Abstract

This paper studies the impact of subsidies for Plug-in hybrid vehicles (PHEV) on carbon emissions. I show that subsidizing innovations without considering consumer behavior can harm the environment. I provide descriptive evidence on charging instances of PHEV and combine it with a structural model of demand for new passenger vehicles to evaluate the market outcomes had subsidies for PHEV not been in place. I show that PHEV subsidies were used by consumers to purchase larger and heavier vehicles and that consumers of PHEV seldom charge their vehicle. Taking into account the observed consumer behavior, I find that the elimination of subsidies for PHEV would have led to a yearly reduction of 167,139 tons of carbon emissions which are equivalent to the yearly carbon emissions 52,916 households emit due to energy consumption.

Keywords: Environmental regulation, Substitution, Carbon emissions, Automobiles, Demand estimation

JEL Codes: D12, H23, H71, Q48, Q58

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1 Introduction

Reducing our environmental footprint is of high priority for many economies worldwide. One of the main strategies to combat emissions is the introduction of policies encouraging the development and adoption of emissions reducing innovations. The environmental benefit of such innovations sometimes depends on consumer's usage behavior. Plug-in hybrid vehicles (PHEVs) provide an example – PHEVs when their battery is fully charged reduce driving related carbon emissions to a third of its internal combustion engine vehicle (ICE) counterpart, yet when driven uncharged, PHEVs emit three-folds more emissions than officially claimed. PHEVs sales in Europe increased rapidly over the past years, from a market share of less than 1 percent in 2016, to a share of 10 percent in 2021. Part of this increase is attributed to generous subsidy schemes for PHEVs, which governments across Europe offer. The increase in PHEVs is also partly attributed to supply side efforts – as I show, for some automobile manufacturers, PHEVs had a key role in achieving compliance with the EU emissions regulations. Notwithstanding the introduction of new innovations in the automobile industry, the transportation sector is one of the few sectors in the EU which saw CO_2 emissions rise, compared to their 1990 levels.[1] In order to evaluate and design better policies for emissions reductions in the transportation sectors, it is important to understand the contribution of PHEVs to CO_2 emissions.

This paper contributes an empirical examination of consumers' adoption and usage patterns of new emission-reducing innovations and their impact on carbon emissions. I quantify the environmental benefits of PHEVs adoption in Germany by taking into account PHEVs charging behavior, and evaluate the effects purchase subsidies had on consumers' PHEVs purchasing decision. Moreover, as PHEVs consumers are not informed of uncharged PHEVs fuel consumption values,[2] I quantify the role this lack of information has on purchasing decisions. This paper also extends the literature analyzing emission standards (Reynaert, 2020;

[1] See figure C.1 in the appendix.

[2] Fuel consumption values of PHEVs are not advertised by automobile manufacturers.

Jacobsen, 2013; Goldberg, 1998) by offering a framework to analyze manufacturers reaction to emission standards.

I present evidence on the lack of PHEVs charging, and calculate PHEVs real-usage fuel consumption values. On the supply side, I show that for some manufacturers, sales of PHEVs were important for achieving compliance with the EU emissions standards. These stylized facts combined portray an alarming picture: a significant share of the declared emission reductions do not translate to real world emission reductions. These results motivates my analysis of consumer purchasing decisions. I estimate a discrete choice model of consumers demand in the automobile market, I use the estimated model to evaluate consumers' choices under two main counterfactual scenarios: (1) had subsidies for PHEVs not been in place and (2) had consumers been informed of uncharged fuel consumption values of PHEVs. A back on the envelope calculation shows that in the short term, elimination of subsidies for PHEVs can reduce yearly carbon emissions by 167,139 tons. This is the equivalent of the yearly carbon emissions due to energy consumption of 52,916 households. Moreover, I show that eliminating PHEVs subsidies reduces the number of SUV sold by 10 percent, which indicates that the subsidies were used by some consumers as an upgrading opportunity.[3]

This paper relates to a burgeoning literature analyzing the impact of policies on the adoption of energy efficient technologies (Houde and Aldy, 2017; Allcott et al., 2015; Boomhower and Davis, 2014; Davis et al., 2014), and in particularly the adoption of energy efficient technologies in the automobile industry (Muehlegger and Rapson, 2022; Chen et al., 2021; Clinton and Steinberg, 2019; Chandra et al., 2010). The literature is unanimous in its conclusion that energy-efficiency programs mostly target inframarginal consumers – consumers who would have purchased energy efficient products also without these programs. Houde and Aldy (2017) use difference-in-differences approach to evaluate consumers' response to the U.S. energy efficient appliance rebate program. They find that in the long run, the pro-

[3] Recent research (for example Anderson and Auffhammer (2013)) indicates that the safety externality SUVs impose on non-SUV drivers might even exceed the environmental externality of these vehicles. Therefore the reduction of the market share of SUVs might serve in itself as a policy goal.

gram didn't increase the market share of energy efficient appliances, since most consumers participating in the program would have purchased energy efficient appliances in any case. The implied energy reduction of the program is small, because the rebates were used to upsize participants' appliances, which in turn led to a higher energy consumption in comparison to participants' previously owned smaller models. Boomhower and Davis (2014) and Davis et al. (2014) evaluate an appliance replacement program in Mexico using difference-in-differences and regressions discontinuity approaches respectively. Boomhower and Davis (2014) find that over two thirds of the participants in the program are inframarginal and would have replaced their old appliances also without the program. Davis et al. (2014) show that usage behavior reduced the energy saving outcome of the program – program participants used their new air conditioners more often than before their program participation, hence reducing the program's energy savings. In the market for automobiles Chen et al. (2021) and Chandra et al. (2010) evaluate energy-efficiency programs using difference-in-differences and structural demand model approach respectively. Both find most consumers to be inframarginal. Notwithstanding the rapid growth in the literature analyzing the adoption of Battery electric vehicles (BEVs)[4] and PHEVs (Remmy, 2022; Springel, 2021; Xing et al., 2021; Clinton and Steinberg, 2019; Holland et al., 2019; Li, 2019; Li et al., 2017; Yu et al., 2016), the literature focuses mainly on the network effects of charging stations on BEVs adoption (Remmy, 2022; Springel, 2021; Li, 2019; Li et al., 2017; Yu et al., 2016) rather than consumers' substitution patterns and the derived environmental benefits. Xing et al. (2021) and Holland et al. (2019) are the exceptions: Xing et al. (2021) use a structural demand estimation framework to assess what BEVs and PHEVs buyers would have purchased had these vehicles not existed. They show that assessments of environmental benefits which ignore these substitution patterns would overestimate the adoption benefits. Holland et al. (2019) estimate the effect of BEVs adoption on local pollutant such as $PM_{2.5}$ and SO_2 by exploiting survey data on second choice vehicle to determine BEVs replacement

[4]I use the term BEVs to describe pure electric vehicles, which don't posses an additional internal combustion engine for propulsion.

vehicle. They find that high-income groups benefit from BEVs adoption, yet low-income groups experience an increase in local pollution.

The rest of the paper is organized as follows: section 2 introduces the German market for automobiles and the EU emission standards. Section 3 presents the data. Section 4 presents stylized facts on the charging behavior of PHEVs and reduced form evidence on the important role PHEVs had in achieving compliance with EU emissions regulations. Section 5 presents the demand and supply model. Section 6 describes the model's estimation procedure and presents the estimation results, which are used in section 7 to evaluate the impact the subsidies had on consumer adoption of PHEVs and carbon emissions. Section 8 concludes and discusses the findings.

2 Industry and policy background

2.1 National subsidies for Germany

Germany is the largest market for automobiles in Europe, and is the largest adopter of PHEVs and BEVs in the EU. In 2021, Germany accounted for 25 percent of new vehicle sales, 36 percent of all PHEVs sales, and 36 percent of BEVs sales in the EU.[5] Germany is also a home to numerous automobile manufacturers. In 2015, the automobile industry accounted for 4.5 percent of total gross value added in Germany.

In 2016, the government announced a subsidy scheme for BEVs and PHEVs. The subsidies, available to private consumers as well as companies, foundations, and associations, were offered for selected vehicles[6] which were purchased after May 18 2016 and remained registered by the buyer for at least six months. For a PHEV to be eligible for the subsidy it must emit no more than 50g CO_2 per kilometer, and its price must be below 65,000 Euros

[5]For comparison, the next largest markets are France and Italy, which accounted for 18 percent and 15 percent of new vehicles sales in the EU, respectively.

[6]The eligible vehicles were published in a list by the Federal Office of Economics and Export Control (BAFA).

(the same price limit applies to BEVs as well). The subsidy scheme was designed to be paid half by the government and half by the automobile manufacturers. It was set at 3,000 Euros for PHEVs, and 4,000 for BEVs. By 2021, the subsidies rates rose to 6,750 and 9,000 Euros for PHEVs and BEVs with a net price below 40,000 Euros, and 5,625 and 7,000 Euros for PHEVs and BEVs with a net price between 40,000 and 65,000 Euros. The subsidies were in place until the end of 2022. From 2023 on, PHEVs weren't subsidized anymore.[7]

2.2 The EU emissions standard

As of 2022, the EU carbon emission standard for passenger vehicles is one of the strictest standards worldwide. For comparison, as of 2022, the U.S. standard for passenger vehicles is set at 148.5g CO_2/km while the European standard is 95g CO_2/km. The EU carbon emissions standard sets a target on the manufacturers' weight-adjusted average of carbon emissions of all vehicles sold in the EU. Surplus of emissions is not tradable or storable for future years. The standards were initially announced in 2007 at a level of 130g CO_2/km and came into force in 2014. Many automobile manufacturers complied with the initial standard well before it became binding. In 2014, a stricter standard of 95g CO_2/km was announced. Automobile manufacturers had time until 2021 – the year the standard became fully effective – to adjust their fleet accordingly.[8] Penalties are imposed on non-compliers. In 2021, all automobile manufacturers complied with the standard and paid no penalty fees.

For illustration, equation (1) shows how a manufacturer's fleet emissions are calculated:

$$E_i^{EU} = \frac{\sum_{j \in i} q_j (e_j - \alpha(w_j - w_0))}{\sum_{j \in i} q_j} \tag{1}$$

where q_j denotes the EU-wide sales of vehicle j of fleet i, e_j is the carbon emissions of vehicle

[7]On January 2023, the government introduced new, significantly lower subsidy rates for BEVs only.
[8]2020 was a transitional year in which the standard became partially binding.

j, w_j is the weight of the vehicle, α is a weight adjustment factor, and w_0 is a pivot weight which is equal to the average weight of new passenger vehicles registered in the previous three years. From 2020 on, the value of α was set at a value 0.0333 and the value of w_0 was 1,379.88.[9] Notice that the standard penalize the carbon emissions of light-vehicles while subsidizing the emissions of heavy-vehicles.

