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Citation for the original published paper (version of record):
Mandev, A., Plötz, P., Sprei, F. (2024). Factors impacting real-world fuel economy of plug-in hybrid electric vehicles in Europe - an
empirical analysis. Environmental Research Communications, 6(5).
http://dx.doi.org/10.1088/2515-7620/ad419f

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ENVIRONMENTAL RESEARCH
COMMUNICATIONS

LETTER • OPEN ACCESS

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To cite this article: Ahmet Mandev *et al* 2024 *Environ. Res. Commun.* **6** 051001

Environmental Research Communications

OPEN ACCESS

RECEIVED
30 June 2023

REVISED
10 April 2024

ACCEPTED FOR PUBLICATION
22 April 2024

PUBLISHED
3 May 2024

LETTER

Factors impacting real-world fuel economy of plug-in hybrid electric vehicles in Europe – an empirical analysis

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Keywords: plug-in hybrid electric vehicles, electric driving share, utility factor, real-world operation

Abstract

Plug-in hybrid electric vehicles (PHEVs) combine an electric motor with an internal combustion engine and can reduce greenhouse gas emissions from transport if mainly driven on electricity. The environmental benefit of PHEVs strongly depends on its usage and charging behavior. Several studies have demonstrated low electric driving shares (EDS) of many PHEVs. However, there is limited evidence on which vehicle properties affect the EDS of PHEVs to which extent. Here, we provide an empirical and quantitative analysis of real-world EDS and fuel consumption and look at how they are impacted by factors related to vehicle properties such as range, system power and mass. We complement previous studies on real-world EDS and fuel consumption of PHEVs by combining two different data sets, with almost 100,000 vehicles in total, over 150 models in 41 countries, which is combined the largest PHEV sample in Europe to date to be analyzed in the literature. We find that an increase of 10 km of type approval range leads on average to 13%–17% fuel consumption decrease and 1%–4% EDS increase. Furthermore, a 1 kW increase in system power per 100 kg of vehicle mass is associated with an average increase of 7%–9% in fuel consumption and a decrease of up to 2% in EDS. We also find that long-distance driving and charging behavior are the largest non-technical factors for the deviation between type-approval and real-world data. Furthermore, PHEV fuel consumption and related tail-pipe emissions in Europe are on average higher than official EU values.

1. Introduction

Electrification of transport plays a crucial role in meeting the climate goals in Europe and the Paris Agreement [1–5]. One of the available technologies for passenger cars are plug-in hybrid electric vehicles (PHEV) since they combine an internal combustion engine with an electric motor [6]. However, the actual impact of PHEVs on emissions depends on real-world driving behavior and the utility factor (UF), which is the share of kilometers driven on electricity or the electric driving share (EDS), a similar metric to the UF [1, 7–9]. Assessing PHEV fuel consumption is challenging because it depends on various factors, including vehicle characteristics, charging patterns, and driving behavior [10–15].

To evaluate PHEV fuel consumption, standardized testing procedures or test cycles are commonly used. In Europe, the New European Driving Cycle (NEDC) and the Worldwide Harmonized Light-Duty Vehicles Test Procedure (WLTP) are the most relevant [16, 17]. However, previous studies have shown that the UFs used in these procedures are outdated and may overestimate UFs and underestimate the actual fuel consumption and emissions of PHEVs [16, 18–23], with some studies finding that the gap between standard values and real-world UF is more apparent in shorter range PHEVs, yet can shrink and level up as PHEV range increases for certain PHEV variants in certain regions [24]. Similarly, the WLTP cycle often underestimates the fuel consumption of internal combustion engine vehicles as well. The aim of this paper is to complement previous studies with newer and more data to provide better empirical support for revisions of the measurement of fuel consumption and tail-pipe emissions of PHEVs in EU regulations.

Previous studies have specifically looked at the effects of charging behavior [11, 13, 15, 22], the role of driving patterns, especially long-distance driving [3, 14, 15], and how household factors such as the number of conventional vehicles [25] may affect fuel consumption and UF. A second branch of literature that focuses on the effect of vehicle characteristics has used simulations or real-world data from a mostly small set of vehicles [21, 26–28]. Only very few studies have used large real-world data sets to analyze the actual UF, fuel consumption and impact of several aspects of user behavior such as charging. Thus, the empirical basis to make robust conclusions on the relation between main vehicle properties, user behavior, and UF is weak.

In this study, we complement previous studies on real-world fuel consumption and electric driving of PHEVs by combining two large empirical data sets on real-world PHEV usage to study the real-world fuel consumption and electric driving share and how these are affected by technical factors. The novelty lies in combining two data sets: each with several thousand PHEV, one covering many makes and models while the second data set covers a large number of countries. The combination of both data sets, to the authors' best knowledge, results in the analysis of the largest PHEV sample to date in Europe with almost 100,000 vehicles, over 150 models and covering 41 countries.

In addition, as recent statistical literature shows [29], even large samples can lead to strongly biased results, we thus combine two PHEV data sets in the present study to obtain more robust findings. This allows us also to investigate if results from previous studies still are valid given 1) an update with new data and 2) a complementary data set. We focus on technical properties and their correlation to user behavior of the vehicle such as range (also studied in [6, 30, 31]) and power-to-mass ratio and do this based on real-world driving data.

Our work extends previous studies in several aspects. Firstly, this is the largest combined sample of real-world PHEV usage data for Europe available in the literature. Secondly, by performing the same regression on two similar data sets we reduce sample selection bias and over confidence in regression results. Thirdly, our results cover a large number of makes and countries globally.

The outline of this paper is as follows. The data and methods are presented in section 2, followed by the results in section 3 and discussion in section 4. We close with summary and conclusions in section 5.

2. Data and methods

2.1. Data

We collected two primary data sets on real-world fuel consumption and electric driving share (EDS) of PHEVs in Europe. The first data set combines different online sources, company car data, and a PHEV user survey. It has been collected during the years 2021 and 2022 [32]. The second data set covers on-board measurement of many PHEVs in Europe from a single manufacturer, collected during the years 2018 to 2021.

