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Article

Energy Consumption of Electric Vehicles in Europe

Martin Weiss ^{1,*}, Trey Winbush ², Alexandra Newman ² and Eckard Helmers ^{1,*}

¹ University of Applied Sciences Trier, Umwelt-Campus Birkenfeld, Environmental Planning and Technology Department, P.O. Box 1380, 55761 Birkenfeld, Germany

² Colorado School of Mines, Department of Mechanical Engineering, 1610 Illinois Street, Golden, CO 80401, USA; trey.winbush.3@gmail.com (T.W.); anewman@mines.edu (A.N.)

* Correspondence: weisstn@mailbox.org (M.W.); e.helmerts@umwelt-campus.de (E.H.)

Abstract: With firm commitment to energy labelling, it is not a question of if but only of when the European Union will introduce an energy label for electric cars. To support such policy efforts, we conducted a scoping analysis of energy consumption and efficiency trade-offs for 342 electric car models sold in Europe. The results suggest that certified and real-world energy consumption average 19 ± 4 kWh/100 km and 21 ± 4 kWh/100 km, translating into drive ranges of 440 ± 120 km and 380 ± 110 km, respectively. Energy consumption is correlated with vehicle mass, frontal area, and battery capacity, but less so with rated power and vehicle price. Each 100 kg of vehicle mass and 0.1 m² of frontal area tend to increase energy consumption by 0.20 ± 0.06 kWh/100 km and 0.72 ± 0.05 kWh/100 km. Raising battery capacity by 10 kWh increases vehicle mass by 145 kg, energy consumption by 0.6 kWh/100 km, and drive range by 45 km. Efficient vehicles are available at any price but drive range has a cost. Our findings point to considerable efficiency trade-offs that could be tapped by a dedicated energy label. We propose several options for categorizing vehicles on an efficiency scale from A to G, with and without additional utility parameters. Our analysis provides rationale for energy labelling of electric cars in Europe and could inspire similar analyses for other vehicle categories such as e-scooters, lightweight three- and four-wheelers, e-busses, e-trucks, and electric non-road machinery.

Keywords: electric vehicles; energy consumption; efficiency trade-offs; energy label; labelling metrics; consumer information

1. Introduction

The market for electric vehicles is booming. In 2022, annual sales of fully electric cars surpassed one million in the European Union (EEA, 2023) and 10 million worldwide (IEA, 2023). With an average annual growth of more than 50% over the past decade, electric cars are no longer niche products. They accounted for 15% of all new registrations in Europe in 2022 (ACEA, 2024) and may soon dominate the market if the European Union pursues its ambition to cut CO₂ emissions from new cars sold to zero by 2035 (EC, 2023a).

Rising sales have been accompanied by a surge in model variety. In 2016, just about 30 models were available (EEA, 2016). To date, consumers can choose between several hundred models, including small electric city cars, luxurious sedans, and sport utility vehicles (EVD, 2023). High learning rates have been reducing production costs (Weiss et al., 2019), while electric vehicles benefit from an increased power density of batteries (Xu et al., 2023), an overall advanced energy management, and the use of wide bandgap semiconductors. The latter, representing a leap innovation, boosted charging efficiency from 60% a decade ago (Helmerts and Marx, 2012) to 99.5% today (Yadlapalli et al., 2022).

Rapid innovation and growing market diversification will arguably increase the variability in the energy consumption values of vehicles. Energy labelling could address this situation. However, a dedicated energy label for electric cars does not exist yet in Europe. Instead, these vehicles are covered by a 'car label', comprising combustion, hybrid, and electric cars (EC, 1999). The label rating is based on the certified tailpipe CO₂ emissions (EC, 2007a,b). Because electric cars do not emit CO₂ at the tailpipe, they uniformly receive the highest rating (A to A+++), depending on the scheme in the

respective country). Consumers can therefore not easily identify if a car is efficient or inefficient relative to its competitors.

We aim to address this shortcoming and establish the empirical basis for a dedicated energy label for electric cars in Europe. To this end, we collect and analyze vehicle attributes for 342 electric car models available on the European market in the autumn of 2023. The data are used to: i) characterize energy consumption and other vehicle characteristics, ii) identify energy efficiency trade-offs and statistical relationships between the vehicle characteristics, and iii) deduct options for a dedicated energy labelling scheme.

The article provides policymakers with an empirical basis for implementing a dedicated energy label for electric cars in Europe and could inspire similar analyses for other electric vehicles such as e-scooters, lightweight four-wheelers, e-busses, e-trucks, and electric non-road machinery.

Our research makes a timely contribution to Europe's transition towards a decarbonized, digital, and resilient transport sector (EC, 2024), envisaging a 90% cut in greenhouse gas emissions by 2050 (EC 2020). As an interim target, the deployment of at least 30 million zero-emission vehicles is projected by 2030 (EC, 2020). So far, however, only 1.2% of the total EU car fleet (3 million vehicles) consists of battery electric or plug-in hybrid vehicles, while 0.1% of the trucks (6500 vehicles) have a zero-emission powertrain (ACEA 2024, numbers for 2022). Whereas the target of 30 million electric vehicles is a long way off, the time frame of 2030 is not. Hence, there is urgency in advancing the regulatory framework for electric vehicles. Energy efficiency is a key priority in this respect because economy-wide decarbonization and electrification will increase electricity demand (E-CUBE, 2020). The Energy Efficiency Directive (EC, 2023b) seeks to address this challenge and reduce the overall energy consumption in the European Union. In this context, it becomes increasingly important to support efficiency improvements for electric road vehicles, which are expected to consume 11% of the gross electricity supply in Germany by 2030 (Prognos, 2021), for example.

2. Methods

2.1. Data Collection

We begin by collecting vehicle data from the *Electric Vehicle Database*, which provides complete overview of all electric vehicles available in Europe (EVD, 2023). At the point of data collection in fall 2023, this database covered 342 individual vehicle models sold either in Germany, the Netherlands, or the United Kingdom. For these models, we obtained quantitative information on the following attributes: price [EUR], power [kW], vehicle mass [kg], length, width, and height [m], nominal and usable battery capacity [kWh], certified energy consumption according to the Worldwide harmonized Light vehicles Test Procedure (WLTP; EC, 2007a; UNECE, 2021) – separately for vehicle configurations with the lowest energy consumption (TEL - test energy low) and the highest energy consumption (TEH - test energy high) [kWh/100 km] during certification, minimum and maximum real-world energy consumption [kWh/100 km], minimum and maximum real-world drive range [km], as well as the drivetrain configuration (i.e., two-wheel or all-wheel drive). We benchmarked the collected data against information from BEV (2023) and the websites of vehicle manufacturers. We then supplemented the data with information on minimum, mean, and maximum real-world energy consumption [kWh/100 km] from Spritmonitor (2023), which reflects operating conditions in Germany. The data collection took place in the period between May and August 2023.

Our data set includes fully-electric passenger cars and light-commercial vehicles, classified as M1 and N1 vehicles, respectively (EC, 2007b). These vehicles are powered by an electric motor that draws electricity exclusively from an externally rechargeable battery. We excluded: i) fuel-cell vehicles running on hydrogen as well as ii) hybrid and plug-in hybrid vehicles equipped with an internal combustion engine. We included data for certified as well as real-world energy consumption as both parameters can deviate from each other depending on operating conditions. Certified energy consumption is understood here as the consumption value declared by manufacturers or certification bodies according to the standardized regulatory test procedure (EC, 2017). Real-world energy consumption refers to the energy consumption observed by vehicle users on the road.

Given the number of models included, we consider our data set (see Table S1 in the Supplementary Material) to be representative of electric car models sold in Europe in the period from autumn 2023 to summer 2024.

2.2. Data Analysis

First, we checked and corrected the data for typos, outliers, and implausible values. Second, we calculated for all vehicles:

- frontal area [m²] by multiplying vehicle width and height [m] and applying a generic correction factor of 85% (Bowling, 2010) to account for areas not covered by the vehicle;
- average real-world energy consumption [kWh/100 km] and drive range [km] as the arithmetic mean of the minimum and maximum values obtained from EVD (2023);
- average real-world drive range [km] based on the energy consumption data obtained from Spritmonitor (2023), by assuming direct proportionality between certified and real-world energy consumption and the corresponding drive range.

We characterized the data set by calculating mean, standard deviation, median, minimum, and maximum values of vehicle attributes (Table 1). Based on this analysis, we express values in the text as mean \pm standard deviation, unless stated otherwise. Commas in between numbers separate order of magnitude in triples.

We then conducted two linear regression analyses. We started out with a simple univariate regression to model energy consumption E_i of vehicle model i as a function of a single vehicle attribute:

$$E_i = \alpha_1 + \beta_1 A_i + \varepsilon_i \quad \text{Model 1}$$

where α_1 stands for the regression constant, β_1 represents the regression coefficient, A_i denotes the attribute under consideration, and ε_i the unexplained regression residual. This model was applied separately to certified and real-world energy consumption and considered the following attributes: vehicle mass [kg], power [kW], frontal area [m²], drivetrain configuration (two-wheel *versus* all-wheel drive), price [EUR], as well as two battery-related attributes, namely nominal battery capacity [kWh] and drive range [km].

Next, we applied multiple linear regression to model energy consumption as a function of several vehicle attributes, considering those that are statistically independent of each other (i.e., a Pearson correlation coefficient $r < 0.7$; see Figure A1 in the Appendix) as:

$$E_i = \alpha_2 + \beta_2 M_i + \beta_3 P_i + \beta_4 F_i + \beta_5 D_i + \varepsilon_i \quad \text{Model 2}$$

where M_i represents vehicle mass [kg], P_i power [kW], F_i frontal area [m²], and D_i the drivetrain configuration (two-wheel *versus* all-wheel drive). The multiple regression model was applied separately to certified and real-world energy consumption.