3 Data

3.1 Vehicle sales and characteristics

The data used in this paper covers the universe of vehicle registrations in the EU between the years 2014-2021. I use new vehicle registrations as a proxy for sales. For the main analysis presented in this paper, I use the subset of new vehicles registered in Germany during 2015 – 2021.[10] Each vehicle is defined as a brand-model-trim combinations, which captures the brand, model, series, motor-type and body-type combination. An example of a brand-model-trim vehicle in the dataset is "BMW X1 xDrive25e" where BMW is the brand, X1 is the model name and xDrive25e is the trim. I complement the vehicle registrations data with data on vehicle characteristics for vehicles sold in Germany: the list price and an array of characteristics such as horsepower, size, weight, fuel consumption and battery range. To identify which vehicles were subsidized, I use the official lists of eligible vehicles published by the Federal Office for Economic Affairs and Export Control. In addition, I use information from the Federal Statistical Office regarding median households' income by year. I eliminate brand-model-trims with low sales.[11] A market in my data is a year; there are in total 2,322 brand-model-trim/year observations. I define the market size as a quarter of households in a given year.[12] Table 1 shows the mean and standard deviation for key variables in the final

[9] Source: Regulation (EU) 2019/631 of The European Parliament and of the Council.

[10] The main analysis focuses on Germany due to data availability: I do not observe prices for vehicles sold in other EU countries.

[11] Additional details are presented in appendix A.1.

[12] This definition assumes that a households considers to purchase a new vehicle every four years.

dataset for Germany, in addition to a breakdown of the means for the years 2015 and 2021.

Table 1: Summary statistics of Vehicles' sales and characteristics in Germany

	All years		2015	2021
	Mean	SD	Mean	Mean
Sales (1,000 units)	4.5	4.7	4.5	4.2
Price/income	1.5	0.8	1.4	1.9
Fuel Costs (per km)	6.1	2.0	6.4	6.2
Fuel consumption (l/100 km)	4.9	1.5	5.0	4.7
Volume (m^3)	12.5	2.0	12.1	12.9
Horsepower	158.3	79.2	134.9	198.7
Weight (kg)	1,488.1	325.6	1,404.3	1,645.5
PHEV	0.1	0.3	0.0	0.2
BEV	0.0	0.2	0.0	0.1
Number of models	339.6	45.2	309.0	219.0

Notes: The table presents means and standard deviations of the main characteristics of vehicles sold in Germany for all years and for the years 2015 and 2021 separately. The total number of observations (trim-model/market) is 2,322 where a market refer to a given year - 7 in total.The variable Price/income include subsidies for PHEVs and BEVs from 2016 on. Fuel consumption values exclude values for BEVs due to the different measurement scales.

Even though the average vehicle sold in 2021 was larger, heavier, and more powerful, it was more energy efficient than the averagely sold vehicle in 2015. Compared to a share of zero in the sample in 2015,[13] 20 percent of the vehicles sold in 2021 were PHEVs and 10 percent were BEVs. The number of different vehicles sold in 2021 decreased significantly compared to 2015. This is due to discontinuation of many diesel model-trims.

Table 2: Summary statistics by motor

	2015			2021		
	ICE	PHEV	BEV	ICE	PHEV	BEV
Share out of sales	99.4%	0.4%	0.2%	62.2%	13.0%	24.7%
Price/income	1.3	2.3	1.7	1.3	2.4	1.3
Volume (m^3)	11.7	11.8	9.8	11.7	14.1	11.1
Weight (kg)	1338.8	1670.7	1391.8	1345.2	2008.3	1579.9
Fuel Costs (per km)	6.4	2.3	4.0	6.5	2.3	4.6
Fuel consumption (l (kWh)/100 km)	4.9	1.7	13.8	4.8	1.6	15.2
Number of models	297	7	5	156	35	28

Notes: The table presents summary statistics by motor type (ICE, PHEV or BEV) in the years 2015 and 2021 for vehicles sold in Germany. The variable Price/income include subsidies for PHEVs and BEVs from 2016 on. All variables except "share out of sales" are sales weighted averages.

[13]This is not a result of the elimination of low selling vehicles mentioned above: in 2015 the share of BEV and PHEV sales was less than 0.01 percent.

Table 2 provides a more disaggregated view at sales weighted averages broken down by year and motor type. Prices of BEVs decreased significantly between 2015 and 2021, the decrease is partly attributed to the generous subsidies, and to the introduction of cheaper BEVs models by the manufactures. PHEVs prices remained constant even after the introduction of subsidies, which indicates that sold PHEVs got more expensive in 2021 than in 2015. PHEVs weigh on average about 50 percent more than their ICE counterparts, which explains the dramatic increase in manufacturers' fleets' sales-weighted weight with a high share of PHEVs sales obsereved in figure 2. Even though, the weight of the average sold ICE remained constant during 2015-2021, the weight of the average sold PHEVs increased by more than a fifth. With an average volume (height $\times$ width $\times$ length) of 14.1 m^3, PHEVs are also significantly larger than the averagely sold ICE vehicles and BEVs with respective average volumes of 11.7 m^3 and 11.1 m^3. The higher prices (after subsidies) of PHEVs and their larger size indicate that PHEVs target more affluent consumers. Therefore the environmental impact of PHEVs subsides hinges on the substitution patterns towards PHEVs: had there been no subsidies for PHEVs would these consumers still participate in the market and buy a large ICE vehicle?

3.2 PHEVs charging behavior

PHEVs have the potential to emit less emissions compared to their ICE counterparts by substituting fuel for electricity. In order to achieve the officially declared carbon emissions values drivers need to charge their PHEVs regularly. Therefore, PHEVs carbon emissions are highly dependent on the driver's charging behavior. Manufacturers don't publish uncharged PHEVs fuel consumption values, therefore to evaluate the real-usage fuel consumption and carbon emissions of PHEVs, I employ data on PHEVs usage patterns which was obtained from a German based app which helps drivers track vehicle's related costs. For each user I observe their vehicle type (brand, model and production year) and their vehicle's related costs and refueling instances. I focus on refueling observations which took place between

2015-2022. For each user-vehicle pair, I observe data on the refueling and battery charging date, the odometer reading, and the quantity of fuel and electricity charged. This data allows me to observe the real frequency with which drivers refuel their PHEVs and subsequently the real fuel consumption values of PHEVs. Since the data is user generated, I clean the data from unreasonable and incomplete observations. Additionally I retain only observations that can be matched to the sales and characteristics data described in section 3.1. The final dataset contains 391,594 observations for 77 PHEV models[14] and 4,087 users with an average of 95.8 observations per user.[15]

Table 3: Summary statistics of PHEV's usage data

	Mean	SD	Minimum	Maximum
Share of charging instances	0.5	0.5	0.0	1.0
Distance since last charging (km)	218.9	731.2	0.0	96,324.0
Distance since last fueling (km)	774.7	546.6	2.6	24,300.0
kWh charged (kWh)	21.3	67.9	0.0	3,000.0
kWh charged (kWh/100km)	2.5	8.0	0.0	200.0
Battery capcity (kWh)	116.2	37.2	44.0	400.0
Battery range (km)	131.9	25.6	93.0	311.5
Liters fueled	35.6	16.5	0.1	1,090.0
Fuel consumption (l/100km)	5.5	2.3	0.8	15.4
Offical fuel consumption (l/100km)	1.6	0.4	0.6	3.5
Production year	2,018.6	2.6	2,009.0	2,022.0
Horsepower	234.6	73.9	122.0	680.0
Price (EUR)	45,273.4	12,923.4	29,900.0	185,736.0
Subsidized	0.8	0.4	0.0	1.0
Diesel	0.1	0.2	0.0	1.0
SUV	0.4	0.5	0.0	1.0
Winter	0.2	0.4	0.0	1.0
Spring	0.2	0.4	0.0	1.0
Summer	0.3	0.4	0.0	1.0

Notes: The table presents means, standard deviation, minimum and maximum values of the main PHEVs usage variables and the PHEVs matched characteristics. The total number of observations (user/vehicle/date combinations) is 391,594.

Table 3 presents the summary statistics of the PHEVs usage data. The table shows that about half of the recorded observations are of battery charging type (the rest are of gaso-

[14] A total of 83 PHEV models were sold in Germany between 2015-2021.

[15] Additional details on the data preparation process are in appendix A.2.

line/diesel refueling). The high distance values some observations exhibit, is a result of users bundling a couple of refueling instances into one entry in the app.[16] Charging instances occur more frequently than fueling instances distance-wise. The average charged amount of kWh (kilowatts hours), both per a charging instance and per 100 kilometers, is lower than the battery capacity, which might be due to the longer charging times required for PHEVs compared with BEVs.[17] This observation highlights the underutilization of the electric motor by PHEVs drivers. A striking result is the large difference between the real fuel consumption of PHEVs drivers and the official fuel consumption: a 3.4 folds difference! This translates to a 3.4 folds difference between the real carbon emissions values and the official ones.[18] If real average usage emissions values were used, fewer PHEVs in the sample would have been subsidized in Germany, as PHEVs have to emit no more than 50 g/km carbon emissions in order to be eligible for subsidies. About 80 percent of the vehicles in the sample are subsidized, and about 40 percent of the vehicles are Sport Utility Vehicles (SUVs). Only 10 percent of the models in the sample are fueled with diesel.

4 Reduced form evidence on PHEVs

4.1 Usage behavior of PHEV

In order to determine uncharged PHEVs fuel consumption values, I use the refueling data to estimate the PHEVs fuel consumption under different battery charging scenarios. For that purpose I estimate the following equation using an OLS estimator:

[16] For example, the observation with 24,300 kilometers since last fueling instance corresponds to a purchase of 780 liters of fuel, which corresponds to a fuel consumption value of 3.2 liters per 100 kilometers (the official fuel consumption of the vehicle is 1.4).

[17] BEVs are usually equipped with a fast charging plug which reduces significantly the time needed to fully charge the battery.