Data set 1 is a combination of different data sources. Here, we combined real world fuel consumption of individual PHEVs from online fuel logs (e.g., the app and website Spritmonitor.de), as well as fleet software data from individual companies concerning their company cars, and vehicle usage survey data. Plötz, Link [32] contains a full description of the individual sources, data cleaning, and representativeness. Data set 1 covers 27 countries, including almost all Member States of the European Union, as well as the UK, Switzerland, and Norway. Most data is from Germany (N = 7123 and Western Europe (ten other countries with at least 50 vehicles). It includes data from private (N = 5808) and company cars (N = 3047), i.e., vehicles owned by an organization and assigned to an individual user for both business and private purposes. About 70% of the vehicles in our sample have WLTP values reported and most of these vehicles also have NEDC type-approval values. The sample covers 27 vehicle manufacturers, over 100 PHEV models, and over 400 model variants. BMW (24%), Mercedes-Benz (14%), and VW (11%) are the top three brands and Mitsubishi Outlander (9%), VW Passat (5%), and BMW X3 (5%) the top three models. Data set 1 was cleaned in several steps: (1) Only vehicles with build years >2010 were kept. (2) Entries with partial fuel consumption larger than 20 l/100 km were omitted. (3) Only vehicles with at least five refueling stops or a recorded distance of at least 1,500 km were kept. (5) Careful consideration was given to erase mild or full hybrids (HEV) which were mistakenly entered as PHEV in the data by checking electric charging events, official model specifications, build year, and vehicle power information to make sure only actual PHEV are kept. The final aggregated data is freely available for download under [32].

The second data is from a single manufacturer with Europe-wide operation. The data is collected between the first and last workshop visit of the vehicles and is aggregated over the time in between. The data contains the vehicle kilometers travelled (VKT) with internal combustion engine (ICE) on, idle, and off. Here, 'ICE on' refers to ICE being the only engine for propulsion, 'ICE off' refers to when only the electric engine is used for propulsion, and 'ICE idle' refers to when the electric engine is used for propulsion, but the PHEV can make use

Table 1. Overview of vehicle data sources by number of PHEV makes and model variants covered, sample size, predominant user group, and country.

Source	# makes	# models	Sample	User groups	No. of countries
Data set 1	27	>150	8,855	private & company car	27
Data set 2	1	9	87,509	mixed private & company car	41

of the ICE under certain conditions e.g. the load and operation temperatures. It contains over 85,000 vehicles of nine different PHEV models in 41 countries in Europe (EU27 + EU Candidates (exc. Serbia) + EFTA (exc. Liechtenstein) + UK + Russia + Georgia + Azerbaijan). The battery sizes range from 10.4 to 11.6 kWh for eight of the models and 34 kWh for one model. WLTP range is from 34 to 54 km on average for eight models and 124 km for vehicles with a large battery. The mean observation period (time between two workshop visits) is 580 days. The data is mixed in user groups and is assumed to contain both private and company cars. Further details regarding the specific make and model of the vehicles in data set 2 are protected by a data licensing agreement and the data is not publicly accessible. Data set 2 was initially cleaned and anonymized by the data provider, and it was further cleaned for this study by (1) omitting vehicles with less than 100 observation days, therefore focusing the analyses on vehicles that were driven long-term, (2) omitting inconsistent observations such as where the total VKT did not match the sum of VKT with ICE on, idle and off.

Table 1 contains an overview of both data sets, the number of makes, models and the total sample size.

In terms of vehicle classes, data set 1 has a variety of vehicle classes ranging from Euro C-segment to E-segment and several different SUV classes. Similarly, data set 2 has a variety of vehicle classes; Euro D-segment and E-segment for station wagon and sedans, several different SUV classes, and a sports car. Different SUV classes here refer to small, medium and large size SUVs as advertised in the European market, whereas the North American classification would be subcompact, compact and mid-size for the same vehicles. In data set 2, D and E-segment vehicles make up 29% of the data set, medium SUVs make up 43% of the data set, large SUVs make up 25% of the dataset, small SUV and sports vehicles make up 3% of the data set. The combined data set reflects the variety seen in data set 2.

Model years for private cars in data set 1 range from 2011 to 2021, with the average model year being 2018; whereas for company cars model years range from 2014 to 2021, with the average being 2020. For the mixed fleet in data set 2, the model years range from 2019 to 2021, with the average being 2019. Overall, the vehicles in both data sets were on average quite new models (one to two years old) during the data collection.

2.2. Methods

2.2.1. Derivation of electric driving share

PHEVs can drive with the combustion engine on or off. We define the electric driving share (EDS), denoted by EDS^{real}, as share of total distance $dist_{total}^{real}$ driven with the combustion engine off while in charge depleting mode, i.e., driven purely on electricity $dist_{electric}^{real}$. Note that in WLTP, the utility factor (UF) does not match the EDS directly. In WLTP, the UF corresponds to the share of distance driven in charge depleting (CD) mode, which is mostly electric but not fully electric [33]. Please note that the EDS is not only the quantity describing the share of the different PHEV modes of operation. A closely related quantity is the Utility Factor (UF) with several definitions in the engineering literature (e.g. the Fleet UF, the Individual UF, the Single Day Individual UF, the Multiple Day Individual UF, the Specific UF, the City Specific Fleet UF, and the Highway Specific Fleet UF, cf [30]). However, we use the EDS here for several reasons: (1) it is standard in a large part of the PHEV literature; (2) it is much easier to understand; and (3) it is easy and clearly defined as the share of km with combustion engine off.

