

## Article

# Energy Consumption of Electric Vehicles in Europe

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**Abstract:** As the European Union advances its regulatory framework on energy efficiency, the introduction of an energy label for electric cars appears increasingly relevant. Anticipating this policy development, we present a scoping analysis of energy consumption and efficiency trade-offs across 342 fully electric cars available in Europe. Our results suggest that certified and real-world energy consumption average  $19 \pm 4$  kWh/100 km and  $21 \pm 4$  kWh/100 km, translating into drive ranges of  $440 \pm 120$  km and  $380 \pm 110$  km, respectively. Energy consumption is correlated with mass, frontal area, and battery capacity but less so with rated power and vehicle price. Each 100 kg of vehicle mass and  $0.1 \text{ m}^2$  of frontal area increases energy consumption by  $0.2 \pm 0.1$  kWh/100 km and  $0.9 \pm 0.1$  kWh/100 km, respectively. Raising battery capacity by 10 kWh elevates vehicle mass by  $143 \pm 4$  kg, energy consumption by  $0.6 \pm 0.1$  kWh/100 km, drive range by  $44 \pm 2$  km, and vehicle price by  $12,000 \pm 600$  EUR. Efficient cars are available at any price, but long drive ranges have a cost. These findings point to considerable efficiency trade-offs that could be revealed to consumers through a dedicated energy label. We propose several options for classifying vehicles on an efficiency scale from A to G, with and without drive range and battery capacity as utility parameters. Our analysis provides a rationale for the energy labeling of electric cars in the European Union and could inspire similar analyses for other vehicle categories such as e-scooters, lightweight electric three- and four-wheelers, e-busses, e-trucks, and electric non-road machinery.

**Keywords:** electric cars; fully electric vehicles; energy consumption; efficiency trade-offs; energy label; consumer information



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## 1. Introduction

Annual sales of fully electric cars have surpassed one million in the European Union [1] and 10 million worldwide [2,3]. With an average yearly growth of more than 50% over the past decade, electric cars are no longer niche products. In 2022, they represented 15% of all new car registrations in Europe [4] and may soon dominate the market if the European Union pursues its ambition to cut tailpipe CO<sub>2</sub> emissions from new cars to zero by 2035 [5].

Rising sales have been accompanied by increasing model variety. In 2016, just about 30 fully electric car models were available in Europe [6]. At the time of this writing, consumers can choose from several hundred models, ranging from small cars to luxurious sedans and sport utility vehicles [7]. High learning rates have lowered the production costs of electric vehicles [8] that benefited from an increasing power density of batteries [9], overall advanced energy management, and the use of wide bandgap semiconductors. The latter, representing a leap in innovation, boosted charging efficiency from 60% a decade ago [10] up to 99.5% today [11].

Rapid innovation and market diversification have likely amplified the variability of vehicle attributes, including energy consumption. Although energy labeling could elucidate this variability for consumers, Europe lacks a dedicated label that classifies the energy consumption of electric cars in a transparent manner. Instead, electric cars are covered

under the ‘car label’, comprising all combustion, hybrid, and electric cars [12]. The label rating is based on the certified tailpipe CO<sub>2</sub> emissions of vehicles [13,14]. Because electric cars do not emit CO<sub>2</sub> at the tailpipe, they uniformly receive the highest rating (A to A+++, depending on the labeling scheme in the respective country). Therefore, consumers cannot easily identify if an electric car is efficient or inefficient relative to its competitors.

We aim to address this situation and establish an empirical basis for the energy labeling of electric cars in the European Union. To this end, we collect and analyze vehicle attributes for 342 fully electric cars that were 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 efficiency trade-offs and statistical relationships between vehicle attributes, and (iii) deduce options for classifying electric vehicles by a dedicated energy label.

This article provides policymakers with a rationale for implementing an energy labeling scheme for electric cars in Europe. Thereby, it seeks to support efficiency improvements in the transport sector and to inspire similar analyses for other electric vehicles, such as e-scooters, lightweight electric three- and four-wheelers, e-busses, e-trucks, and electric non-road machinery.

On a broader scale, our research supports Europe’s transition towards decarbonized and sustainable transportation [15], which aims for a 90% reduction in greenhouse gas emissions by 2050. As an interim target, the goal is to deploy at least 30 million zero-emission vehicles by 2030 [16]. However, as of 2022, only 3 million vehicles, or 1.2% of the EU car fleet, consisted of battery electric or plug-in hybrid vehicles, with just 0.1% of trucks (6500 vehicles) having a zero-emission powertrain [4].