[18] A vehicle's carbon emissions are proportional to its fuel consumption: one liter of gasoline (diesel) emits 2.3 (2.6) kilograms of carbon emissions.

$$Consumption_{it} = \beta_{kWh} kWh_{it} + \beta_x X_{it} + \epsilon_{it} \tag{2}$$

where consumption is the quantity of fuel bought (gasoline or diesel) in a full tank refill divided by the distance since the last full-refueling times 100,[19] kWh is is a measure for the utilization of the electric motor of the PHEVs: it is the sum of kWh charged per kilometer driven since the last full-refueling.[20] X includes 3 sets of control variables: (1) vehicle characteristics which potentially affect fuel consumption such as: officially stated fuel consumption, volume, dummy variable for diesel and brand dummies; (2) time fixed effects - dummies for season of the year (winter, spring and summer) and year dummies, which control for potential weather effects on fuel consumption and changes in charging behavior due to charging network expansions which are common to all users, and lastly (3) a set user dummies which control for driver specific driving style which affects fuel consumption. I use the coefficients estimates to predict the fuel consumption of PHEVs under different values of kWh charged per 100 km.

Table 4 shows the estimated coefficients of equation (2). A significant share of the variation in fuel consumption is explained when fixed effects are included: R-squared value of 0.51. As expected the charging coefficient is negative and significant. The coefficient of -3.28 magnitude suggests that charging 100 kWh for 100 kilometers driven, would reduce the fuel consumption of the vehicle by 3.38 l/100km. In order to gain better intuition regarding the relationship between battery charging, official and real-usage fuel consumption values, column (3) presents the estimation results when only user and year fixed effects are added as control variables. Column (3) clearly illustrates the importance of charging PHEVs for low fuel consumption. When PHEVs are not charged (i.e. kWh charged is zero), even the

[19]The fuel consumption values in the vehicle sales and characteristics data are in liters per 100 kilometer units.

[20]In contrast to the fuel consumption variable, kWh is not a measure of electricity consumption since instances of partial recharging are included. Additional details on the treatment of partial refueling instances are presented in appendix A.2.

most efficient PHEV sold in Germany achieves fuel consumption of 4.37 l/100km.[21] For the calculation of the counterfactual fuel consumption values, column (2) coefficients estimates will be used.

Table 4: Real fuel consumption regression results

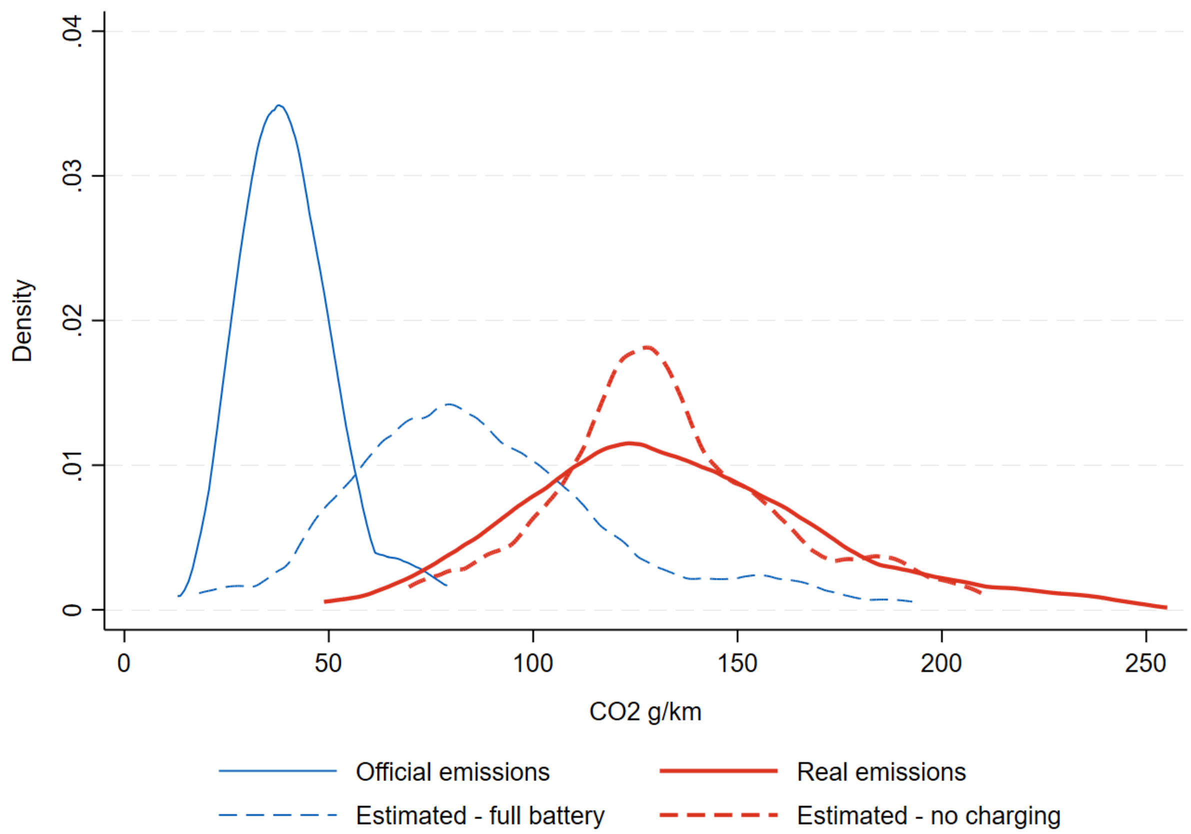
	(1)	(2)	(3)
Intercept	-2.63	-2.26	3.23
	(0.36)	(1.28)	(0.47)
kWh charged (kWh/km)	-4.89	-3.38	-3.28
	(0.38)	(0.24)	(0.24)
offical fuel consumption (l/100km)	0.25	0.79	1.43
	(0.09)	(0.26)	(0.28)
horsepower (100 ps)	0.39	0.05	
	(0.07)	(0.14)	
weight (100 kg)	0.04	0.20	
	(0.05)	(0.11)	
volume	0.51	0.22	
	(0.07)	(0.19)	
diesel	-0.84	-0.88	
	(0.15)	(0.44)	
winter	0.48	0.53	
	(0.02)	(0.02)	
spring	0.03	0.01	
	(0.02)	(0.02)	
summer	0.04	0.06	
	(0.02)	(0.02)	
R-squared	0.21	0.51	0.50
User fixed effects	No	Yes	Yes
Year fixed effects	No	Yes	Yes
F-statistics	115.30	69.99	111.25
Observations	180,458	180,457	180,457

Notes: The table shows the coefficient estimates and standard errors of OLS regressions of PHEVs fuel consumption on electric motor utilization and controls. Column (1) shows the regression estimates when no fixed effects are used; Column (2) presents the OLS regression results when the full set of fixed effects and control variables is used; In order to gain intuition regarding the relationship between the official announced fuel consumption, the amount of electric motor utilization and the real fuel consumption values, column (3) presents the OLS regressions estimates when the only controls used are user and year fixed effects. The number of observations is lower than the total sample since only refueling instances are used. Standard errors are clustered on the user level.

Figure 1 shows the kernel estimated distribution of PHEVs' carbon emissions - the official

[21] The most efficient PHEV I observe in the sample is Volvo V60 with a fuel consumption value of 0.8 l/100 km. For comparison, Toyota Yaris is the most efficient ICE vehicle in the sample with a fuel consumption value of 2.8 l/100 km.

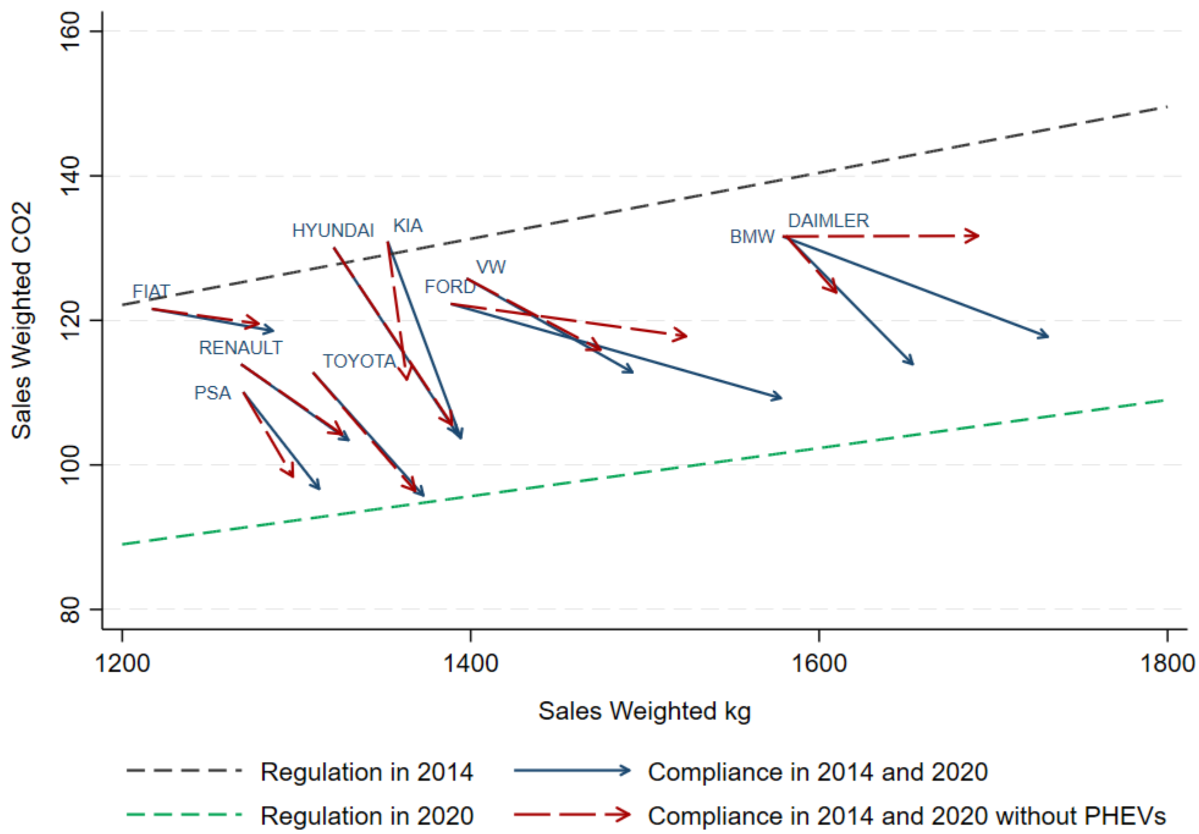
Figure 1: Distribution of estimated CO_2 emissions