$$EDS^{real} := \frac{dist_{electric}^{real}}{dist_{total}^{real}} \tag{1}$$

The EDS can be approximately derived from the real-world fuel consumption FC_{total}^{real} (as part of the PHEV usage data in data set 1) and from the real-world fuel consumption of driving solely in charge-sustaining mode FC_{CS}^{real} [32]:

$$EDS^{real} = 1 - \frac{FC_{total}^{real}}{FC_{CS}^{real}} \tag{2}$$

The real-world fuel consumption of driving in charge-sustaining mode FC_{CS}^{real} can be estimated from NEDC or WLTP type-approval values $FC_{CS}^{type-approval}$ and a correction factor X explained in the following:

$$FC_{CS}^{real} = X \ * \ FC_{CS}^{type-approval} \tag{3}$$

As discussed in Plötz, Link [32], $FC_{CS}^{type-approval}$ can be obtained from NEDC or WLTP type-approval combined fuel consumption values and the corresponding NEDC all-electric range or WLTP equivalent all-electric range as provided by the ADAC Autokatalog database [34]. Based on existing studies on the deviation of real-world and type-approval fuel consumption of hybrid electric vehicles that are not externally chargeable, X is approximately equal to 1.47 for NEDC and 1.23 for WLTP type-approval values, i.e., FC_{CS}^{real} is on average 47% higher than its NEDC type-approval value [18]. The 1.23 for WLTP is taken from the deviation between WLTP and NEDC observed empirically in [18] where NEDC is on average 20% higher than WLTP resulting in a WLTP pre-factor of $1.47/1.2 = 1.23$. Further details are given in Plötz, Link [32].

This leads to:

$$EDS^{real} = 1 - \frac{FC_{total}^{real}}{1.47 \quad FC_{CS}^{NEDC}} \text{for NEDC type approval vehicles and} \tag{4}$$

$$EDS^{real} = 1 - \frac{FC_{total}^{real}}{1.23 \quad FC_{CS}^{WLTP}} \text{for WLTP type approval vehicles.} \tag{5}$$

When both NEDC and WLTP values are available, the two derived values for the real-world fuel consumption in charge-sustaining mode FC_{CS}^{real} do not necessarily match. In that case, we use the average of the two values.

Contrary to data set 1, in data set 2, the real-world fuel consumption is not available; however, the real-world electric driving share is. Therefore, in data set 2, to calculate the real-world fuel consumption, we follow equation (4) and equation (5) in reverse to reach the real-world fuel consumption. Similarly, if both NEDC and WLTP values are available, we take the average of the two values.

2.2.2. Regression analysis

The all-electric range and other vehicle properties such as system power affect fuel consumption and EDS. We use two separate regression models to quantify the effect of these external factors on fuel consumption and EDS. Our aim is to derive robust values for the effect of range and other vehicle properties on PHEV fuel consumption and EDS from the combination of different data sets and different regression models. Please note that we do not analyze the effect of system power on fuel consumption from an engineering point of view via, e.g. physical laws, but from social science or behavioral aspect, i.e., PHEV users with long-ranged or highly powered PHEV could use them differently.

We use the WLTP values for the all-electric range, as it is readily available for most PHEV models. The power of the vehicle in terms of combustion engine power, electric motor power, and system power, i.e., the maximum power of all motors and engines, are included to account for different vehicle sizes or types and engine capacity. Strictly speaking, the system power is the maximal power available for propulsion. For some PHEV models, this is the sum of combustion engine and electric motor power but we looked up the maximal available power for each PHEV model. In range extended electric vehicles, however, the system power is smaller than the sum of engine and electric motor power because the combustion engine is not directly used for propulsion but for battery charging.

Since fuel consumption is strictly non-negative, we use an exponential function for the effect of vehicle models' all-electric range and power with the following model based on [3, 32]:

$$FC^{real} = \exp\left(\beta_0 + \beta_1 Power/Mass + \beta_2 Range + \alpha \mathrm{Controls}\right) + \varepsilon. \tag{6}$$

Here, $Power/Mass$ is the system power in kW divided by the vehicle empty mass in kg, and $Range$ is the PHEV's all-electric range measured in units of 10 km. The chosen dependence is physically meaningful: For Range$\to$0, the fuel consumption approaches a finite value (i.e., the fuel consumption in charge-sustaining mode) and goes to zero for Range$\to\infty$ (for negative β_2). Likewise, the fuel consumption approaches zero for system power tending to zero and grows with increasing system power (for positive β_1). We choose system power divided by vehicle mass as power and mass are often strongly correlated which would lead to potential collinearity issues in the regression. Furthermore, we add several control variables (Abbreviated as *Controls* in equation (6) such as model year, annual vehicle kilometers traveled (VKT), country and user group (private or company car) to account for additional effects. The linear regression is performed after taking logarithms by weighted least squares (with the square root of sample size as weights).

We also perform a regression analysis with the EDS as dependent variable. As the EDS is a non-negative fraction, we use a fractional logit model and include the same independent variables as for the real-world fuel consumption, likewise weighted by the square root of sample size for aggregated data (implemented as quasi-binomial regression model, see [35]). We calculate average marginal effects to quantify the impact of different factors on EDS using the statistical software R [36] and the package margins [37].

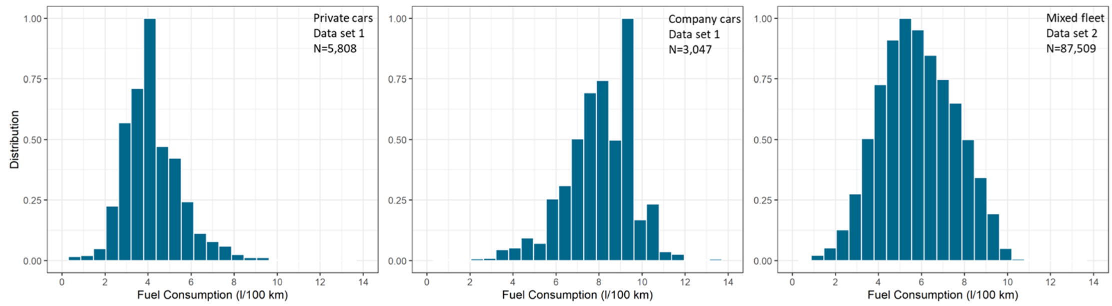

Figure 1. Distribution of fuel consumption (l/100 km) in private and company vehicles in Data set 1 and in the mixed fleet in Data set 2; normalized to maximum 1. *N* refers to the total number of vehicles aggregated within subsamples.