Models 1 and 2 assume a linear relationship between energy consumption and vehicle attributes, which may not always hold. We therefore follow the approach of Knittel (2011) and model energy consumption also as a power-law function of vehicle attributes, which equates to a linear relationship between the logarithms of dependent and explanatory variables. The model specifications are as follows:

$$\log E_i = \alpha_3 + \beta_6 \log A_i + \varepsilon_i \quad \text{Model 3}$$

$$\log E_i = \alpha_4 + \beta_7 \log M_i + \beta_8 \log P_i + \beta_9 \log F_i + \beta_{10} \log D_i + \varepsilon_i \quad \text{Model 4}$$

where \log depicts the logarithm base 10. A preliminary screening of residual plots reveals heteroscedasticity, which tends to bias the regression errors. Therefore, we follow the approach of Tietge et al. (2017) and estimate heteroscedasticity-robust standard errors for all regression coefficients with the '*estimatr*' package (Blair et al., 2018).

We also applied univariate regression analysis to explore associations between i) real-world *versus* certified energy consumption, ii) usable *versus* nominal battery capacity, iii) vehicle mass *versus* nominal battery capacity, iv) frontal area and power *versus* vehicle mass, v) certified drive range

versus nominal battery capacity, vi) real-world drive range versus usable battery capacity, v) price versus usable battery capacity and vi) price versus real-world drive range.

We consider results to be significant at a 5% level, unless stated otherwise. All analyses are conducted with R (R Core Team, 2022).

In a final step, we use our findings to propose metrics for the classification of vehicles on a future energy label. This involves subjective value judgements and intends to open a broader stakeholder discussion about energy labelling of electric cars. To classify vehicles, we consider the certified energy consumption of models, including all data for vehicle configurations with the lowest as well as highest energy consumption (WLTP TEL and TEH values). We adhere to the generally accepted A to G classification and distinguish seven efficiency classes, with and without additional utility parameters.

3. Results

3.1. Overview – Vehicle Attributes

Energy Consumption

The certified energy consumption of electric cars averages at 19 ± 4 kWh/100 km (31 ± 6 kWh/100 miles); the real-world energy consumption averages at 21 ± 4 kWh/100 km (33 ± 6 kWh/100 miles; see Table 1 and Figure 1). The corresponding drive ranges are 440 ± 120 km (272 ± 76 miles) and 380 ± 110 km (238 ± 68 miles), respectively. The difference between certified and real-world energy consumption is statistically significant based on a two-sided t-test at $\alpha=0.05$ (95% significance level). This finding suggests that the European certification test underestimates, on average, energy consumption. However, the TEH energy consumption values, which comprise the least efficient variants of a vehicle model, are in fact a good proxy for the average real-world energy consumption of electric vehicles (Table 1).

Table 1. Descriptive statistics of vehicle attributes; SD - standard deviation; Min – minimum value; Max – maximum value; comma depicts the thousand separator.

Parameter [Unit] (Sample size)	Mean	SD	Median	Min	Max
Energy consumption					
Certified ^a [kWh/100 km] (501)	19.4	3.8	18.5	13.0	30.7
Certified - TEL [kWh/100 km] (312)	18.5	3.4	17.6	13.0	28.3
Certified - TEH [kWh/100 km] (189)	20.7	3.9	19.8	144.3	30.7
Real-world ^b [kWh/100 km] (496)	20.7	3.7	19.8	13.0	38.9
Drive range, based on					
Certified energy consumption ^a [km] (501)	438	123	440	190	883
Certified energy consumption - TEL [km] (312)	449	128	455	190	883
Certified energy consumption - TEH [km] (189)	422	113	420	203	828
Real-world energy consumption ^b [km] (496)	383	109	384	147	732
Certified drive range per 1000 EUR vehicle price (549)	7.00	2.47	7.02	1.34	17.17
Real-world drive range per 1000 EUR vehicle price (493)	6.50	2.06	6.69	1.25	11.00
Nominal battery capacity [kWh] (342)	76	22	77	23	128
Usable battery capacity [kWh] (342)	71	21	71	21	123
Mass [kg] (342)	2,102	351	2,128	1,012	2,975
Power [kW] (342)	230	139	190	33	828
Frontal area [m ²] (342)	2.59	0.28	2.55	2.09	3.25
Length [m] (342)	4.71	0.39	4.75	3.60	5.45
Width [m] (342)	1.89	0.07	1.90	1.62	2.08

Height [m] (342)	1.62	0.14	1.61	1.35	1.94
Price ^c [EUR] (339)	70,135	40,215	58,844	22,150	387,645

^aincluding the two data sets on certified energy consumption TEL and TEH. ^bincluding the mid-point real-world energy consumption data obtained from EVD (2023), and the mean energy consumption data obtained from Spritmonitor (2023). ^cconsidering the average price in Germany and the Netherlands.

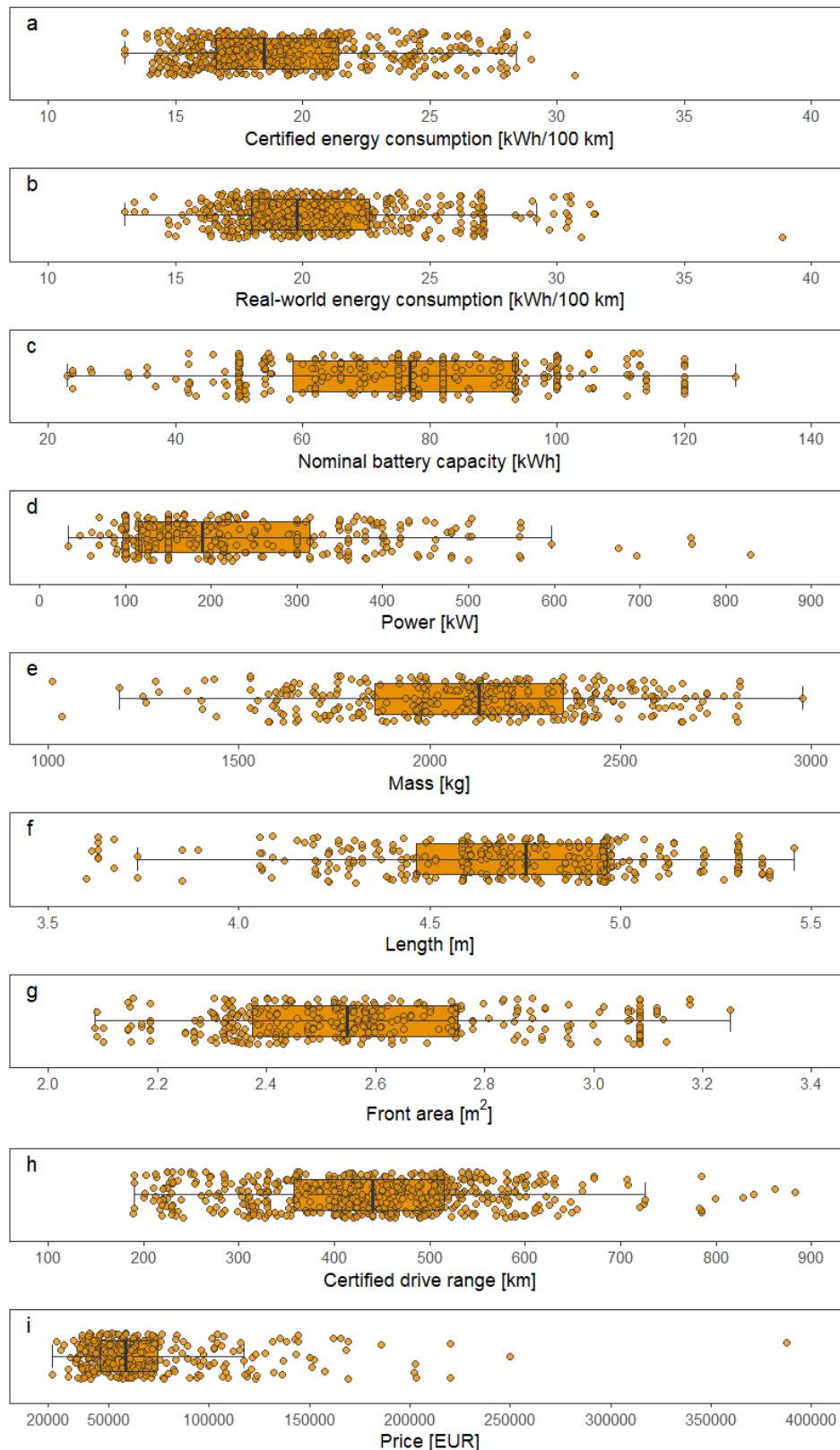


Figure 1. Box plots of vehicle attributes; dots represent individual vehicle models, vertical lines depict the median, upper and lower quartiles, and 1.5 times the interquartile range of the data; the y-axis is used to disperse the data and is unitless.

Brands differ in their average certified energy consumption and the drive range for a given price (Figure 2). Yet, drawing a conclusion about powertrain efficiency from Figure 2 is not straightforward as manufacturers vary in the types of vehicles produced and the market segment covered.