Notes: The figure shows four kernel estimated distributions of PHEVs carbon emissions: the official values and the real-usage values are taken directly from the usage data; the estimated values are estimated using the coefficient estimates presented in table 4, column (2) under two scenarios: when the battery is not charged (kWh is set to Zero) and when the battery is fully charged (kWh is set to official battery capacity divided by the battery driving range).

values, the average real-usage values which are taken directly from the data, and the estimated values under two different battery scenarios: no charging (kWh is set to zero) and fully-charged battery (kWh is set to official battery capacity divided by the battery driving range). The "no charging" scenario follows closely the real-usage emissions distribution, which is expected as the average amount charged per 100 km driven is very low in the data (on average 2.5 kWh/100 km). Notwithstanding the high variation in real-usage carbon emissions values, the overlap between the real-usage and the official values distributions is small, and most of the real-usage values are above the official ones. The figure shows a clear bunching of official emissions values right below the value of 50 g/km which is the car-

Figure 2: Compliance of manufacturers in 2014 and 2020



Notes: The figure plots the EU-wide sales weighted average of vehicles' carbon emissions and weight for each of Europe's most sold automobile manufacturers. The starting point of each arrow is the sales-weighted carbon emissions and weight averages in 2014. The end of each arrow reflects the corresponding values for each manufacturer in 2020. The end of each dashed arrow reflects the corresponding values for each manufacturer in 2020 had no PHEVs been sold. The dashed upper diagonal line depicts the standard in 2014, the dashed lower diagonal line is the standard values in 2020.

bon emissions threshold for the eligibility of a PHEV for a subsidy. Although some overlap exists between the official carbon emission values and the estimated "full' battery" values, the 'full' battery" values exhibit much higher variation. This discrepancy is not surprising given that real driving behavior and weather conditions deviate greatly from conditions used in laboratory tests.An additional illustration of the results is available in table D.1 in the appendix.

4.2 Manufacturers' compliance strategies

Figure 2 illustrates the development of average fleet emissions of manufacturers with the highest sales in the EU. Up to 2020, most automobile manufacturers have over-complied with the old EU fleet emissions targets set in 2007. The figure demonstrates that the reductions in average fleet emissions were driven both by an increase in weight and a decrease in emissions of sold vehicles. The dashed arrows illustrates the fleets' average emissions and weight had the manufacturers not sell any PHEVs. Sales of PHEVs had a major role in the successful compliance of BMW, Daimler (Mercedes-Benz) and Ford with the EU standard.[22]

Table 5: Summary statistics of EU fleet sales

	CO2 g/km		weight kg		PHEV		BEV		sales	
	2014	2020	2014	2020	2014	2020	2014	2020	2014	2020
BMW	131.7	113.8	1,581.0	1,655.8	0.5%	11.9%	0.4%	4.8%	799,550	816,584
DAIMLER	131.6	117.6	1,579.0	1,736.4	0.1%	14.5%	0.5%	5.9%	686,711	742,519
FIAT	121.6	119.5	1,217.0	1,289.2	0.0%	1.3%	0.0%	1.0%	733,467	617,357
FORD	122.3	109.3	1,388.5	1,576.8	0.4%	10.9%	0.0%	1.5%	1,176,013	951,285
HYUNDAI	130.1	103.8	1,321.3	1,400.5	0.0%	1.3%	0.0%	14.4%	409,504	399,434
KIA	130.9	103.9	1,352.3	1,401.4	0.1%	7.5%	0.0%	9.1%	347,451	413,593
RENAULT	113.9	103.3	1,268.1	1,333.9	0.0%	1.1%	1.2%	9.2%	1,715,193	1,486,998
PSA	110.1	96.7	1,269.4	1,311.4	0.2%	2.4%	0.0%	4.0%	1,360,966	1,754,325
TOYOTA	112.8	96.3	1,309.4	1,386.4	6.3%	0.9%	0.0%	0.1%	539,080	682,608
VW	125.8	112.1	1,397.6	1,498.2	0.1%	4.2%	0.1%	6.7%	3,160,154	2,964,391
Total	121.8	107.5	1,364.4	1,454.2	0.5%	5.0%	0.3%	5.6%	10,928,089	10,829,094

Notes: The table presents the fleets' averages of Europe's most selling manufacturers. The columns PHEVs and BEVs present the share of these vehicles out of the whole EU fleet, the columns sales display the manufacturers' total sales in the EU.

Table 5 present the emissions and weight values for each of the manufacturers presented in figure 2. The columns PHEV and BEV present the respective shares of PHEVs and BEVs out of the total EU fleet. Daimler (Mercedes-Benz), BMW and Ford have significantly increased the share of PHEVs in their fleets - by 14.4, 11.4 and 10.5 p.p. respectively. This is more than double the average of Europe's top selling manufacturers (5 percent). These

[22] In 2020, all manufacturers complied with the standard due to two special transitional period exceptions: first, only 95 percent of the vehicles sold were taken into account in order to calculate the fleets' weight-average emissions, and second, manufacturers were able to reduce their fleets' emissions by using special innovation credits which were awarded to manufacturers that developed and deployed special emission reducing innovations. These special exceptions didn't apply in 2021.

brands combined account for 29 percent of the total sales in Germany.[23]

As figure 2 shows, Daimler, BMW and Ford also present the highest increase of sales weighted average weight. This increase is partially explained by the increased share of sold PHEVs.[24]

4.3 Decomposition of EU fleet emissions

In order to evaluate the forces behind the reduction in emissions, I decompose the EU fleet's carbon emissions weight-adjusted average into four terms as follows:[25]

$$\Delta \bar{E}_t = \underbrace{\sum_j s_{j,t-1} \Delta e_{j,t}}_{\Delta \text{ within}} + \underbrace{\sum_j \Delta s_{j,t} \tilde{e}_{j,t-1}}_{\Delta \text{ between}} + \underbrace{\sum_j \Delta s_{j,t} \Delta e_{j,t}}_{\Delta \text{ cross term}} + \underbrace{\sum_{j \in New} s_{j,t} \tilde{e}_{j,t} - \sum_{j \in Exit} s_{j,t-1} \tilde{e}_{j,t-1}}_{\text{net entry}} \quad (3)$$

where $\bar{E}_t$ is the carbon emissions weight-adjusted average of all vehicles sold in the EU in year t, $s_{j,t}$ is the share of vehicle model j out of all sales in the EU in year t, $\tilde{e}_{j,t} = e_{j,t} - \bar{e}_{t-1}$, $\tilde{e}_{j,t-1} = e_{j,t-1} - \bar{e}_{t-1}$ and $\bar{e}_t = \sum_j s_{j,t} e_{j,t}$.[26] For this exercise, I define vehicle model j as a brand/ model /motor type combination, an example of a vehicle model is "BMW X1 plug-in hybrid" .

"Δ within" captures the average change of existing products' emissions due to technological gains.[27] "Δ between" captures the average change in existing products' emissions due to changes in the sales-mix, that is substitution between products, which can occur either because of changes in consumers' tastes or because of changes in manufacturers' marketing strategies. "Δ cross" measures the correlation between emissions and market shares, this component is crucial to ensure correct measurement of the other terms. The "net entry"

[23] Together with the Volkswagen group, they account for two thirds of the whole German market.

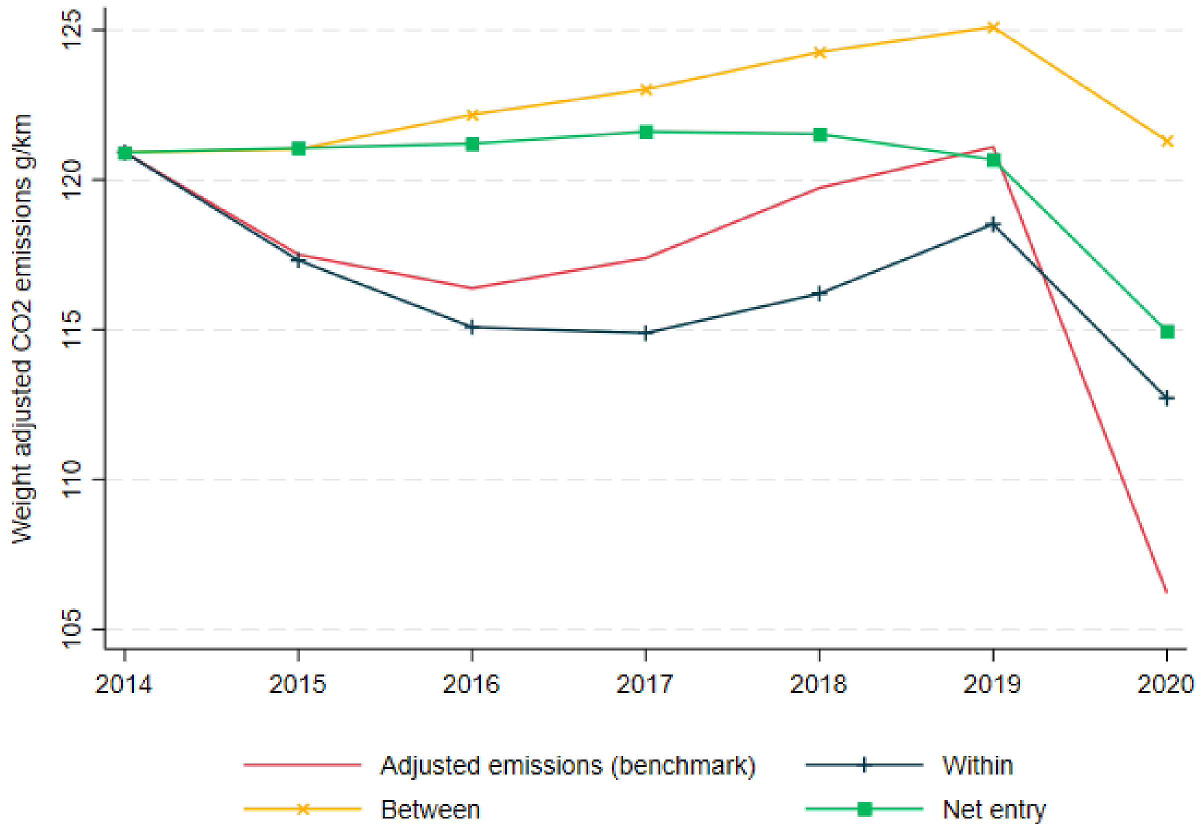
[24] On average PHEVs weight more than their ICE counterpart as they accommodate an additional electric motor.