Table 2. Summary statistics of fuel consumption and electric driving share in both data sets.

			Min	0.25 quantile	Median	Mean	0.75 quantile	Max	Std. dev.	N*
Fuel consumption (l/100 km)	Data set 1	Private cars	0.02	3.1	**4.2**	**4.4**	5.5	13.0	1.9	5,808
		Company cars	0.3	6.1	**7.4**	**7.5**	8.8	17.1	2.2	3,047
	Data set 2	Mixed fleet	0.1	4.6	**5.7**	**5.8**	7.1	11.5	1.7	87,509
Electric driving share (%)	Data set 1	Private cars	0.0%	34.3%	**46.6%**	**46.3%**	59.0%	99.7%	18.8%	5,808
		Company cars	0.0%	2.1%	**9.7%**	**15.1%**	22.0%	97.0%	16.9%	3,047
	Data set 2	Mixed fleet	0.0%	28.1%	**39.2%**	**39.9%**	50.5%	98.9%	15.5%	87,509

*N refers to the total number of vehicles aggregated within subsamples.

3. Results

3.1. Descriptive statistics

Summary statistics of fuel consumption and electric driving share for both datasets are given in table 2. It should be noted that the summary statistics reflect the overall fuel consumption and electric driving share for all vehicles in a user group, without distinguishing for ranges of the vehicles or other factors that can impact. We look at factors that can affect fuel consumption and EDS separately in sections 3.2 and 3.3.

We observe that the mean fuel consumption is higher for company cars in data set 1, with 7.5 l/100 km, compared to the 4.4 l/100 km for private cars. For the mixed fleet in data set 2, the fuel consumption on average is 5.8 l/100 km. If the private and company cars in data set 2 are assumed to have the mean fuel consumption as estimated in data set 1, this would mean that the approximate share of company cars in data set 2 is around 55%. The share of company cars (among newly sold PHEVs) in western and northern European countries range from 57% to 69% [38]. This shows that the mixed fleet in data set 2 has a ratio of private to company cars that is close to expectations.

A visual representation of the distribution of fuel consumption for both data sets is given in figure 1. We observe that the distribution of private cars in data set 1 has a right skew and the distribution of company cars has a left skew, mirroring each other. This clearly shows the stark difference between the two user groups. The mixed fleet in data set 2, however, has more symmetric distribution as expected.

The EDS for private cars in data set 1 is on average 46%, much higher compared to the 15% for company cars. This inversely mirrors the average fuel consumption from those user groups as expected, meaning that company cars have higher fuel consumption and lower EDS on average, and private cars have lower fuel consumption and higher EDS on average. On the other hand, for the mixed fleet in data set 2, the average EDS is 40% which is expectedly between the values observed separately for private and company cars.

A visual representation of the distribution of electric driving share for both data sets is given in figure 2. We observe that the distribution of private cars in data set 1 has a slight left skew and the distribution of company cars has a right skew. EDS for private cars in data set 1, albeit having a slight left skew, has a more symmetric distribution, compared to company cars. This indicates that although on average, EDS is higher for private cars compared to company cars, there is more variance in electric driving behavior for private users, whereas for

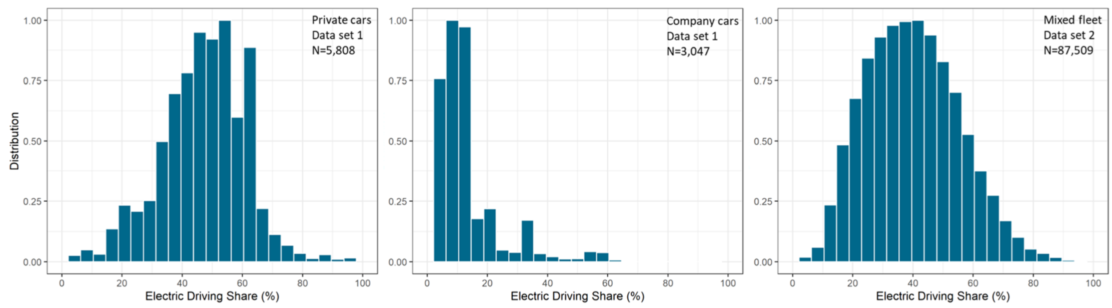

Figure 2. Distribution of electric driving share (in %) for private and company vehicles in Data set 1 and in the mixed fleet in Data set 2; normalized to maximum 1. *N* refers the total number of vehicles aggregated within subsamples.

Table 3. Regression results on fuel consumption (l/100 km).

	Data set 1			Data set 2		
	Estimate	Std. error		Estimate	Std. error	
Intercept	−111.20	25.12	***	−464.10	4.23	***
WLTP range (10 km)	−0.13	0.01	***	−0.17	0.002	***
System power / mass (kW/kg)	7.42	0.60	***	8.60	0.15	***
Model year	0.06	0.01	***	0.23	0.002	***
Annual VKT (1,000 km)	0.004	0.001	***	0.01	0.0001	***
User group: private	−0.50	0.03	***			
+ Country dummies						
N	779			87,509		
Adjusted R^2	0.63			0.28		
F-statistic	45.1***			771.3***		
Significance levels '***' 0.1%, '**' 1%, '*' 5%, '.' 10%						

Sample size N = 779 for data set 1 refers to the number of aggregated subsamples where each observation contains multiple vehicles. The number of vehicles in data set 1 used for regression is 3,865 vehicles after omitting incomplete observations.

more than 75% of the company cars EDS is lower than 22% indicating a more uniform electric driving behavior that results in lower EDS.