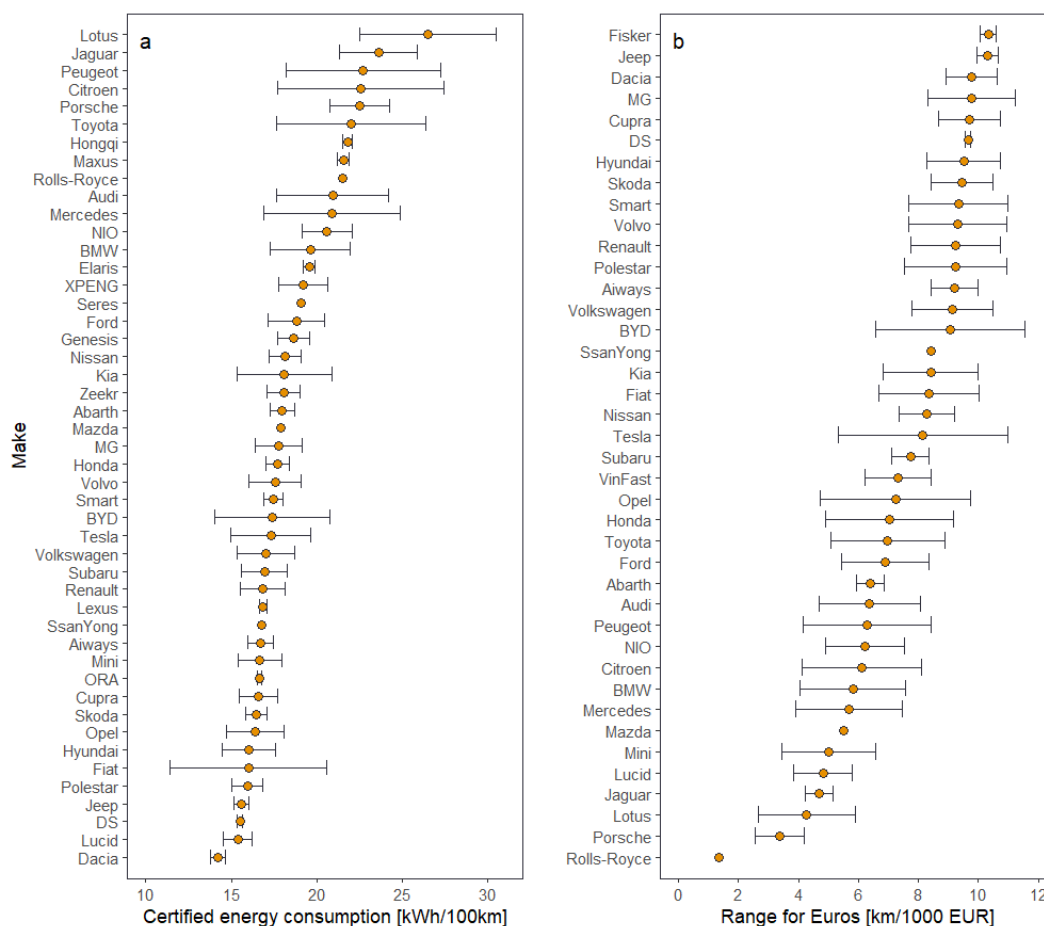


Figure 2. Mean and standard deviation of certified energy consumption (a) and drive range per Euro vehicle price (b) by vehicle manufacturer.

Other Vehicle Attributes

Electric cars sold in Europe in 2023 cost $70,000 \pm 40,000$ EUR. They have a mass of 2100 ± 350 kg and a rated motor power of 230 ± 140 kW. They are on average 4.70 ± 0.40 m long, 1.89 ± 0.07 m wide, and 1.62 ± 0.14 m high, and feature a frontal area of 2.59 ± 0.28 m². Their nominal battery capacity of 76 ± 22 kWh exceeds usable battery capacity of 71 ± 21 kWh by some 5 kWh or 7% (Table 1). Many models are available in two-wheel and four-wheel drive mode (see Table S1 in the Supplementary Material) but there was not a single model available for less than 20,000 EUR at the point of data collection. These findings show that attributes span a wide range (Figure 1), which we expect to increase, if the market for electric vehicles continues to grow (IEA, 2023).

3.2. Regression Analyses – Efficiency Trade-Offs

The univariate regression models suggest that the energy consumption of electric cars depends strongly on frontal area as well as on vehicle mass and thus battery capacity, but less so on rated motor power and drivetrain configuration (two-wheel versus four-wheel drive; Figure A1 in the Appendix). Together, frontal area, mass, power, and number of driven axles can explain 55% and

60% of certified and real-world energy consumption. The multiple linear regression analysis reveals the following (see Figure 3 and Table A1):

- Each 100 kg of *vehicle mass* increases certified and real-world energy consumption by 0.20 ± 0.06 kWh/100 km and 0.17 ± 0.05 kWh/100 km, respectively (Figure 3a; Model 2); each doubling of mass increases certified and real-world energy consumption by around $24 \pm 6\%$ (Model 4).
- Each 1 m² of *frontal area* increases certified and real-world energy consumption by 8.5 ± 0.6 kWh/100 km and 9.1 ± 0.5 kWh/100, respectively (Figure 3b; Model 2); each doubling in frontal area doubles the certified and real-world energy consumption (Model 4).
- Each 100 kW of *rated power* increases certified energy consumption by only 0.42 ± 0.18 kWh/100 km, whereas the effect on real-world energy consumption is insignificant (Figure 3c; Model 2); likewise, log-transformation suggests rated power does not affect significantly certified and real-world energy consumption (Model 4).
- *Four-wheel drive* does not significantly increase certified energy consumption but it tends to increase real-world energy consumption by 1.0 ± 0.3 kWh/100 km compared to two-wheel drivetrains (Model 2).
- *Cheaper vehicles* are more efficient (Figure 3f); vehicle prices cover a wide range and are weakly correlated with energy consumption; each 10,000 EUR in price increases certified and real-world energy consumption by some 0.3 ± 0.1 kWh/100 km (Model 1g); a doubling of vehicle price increases energy consumption by some 0.2 kWh/100 km (Model 3g).

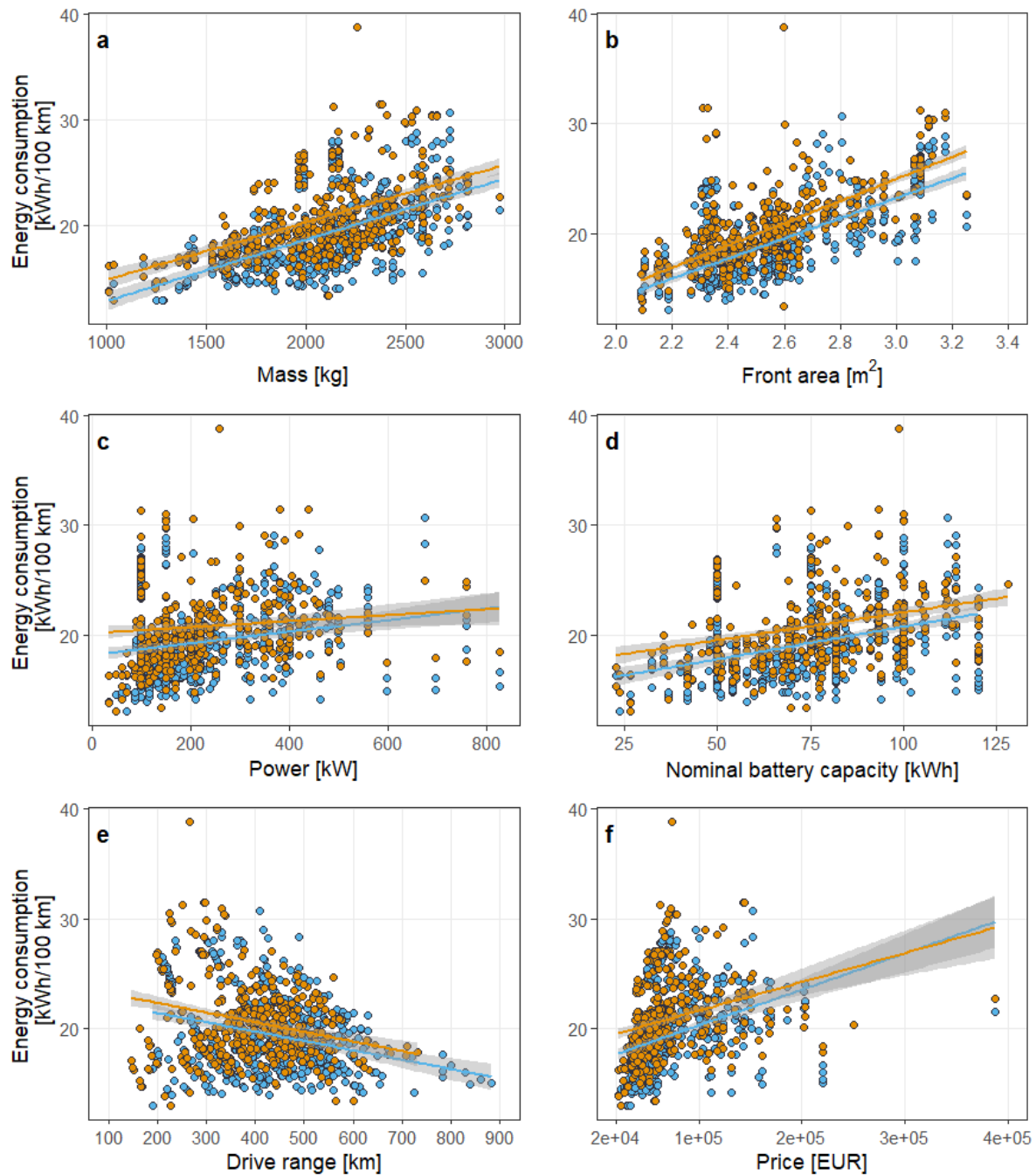


Figure 3. Certified energy consumption (light blue) and real-world energy consumption (yellow) as a function of vehicle mass, frontal area, power, nominal battery capacity, and drive range; shaded areas represent the 95%-confidence interval of the regression line.

The weak correlation of energy consumption and rated power contrasts with the findings for combustion engine vehicles, where both variables are strongly correlated (Weiss et al., 2020b). This difference can be explained, among others, by the recuperation of kinetic energy when braking and the absence of idling losses in electric cars.

But what about battery characteristics? The univariate regression analyses suggest that:

- Each additional 10 kWh of *nominal battery capacity* increases certified and real-world energy consumption by 0.59 ± 0.07 kWh/100 km and 0.51 ± 0.07 kWh/100 km, respectively (Model 1e); each doubling of battery capacity increases certified and real-world energy consumption by around 20% (Model 3e; Table A2).
- Each additional 100 km *drive range* tends to decrease certified and real-world energy consumption by 0.85 ± 0.13 kWh/100km and 0.88 ± 0.16 kWh/100 km, respectively (Model 1f);

each doubling of drive range decreases certified and real-world energy consumption by roughly 15% (Model 3f; Table A2).

It is counterintuitive that drive range and energy consumption (Figure A1) show a negative correlation, because drive range can be boosted by larger batteries that increase vehicle mass, and hence energy consumption. However, there is a second mechanism, namely extending drive range by increasing the energy density of batteries and improving the overall drivetrain efficiency. Our data suggest that this second mechanism is statistically prevalent in the electric cars available to date (Figure 3e).