[25] This decomposition exercise has a long tradition in the productivity literature which started with Foster et al. (2007), for a most recent application see De Loecker et al. (2020).

[26] Following Haltiwanger (1997), I demean the vehicle model emissions by the appropriate share weighted averaged emissions.

[27] Since the emissions are weight adjusted, in principal emissions reductions might be due to increased vehicle weight. Running the same exercise while separating between the weight and the emissions component indicates that this is not the case.

Figure 3: Decomposition of the change in EU fleet emissions



Notes: The figure shows the development of carbon emissions weight-adjusted average of all vehicles sold in the EU and the results of three counterfactual scenarios which use 2014 as the base year: the development of weight-adjusted emissions if manufacturers were only reducing the emissions of existing models (within), the development of weight-adjusted emissions if manufacturers were only changing the sales-mix of their existing products (between), and the development of weight- adjusted emissions if manufacturers were only introducing new products (Net entry). The cross term is omitted as it is almost constant at an average value of 0.4.

term captures the change in average emissions due to the introduction of new vehicle models net the discontinuation of old vehicle models.

Figure 3 plots the results of the decomposition exercise. I set the initial emissions level to 2014 levels, when the stricter standard was announced, and cumulatively add the changes of each component in equation (3). The red line plots the carbon emissions weight-adjusted average of all vehicles sold in the EU ($\bar{E}_t$). The other three plotted terms (within, between and net entry) can be interpreted as counterfactual experiments which explore the development of carbon emissions weight-adjusted average had these terms were the only force in play.[28] The first counterfactual (blue + line) shows the evolution of the carbon emissions weight-adjusted average if manufacturers only been reducing emissions values of existing products. Up until 2017, manufacturers were constantly reducing the emission values of existing vehicles, between 2017-2019 this trend was reversed, with a sharp decline in 2020. This sharp decline might hint on potential gaming of emission tests.[29] The second counterfactual (orange × line) shows the path of carbon emissions weight-adjusted average if only changes in the mix-sales were taking place. Compared with 2014, a shift towards more emissions-intensive vehicles is observed. A reverse of the trend is noticeable in 2020, which might be due to manufacturer efforts to steer consumers towards less emissions-intensive vehicles. The third counterfactual (green square line) shows the evolution of carbon emissions weight-adjusted average if the only change taking place was the net entry of new vehicles. Given the definition of a vehicle model for the analysis (brand/model group/motor type combination), net entry is driven almost entirely by the introduction of PHEVs and BEVs as they capture the highest share of new product introductions in the years leading up to 2020.[30] Evidently, net entry didn't play a role in emission reduction efforts up to 2019. To summarize, the decomposition exercise shows that the main forces behind of the sharp decline in emission in 2020 are net entry and the technological improvements of existing vehicles.

Figure 4 shows the results of the decomposition exercise for manufacturers with most sales in Germany. The impact of the net entry component is especially high for BMW, Daimler, and Ford. These manufacturers, as table 5 shows are also the ones with the highest share of PHEVs in their fleet in 2020.

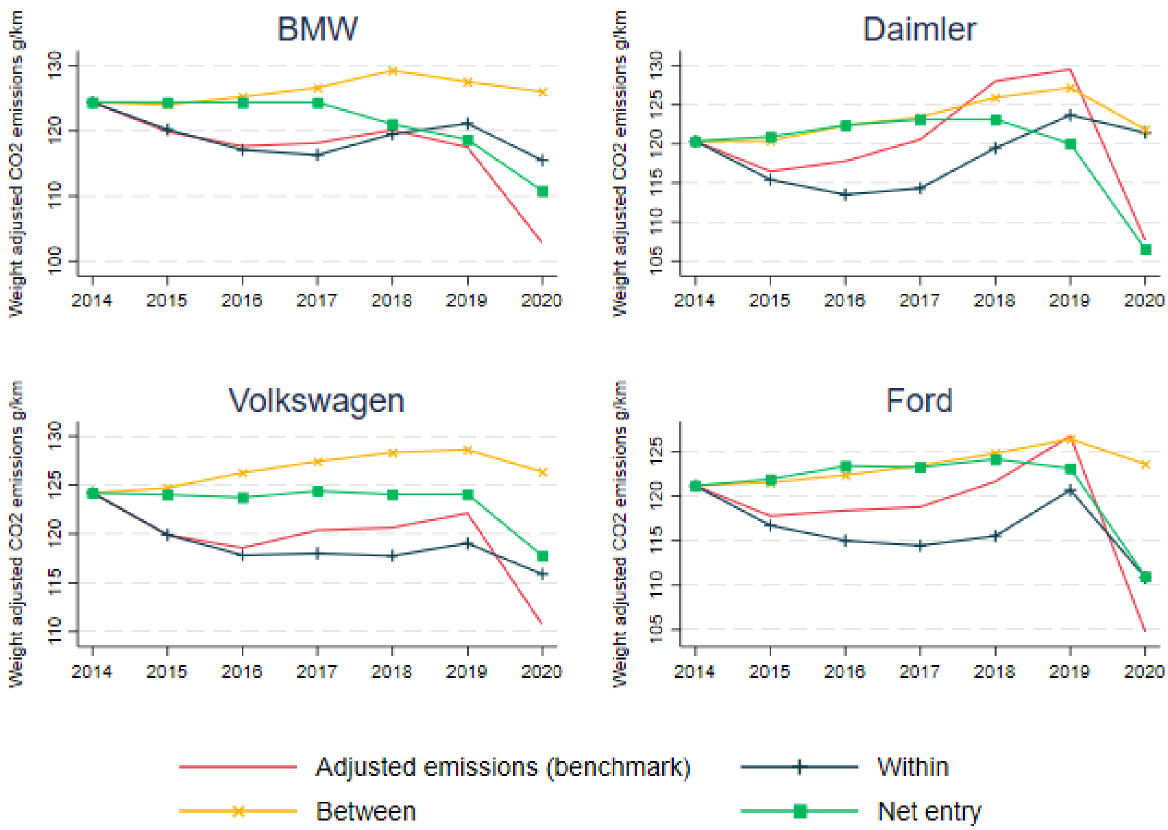
These results illustrates the important role new product introductions had in complying with the new emissions standard. These results combined with the information in table 5

[28]The cross term is left out as its value is always close to zero.

[29]See work by Reynaert (2020) and Reynaert and Sallee (2021) for more details regarding emission gaming in the European automobile market.

[30]Automobile manufacturers rarely introduce a whole new model group, instead they usually introduce new releases of the same existing model group lines.

Figure 4: Decomposition of the change in fleet emissions of selected manufacturers



Notes: The figure show the development of carbon emissions weight-adjusted averages of vehicles sold in the EU and the results of three counterfactual scenarios using 2014 as a base year, for the four most sold manufacturers in Germany: the development of carbon emissions weight-adjusted average if manufacturers were only improving the emissions of existing model (within), the development of carbon emissions weight-adjusted average if manufacturers were only changing the sales-mix of existing products (between), and the development of carbon emissions weight-adjusted average if manufacturers were only introducing new products (Net entry). The cross term is omitted.

regarding the share of PHEVs in EU fleets, indicate that some of the documented decrease in emissions might have taken place only on paper, since it assumes PHEVs are charged regularly. As I illustrate in section 3.2, most PHEVs are not regularly charged and therefore their corresponding emission values are higher than officially claimed. In order to evaluate the effect of government subsidies for PHEVs on emissions, consumers' vehicle purchasing decisions in the absence of incentives for PHEVs needs to be evaluated. For that purpose, I develop and estimate a consumer choice model for the market of automobiles.

5 Structural model

5.1 Demand

To evaluate the environmental implications of the introduction of PHEVs subsidies in Germany, I use a random-coefficient discrete choice model to describe consumers' vehicle purchasing decision. This choice of modeling, which relays on Berry et al. (1995), follows a long tradition in the industrial organization literature that analyses automobile markets.[31] I model demand to be static, which assumes that consumers don't take into account future prices and future available products. Each consumer i maximizes her utility by deciding whether to purchase a vehicle among J available products or to opt for the outside good. The outside good consists of all other unobservable options which do not consist of purchasing a new vehicle, such as using public transportation or buying a used vehicle. The utility consumer i derives from purchasing vehicle j in year t is:

$$u_{ijt} = \beta_{it} x_{jt} + \alpha p_{jt} + \xi_{jt} + \epsilon_{ijt} \tag{4}$$

where x_{jt} is the $(1 \times K)$ vector of observed vehicle characteristics, p_{jt} is the price of vehicle j, ξ_{jt} is a demand shock that is observed by consumers and manufacturers but not by the econometrician, and ϵ_{ijt} is an individual specific taste shock which is assumed to be a i.i.d draw from type-1 extreme value distribution with a scale parameter normalized to 1. The mean utility of the outside good is normalized to 0, hence consumers who choose the outside good receive a utility of ϵ_{i0t}. β_{it}, a $(K \times 1)$ vector, and α are parameters which capture the marginal utilities of the product characteristics and price. Let β_{it}^k be the marginal utility of characteristic x_{it}^k then:

$$\beta_{it}^k = \beta_0^k + \beta_\nu^k \nu_{it}^k \tag{5}$$

[31] For recent applications in the automobile market see for example: Reynaert (2020), Springel (2021), Xing et al. (2021), and Grigolon et al. (2018).

where β_0^k captures the mean marginal utility of characteristic k across all consumers, and β_ν^k captures the standard deviation of characteristic k's marginal utility. Let

$$\delta_{jt} = \beta_0 x_{jt} + \alpha p_{jt} + \xi_{jt} \tag{6}$$

be the mean utility – the non-idiosyncratic part of the utility for product j, which is common to all consumers and let

$$\mu_{ijt} = (x_{jt})\Sigma\nu_{it} \tag{7}$$

be the individual deviations from the mean utility captured by the interaction of consumers' taste preferences with product characteristics, where Σ is a $(K \times K)$ diagonal matrix with its diagonal equal to $(\beta_\nu^1,...\beta_\nu^K)$. Then, after integrating over the distribution of ϵ, the probability that consumer i purchases vehicle j in year t is

$$Pr_{ijt} = \frac{exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{q=1}^{J} exp(\delta_{qt} + \mu_{qt})} \tag{8}$$

and the predicted aggregated market share of vehicle j in year t is:

$$s_{jt} = \int_i Pr_{ijt} dF(\nu_{it}) \tag{9}$$

Lastly, the corresponding price elasticities are equal to:

$$\frac{\partial s_{kt}}{\partial p_{jt}} \frac{p_{jt}}{s_{kt}} = \begin{cases} -\frac{p_{jt}}{s_{kt}} \int \alpha s_{it}(1 - s_{ijt}) dF(\nu_{it}) & \text{if } j = k \\ -\frac{p_{jt}}{s_{kt}} \int \alpha s_{ijt} s_{ikt} dF(\nu_{it}) & \text{otherwise} \end{cases} \tag{10}$$

5.2 Supply

I model the supply side using a static game where manufacturers have complete information on all observable and unobservable product characteristics. I do not model the manufacturers' decision which products to offer. In addition, I assume manufacturers cannot change product characteristics in the short term. Given the set of offered products and their characteristics, after the realization of the demand and costs shocks, manufacturers determine their products' prices.