There is an urgent need to advance the regulatory framework for electric vehicles. Energy efficiency is a key priority in this respect because economy-wide decarbonization and electrification will increase, not decrease, demand for electricity in the future [17]. Electric road vehicles, for example, are expected to consume 11% of the gross electricity supply in Germany by 2030 [18].

The Energy Labelling Directive [19] and the Energy Efficiency Directive [20] aim to address part of this challenge. Both directives emphasize the importance of efficiency improvements to curb energy consumption. Energy labels have long helped consumers to identify efficient products, and they have motivated manufacturers to innovate. Following their introduction for household appliances in 1994 [21], the European Union has updated and expanded the labeling scheme to eventually include tires [22], space heaters [23], and electronic displays [24], as well as smartphones and tablets [25]. Including electric vehicles would ultimately cover a technology whose electricity consumption may soon exceed that of any other labeled product.

## 2. Methods

### 2.1. Data Collection

This article covers fully electric passenger cars and light-duty vehicles powered by an electric motor that draws electricity exclusively from an externally rechargeable battery. We include vehicles classified in the European Union as categories M1 and N1 [14]. We exclude (i) fuel-cell vehicles running on hydrogen, as well as (ii) hybrid, plug-in hybrid, and any other vehicles equipped with an internal combustion engine.

We begin by collecting data from the *Electric Vehicle Database (EVD)*, which provides a complete overview of all fully electric cars and vans available either in Germany, the Netherlands, or the United Kingdom [7]. At the point of data collection in the fall of 2023, this database covered 342 individual vehicle models, for which we obtained data 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) [13,26]—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]; minimum and maximum real-world energy consumption [kWh/100 km]; minimum and maximum

real-world drive range [km]; and the drivetrain configuration (i.e., two-wheel or all-wheel drive). We benchmarked the collected data against information from BEV [27] 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 [28], which reflects operating conditions in Germany. The data collection took place between May and September 2023.

We included data for certified and real-world energy consumption because both parameters can deviate from each other depending on the actual driving conditions on the road. Certified energy consumption is understood here as the energy consumption declared by manufacturers or certification bodies according to the standardized type-approval test procedure [13,19]. Real-world energy consumption refers to the energy consumption observed by vehicle users on the road.

Given the number of models covered, we consider our dataset (see Table S1 in the Supplementary Materials) 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, for all vehicles, we calculated:

- Frontal area [m<sup>2</sup>] by multiplying vehicle width and height [m] and applying a generic correction factor of 85% [29,30] 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 [7];
- Average real-world drive range [km] based on the energy consumption data from Spritmonitor [28] by assuming direct proportionality between certified and real-world energy consumption and the corresponding drive ranges;
- Average price as the arithmetic mean of vehicle prices in Germany and the Netherlands.

Next, we characterized the dataset by calculating the mean, standard deviation, median, minimum, and maximum values of vehicle attributes. Based on this analysis, we express values in the text as mean  $\pm$  standard deviation unless stated otherwise. A comma between numbers denotes the thousands separator.

We then conducted two linear regression analyses. We began by applying simple univariate regression to model energy consumption  $E_i$  of vehicle model  $i$  as a function of a single vehicle attribute:

$$E_i = \alpha_1 + \beta_1 A_i + \varepsilon_i \quad (1)$$

where  $\alpha_1$  stands for the regression constant,  $\beta_1$  represents the regression coefficient,  $A_i$  denotes the attribute under consideration, and  $\varepsilon_i$  the unexplained regression residual. This model was applied separately to certified and real-world energy consumption. The following attributes were considered: vehicle mass [kg], power [kW], frontal area [m<sup>2</sup>], drivetrain configuration (two-wheel versus all-wheel drive), price [EUR], and 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., at a Pearson correlation coefficient  $r < 0.7$ ; see Figure A1 in the Appendix A) as:

$$E_i = \alpha_2 + \beta_2 M_i + \beta_3 P_i + \beta_4 F_i + \beta_5 D_i + \varepsilon_i \quad (2)$$

where  $M_i$  represents vehicle mass [kg],  $P_i$  power [kW],  $F_i$  frontal area [m<sup>2</sup>], 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. Therefore, we follow the approach of Knittel [31] 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:

$$\log E_i = \alpha_3 + \beta_6 \log A_i + \varepsilon_i \quad (3)$$

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

where  $\log$  depicts the logarithm base 10. A preliminary screening of residual plots reveals heteroscedasticity, which tends to bias the regression errors. In line with Tietge et al. [32], we, therefore, estimated heteroscedasticity-robust standard errors for all regression coefficients with the R ‘*estimatr*’ package [33].