3.3. Complementary Regression Analyses

Complementary regression analyses reveal the following (Figure 5 and Table A2):

- *Real-world energy consumption* is significantly higher than certified energy consumption (Figure 4a); the discrepancy appears to decrease with higher consumption levels; each 1 kWh/100 km increase in certified energy consumption raises real-world energy consumption by only 0.88 ± 0.03 kWh/100 km (Model 1g).
- *Usable battery capacity* is on average 5 kWh below nominal battery capacity (Figure 4b); the discrepancy appears to increase for larger batteries; each 10 kWh increase in nominal battery capacity raises useable battery capacity by 9.3 ± 0.6 kWh (Model 1h).
- Each 10 kWh of *nominal battery capacity* increases vehicle mass by 143 ± 4 kg (Figure 4c); statistically, vehicles would weigh 1015 ± 34 kg without battery (Model 1i), suggesting that the electric battery accounts for roughly half (i.e., 1100 ± 400 kg) of the average mass of electric vehicles (2102 ± 351 kg; Table 1).
- With each 100 kg of *vehicle mass*, the frontal area of vehicles increases by 395 ± 36 cm² (Model 1i) and power by 26 ± 2 kW (Figure 4d; Model 1k).
- Each 10 kWh in *nominal battery capacity* adds some 45 ± 2 km drive range during both certification and real-world driving (Figures 4e,f; Models 1k and 1l); each 10 kWh costs $12,000 \pm 600$ EUR (Figures 4e and 4f; Models 1m and 1n); a doubling in both nominal and usable battery capacity tends to increase certified and real-world drive range by nearly 80% (Models 3l and 3m).
- Vehicles with a larger battery and a longer drive range are more expensive; each 10 kWh nominal battery capacity raise vehicle price by $1,200 \pm 60$ EUR (Model 1n); each 10 km drive range add $1,500 \pm 30$ EUR to the vehicle price.

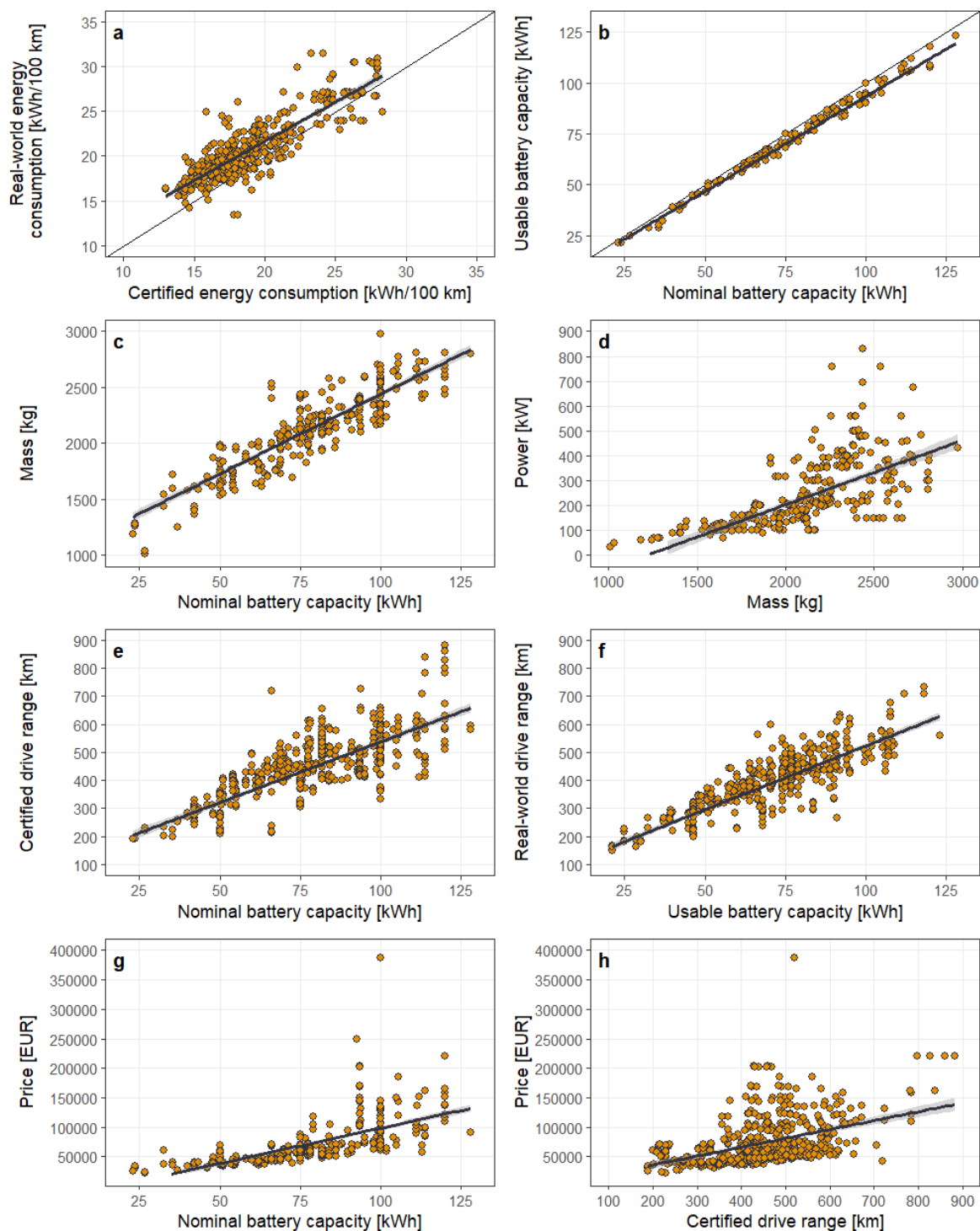


Figure 4. Complementary regression analyses; thin black lines in Figures 4a/b depict a slope of one and a y-axis intercept of zero; shaded areas represent the 95%-confidence interval of the regression line.

The results suggest there are ample benefits of increasing the energy density of batteries, which would allow for the decrease of vehicle mass and energy consumption, thereby increasing drive range.

3.3. Energy Labelling of Electric Cars

Our data allows for the classification of vehicles according to their energy consumption. However, any such classification is subjective and depends on the intended purpose. To be meaningful, classification criteria should be:

- *Relevant* - distinguish energy efficient from less energy efficient vehicles, thereby driving innovation and supporting efficiency improvements.
- *Accurate* - reflect, as correctly as possible, the energy consumption experienced by consumers on the road during normal operating conditions.
- *Accessible* - communicate information in a clear, visible, and easily understandable manner.
- *Long-lasting* - remain relevant in time, by being as technologically neutral and accommodating of innovation as possible.

This way, classification criteria could consider first and foremost the certified energy consumption [kWh/100 km] of electric cars. Although there is systematic deviation between real-world and certified consumption data (Figure 3a), certified energy consumption is established through a standardized type-approval test and information is readily available for all vehicles on the European market. Table A3 shows the energy consumption values across seven classes from A to G. We present values for four scenarios in which classes are equally spaced over the data range (Figure 5a) and for which class A comprises the 10%, 5%, and 1% most efficient models with classes B to G being equally spaced over the remaining data range (Figures 5b-d). If such a classification scheme was adopted, most vehicles would fall in classes B and C.

Classifying vehicles according to their energy consumption avoids perverse incentives for, e.g., rebound effects and market distortions. It leaves manufacturers any degree of freedom to improve efficiency and would penalize large and heavy vehicles that pose more of a sustainability challenge in urban areas. However, efficiency improvements may be achieved through diminishing vehicle utility, for example, by decreasing cabin space or battery capacity. It could therefore be desirable to include additional utility parameters for the classification of vehicles. Germany and Spain follow such an approach by considering the mass and footprint of vehicles (Haq and Weiss, 2016). If utility parameters are considered, they should be quantifiable and reflect consumer utility in a meaningful manner. The higher the correlation of a utility parameter with energy consumption, the higher the risk of perverse market incentives.

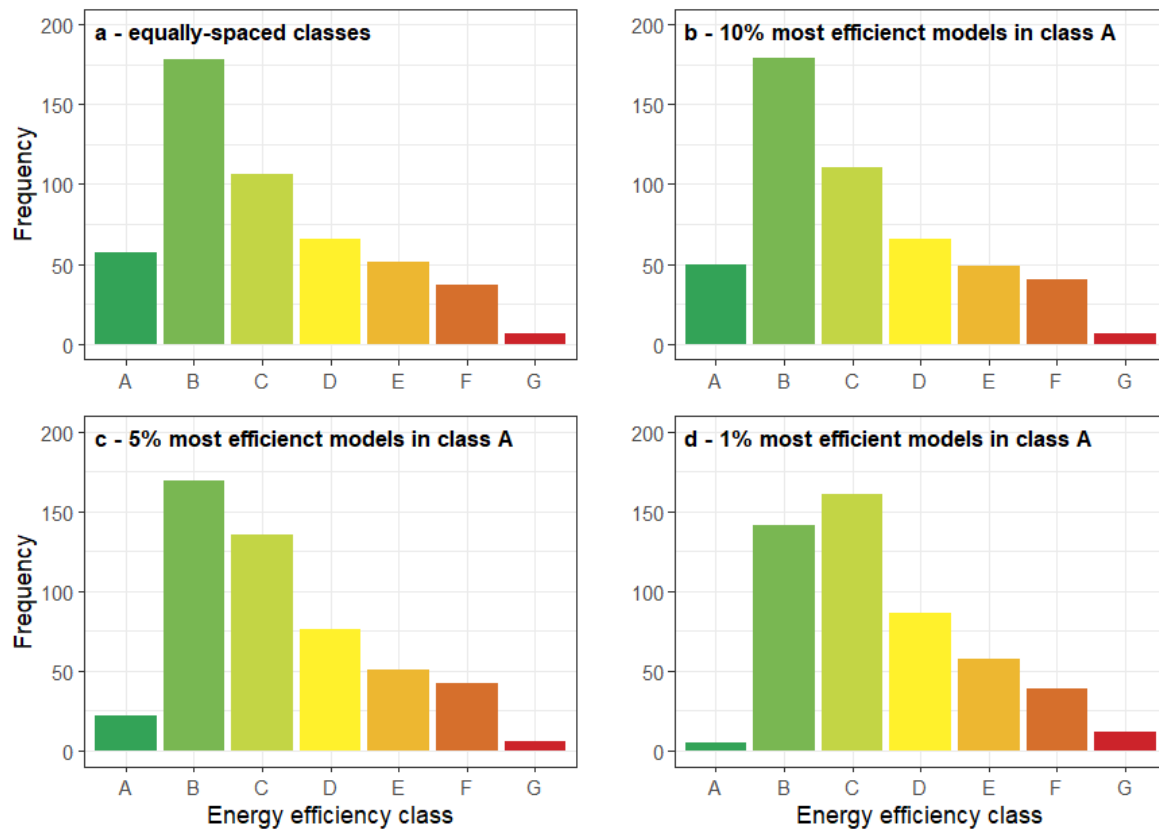


Figure 5. Distribution of vehicle models across efficiency classes A to G, based on all certified TEL and TEH energy consumption values; panel a) displays classes of equal size; panels b), c), and d) display class A representing the 10%, 5%, and 1% most efficient models, respectively while classes B to G comprising the remaining data points divided into equally sized intervals.