I follow previous literature on emission standards (Reynaert (2020), Jacobsen (2013) and Goldberg (1998)) and incorporate the EU carbon emission standard in the profit maximization problem:

$$\begin{aligned} \max_{p_{j\in it}} \Pi_{it} &= \sum_{j\in i}(p_{jt} + \gamma_{kt} - mc_{jt})s_{jt}M_t \\ \text{s.t. } & \frac{\sum_{j\in i} q_{jt}e_{jt}^{adjusted}}{\sum_{j\in i} q_{jt}} \leq \kappa \end{aligned} \tag{11}$$

where p_{jt}, mc_{jt}, and s_{jt} are respectively the price, marginal costs, and the market share of vehicle j manufactured by manufacturer i at year t. M_t is the market size at year t. γ_{kt} is the government subsidy. $e_{jt}^{adjusted} = (e_j - \alpha(w_j - w_0))$ where e_j is the official carbon emissions of the vehicle, w_j is the vehicle's weight, α and w_0 are given parameters governing the emissions weight adjustments. κ is the emissions standard value. The Lagrangian associated with (11) yields the following first-order condition with respect to price:

$$q_{jt} + \sum_{k\in i}(p_{kt} + \gamma_{kt} - (mc_{kt} + \lambda_i L_{jt}))\frac{\partial s_{kt}}{\partial p_{jt}} = 0 \tag{12}$$

where L_{jt} is the distance of each product from the emissions target and λ_i is the scalar Lagrange multiplier for manufacturer i, which is associated with the emissions standard constraint, and captures the shadow costs of complying with the standard. Equation (12) can be inverted to obtain the value of the sum of the marginal costs and the standard's shadow costs. In my analysis, I use the total sum of the marginal costs and the shadow costs of the regulation, as the paper's focus is on the effects of the government subsidies on consumer choice while taking the emission standards and the products set as given.

6 Estimation

I include in the model taste parameters for BEV and volume for which I estimate both a mean and standard deviation. I specify α to be proportional to income y_{it}. Additionally I include a set of vehicle characteristics for which I estimate only the mean taste: fuel costs per km, volume, horsepower, and dummies for PHEV and BEV, vehicle class,[32] body type,[33] brand, and market. I closely follow the common estimation procedure outlined in Berry et al. (1995) and account for computation concerns raised in Knittel and Metaxoglou (2014). Detailed description of the estimation procedure is presented in appendix B.

6.1 Instruments

Instruments have two roles in identifying the demand model parameters. First, instruments are needed to account for a common endogeneity concern since prices might be correlated with the unobservable characteristics (which are observed by the manufacturers but not by the econometrician). Second the instruments are needed in order to identity the taste parameters. I address recent concerns regarding the performance of the "traditional" BLP instruments,[34] by employing the refinement proposed by Gandhi and Houde (2019) which improves the instruments performance. Specifically, the set of instruments includes all characteristics except of price, and a set of "differentiation instruments": the number of own products which belong to the same product set of j and are within a certain band of j:

[32] The classes are micro-vehicle, minicompact, subcompact, compact, mid-size, and executive.

[33] The body types are hatchback, notchback, station wagon, van and SUV.

[34] Traditional BLP instruments usually consist of the sum of characteristics of other products produced by the same firm, and the sum of characteristics of competitors' products.

$\sum_{j' \neq j, j' \in C(j)} \mathbf{1}(|x_{jt}^k - x_{j't}^k| < \kappa^k)$,[35] and the number of competitors' products which belong to the same product set of j and are within a certain band of j. I use two product set definitions to calculate the instruments: (1) all vehicles which share the same vehicle class. (2) all vehicles which are produced by the same manufacturer.

To improve the efficiency of the taste parameters estimates, I follow Reynaert and Verboven (2014) approach to compute Chamberlain (1987) optimal set of instruments: the expected value of the derivatives of ξ with respect to the estimated parameters, which are evaluated at its initial estimated parameters values.[36]

6.2 Results

Table 6 report the estimated coefficients of the demand model and their standard errors. Two specifications are presented: a Logit specification which was estimated following a two-staged GMM procedure, and a Random-Coefficients Logit specification which was estimated following the procedure described above.

As expected the demand parameters show that consumers dislike higher prices and higher fuel costs; consumers also on average dislike PHEVs and BEVs. The standard errors of the BEV coefficient are high, which indicates heterogeneity in the taste for BEVs. The estimated coefficients indicates that although there is a general aversion from PHEVs, some consumers might choose to buy them due to their advertised low fuel costs, larger size and lower subsidized prices compared to other vehicles of the same size. The estimated standard deviation for the marginal utility of volume is significant yet low, which indicate that the tastes for volume are similar across consumers, hence volume has a low weight in governing substitution patterns. The standard deviation coefficient for BEV is both statistically and economically significant, it indicates that buyers of BEVs would substitute toward other BEVs, were the price of their chosen vehicle to increase.

[35] For dummy variables the indicator variables are replaced by $\mathbf{1}(|x_{jt}^k - x_{j't}^k| = 0)$.

[36] Additional details on the computation of Chamberlain (1987) optimal set of instruments are given in appendix B.

Table 6: Demand estimation results

	Logit	RC logit	RC logit S.D.
Intercept	-8.00	-7.92	
	(0.51)	(0.56)	
Price/income	-5.93	-5.73	
	(0.93)	(0.77)	
Fuel costs (Euro/km)	-0.14	-0.14	
	(0.05)	(0.04)	
Horsepower	0.04	0.04	
	(0.01)	(0.01)	
Volume	0.72	0.61	0.08
	(0.12)	(0.07)	(0.03)
PHEV	-2.90	-2.90	
	(0.55)	(0.47)	
BEV	-0.56	-1.59	2.31
	(0.21)	(1.16)	(0.36)

Notes: The table reports the estimated coefficients of the demand model. The first column presents the estimates of the mean-taste coefficients of a Logit specification estimated by two-staged GMM. The second and third columns presents respectively the mean and standard deviation parameters of a Random Coefficient Logit specification estimated following the procedure described above with additional details available in appendix B.

7 Counterfactual simulations

I use the estimated model to compare the outcomes of two changes to the current status quo where both PHEVs and BEVs are subsidized and consumers are not aware of the fuel consumption of uncharged PHEVs. The first change consists of informing consumers of PHEVs' fuel consumption values when uncharged. As I don't model consumers' decision to charge the vehicle, informing consumers regarding uncharged fuel consumption values will result in increasing the dis-utility of PHEVs, and therefore will reduce mechanically the market shares of PHEVs. This in turn might be a plausible assumption following the evidence presented in section 3.2 regarding the low share of drivers who charge their vehicles, and the observation that consumers don't increase the amount of charging after learning the uncharged fuel consumption values.[37] The second change is the elimination of subsidies for PHEVs. I start

[37]In the sample of PHEVs users, charging behavior remains unchanged after users learn about the vehicles fuel consumption values when uncharged. This behavior might be a result of the difficulty to spontaneously

the counterfactual analysis by using the estimated demand model parameters to simulate the demand outcomes of the proposed changes in fuel costs and prices, while holding the manufacturers list prices fixed. In a second step, I conduct again the counterfactual analysis and simulate the short-term equilibrium effect by calculating the new prices manufacturers will set using the first order condition described in equation (12).[38] In the second step I simulate two scenarios: (1) the subsidies for PHEVs are eliminated and (2) the subsidies are eliminated and consumers are informed about the fuel costs of PHEVs when uncharged. In order to compute manufacturers' price adjustments, I assume constant marginal costs and use the first order condition described in equation (12) to recover manufacturers marginal costs. As mentioned in section 5.2 the computed marginal costs include also the emission standard's shadow costs. The implied markups (price over marginal cost) are on average 18 percent.

Table 7 presents the results of the counterfactual analysis. The first column presents the market outcomes of 2021 (henceforth the status quo). Columns (1) – (4) present the outcomes' changes under the different counterfactual scenarios: column (1) presents the change in demand and subsequently market outcomes when consumers are informed about PHEVs fuel consumption when uncharged. In section 3.2, I show that many consumers don't charge their PHEVs. This behavior doesn't change after consumers learn the uncharged fuel consumption values. Therefore, it is reasonable to assume that had consumers been aware of the uncharged fuel consumption costs, these consumers would have chosen a different vehicle, rather than charge the vehicle more often. The results presented in column (1) can serve as an upper bound on the effect of fuel consumption information on PHEVs sales, as some consumers aware of the uncharged fuel costs might nevertheless purchase the vehicle and decide to charge it more often. Column (2) shows the counterfactual results when subsidies for PHEVs are eliminated and list prices remain unchanged.

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charge vehicles: as of 2022, a subscription to a charging network is needed in order to charge a vehicle using public infrastructure.

[38] In Bertrand competition with multiproduct firms, multiple equilibria are possible. I cannot show that the found equilibria are unique, yet I find no other solution when changing the starting values.