We also applied univariate regression analysis to explore associations between several attributes, namely (i) real-world versus certified energy consumption, (ii) usable versus nominal battery capacity, (iii) vehicle mass versus nominal battery capacity, (iv) vehicle mass versus frontal area, (v) power versus vehicle mass, (vi) certified drive range versus nominal battery capacity, (vii) real-world drive range versus usable battery capacity, (viii) price versus usable battery capacity, and (ix) 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 version 4.4.0 [34].

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

### 3. Results

#### 3.1. Overview—Vehicle Attributes

##### 3.1.1. Energy Consumption

The certified energy consumption of electric cars averages  $19 \pm 4$  kWh/100 km ( $31 \pm 6$  kWh/100 miles or 3.2 miles/kWh); the real-world energy consumption averages  $21 \pm 4$  kWh/100 km ( $33 \pm 6$  kWh/100 miles or 3.0 miles/kWh; see Table 1 and Figure 1). The corresponding drive ranges reach  $440 \pm 120$  km ( $272 \pm 76$  miles) and  $380 \pm 110$  km ( $238 \pm 68$  miles), respectively. The difference between certified and real-world energy consumption is statistically significant based on a two-sided *t*-test. This finding suggests that, on average, the European certification test underestimates energy consumption. However, the certified TEH energy consumption values, which comprise the least efficient variants of a vehicle model, appear to be, in fact, a good proxy for the average real-world energy consumption of electric vehicles (Table 1).

Brands differ in their average certified energy consumption and the drive range they offer for a given price (Figure 2). Yet, drawing conclusions from Figure 2 about the powertrain efficiency is not straightforward. First, the number of available models differs between manufacturers. Some offer one or a few models in certain market segments; others offer models in virtually all market segments. Second, the technical characteristics and attributes of models vary between manufacturers. We see in Section 4.2 how differences in, e.g., mass, frontal area, or battery capacity incur considerable efficiency trade-offs.

**Table 1.** Descriptive statistics of vehicle attributes; SD—standard deviation; Min—minimum value; Max—maximum value.

Parameter [Unit] (Sample Size)	Mean	SD	Median	Min	Max
Energy consumption					
Certified <sup>a</sup> [kWh/100 km] (501)	19.4	3.8	18.5	13.0	30.7

Table 1. Cont.

Parameter [Unit] (Sample Size)	Mean	SD	Median	Min	Max
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	14.3	30.7
Real-world <sup>b</sup> [kWh/100 km] (496)	20.7	3.7	19.8	13.0	38.9
Drive range, based on					
Certified energy consumption <sup>a</sup> [km] (552)	438	122	440	190	883
Certified energy consumption - TEL [km] (339)	449	128	455	190	883
Certified energy consumption - TEH [km] (213)	420	111	420	203	828
Real-world energy consumption <sup>b</sup> [km] (496)	383	109	384	148	733
Certified drive range per 1000 EUR vehicle price (548)	7.00	2.43	7.01	1.34	11.93
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)	2102	351	2128	1012	2975
Power [kW] (342)	230	139	190	33	828
Frontal area [m <sup>2</sup> ] (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 <sup>c</sup> [EUR] (339)	70,135	40,245	58,844	22,150	387,645

<sup>a</sup> Including certified TEL and TEH energy consumption values. <sup>b</sup> Including the mid-point real-world energy consumption data obtained from EVD [7] and the mean energy consumption data obtained from Spritmonitor [28].

<sup>c</sup> Considering the average price of vehicles sold in Germany and the Netherlands.