Suitable utility factors could include battery capacity or drive range. Opting for drive range would address range anxiety, which is a major market barrier for electric cars (She et al., 2017; Pamidimukkala et al., 2024). The label would then consider two dimensions, make the trade-offs between energy consumption and drive range transparent to consumers in relation to a given vehicle price. In fact, efficient vehicles are available at any price, but drive range has a cost – with the noteworthy exception of a few mid-priced cars that lie below the horizontal 15 kWh/100km line in Figure 6.

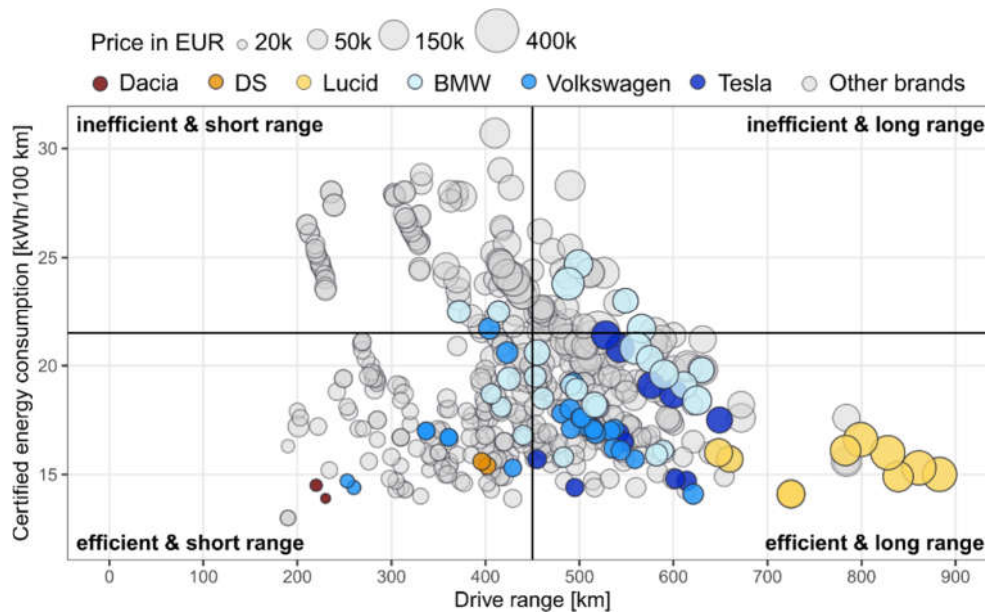


Figure 6. Scatterplot of certified energy consumption and drive range, highlighting the three most popular brands (Tesla, Volkswagen, and BMW) and the three brands with the lowest average energy consumption (Dacia, DS, and Lucid); dot size is proportional to vehicle price.

If so, the inclusion of such a utility parameter could reveal important information to consumers and provide incentive for manufacturers to increase drive range through efficiency improvements. The lower part of Table A3 provides numerical examples for a classification scheme with battery capacity and drive range as additional utility parameters.

4. Discussion

4.1. Strengths and Limitations of the Research

Based on EVD (2023), we have compiled a comprehensive dataset of attributes for 342 fully electric vehicles sold in the Netherlands, Germany, and the United Kingdom (Table S1 in the Supplementary Material). We consider the dataset to be representative for mass-produced electric cars available in Europe in 2023 and 2024. The identified trade-offs reflect the current state of technology and may hold for electric cars elsewhere in the world, given the global technology transfer across multinational manufacturers.

Our findings provide scientists with vehicle data for energy, transport, and economic modelling, and they offer policymakers an empirical basis from which to develop a dedicated energy label for electric cars. Additionally, our results could also inspire similar analyses for other categories of electric vehicles such as e-bikes, e-scooters, light electric three- and three-wheelers, as well as heavy-duty vehicles and non-road machinery.

Nevertheless, there are noteworthy limitations:

- *Timeliness:* The analysis reflects the characteristics of electric cars available in Europe in 2023 and early 2024. While our results may roughly hold for the short-term future and other markets, they will become less accurate over time. Incremental innovation, technological breakthroughs, and pricing policy in a growing market will affect vehicle attributes and their trade-offs.
- *Vehicle sales:* We capture vehicle models available to consumers but not actual vehicle sales. Therefore, our findings characterize the electric car market but not the fleet of electric cars operated on the road. Caution should be applied when using the energy consumption data for fleet-wide energy and emissions modelling.
- *Vehicle models:* The boundary of what constitutes a vehicle model rather than a variant of a model is not straightforward. We consider vehicles to be individual models if they differ by name or battery capacity. This way, similar vehicles such as Citroen e-SpaceTraveller, Fiat E-Ulysses, Peugeot e-Traveller, Opel Zafira, and Toyota Proace are included as individual models in our

analysis. This approach causes an overrepresentation of vehicles that are technologically identical but sold under several brands. However, we consider it practical and justifiable given the challenges associated with implementing alternative system boundaries.

- *Energy consumption:* Real-world energy consumption reflects actual operating conditions that drivers experience on the road. However, these conditions can vary greatly depending on, e.g., ambient temperature, driver behavior, or road profile. There can be considerable variability in the real-world energy consumption of electric cars. Furthermore, data samples of real-world consumption values in Spritmonitor (2023) are still small for most models. Overall, we consider the real-world energy consumption values to be indicative of normal operating conditions, although they may not capture any specific conditions such as very low winter temperatures.
- *System boundary:* We focus here on the energy consumption during the use phase of electric vehicles. Evaluating the overall energetic and environmental impacts of such vehicles requires holistic life cycle assessment and includes vehicle production and end-of-life treatment (Helmers et al., 2020).
- *Methods:* Regression analysis requires that the data meet certain criteria, such as normality, homogeneity and independence (Zuur et al., 2011). Regression residuals should be uncorrelated with the independent variable. The diagnostic plots in Figures S1-S41 in the Supplementary Material suggest that this requirement may not always be met and that residuals can be heteroscedastic. We address the observed heteroscedasticity, as far as feasible, by estimating heteroscedasticity-robust standard errors for all regression coefficients (Blair, 2018).

4.2. Comparison of Results

The average certified and real-world energy consumption values (19 ± 4 kWh/100 km and 21 ± 4 kWh/100 km) are consistent with the literature. For example, consumption values of 19 kWh/100 km were reported by Madziel and Campisi (2023) based on a sample of 123 vehicles, whereas an average energy consumption of 22.5 kWh/100 km for electric cars certified and sold in the USA were found by Galvin (2022). Weiss et al. (2020a) reported certified and real-world energy consumption values of 16 ± 4 kWh/100 km and 18 ± 5 kWh/100 km, albeit for a sample of 218 vehicles produced between 1989 and 2019. The deviation between the values reported in the literature and those documented here is likely caused by an overall trend towards heavier and larger vehicles. In fact, the most efficient electric cars under real-world conditions are mostly smaller vehicles that were available already a decade ago (Spritmonitor, 2024). Considering all new car registrations in the European Union in 2022, EEA (2023) reports an average certified energy consumption of 16.6 kWh/100 km. This value is lower than the averages identified here, suggesting that considering available vehicle models rather than actual vehicle sales overrepresents large and relatively inefficient vehicles.

The identified efficiency trade-offs between vehicle attributes are broadly consistent with previous studies. The observed increase in energy consumption of 0.2 kWh/100 km with each 100 kg of vehicle mass is considerably lower than previously reported. Redelbach et al. (2012) give an increase of 0.4 kWh/100 km and Weiss et al. (2020a) of 0.6 kWh/100 km with each 100 kg of vehicle mass.

4.3. Implications for Policymakers

Deviation between Certified and Real-World Energy Consumption

Real-world energy consumption is significantly higher than certified energy consumption (Figure 4a), suggesting type-approval tends to underestimate the actual energy consumption of electric vehicles on the road. This observation demands attention from policymakers. If verified by other research, type-approval test procedures may need to be adapted to ensure that consumers receive accurate information about the energy consumption of electric vehicles.

Energy Labelling

The range of energy consumption values (Figure 1) suggests consumers would benefit from the implementation of an energy label for electric cars. In fact, labeling may become imperative once electric cars dominate the market, following the phase-out of combustion cars in Europe by 2035 (EC, 2023a). By that time, car owners' electricity costs will likely exceed those of any other labeled product. Although the European Commission has currently no plans to implement an energy label for electric vehicles (EC, 2022), it should review the car labeling directive by 31 December 2024 (EC, 2019). Our analysis offers a timely contribution to this review.

Regarding *labelling metrics*, distance-specific energy consumption [kWh/100 km; km/kWh] is an obvious choice. Standardized data are readily available from type approval; they are easily understandable and appropriate for characterizing the energy efficiency of vehicles. If policymakers prefer to include a utility factor, drive range could be a suitable choice as longer drive ranges present an obvious value added to consumers.

Regarding *scaling*, the energy labels for other products commonly follow a linear scaling (see Wiki, 2024). Such scaling is intuitive and could also be applied to electric vehicles. Non-linear scaling based on percentiles or ranks of values could be considered but may need to be carefully explained to consumers. Behavioral aspects are relevant in this context. Labelling too few or too many models as class A suggests efficient vehicles are unattainable or common. Both discourages efficiency improvements.