Table 7: Results of counterfactual analysis

	Status Quo	(1) Δ Informed	(2) Δ No Subs.	(3) Δ No Subs. Manu. Adj.	(4) Δ All changes
Total Sales	927,351	-60,277	-78,277	10,681	-14,259
		(10,612)	(3,921)	(6,605)	(5,994)
Total PHEV	121,022	-69,388	-90,018	-70,515	-99,745
		(12,220)	(4,517)	(5,486)	(7,842)
Total BEV	230,152	360	474	73,208	73,434
		(64)	(24)	(11,531)	(11,552)
Average offical emissios (g/km)	75.02	3.32	4.49	-2.66	-1.41
		(0.62)	(0.25)	(0.66)	(0.64)
Average real emissios (g/km)	89.78	-5.06	-5.91	-11.16	-13.57
		(0.89)	(0.32)	(1.35)	(1.52)
Government Spending (Billion Euros)	1.78	-0.28	-0.40	0.44	0.45
		(0.05)	(0.02)	(0.07)	(0.07)
Profits (Billion Euros)	3.20	-0.21	-0.27	0.04	-0.04
		(0.02)	(0.02)	(0.02)	(0.02)
SUVs	306,329	-36,962	-40,151	-31,669	-49,232
		(6,231)	(2,014)	(2,518)	(4,191)

Notes: The table presents the results of the counterfactual analysis. The status Quo column shows the market outcomes in 2021 when both PHEVs and BEVs are subsidized. Columns (1)-(4) present the change between the market outcomes in the simulated scenarios and the status quo. Column (1) assumes consumers are informed about PHEVs fuel consumption when uncharged, column (2) simulates the market outcomes changes when PHEVs subsidies are eliminated, column (3) re-calculates scenario (2) while allowing manufacturers to update their prices, in column (4) scenario (3) is recomputed with the addition of consumers being informed about PHEVs fuel consumption values when uncharged. The standard errors are computed by taking 200 draws from the estimated parameters variance–covariance matrix (I assume a joint normal distribution). For each draw of parameters, the supply side is re-estimated and new simulation outcomes are computed.

In both scenarios, between half to two thirds of PHEVs buyers would have left the market without purchasing a new vehicle. Less than 0.5 percent would have substituted to BEVs. Though, the average official carbon emissions over all new vehicles sold increases, the average carbon emissions per vehicle under the premise that PHEVs are not charged decreases by about 5 percent in both scenarios. The share of SUVs sold decreases by 12 and 15 percent respectively. This result further indicates that some consumers used PHEVs subsidies as an upgrade opportunity.[39] Column (3) and (4) present the counterfactual results when manufacturers update their list prices. In column (3) only the subsidies for PHEVs are eliminated,

[39] Anecdotal evidence show that the price of some PHEV SUVs was less than a same brand mid-size ICE vehicle. For example, in 2021, the price after subsidies of a "BMW X2 plug-in hybrid" (a SUV) was 5,000 Euros lower than the "BMW 3" most popular ICE version (a mid-size vehicle) and costed almost the same as the PHEV version of the "BMW 3".

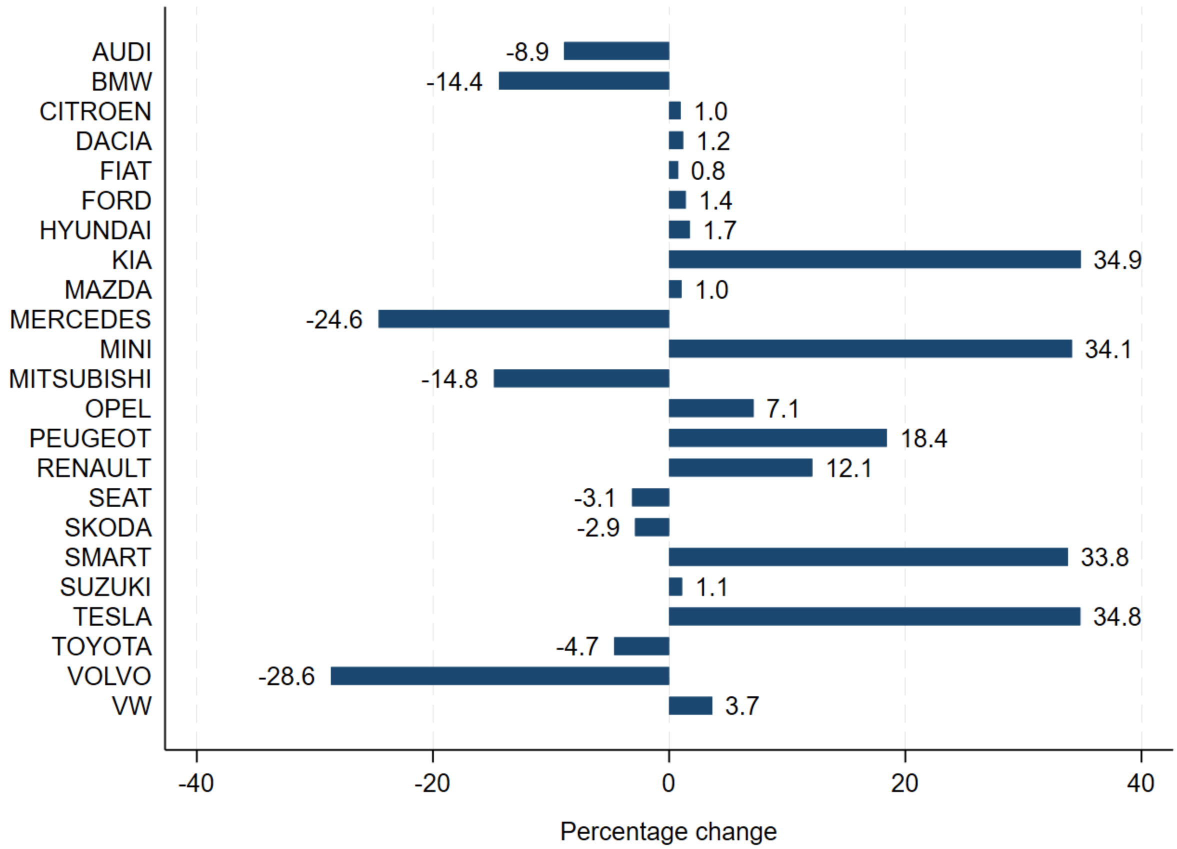
while in column (4) the subsidies are eliminated and consumers know the fuel consumption values of uncharged PHEVs. These results assume manufacturers keep on offering the same set of products with the exact same characteristics. In the long term, given the binding EU emission standards, manufacturers will want to change their offered products, in order to increase sales of low emission products such as BEVs. Therefore the results in column (3) and (4) underestimate the impact of these changes on emissions, and should be interpreted as a lower bound. In both scenarios, the manufacturers' price adjustments increase the uptake of BEVs by about 32 percent, while reducing sales of PHEVs by 58 percent in scenario (3) and by 82 percent in scenario (4). Paradoxically the elimination of subsidies for PHEVs increase the government spending, since manufacturers divert consumers through price adjustments towards BEVs which are subsidized more generously.

When manufactures update their list prices, both the average official carbon emissions per vehicle and the average carbon emissions per vehicle when PHEVs are not charged decrease. To understand the magnitude of such reduction in average carbon emissions, I present a short back of the envelope calculation: assuming the results of scenario (3) (only subsidies for PHEVs are eliminated) – 938,032 vehicles would have been sold in Germany in 2021, with an average official reduction of 2.658g CO_2/km. The average yearly mileage of new vehicles driven domestically in Germany during 2021 was 15,965 kilometer.[40] Hence 938,032 $\times$ 15,965 $\times$ 2.658 equal to 39,805 tons of yearly carbon emissions avoided. The average German household emitted on average 3.1 tons of carbon emissions in 2019 due to energy consumption,[41] 39,805 tons of carbon emissions equals to yearly carbon emissions of 12,840 households. If PHEVs are not charged – as I document is the current case, the amount of carbon emission avoided from the elimination of PHEVs subsidies equals to 167,139 tons, which translates to the yearly carbon emission of 52,916 households.

Table 7 indicates that under scenario (3) (PHEVs subsidies are eliminated and manufacturers update list prices) total profits in the industry increase, to understand who are the potential

[40] Source: Federal Motor Transport Authority.
[41] Source: Federal Statistical Office of Germany.

Figure 5: Change in sales by brand



Notes: The figure shows the percentage change of sales by brand under counterfactual scenario (3) where the PHEVs subsidies are eliminated and manufacturers adjust their prices accordingly.

beneficiaries from the elimination of PHEVs subsidies, figure 5 shows the percentage change of sales by brand. As expected brands which produce larger vehicles (and have a higher share of SUVs sales) lose sales the most from the elimination of PHEVs subsidies, on the other hand one of the largest beneficiaries under this scenario is Tesla – a manufacturer of BEVs, and manufacturers of small size vehicles such as KIA, Smart and Mini Copper. It is interesting to note that mostly European brands lose sales from the elimination of PHEVs subsidies, while foreign brands gain a substantial increase in sales. This result might not come as a surprise given that it was the domestic automobile industry who pressured the government to introduce the subsidies.

8 Discussion and conclusions

This paper evaluates how product subsidies and ignorance regarding energy consumption affected consumers vehicle purchasing decisions and subsequently carbon emissions. I find that the elimination of subsidies for PHEVs can prevent yearly 167,139 tons of carbon emissions. This is partially due to some consumers using the subsidies as an upgrade opportunity to purchase larger vehicles which wouldn't have happened had the subsidies not been offered. Ignorance of consumers regarding fuel consumption values of uncharged PHEVs also had a hand in encouraging some consumers to purchase vehicles that don't match their tastes and cause additional carbon emissions due to energy-inefficient usage. Consumers weren't the only party to take advantage of the subsidies on the expense of the environment: domestic manufactures used PHEVs sales to increase their fleet weight which helped them to achieve compliance with EU emission standards.

The analysis presented in this paper is done in a static framework and focuses only on manufacturers' short term response. The static framework I employ does not take into account purchase-timing considerations: consumers' price sensitivity might be underestimated if consumers postpone their adoption of innovative vehicles, because they expect the vehicles to improve and become cheaper in the future. On the other hand, if consumers believe subsidies might not be available in the future, they might decide to bring forward their purchase, which will lead to an overestimated price sensitivity. Nevertheless, a static model in the German market should serve as a good approximation, since the subsidies were available for almost 7 years (as of 2023), and the decision to purchase a vehicle in a given point in time is mostly affected by current needs rather then future expectations regrading product development.

The presented counterfactual results account only for manufacturers' price adjustments and not for product set adjustments, therefore the estimates presented in this paper act as a lower bound for the potential reduction in carbon emissions of the explored scenarios. In the long term, given the binding EU carbon emissions standard, manufacturers will wish to divert more sales toward low emitting vehicles by changing the characteristics of their vehicles and the set of offered vehicles, which subsequently will lead to further carbon emissions reductions.