### 3.1.2. Other Vehicle Attributes

Electric cars sold in Europe cost  $70,000 \pm 40,000$  EUR, with a median price of 59,000 EUR. At the point of data collection, there was not a single model available for less than 20,000 EUR. The cars have a mass of  $2100 \pm 350$  kg and a rated motor power of  $230 \pm 140$  kW. On average, they are  $4.71 \pm 0.39$  m long,  $1.89 \pm 0.07$  m wide,  $1.62 \pm 0.14$  m high, and feature a frontal area of  $2.59 \pm 0.28$  m<sup>2</sup>. Their nominal battery capacity of  $76 \pm 22$  kWh exceeds the usable battery capacity of  $71 \pm 21$  kWh by some 5 kWh or 7% (Table 1). Many models are available as two-wheel drive and all-wheel drive versions (see Table S1 in the Supplementary Materials). Our findings show that vehicle attributes span a wide range (Figure 1). We expect this range to increase if the market for electric vehicles continues to grow (see, e.g., [2,3]).

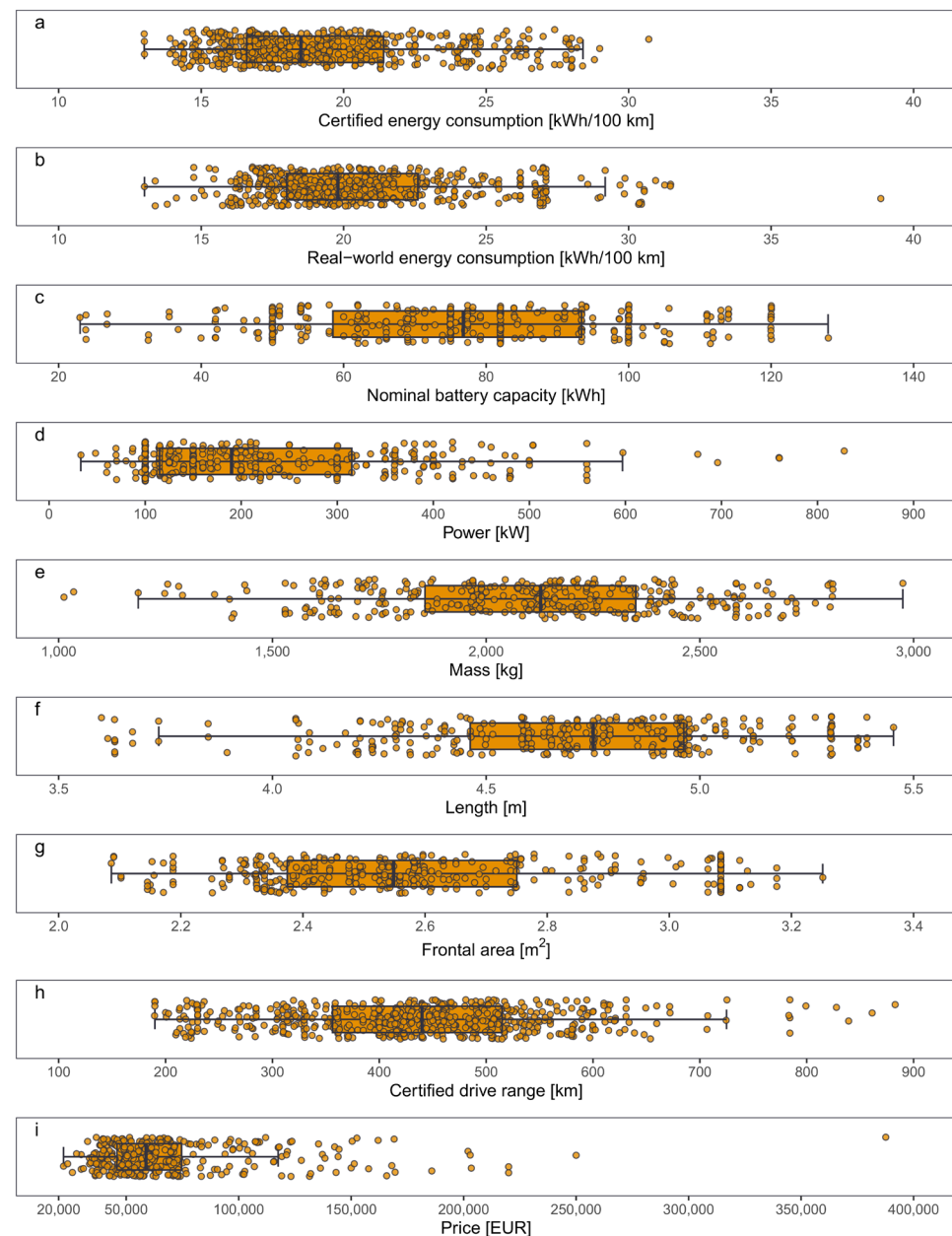
### 3.2. Regression Analyses—Efficiency Trade-Offs

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 power, price, and drivetrain configuration (two-wheel versus all-wheel drive; Figure A1 in the Appendix A). Together, frontal area, mass, power, and number of driven axles can explain 55% and 60% of certified and real-world energy consumption.