Regarding *complementary information*, the energy label may inform consumers about the drive range of vehicles and their electricity costs per year and/or distance driven. This way, the label would address important consumer concerns and it would prevent information asymmetry regarding the actual cost of vehicle ownership.

By addressing these points, policymakers can ensure that the energy label informs consumers adequately and creates a level playing field for vehicle manufacturers.

Efficiency Improvements

The wide range of energy consumption values (Figure 1 a-b) suggests that there is ample potential for efficiency improvements. In fact, electric cars have become less, not more, efficient in recent years mainly due their increasing size and mass. If we compare our findings with data for electric vehicles built between 1988 and 2019 (Weiss et al. 2020), it appears that electric cars have become 24% heavier (from 1690 ± 470 kg to 2100 ± 350 kg) and 35% more powerful (from 150 ± 127 kW to 230 ± 139 kW). Nominal battery capacity has increased 65% (from 46 ± 26 kWh to 76 ± 22 kWh) whereas certified energy consumption has increased 21% (from 16.0 ± 3.7 kWh/100 km to 19.4 ± 3.8 kWh/100 km). These findings are worrying because technical efficiency improvements (Yadlapalli et al., 2022; Xu et al., 2023) appear to trigger rebound effects, similar to those observed in past decades for conventional cars (Knittel, 2011; Weiss et al., 2020b).

Next to existing technical efficiency potentials (Zhao et al., 2019; Yadlapalli et al., 2022; Xu et al., 2023), these findings underscore the potential of downsizing and mode shift towards smaller electric cars and lightweight vehicles such as e-bikes, electric kick-scooters, or light electric three- or four-wheelers (see also Weiss et al., 2020a). As the electric vehicle fleet grows, rising electricity demand will increasingly challenge green electricity production and network transmission capacity (Lauvergne et al., 2022; Garcia et al., 2024). Reducing the size of vehicles decreases electricity consumption and can help manage peak electricity demand in combination with smart charging (Anastasiadis et al., 2019). Downsizing also reduces resource consumption of rare earth metals (Gielen and Lyons, 2022), for example, thereby contributing to more resilient and sustainable transportation.

5. Conclusions

This paper presents a comprehensive analysis of energy consumption and related trade-offs for electric cars sold in Europe. We draw the following conclusions:

- A large variety of electric cars is available to consumers; models sold in Europe have an average certified and real-world energy consumption of 19 ± 4 kWh/100 km and 21 ± 4 kWh/100 km, respectively.
- There are considerable efficiency trade-offs; energy consumption is positively correlated with frontal area, vehicle mass, and battery capacity, but less so with rated power; energy consumption is negatively correlated with drive range.
- Real-world energy consumption tends to be higher than certified energy consumption; however, our data suggest that the certified energy consumption of the least efficient model variants (TEH – test energy high) may provide a good proxy for real-world energy consumption.
- The electric battery accounts for roughly half (i.e., 1100 ± 400 kg) of the vehicle mass; nominal battery capacity is on average 5 kWh higher than usable battery capacity; each 10 kWh of nominal battery capacity adds some 143 kg to vehicle mass and 45 km drive range.
- Efficient vehicles are available at any price but drive range has a cost; models with low energy consumption are available across the entire price range; however, models with a long drive range tend to be more expensive than those with a shorter drive range; this points to an important range-price trade off consumers have to make when purchasing electric vehicles.
- Increasing model variability suggests that consumers need to be informed adequately about energy consumption, energy-related costs, and trade-offs they face when purchasing an electric car. We provide empirical examples of how to categorize the energy efficiency of electric cars on a labelling scale from A to G, with and without additional utility parameters such as battery capacity or drive range.

With firm commitment to energy labelling (Wiki, 2024) and continued market growth, it is only a matter of time until electric vehicles receive a dedicated energy label in Europe. Our findings support policy efforts in that direction and could inspire similar analyses for other electric vehicles such as e-bikes, e-scooters, and light electric three- and four-wheelers, e-busses, e-trucks, and electric non-road machinery.

Supplementary Materials: The following supporting information can be downloaded at: www.mdpi.com/xxx/s1, Figure S1: title; Table S1: title; Video S1: title.

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List of abbreviations and units

kg	-	kilogram
km	-	kilometer
kW	-	kilowatt
kWh	-	kilowatt-hour
m	-	meter
MAX-		maximum value
MIN-		minimum value
SD	-	standard deviation
TEH	-	'test energy high'; energy consumption value for the vehicle configuration with the highest energy consumption during type approval

TEL - 'test energy low'; energy consumption value for the vehicle configuration with the lowest energy consumption during type approval

Appendix A

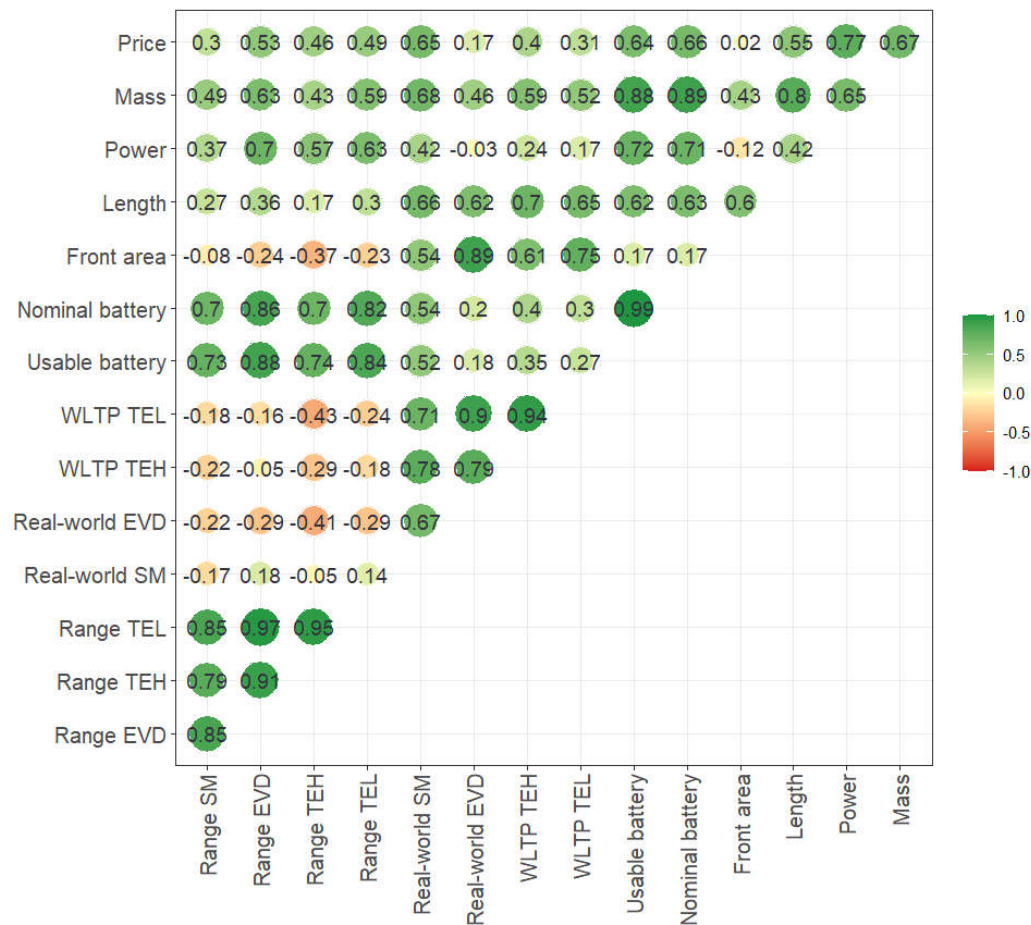


Figure A1. Correlation plot of vehicle attributes; color gradient, dot size, and numbers indicate the Pearson correlation coefficient; trailing zeros in the second decimal place are omitted; Range SM – drive range based on the average real-world energy consumption as given by Spritmonitor (2023); Range EVD – drive range based on average real-world energy consumption as given by EVD (2023); Range TEH – drive range based on certified TEH energy consumption values; Range TEL – drive range based on certified TEL energy consumption values; Real-world SM – real-world energy consumption as given by Spritmonitor (2023); Real-world EVD – real-world energy consumption as given by EVD (2023); WLTP TEH – certified TEH energy consumption; WLTP TEL – certified TEL energy consumption; Usable battery – usable battery capacity; Nominal battery – nominal battery capacity.

Table A1. Summary statistics of regression analysis of certified and real-world energy consumption as a function of vehicle attributes; coefficients are significance at 1% level (***), 5% level (**), and 10% level (*).