The CO_2 emissions target for newly sold passenger cars in the European Union for the period of 2020–24 is 95 gCO_2/km [39]. Based on the conversion values of the Environmental Protection Agency in the US [40], this corresponds to 4.1 l/100 km in fuel consumption. The average fuel consumption in both data sets (for both private and company cars) is above this value. For comparison, the average fuel consumption of 4.4 l/100 km for private cars in data set 1 corresponds to 102 gCO_2/km in tail-pipe emissions, for company cars this corresponds to 173 gCO_2/km and for the mixed fleet in data set 2 to 134 gCO_2/km; all of which are significantly above the target level of 95 gCO_2/km.

3.2. Regression results on fuel consumption

The results of the regression analysis on fuel consumption are given in table 3. For both data sets, all coefficients are statistically significant (at 0.1% significance level) and have the expected signs. Data set 1 has a higher goodness of fit compared to data set 2, which can be explained with a lower variance in a smaller sample with fewer countries.

We find that a 10 km increase of WLTP range leads on average to a 13% decrease (11%–15% with 95% confidence interval) in fuel consumption in data set 1 compared to a 17% decrease (16.6%–17.3% with 95% confidence interval) in data set 2. The similarity in estimated coefficients and the level of significance for two data sets (which are starkly different from each other in sample size and model variance) shows that the effect of range on fuel consumption is consistent across PHEV models and countries in Europe.

We also find that every 1 kW increase in system power for 100 kg of vehicle mass leads on average to a 7.4% increase (6.2%–8.6% with 95% confidence interval) in fuel consumption in data set 1 compared to an 8.6% increase (8.3%–8.9% with 95% confidence interval) in data set 2. This shows that PHEVs with higher system power on average lead to higher fuel consumption across model variants and countries.

Table 4. Regression results on electric driving share (scaled 0 to 1).

	Data set 1			Date set 2		
	Estimate	Std. error		Estimate	Std. error	
Intercept	123.73	56.7	***	135.50	8.71	***
WLTP range (10 km)	0.16	0.02	***	0.06	0.01	***
System power / mass (kW/kg)	−6.12	1.12	***	−1.35	0.32	***
Model year	−0.06	0.03	***	−0.07	0.004	***
Annual VKT (1,000 km)	−0.02	0.003	***	−0.02	0.0002	***
User group: private	1.73	0.09	***			
+ Country dummies						
N	779			87,509		
Significance levels '***' 0.1%, '**' 1%, '*' 5%, '.' 10%						

Sample size N = 779 for data set 1 refers to the number of aggregated subsamples where each observation contains multiple vehicles. The number of vehicles in data set 1 used for regression is 3,865 vehicles after omitting incomplete observations.

Table 5. Average marginal effects on electric driving share (scaled 0 to 1).

	Average marginal effect	Std. err.	Lower bound 95% confidence level	Upper bound 95% confidence level
Data set 1				
WLTP range (10 km)	0.03	0.004	0.03	0.04
System power / mass (kW/kg)	−1.30	0.26	−1.81	−0.79
Model year	−0.01	0.01	−0.02	−0.002
Annual VKT (1,000 km)	−0.004	0.001	−0.005	−0.002
User group: private	0.32	0.01	0.30	0.34
Data set 2				
WLTP range (10 km)	0.01	0.001	0.01	0.02
System power / mass (kW/kg)	−0.32	0.08	−0.46	−0.17
Model year	−0.02	0.001	−0.02	−0.01
Annual VKT (1,000 km)	−0.01	0.0001	−0.005	−0.005

The significance levels are the same as shown as in table 4. All coefficients in both data sets are statistically significant at the 0.1% significance level.

We also observe in data set 1 that private PHEVs have on average about 50% lower fuel consumption. This is in line with the observed behavior of private cars having lower fuel consumption as shown in section 3.1. Considering the dependency of the model year, an additional increase of 6% on average in fuel consumption with every built year is observed in data set 1, compared to 23% increase in dataset 2. This discrepancy might arise from data set 2 having much less variance in model years and no variance in the make of the vehicle (single manufacturer). We also observe that every 1,000 km increase in annual VKT is associated with a slight increase of 0%–1% in fuel consumption in both data sets.

3.3. Regression results on electric driving share

The results of the regression analysis on electric driving share are given in table 4. We observe that all coefficients are statistically significant (at 0.1% significance level) and have the expected signs.

The regression model is a quasi-binomial regression model, which means only the coefficient signs can be directly interpreted, not the coefficient estimates. Therefore, the average marginal effects must be calculated separately. See table 5 for the average marginal effects on electric driving share for both data sets.

We observe that a higher WLTP range is associated with a higher EDS in both data sets. An increase of 10 km in WLTP range leads on average to 3%–4% increase in EDS in data set 1, and 1%–2% increase in data set 2. The effect of range in data set 1 is almost three times that of data set 2. This difference can be due to the higher number of model variants and thus higher variation in ranges in data set 1, whereas the range variation is quite limited in data set 2.

We also observe that a higher system power per mass is associated with a lower EDS in both data sets. Every kW increase in system power for 100 kg of vehicle mass leads on average to 0.8%–1.8% decrease in EDS in data

Table 6. Contributions to results on electric driving share and real-world fuel consumption. Percentage differences in percentage points (pp).

Factor	Electric driving share			Fuel consumption [l/100 km]		
	Private	Company cars	Mixed	Private	Company cars	Mixed
Mean WLTP type approval value	77%	77%	70%	1.67	1.73	2.57
Lower CD mode range	−6 pp	−6 pp	−6 pp	+0.4	+0.4	+0.4
Long-distance driving	−5 ± 5 pp	−35 ± 10 pp	−22 ± 10 pp	+0.4	+2.1	+1.4
Charging behaviour	−20 ± 5 pp	−21 ± 10 pp	−2 ± 10 pp	+1.5	+1.6	+0.2
Higher CS mode fuel consumption	—	—	—	+0.8	+1.5	+1.2
Total real-world value	46%	15%	40%	4.4	7.4	5.8

set 1, and 0.2%–0.5% decrease in data set 2. Similarly, the effect is larger in data set 1, which can again be due to the limited model variation in data set 2. We also find that having a private car is also significantly associated with having a higher EDS, increasing EDS by 32% on average. More driving is associated with a decrease in EDS although the effect is quite small where an increase of 1,000 km in annual VKT leads to 0%–1% decrease in EDS in both data sets.