The regression analyses reveal the following (see Figure 3 and Table A1):

- Each 100 kg of *vehicle mass* increases certified and real-world energy consumption by  $0.20 \pm 0.06$  kWh/100 km and  $0.17 \pm 0.05$  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 m<sup>2</sup> of *frontal area* increases certified and real-world energy consumption by  $8.5 \pm 0.6$  kWh/100 km and  $9.2 \pm 0.5$  kWh/100, respectively (Figure 3b; Model 2); each doubling of frontal area doubles the certified and real-world energy consumption (Model 4).

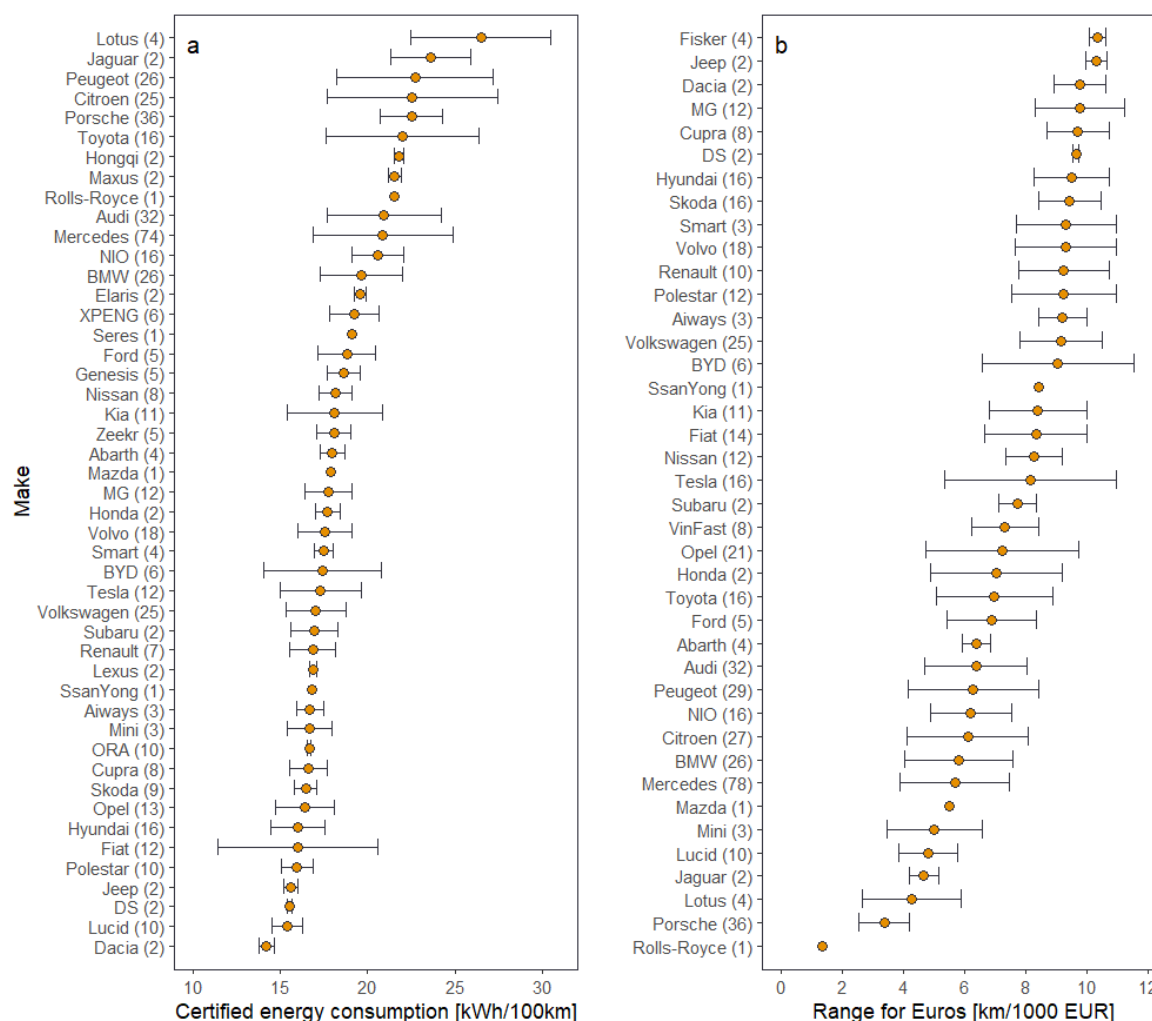




**Figure 1.** Boxplots of vehicle attributes; dots represent individual vehicle models; vertical lines depict the median, upper and lower quartiles, and 1.5 times the interquartile range of the data; certified energy consumption is based on TEL and TEH values; real-world energy consumption is based on mid-point values of data obtained from EVD [7] and mean values obtained from Spritmonitor [28]; the y-axis is used to disperse the data and is unitless; letters (a–i) within the plot areas are used to identify plots for individual vehicle attributes in the main text.

- Each 100 kW of *rated power* increases certified energy consumption by only  $0.42 \pm 0.18$  kWh/100 km, whereas the effect on real-world energy consumption is insignificant (Figure 3c; Model 2); log-transformation suggests rated power does not significantly affect certified energy consumption and may slightly decrease real-world energy consumption (Model 4).
- *All-wheel drive* capability does not significantly increase certified energy consumption, but it tends to increase real-world energy consumption by  $1.0 \pm 0.3$  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 of vehicle price

increases certified and real-world energy consumption by some  $0.3 \pm 0.1$  kWh/100 km (Model 1g); a doubling of vehicle price increases energy consumption by some 0.2 kWh/100 km (Model 3g).