This paper illustrates that the adoption alone of low emissions innovations is not always enough. Consumers must be aware of how to use these products efficiently energy-wise, and be informed about the costs of not doing so before the purchase is made. As the paper shows, a failure to do so can lead to an increase of emissions that is usually left unobserved. An increasing number of products are marketed as environmentally friendly due to their low energy consumption, though, just like PHEVs, their energy consumption might be higher due to consumers' usage behavior. Other examples are house appliances with energy efficient "eco" modes. Consumers are usually informed only of energy consumption values under the most efficient mode of use and they are rarely aware of the whole range of possible energy consumption values the different usage modes entail. Therefore, understanding and quantifying the environmental harm of energy-inefficient usage is important in order to design policies that are effective at reducing emissions. A main policy implication of the presented results is that subsidization alone of innovations, which require specific consumers behavior in order to achieve energy-efficiency, can be detrimental for the environment and achieve the opposite effect as intended.

In the absence of a good charging infrastructure, PHEVs offer a good substitute for BEV, since when charged they reduce emissions significantly on short-distance trips compared to ICE vehicles, and allow for long-distance trips regardless of the charging infrastructure state. Given the low charging rates of PHEVs documented in this paper, understanding how to catalyze drivers to charge their PHEVs is a key in unlocking the full potential of this innovation. Future research should explore this topic further.

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Appendix

A Data preparation

A.1 Vehicle Sales and characteristics

I follow closely the literature of demand estimation for automobile and reduce the sample size for tractability. I follow the procedures employed by Reynaert (2020) and Grigolon et al. (2018): for each year I eliminate the 10 percent models with the least amount of sales, then for each year/ model/ motor combination I retain the the trims which are responsible for at least 20 percent of the sales of the respective year/ model/ motor combination, lastly I exclude trims with less than 100 sales in a given year. Brand/ model/ trim combination can be offered with different technical specifications (such as horsepower and consequently fuel consumption values) and therefore with different prices, for each brand-trim combination I take the median value of the brand-trim characteristics .

A.2 PHEVs charging behavior

I remove observations with a missing value or a negative value for distance since last refueling instance or with a missing refueling quantity. For each observation I calculate the fuel consumption per 100 km value as quantity of fuel purchased in a full-tank refuel divided by the distance driven since last full-tank refuel and multiply it by 100. Fuel quantities of partial tank refueling instances are summed up and added to the most adjacent full-tank refueling instances. For each of the 3 fuel types: electricity diesel and gasoline, I remove observations with consumption values in the the upper and lower 0.5% percentiles . In addition, I remove users with less than 10 refueling and charging instances and users that have documented less then 5,000 kilometers of distance traveled. Lastly, by using the brand, model name and type of fuel used (gasoline / diesel) I match the PHEV's usage data to the vehicle sales and characteristics data. For each brand-model-fuel match I retain the match with the closest production year and horsepower values, observations with unmatched vehicles models are removed.

B Estimation details

I denote θ as the vector of parameters to be estimated. θ consists of the taste parameters for BEV and volume for which I estimate both a mean and standard deviation. I specify α to be proportional to income y_{it}. Additionally I include in θ a set of vehicle characteristics for which I estimate only the mean taste, these include fuel costs per km, volume, horsepower, dummies for PHEV and BEV, vehicle class[42], body type[43], brand, and market. I estimate the parameters by minimizing the GMM criterion:

$$\min_{\theta} \xi(\theta)' Z W Z' \xi(\theta) \tag{A.1}$$

The identifying assumption is $E[\xi|Z] = 0$, where $\xi(\theta)$ is the remaining unexplained variation in market shares which is commonly referred to as the unobserved product characteristics, Z is a matrix of instruments and W is a weighting matrix. Since $\xi(\theta)$ enter the market shares non-linearly, I follow the work of Berry et al. (1995) and first approximate the market shares using a Monte Carlo simulation. Then I find the mean-utility parameter value that equates the approximated market shares to the observed ones using a contraction mapping and subsequently calculate ξ for each market. Following the critique introduced in Knittel and Metaxoglou (2014), I account for a variety of computational issues to ensure that I obtain a global minimum: (i) I approximate the market share integral for each market using 200 draws of a Halton sequence; (ii) I use a tight convergence criteria for the contraction mapping: $1e-14$; (iii) I do a grid search over a set of starting values to search for a global minimum; (iv) I check the first and second order conditions to verify the solution.

To improve the efficiency of the non-linear taste parameters variance estimates, I follow Reynaert and Verboven (2014) approach to compute Chamberlain (1987) optimal set of instruments - the expected value of the derivatives of ξ with respect to θ which are evaluated at its initial estimate $\hat{\theta}$. To compute Chamberlain's optimal set of instruments, I first derive an approximation of the optimal set of instruments using the GMM estimates of the linear parameters as an initial guess for θ, I then use the approximated optimal set of instruments and the instruments described above to estimate the non-linear model's parameters. The estimated $\hat{\theta}$ is then used to compute the optimal set of instruments by evaluating the Jacobian of the mean utilities with respect to $\hat{\theta}$. Finally, I re-estimate the model using the computed optimal set of instruments.

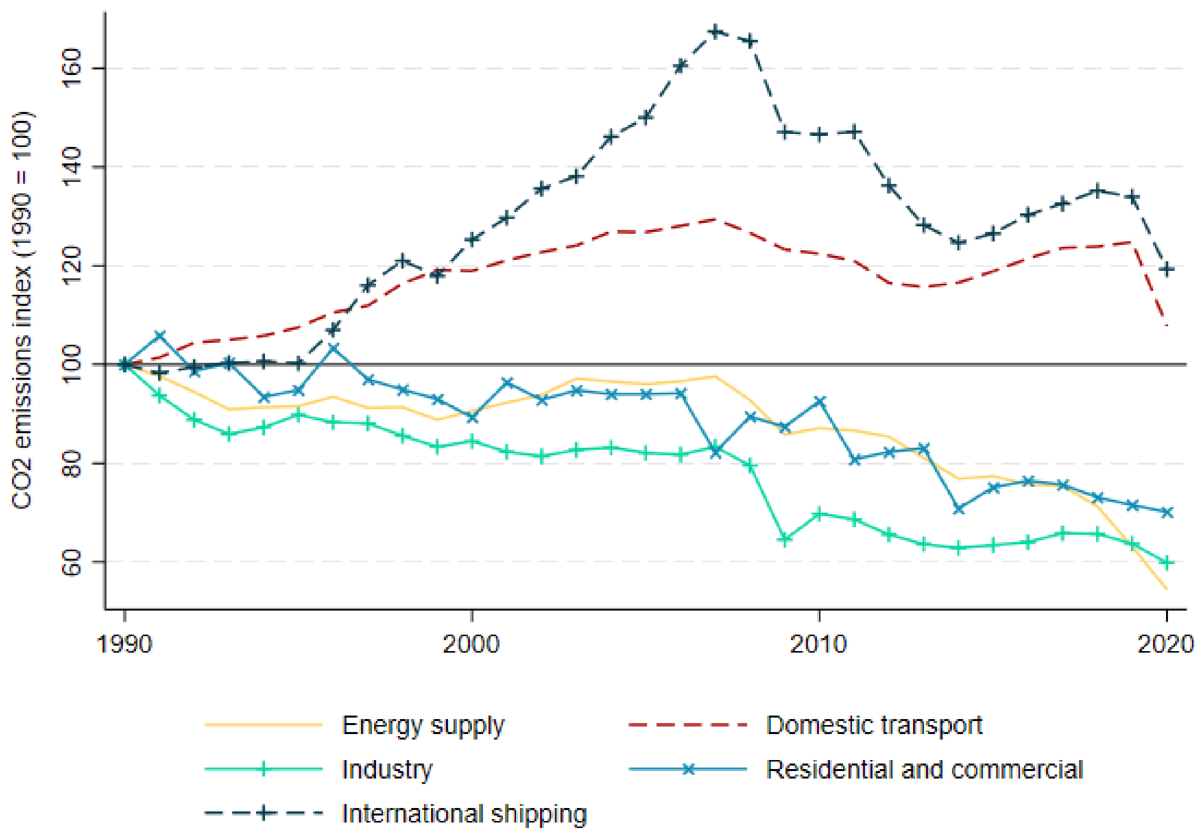
C Additional figures

Figure C.1 plots the carbon emissions development for the five most carbon intensive sectors in the EU taking 1990 levels as the base values. Out of the five most carbon intensive sectors

[42]The classes are micro-vehicle, minicompact, subcompact, compact, mid-size, and executive.

[43]The body types are hatchback, notchback, station wagon, van and SUV.

Figure C.1: CO_2 developmenet in Europe by indsuty



Notes: The figure plots the development of carbon emissions between the years 1990 and 2020, for the most carbon intensive industries in the European Union. The values of the base year (1990) are normalized to 100.

in the EU only the transportation related sectors (Domestic transport and international shipping) experience and increase in carbon emissions compared to their 1990 levels.

D Additional tables

Table D.1 shows official, real-usage and estimated values for the most selling PHEVs in 2021. The table illustrates the deviations between official and real-usage fuel consumption values, and the estimated carbon emissions values under full battery and empty battery regimes.

Table D.1: Fuel consumption values for best selling PHEVs in 2021

	offical	estimated full battery	real-usage	estimated no charging	no. obs.
AUDI A3	1.4	2.4	4.1	4.8	145
BMW X1	1.9	3.8	4.5	5.7	334
FORD KUGA	1.4	2.2	4.7	4.7	1506
MITSUBISHI OUTLANDER	1.8	3.4	5.5	5.7	538
VOLKSWAGEN GOLF	1.2	2.1	5.2	4.5	275

Notes: The table presents the official and real usage carbon emission values which are computed directly form the data, in addition to the estimated carbon emissions values under full battery and empty battery regimes for the 5 best selling PHEVs in Germany in 2021.

Table D.2 presents the model's out of sample fit. To evaluate the estimated model ability to predict consumer purchasing decision, I use vehicle registration data for the year of 2014, which is not used in the estimation procedure to evaluate the model's out of sample fit.

Table D.2: Model fit

	True	Prediction
Price/inocme	1.30	1.16
Fuel costs	7.72	7.92
CO2	126.96	126.46
Volume	11.70	11.37
Weight	1,348.30	1,292.36
SUV	0.23	0.21

Notes: The table presents the true sales-weighted averages of vehicles characteristics for the year 2014 and their model's estimates using only the coefficients estimates of the demand model's taste parameters. The estimation was done by setting year fixed effects and demand unobservables to zero.