Please note that the regression results apply only around the observed mean values and that much larger changes, e.g., 100 km instead of 50 km CD mode range need to be analyzed separately. In such a case, higher order terms should be added, or existing non-linear relationships be used, for example the WLTP UF curve for remarkably high ranges (potentially corrected for behavioral factors—see section 3.4 below).

3.4. Deviation between type approval and actual PHEV fuel consumption

In the present section, we extend the analysis of factors affecting PHEV EDS and fuel consumption beyond technical vehicle attributes such as range and power to include user specific factors such as charging behavior and long-distance driving. To this end, we extend the discussion in [32] by (1) differentiation of charging behavior and long-distance driving, (2) explicitly analyzing the EDS, and (3) adding the mixed fleet of data set 2.

We start with the average WLTP type-approval EDS and fuel consumption values: 77% EDS for both private and company cars in data set 1, as well as 70% EDS for the mixed fleet in data set 2. The corresponding WLTP mixed fuel consumption values are 1.67 l/100 km for private and 1.73 l/100 km for company cars in data set 1 as well as 2.57 l/100 km for data set 2.

The difference between type-approval and real-world EDS can be decomposed into (1) the effect of lower CD mode driving range, (2) more long-distance driving, and (3) lower charging frequency than once per driving day. For the fuel consumption, an additional contribution arises from (4) the higher fuel consumption in charge sustaining (CS) mode than expected from type-approval. The joint effect of these factors results in the actual average real-world EDS and fuel consumption, respectively. The contribution of the individual factors is summarized in table 6 and explained in the following. Please note that the analysis here refers only to average values. On an individual level, actual EDS and fuel consumption can be better or much lower than type approval value and further factors such as, e.g., aggressiveness of driving or weather can be important.

The real-world CD mode range and thus the EDS is lower than in type-approval since type-approval energy consumption is on average lower than actual energy consumption which also applies to the electricity consumption in the CD mode. We use the WLTP UF curve for the EDS with the all-electric range (AER) instead of the CD mode range to quantify this effect. Assuming that the electricity consumption of the CD mode in real-world usage is about 20% higher than in WLTP type-approval [28], the mean WLTP CD mode range in data set 1 of 56 km would be 17% lower in real-world usage, at about 46 km. The difference in the WLTP UF between a CD mode range of 46 km and 56 km is about 6 percentage points. For our PHEV models with a typical WLTP CS mode fuel consumption of 7.1 L/100 km, this increases the average fuel consumption by about 0.4 l/100 km. Thus, we arrive at –6 percentage points in EDS and +0.4 l/100 km for private, company car, and mixed fleets from lower real-world electric driving range.

Another aspect that is underrepresented in WLTP is the importance of long-distance driving. In the original WLTP UF curve derivation [41] the input data came from conventional vehicles with (1) limited observation period and (2) vehicles with high daily vehicle-km were explicitly excluded. Yet, the vehicles in the original definition of WLTP seem to include some long-distance driving as the UF curve would otherwise reach 100% already for small ranges. Please note that the share of long-distance driving in annual vehicle km travelled increases with the observation period of vehicles [42, 43]. The mean WLTP range in our data is about 55 km resulting in 77% WLTP UF. This would correspond to about one quarter of long-distance driving days with more than 100 km, as $55/400^{*}0.265 + 100\%^{*}0.735 = 77\%$ (assuming about 400 km daily km on long-distance driving days and full recharge every night). More realistic is about one third of long-distance driving days, resulting in about 73% UF. Thus, the underestimation of long-distance driving in WLTP results in about 5 percentage points (pp) lower UF for private vehicles. Company cars have higher annual VKT and more days of long-distance driving. For company cars with their much higher annual VKT, long-distance driving is much more frequent. E.g., driving 50 km on a regular commute yields 10,000 km over 200 working days per year, resulting in 1/3 of the average annual mileage of 30,000 km from short-distance driving. Accordingly, the reduction in UF due to long-distance driving is 35 percentage points ($55.4/350^{*}0.67 + 0.33 = 43\%$ instead of 78% WLTP). For the mixed fleet in data set 2, the share of company cars is about 55% yielding a weighted average reduction of about $0.45^{*}5$ pp + $0.55^{*}35$ pp = 22 pp. As the underlying data in the derivation of the WLTP UF curve is not publicly available, all the estimates come with noteworthy uncertainty which we estimate as ± 5 percentage points for private and ± 10 percentage points for company cars.

For EDS, the remaining difference to real-world EDS must be due to less charging than assumed in WLTP. As we observe EDS of 46% for private, 15% for company cars, and 40% for the mixed fleet of data set 2, the resulting effect from less than daily charging is –20 ± 5 percentage points for private, −21 ± 10 percentage points for company cars, and –2 ± 10 percentage points for the mixed fleet in data set 2. Again, the uncertainty from the share of long-distance driving is present in the uncertainty of these estimates.

Finally, we study the effect from a higher CS mode fuel consumption than in type-approval conditions. We take the average real-world fuel consumption values of 4.2 l/100 km for private and 8.0 l/100 km for company PHEVs as an example. As described in section 2.3, we assume that the real-world fuel consumption when driving on fuel can be approximated by the CS mode fuel consumption and that the real-world CS mode fuel consumption is 23% higher than the WLTP CS mode fuel consumption. Thereby, +0.8 l/100 km for private cars and +1.5 l/100 km for company cars as well as 1.2 l/100 km for the mixed fleet in data set 2 can be attributed to the deviation of real-world and type-approval CS mode fuel consumption values. Note that the contribution of the difference in fuel consumption when driving on fuel is proportional to the fuel consumption resulting from the realized EDS and CD mode driving share. The higher value for company than for private cars is linked to their lower EDS.