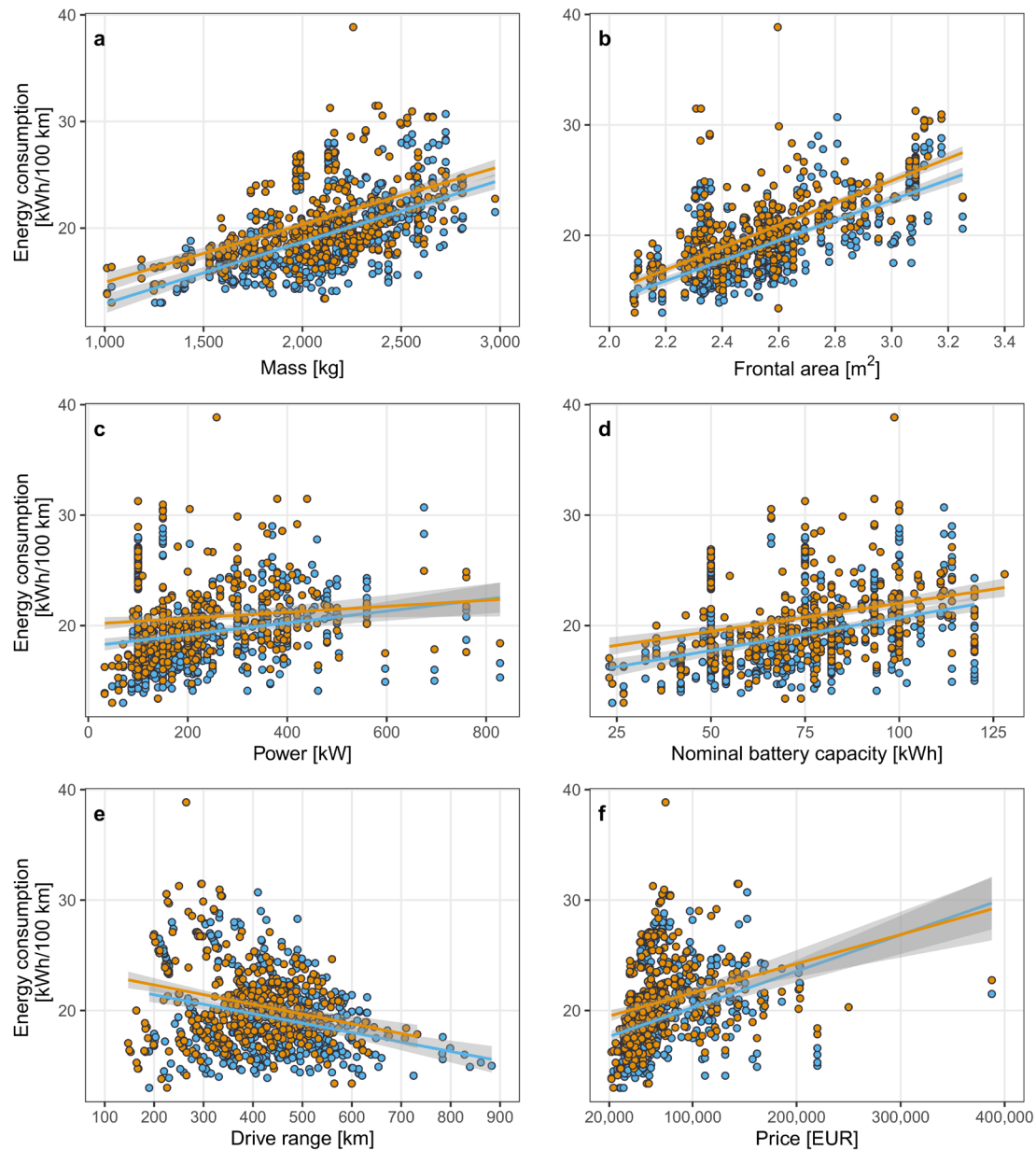


**Figure 2.** Mean and standard deviation of certified energy consumption (a) and drive range per Euro vehicle price (b) by vehicle manufacturer; numbers in parentheses indicate the sample size; we exclude manufacturers for which no data are available; certified energy consumption is based on TEL and TEH values.

The weak correlation between energy consumption and rated power contrasts with the findings for combustion engine vehicles, in which both variables are strongly correlated [35]. This difference can be explained, among others, by the recuperation of kinetic energy when braking and the absence of idling losses in electric cars.

Regarding battery characteristics, the univariate regression analyses (see Table A1) suggest that:

- Each additional 10 kWh of *nominal battery capacity* increases certified and real-world energy consumption by  $0.59 \pm 0.07$  kWh/100 km and  $0.51 \pm 0.07$  kWh/100 km, respectively (Model 1e); each doubling of battery capacity increases certified and real-world energy consumption by around 20% (Model 3e).
- Each additional 100 km of *drive range* tends to decrease certified and real-world energy consumption by  $0.86 \pm 0.13$  kWh/100 km and  $0.88 \pm 0.16$  kWh/100 km, respectively (Model 1f); each doubling of drive range decreases certified and real-world energy consumption by  $15 \pm 3\%$  and  $12 \pm 3\%$ , respectively (Model 3f).



**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, drive range, and price; shaded areas represent the 95% confidence interval of the regression line; certified energy consumption is based on TEL and TEH values; real-world energy consumption is based on mid-point values of data obtained from EVD [7] and mean values obtained from Spritmonitor [28]; letters (a–f) within the plot areas are used to identify plots for individual vehicle attributes in the main text.