Energy consumption	Coefficient	Value	Standard error	<i>t</i> value	Pr (>abs <i>t</i>)	<i>p</i> value	Adjusted <i>R</i> ²
<i>Model 1a: energy consumption = $\alpha + \beta^{\text{mass}}$</i>							
Certified	(Intercept)***	7.11	0.65	10.98	2.97×10^{-25}	$<2.2 \times 10^{-16}$	0.30
	Mass***	5.80×10^{-3}	3.21×10^{-4}	18.07	1.56×10^{-56}		
Real-world	(Intercept)***	9.47	0.61	15.42	4.40×10^{-44}	$<2.2 \times 10^{-16}$	0.26
	Mass***	5.44×10^{-3}	3.19×10^{-4}	17.03	1.63×10^{-51}		
<i>Model 1b: energy consumption = $\alpha + \beta^{\text{power}}$</i>							
Certified	(Intercept)***	18.11	0.37	48.73	7.69×10^{-192}	6.41×10^{-5}	0.04
	Power***	5.33×10^{-3}	1.32×10^{-4}	4.03	6.41×10^{-5}		
Real-world	(Intercept)***	20.13	0.34	59.24	1.35×10^{-226}	0.02	<0.01
	Power**	2.70×10^{-3}	1.19×10^{-3}	2.27	2.36×10^{-2}		
<i>Model 1c: energy consumption = $\alpha + \beta^{\text{frontal area}}$</i>							
Certified	(Intercept)***	-4.24	1.23	-3.46	5.87×10^{-4}	$<2.2 \times 10^{-16}$	0.45
	Frontal area***	9.15	0.47	19.36	1.05×10^{-62}		
Real-world	(Intercept)***	-5.30	0.99	-5.35	1.38×10^{-7}	$<2.2 \times 10^{-16}$	0.56
	Frontal area***	10.08	0.38	26.62	1.65×10^{-97}		
<i>Model 1d: energy consumption = $\alpha + \beta^{\text{driven axles}}$</i>							
Certified	(Intercept)***	18.75	2.38×10^{-1}	78.77	1.20×10^{-283}	5.90×10^{-6}	0.04
	Driven axles***	1.45	3.17×10^{-1}	4.58	5.90×10^{-6}		
Real-world	(Intercept)***	20.25	2.28×10^{-1}	88.68	1.43×10^{-305}	1.11×10^{-4}	0.02
	Driven axles***	1.23	3.15×10^{-1}	3.90	1.11×10^{-4}		
<i>Model 1e: energy consumption = $\alpha + \beta^{\text{nominal battery capacity}}$</i>							
Certified	(Intercept)***	14.78	0.57	25.84	4.65×10^{-94}	1.50×10^{-15}	0.12
	Nominal battery capacity***	5.94×10^{-2}	7.21×10^{-3}	8.243	1.50×10^{-15}		

Real-world	(Intercept)***	16.94	0.55	31.04	3.72×10^{-118}	2.07×10^{-12}	0.09
	Nominal battery capacity***	5.08×10^{-2}	7.04×10^{-3}	7.21	2.07×10^{-12}		
<i>Model 1f: energy consumption = $\alpha + \beta^*$drive range</i>							
Certified	(Intercept)***	23.13	0.68	34.01	4.93×10^{-132}	2.37×10^{-10}	0.08
	Certified drive range***	-8.54×10^{-3}	1.32×10^{-3}	-6.47	2.37×10^{-10}		
Real-world	(Intercept)***	24.07	0.72	33.26	3.72×10^{-128}	9.48×10^{-8}	0.06
	Real-world drive range***	-8.77×10^{-3}	1.62×10^{-3}	-5.42	9.49×10^{-8}		
<i>Model 1g: energy consumption = $\alpha + \beta^*$price</i>							
Certified	(Intercept)***	16.99	0.39	43.42	6.50×10^{-171}	1.41×10^{-9}	0.13
	Price***	3.29×10^{-5}	5.33×10^{-6}	6.17	1.41×10^{-9}		
Real-world	(Intercept)***	18.98	0.38	49.71	9.38×10^{-194}	4.02×10^{-6}	0.06
	Price***	2.63×10^{-5}	5.65×10^{-6}	4.66	4.02×10^{-6}		
<i>Model 2: energy consumption = $\alpha + \beta^*$mass + β^*power + β^*frontal area + β^*driven axles</i>							
Certified	(Intercept)***	-7.96	1.21	-6.59	1.10×10^{-10}	$<2.2 \times 10^{-16}$	0.55
	Mass***	2.03×10^{-3}	5.76×10^{-4}	3.53	4.60×10^{-4}		
	Power***	4.16×10^{-3}	1.83×10^{-3}	2.27	2.35×10^{-2}		
	Frontal area***	8.52	0.59	14.35	2.63×10^{-39}		
	Driven axles	1.57×10^{-1}	3.59×10^{-1}	4.37×10^{-1}	6.63×10^{-1}		
Real-world	(Intercept)***	-6.43	9.48×10^{-1}	-6.78	3.37×10^{-11}	$<2.2 \times 10^{-16}$	0.60
	Mass***	1.65×10^{-3}	5.17×10^{-4}	3.19	1.49×10^{-3}		
	Power	-1.34×10^{-3}	1.47×10^{-3}	-9.10×10^{-1}	3.64×10^{-1}		
	Frontal area***	9.16	0.50	18.48	2.74×10^{-58}		
	Driven axles***	1.02	3.40×10^{-1}	3.01	2.74×10^{-3}		
<i>Model 3a: $\log(\text{energy consumption}) = \alpha + \beta^*\log(\text{mass})$</i>							
log(Certified)	(Intercept)***	-1.61	0.23	-6.893	1.66×10^{-11}	$<2.2e \times 10^{-16}$	0.32
	log(Mass)***	5.96×10^{-1}	3.07×10^{-2}	19.41	5.80×10^{-63}		

log(Real-world)	(Intercept)***	-9.63×10^{-1}	1.99×10^{-1}	-4.83	$1.86e \times 10^{-6}$	$<2.2 \times 10^{-16}$	0.30
	log(Mass)***	$5.22e \times 10^{-1}$	2.64×10^{-2}	19.75	2.12×10^{-64}		
<i>Model 3b: $\log(\text{energy consumption}) = \alpha + \beta \log(\text{power})$</i>							
log(Certified)	(Intercept)***	2.57	8.47×10^{-2}	30.35	2.19×10^{-115}	5.76×10^{-6}	0.05
	log(Power)***	7.11×10^{-2}	1.55×10^{-2}	4.58	5.76×10^{-6}		
log(Real-world)	(Intercept)***	2.78	7.69×10^{-2}	36.17	5.84×10^{-141}	1.73×10^{-3}	0.02
	log(Power)***	4.47×10^{-2}	1.42×10^{-2}	3.15	1.73×10^{-3}		
<i>Model 3c: $\log(\text{energy consumption}) = \alpha + \beta \log(\text{frontal area})$</i>							
log(Certified)	(Intercept)***	1.83	5.72×10^{-2}	32.01	4.60×10^{-123}	$<2.2 \times 10^{-16}$	0.43
	log(Frontal area)***	1.18	5.93×10^{-2}	19.93	1.84×10^{-65}		
log(Real-world)	(Intercept)***	1.85	4.19×10^{-2}	44.21	8.20×10^{-174}	$<2.2 \times 10^{-16}$	0.57
	log(Frontal area)***	1.23	4.31×10^{-2}	28.62	6.06×10^{-107}		
<i>Model 3d: $\log(\text{energy consumption}) = \alpha + \beta \log(\text{driven axles})$</i>							
log(Certified)	(Intercept)	2.91	1.17×10^{-2}	248.07	0.00	9.35×10^{-8}	0.05
	Driven axles***	8.44×10^{-2}	1.56×10^{-2}	5.42	9.35×10^{-8}		
log(Real-world)	(Intercept)	2.99	1.06×10^{-2}	281.06	0.00	1.90×10^{-6}	0.04
	Driven axles***	6.83×10^{-2}	1.42×10^{-2}	4.82	1.90×10^{-6}		
<i>Model 3e: $\log(\text{energy consumption}) = \alpha + \beta \log(\text{nominal battery capacity})$</i>							
log(Certified)	(Intercept)***	1.98	1.00×10^{-1}	19.77	1.18×10^{-64}	$<2.2 \times 10^{-16}$	0.14
	log(Nominal battery capacity)***	2.24×10^{-1}	2.33×10^{-2}	9.63	3.04×10^{-20}		
log(Real-world)	(Intercept)***	2.23	8.61×10^{-2}	25.94	3.12×10^{-94}	$<2.2 \times 10^{-16}$	0.12
	log(Nominal battery capacity)***	1.84×10^{-1}	2.01×10^{-2}	9.17	1.23×10^{-18}		
<i>Model 3f: $\log(\text{energy consumption}) = \alpha + \beta \log(\text{drive range})$</i>							
log(Certified)	(Intercept)***	3.85	0.20	19.66	3.86×10^{-64}	3.34×10^{-6}	0.05
	log(Certified drive range)***	-1.50×10^{-1}	3.18×10^{-2}	-4.70	3.34×10^{-6}		
log(Real-world)	(Intercept)***	3.70	0.18	20.27	6.07×10^{-67}	1.50×10^{-4}	0.04

	log(Real-world drive range)***	-1.16×10^{-1}	3.02×10^{-2}	-3.83	1.46×10^{-4}		
	<i>Model 3g: $\log(\text{energy consumption}) = \alpha + \beta^* \log(\text{price})$</i>						
log(Certified)	(Intercept)***	7.93×10^{-1}	1.85×10^{-1}	4.29	2.18×10^{-5}	$<2.2 \times 10^{-16}$	0.23
	log(Price)***	1.94×10^{-1}	1.68×10^{-2}	11.55	1.69×10^{-27}		
log(Real-world)	(Intercept)***	1.22	1.94×10^{-1}	6.28	7.35×10^{-10}	$<2.2 \times 10^{-16}$	0.16
	log(Price)***	1.63×10^{-1}	1.78×10^{-2}	9.18	1.21×10^{-18}		
	<i>Model 4: $\log(\text{energy consumption}) = \alpha + \beta^* \log(\text{mass}) + \beta^* \log(\text{power}) + \beta^* \log(\text{frontal area}) + \beta^* \text{driven axles}$</i>						
log(Certified)	(Intercept)	-1.38×10^{-1}	3.70×10^{-1}	-3.74×10^{-1}	7.09×10^{-1}	$<2.2 \times 10^{-16}$	0.54
	log(Mass)***	2.43×10^{-1}	6.51×10^{-2}	3.73	2.10×10^{-4}		
	log(Power)	1.29×10^{-2}	2.37×10^{-2}	5.45×10^{-1}	5.86×10^{-1}		
	log(Frontal area)***	1.03	7.71×10^{-2}	13.41	3.28×10^{-35}		
	Driven axles**	3.99×10^{-2}	1.90×10^{-2}	2.10	3.59×10^{-2}		
log(Real-world)	(Intercept)	2.87×10^{-1}	3.26×10^{-1}	8.82×10^{-1}	3.79×10^{-1}	$<2.2 \times 10^{-16}$	0.63
	log(Mass)***	2.44×10^{-1}	6.04×10^{-2}	4.04	$\times 10^{-5}$		
	log(Power)*	-5.49×10^{-2}	1.96×10^{-2}	-2.80	5.38×10^{-3}		
	log(Frontal area)***	1.02	6.93×10^{-2}	14.75	5.21×10^{-41}		
	Driven axles***	7.19×10^{-2}	1.48×10^{-2}	4.86	1.59×10^{-6}		

Table A2. Summary statistics of regression analysis of energy consumption (real-world and certified) and vehicle mass, and power; coefficients are significance at 1% level (***), 5% level (**), and 10% level (*).