Table 6 shows the contributions to results on EDS and real-world fuel consumption for private and company cars in data set 1 as well as the mixed fleet of data set 2.

In summary, the contribution of different non-technical factors to real-world EDS and fuel-consumption can be approximated. We find that long-distance driving and charging behavior are the largest factors for the deviation between type-approval and real-world data despite all uncertainties. These factors also differ between private and company cars.

3.5. Sensitivity analysis and robustness checks

We checked variance inflation factors to account for potential multi-collinearity in our regression models. An initial observation of high variance inflation factors when system power and mass were included as separate variables led to further testing. Pearson correlation coefficients in both data sets between system power and mass were greater than 0.5, indicating a strong correlation. To avoid multi-collinearity, we used system power divided by mass in our regression models. This appears to be a potential issue in other studies where vehicle power and mass have been included separately. The final regression models in the present study for fuel consumption and EDS as dependent variables show variance inflation factors less than 2, which indicates no problems of multi-collinearity.

We tested regression models (for both fuel consumption and EDS) on data set 1 but using only the same make vehicles as in data set 2, to check if the same make vehicles behave similarly in both data sets. We found, for both fuel consumption and EDS, that the coefficient signs were the same with slightly different magnitude. However, except for a few coefficients (range and user group), all variables were statistically insignificant. This can be due to the small sample size of 260 vehicles that were used for the regression models on data set 1 when limited to one make. Yet, the similarity of coefficient signs and estimates proves the comparability of the two data sets. Furthermore, we added further control variables such as vehicle size to the regression models without relevant changes to the results.

The multipliers of 1.47 for NEDC in equations (4) and 1.23 for WLTP in equation (5) directly impact the calculation of EDS in data set 1 and fuel consumption in data set 2. Therefore, we performed a sensitivity analysis where we varied these multipliers ± 10%, meaning the NEDC multiplier is varied between 1.32 and 1.62 and the WLTP multiplier is varied between 1.11 and 1.35. We observed that for the calculation of EDS in data set 1, the variation of these multipliers impacts the EDS ± 6% on average. On the other hand, for the calculation of fuel consumption in data set 2, the variation of these multipliers impacts the fuel consumption ± 0.6 l/100 km on average. Additionally, we also tested how the variation of these multipliers impact the regression results on EDS and fuel consumption. We ran the regression analyses when the NEDC and WLTP multipliers were 10% lower, 5% lower, 5% higher and 10% higher compared to the base values (that is for NEDC multiplier 1.32, 1.39, 1.54, 1.62, and for WLTP multiplier 1.11, 1.17, 1.29, 1.35.). We observe that the coefficient estimates both in the EDS and fuel consumption only slightly change; the coefficients signs are the same and the change in estimates is so small such that if the same number of significant digits are used as in tables 3–5, the difference is not visible to the reader. On the other hand, the statistical significance of the variables is the same, with the exception of 'model year' on the EDS regression. For the model year, we observed that when the multipliers are tested at the lowest value (1.32 for NEDC and 1.11 for WLTP), it is still statistically significant, however at the 10% significance level, instead of the 0.1% level. We did not observe this change for the regression analyses regarding fuel consumption. The sensitivity analyses regarding the multipliers in equation (4) and equation (5) and the following robustness checks on regression analyses show that our results are not significantly impacted by a $\pm$ 10% magnitude change in these multipliers, and therefore can be considered robust.

4. Discussion

To derive the real-world EDS in data set 1, and reversely to derive real-world fuel consumption in data set 2, we assume that the EDS is the share of pure electric driving, meaning the internal combustion engine (ICE) is switched off. In WLTP type-approval calculations, this corresponds to the share of charge depleting (CD) mode driving share. For some PHEVs, CD mode corresponds to ICE switched off, however in others, the PHEV can make use of their ICE under certain conditions depending on e.g., the load and operation temperatures [44, 45]. In cases where the PHEV makes use of its ICE, the estimated electric driving share will be higher; however, in that case the CD mode range will also be higher. In data set 2, we have access to both pure electric driving (ICE switched off) and CD mode driving (ICE switched off and ICE idle where the PHEV can make use of the ICE). We calculated EDS both as share of pure electric driving and as share of CD mode driving. We find that the EDS as share of pure electric driving is on average only 1% lower than CD mode driving. We also find that using CD mode does not result in any difference in our regression analysis, except for negligible changes to coefficient estimates (at the second decimal). Furthermore, our assumptions regarding the calculation of fuel consumption in charge sustaining mode, as shown in equation (3) were validated in Plötz, Link [32] and show only minor deviations in recalculation to WLTP type-approval values. Therefore, we consider our method of deriving real-world EDS and real-world fuel consumption to be sufficiently accurate for the present purpose. Also note that the definition of EDS presented above refers to the share of km driven with engine off 'while in CD mode'. Compared to other studies of the EDS, this definition adds the term 'while in CD mode' to specify the circumstances of engine being off. By this we exclude a small number of km driven with engine off while in charge sustaining (CS) mode operation to be consistent with further assumptions and technical definitions of CD and CS mode in WLTP. Without this addition to the definition, non-plug-in hybrid electric vehicles (HEVs) would have EDS>0. This is not a problem in itself and often the EDS of HEV would be small as most HEV and PHEV in CS mode have the engine off only rarely when they drive at very low speeds for short distances, e.g. while parking or in stop-and-go traffic situations. As such this addition has minor implications when compared to the studies of EDS and can be in the small single digit percent range like the EDS versus CD mode share discussion above.