	Coefficient	Value	Standard error	<i>t</i> value	Pr (>abs <i>t</i>)	<i>p</i> value	Adjusted <i>R</i> ²
Real-world vs. Certified energy consumption	<i>Model 1g: real-world energy consumption = $\alpha + \beta^* \text{certified energy consumption}$</i>						
	(Intercept)***	4.11	4.77×10^{-1}	8.63	1.44×10^{-16}	$<2.2 \times 10^{-16}$	0.75
	Certified energy consumption***	8.77×10^{-1}	2.65×10^{-2}	33.14	8.93×10^{-118}		
Usable vs. Nominal battery capacity	<i>Model 1h: usable battery capacity = $\alpha + \beta^* \text{nominal battery capacity}$</i>						
	(Intercept)	6.41×10^{-2}	4.12×10^{-1}	1.55×10^{-1}	8.77×10^{-1}	$<2.2 \times 10^{-16}$	0.99

	Nominal battery capacity***	9.32×10^{-1}	6.18×10^{-3}	150.85	1.56×10^{-313}		
Mass vs. Nominal battery capacity	<i>Model 1i: mass = $\alpha + \beta$*nominal battery capacity</i>						
	(Intercept)***	1015	34	30	6.28×10^{-97}	$<2.2 \times 10^{-16}$	0.79
	Nominal battery capacity***	14.25	4.14×10^{-1}	34	8.42×10^{-113}		
Mass vs. Frontal area	<i>Model 1j: mass = $\alpha + \beta$*frontal area</i>						
	(Intercept)***	697	184	3.80	1.79×10^{-4}	1.44×10^{-13}	0.18
	Frontal area***	460	60	7.71	1.44×10^{-13}		
Power vs. Mass	<i>Model 1k: power = $\alpha + \beta$*mass</i>						
	(Intercept)***	-315	29	-11.05	1.90×10^{-1}	$<2.2 \times 10^{-16}$	0.43
	Mass***	2.59×10^{-1}	1.52×10^{-2}	17.10	9.77×10^{-48}		
Certified drive range vs. Nominal battery capacity	<i>Model 1l: certified drive range = $\alpha + \beta$*nominal battery capacity</i>						
	(Intercept)***	104	12	8.90	8.03×10^{-18}	$<2.2 \times 10^{-16}$	0.59
	Nominal battery capacity***	4.33	1.61×10^{-1}	26.91	1.73×10^{-102}		
Real-world drive range vs. Usable battery capacity	<i>Model 1m: real-world drive range = $\alpha + \beta$*usable battery capacity</i>						
	(Intercept)***	68	8	8.37	6.10×10^{-16}	$<2.2 \times 10^{-16}$	0.71
	Usable battery capacity***	4.56	1.23×10^{-1}	36.99	1.82×10^{-144}		
Price vs. nominal battery capacity	<i>Model 1n: price = $\alpha + \beta$*nominal battery capacity</i>						
	(Intercept)	-21,119	3,981	-5.74	1.45×10^{-8}	$<2.2 \times 10^{-16}$	0.43
	Nominal battery capacity	1196	59	20.23	1.57×10^{-71}		
Price vs. Certified drive range	<i>Model 1o: price = $\alpha + \beta$*certified drive range</i>						
	(Intercept)	6,059	4,951	1.22	2.22×10^{-1}	$<2.2 \times 10^{-16}$	0.22
	Certified drive range***	150	13	12.02	1.06×10^{-29}		
log(Real-world energy consumption) vs. log(Certified consumption)	<i>Model 3g: log(real-world energy consumption) = $\alpha + \beta$*log(certified energy consumption)</i>						
	(Intercept)***	6.96×10^{-1}	6.22×10^{-2}	11.20	1.41×10^{-25}	$<2.2 \times 10^{-16}$	0.73
	log(Certified consumption)***	7.94×10^{-1}	2.14×10^{-2}	37.03	1.47×10^{-132}		

energy consumption)							
log(Usable battery capacity) vs.	<i>Model 3h: $\log(\text{usable battery capacity}) = \alpha + \beta \cdot \log(\text{nominal battery capacity})$</i>						
log(Nominal battery capacity)	(Intercept)***	-1.16×10^{-1}	2.54×10^{-2}	-4.55	7.65×10^{-6}	$<2.2 \times 10^{-16}$	0.99
	log(Nominal battery capacity)***	1.01	5.91×10^{-3}	170.98	0.00		
log(Mass) vs.	<i>Model 3i: $\log(\text{mass}) = \alpha + \beta \cdot \log(\text{nominal battery capacity})$</i>						
log(Nominal battery capacity)	(Intercept)***	5.51	6.95×10^{-2}	79.36	1.82×10^{-221}	$<2.2 \times 10^{-16}$	0.80
	log(Nominal battery capacity)***	4.96×10^{-1}	1.58×10^{-2}	31.41	1.54×10^{-102}		
log(Mass) vs.	<i>Model 3j: $\log(\text{mass}) = \alpha + \beta \cdot \log(\text{frontal area})$</i>						
log(Frontal area)	(Intercept)***	6.76	1.12×10^{-1}	60.32	1.14×10^{-183}	2.17×10^{-16}	0.21
	log(Frontal area)***	7.90×10^{-1}	9.89×10^{-2}	7.99	2.17×10^{-14}		
log(Power) vs.	<i>Model 3k: $\log(\text{power}) = \alpha + \beta \cdot \log(\text{mass})$</i>						
log(Mass)	(Intercept)***	-13.1	6.89×10^{-1}	-18.97	3.011×10^{-55}	$<2.2 \times 10^{-16}$	0.54
	log(Power)***	2.40	9.13×10^{-2}	26.29	6.36×10^{-84}		
log(Certified drive range) vs.	<i>Model 3l: $\log(\text{certified drive range}) = \alpha + \beta \cdot \log(\text{nominal battery capacity})$</i>						
log(Nominal battery capacity)	(Intercept)***	2.76	9.92×10^{-2}	27.81	5.07×10^{-107}	$<2.2 \times 10^{-16}$	0.62
	log(Nominal battery capacity)***	7.63×10^{-1}	2.29×10^{-2}	33.34	3.09×10^{-134}		
log(Real-world drive range) vs.	<i>Model 3m: $\log(\text{real-world drive range}) = \alpha + \beta \cdot \log(\text{usable battery capacity})$</i>						
log(Usable battery capacity)	(Intercept)***	2.57	8.30×10^{-2}	30.94	1.13×10^{-117}	$<2.2 \times 10^{-16}$	0.73
	log(Usable battery capacity)***	7.97×10^{-1}	1.96×10^{-2}	40.66	9.56×10^{-160}		
log(Price) vs.	<i>Model 3n: $\log(\text{price}) = \alpha + \beta \cdot \log(\text{nominal battery capacity})$</i>						
log(Nominal battery capacity)	(Intercept)***	6.51	1.68×10^{-1}	38.80	4.10×10^{-174}	$<2.2 \times 10^{-16}$	0.59
	log(Nominal battery capacity)***	1.06	3.97×10^{-2}	26.66	1.52×10^{-107}		

log(Price)	vs.	<i>Model 3o: $\log(\text{price}) = \alpha + \beta \cdot \log(\text{certified drive range})$</i>						
log(Certified drive range)	(Intercept)***	6.57	3.14×10^{-1}	20.94	5.77×10^{-72}	$<2.2 \times 10^{-16}$	0.25	
	log(Certified drive range)***	7.45×10^{-1}	5.24×10^{-1}	14.23	2.59×10^{-39}			

Table A3. Vehicle coverage and energy consumption values for alternative labelling schemes; the data set includes 501 data points for certified energy consumption (TEH and TEL values).

Criterion	Classification	Class size	Efficiency class						
			A	B	C	D	E	F	G
Certified energy consumption [kWh/100 km]	Equal class size over the entire data range	2.53	<15.5	15.5-18.0	18.1-20.6	20.7-23.1	23.2-25.6	25.7-28.2	>28.2
	10% vehicles in A, B-G equal class size	2.55	<15.4	15.4-18.0	18.1-20.5	20.6-23.1	23.2-25.6	25.7-28.2	>28.2
	5% in A, B-G equal class size	2.67	<14.7	14.7-17.4	17.5-20.0	20.1-22.7	22.8-25.4	25.5-28.1	>28.0
	1% in A, B-G equal class size	2.78	<14.0	14.0-16.8	16.9-19.6	19.7-22.3	22.4-25.1	25.2-27.9	>27.9
Certified energy consumption per unit nominal battery capacity [10^{-4} km ⁻¹]	Equal class size over the entire data range	8.34	<20.8	20.8-29.1	29.2-37.5	37.6-45.8	45.9-54.2	54.3-62.5	>62.5
	10% vehicles in A, B-G equally spaced	8.67	<18.8	18.8-27.5	27.6-36.1	36.2-44.8	44.9-53.5	53.6-62.2	>62.2
	5% in A, B-G equally spaced	8.95	<17.2	17.2-26.2	26.2-35.1	35.2-44.1	44.2-53.0	53.1-62.0	>62.0
	1% in A, B-G equally spaced	9.59	<13.3	13.3-22.9	23.0-32.5	32.6-42.1	42.2-51.7	51.8-61.3	>61.3
Certified energy consumption	Equal class size over the entire data range	1.56	<3.26	3.27-4.82	4.83-6.38	6.39-7.94	7.95-9.50	9.51-11.06	>11.06

10% vehicles in A, B-G equally spaced	1.61	<2.96	2.97-4.57	4.58-6.18	6.19-7.79	7.80-9.40	9.41-11.01	>11.01
5% in A, B-G equally spaced	1.67	<2.62	2.63-4.29	4.30-5.96	5.97-7.63	7.64-9.29	9.30-10.97	>10.97
1% in A, B-G equally spaced	1.78	<1.94	1.94-3.72	3.73-5.50	5.51-7.28	7.29-9.06	9.07-10.84	>10.84

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