The two data sets we use in this study are clearly complementary and both have strengths and weaknesses. We combine them in the present study to reduce potential sample bias and to obtain more robust results. Data set 1 contains a larger number of different vehicle makes and in general more variance within the control variables as well as more control variables such as user group. Yet, the sample size of data set 1 is noteworthy smaller than in data set 2 and covers fewer countries with a focus on Germany (see Plötz, Link [32] for a discussion). Data set 2, on the other hand, has a much larger sample and covers more countries from the same make, which allows good coverage of country specific differences. However, with the drawback of lower variance in the range, power and other vehicles characteristics, as well as not containing any information regarding user groups (private and company cars). By applying the same regression models and analysis to both data sets, we obtain robust results that are less affected by sampling bias. In addition, the derivation of EDS and fuel consumption apply only to one data set at a time. Data set 1 has real-world fuel consumption, thus EDS is derived, whereas data set 2 has real-world EDS, thus fuel consumption is derived; meaning that each regression model—applied to both data sets—presents results both on real-world and derived EDS or fuel consumption. This allows for detecting any significant inaccuracy regarding the methods we use to derive EDS and fuel consumption, which we do not observe any.

In the regression analysis, all coefficients have the expected signs. Longer ranges and lower annual mileage are associated with more electric driving and less fuel consumption whereas larger combustion engines (combustion engine power dominates system power) correlate with less electric driving and higher fuel consumption (at fixed vehicle mass). Please note that we are studying vehicle usage behavior in large PHEV samples here and not engineering properties of vehicles. Of course, the coefficients differ slightly between the two data sets due to different sample composition and the availability of control variables. Yet, in general, the effect sizes are in line with existing literature reports and underline our findings' robustness.

Please note furthermore, that the aim and contribution of the regression analysis is not to predict the dependent variable (electric driving share and fuel consumption in our case) far away from the dependent variables' mean values but rather to analyze the effect of various contributing factors while controlling for other variables. As such, the regression results from the models presented above cannot directly predict the electric driving share or fuel consumption of PHEV for very large or very small values of independent variables, e.g. very low power or very large all-electric ranges. For such an analysis, higher order terms would need to be incorporated, which is beyond the aim and scope of the present paper.

In this study, we focus on the effect of vehicle characteristics on fuel consumption. However, fuel consumption is also affected by external factors such as fuel prices, electricity prices, availability of chargers, and weather conditions [46, 47]. Future studies could consider these in the analysis focusing on a country comparison rather than vehicle and model comparison.

The empirical data demonstrates clear differences in electric driving and fuel consumption between privately owned PHEV and company cars. As the vehicles are the same, the reasons for the difference are obviously non-technical factors. Company car owners very often receive tax benefits for owning the vehicles irrespective of their charging or usage behavior. Furthermore, many companies hand out fueling cards which allow company car owners to refuel their vehicles without own expenses. Apart from these policy incentives, company car owners show higher annual mileage which correlates with more frequent long-distance driving resulting in lower EDS even when recharging every day. It has long been acknowledged that driving cycles are imperfect representations of real-world driving no matter that driving train. While the WLTP is an improvement compared to NEDC, it is still optimistic when it comes to fuel consumption and related emissions (this does not only apply to PHEVs). A recent report by the European Court of Auditors [48] finds –based on on-board measurements of PHEVs from 2021– that the mean real-world emissions are 3.5 higher than the WLTP values, showing that our findings are in line with large scale data, in addition to [32]. The EPA driving cycle is closer to real-world data; however, studies have shown that even this driving cycle underestimates fuel consumption [49, 50]. These shortcomings have already partially been addressed by revisions of the UF curves used in the estimations of fuel consumption (Annex XIV of COMMISSION REGULATION (EU) 2023/443) [51] changes the WLTP UF curve from 2025 onwards to lower UF compared to today) and should be analyzed in more detail with more empirical data in the future (including alternative measurement procedures such as in-vehicle telematics). Such changes do not necessarily bring the gap between type-approval and real-world fuel consumption to zero but reduce it to the gap size of about 15% known for ICEs.

5. Summary and conclusions

In this study, we analyze fuel consumption and electric driving of PHEVs in Europe with two data sets. The novelty of our study is that by using two data sets with different characteristics in sample size and model variation, we reduce sampling bias to obtain robust results. In addition, the combination of both data sets resulting in almost 100,000 vehicles, over 150 models in 41 countries in Europe is the largest PHEV sample to date to be analyzed in literature. We find that PHEV fuel consumption overall on average is significantly above the EU target of 4.1 L/100 km (95gCO_2/km) set for 2020–24, and private cars tend to have lower fuel consumption and higher electric driving shares compared to company cars. Thus, the deviation between type approval and actual fuel consumption is much larger for PHEV than for internal combustion engine vehicles. We also find that an increase of 10 km in WLTP range leads on average to a decrease of 13% to 17% in fuel consumption and an increase of 1% to 4% in electric driving share. Apart from the effect of range, we also find that a kW increase in system power per 100 kg of vehicle mass leads on average to an increase of 7% to 9% in fuel consumption and a decrease of up to 2% in electric driving share. Our results highlight that PHEVs in Europe have higher carbon emissions compared to EU targets. They also show that apart from range, the system power of the vehicle also has a significant impact on fuel consumption and electric driving share. The policy implications of our study are that (1) incentives for PHEVs should be based on monitoring of real-world fuel consumption and electric driving due to the poor environmental performance of PHEVs compared to type-approval values and (2) apart from range, other factors such as system power of the vehicle should also be considered by policy makers.

Acknowledgments

AM and FS acknowledge the support of the Swedish Electromobility Centre for this research. PP acknowledges funding from the ICCT and from the Profilregion Mobilitätssysteme Karlsruhe, which is funded by the Ministry of Economic Affairs, Labour and Housing in Baden-Württemberg and as a national High Performance Center by the Fraunhofer-Gesellschaft. ICCT funding for the analysis was provided by the European Climate Foundation. We also would like to thank Georg Bieker, Steffen Link, Hermann Ringelschwendner and Peter Mock for stimulating discussions and comments.

Data availability statement

The data cannot be made publicly available upon publication due to legal restrictions preventing unrestricted public distribution. The data that support the findings of this study are available upon reasonable request from the authors.

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