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 the drive range by increasing the energy density of batteries and 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

The complementary regression analyses reveal the following (Figure 4 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  $0.88 \pm 0.03$  kWh/100 km (Model 1g).
- *Usable battery capacity* is generally 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  $9.3 \pm 0.6$  kWh (Model 1h).
- Each 10 kWh of *nominal battery capacity* increases vehicle mass by  $143 \pm 4$  kg (Figure 4c); statistically, vehicles would weigh  $1015 \pm 34$  kg without a battery (Model 1i), suggesting that the electric battery accounts for roughly half (i.e.,  $1100 \pm 400$  kg) of the average mass of electric vehicles ( $2102 \pm 351$  kg; Table 1).
- With each  $0.1 \text{ m}^2$  of *frontal area*, vehicle mass increases by  $46 \pm 6$  kg (Model 1j).
- With each 100 kg of *vehicle mass*, power increases by  $26 \pm 2$  kW (Figure 4d; Model 1k).
- Each 10 kWh of *nominal battery capacity* adds some  $45 \pm 2$  km of drive range during both certification and real-world driving (Figure 4e,f; Models 1k and 1l); a doubling of both nominal and usable battery capacity tends to increase certified and real-world drive range by 80% (Models 3l and 3m).
- Vehicles with a large battery and a long drive range are expensive; each 10 kWh of nominal battery capacity raises *vehicle price* by  $12,000 \pm 600$  EUR (Figure 4g; Model 1n); each 10 km of drive range adds  $1500 \pm 120$  EUR to the vehicle price (Figure 4h; Model 1o).

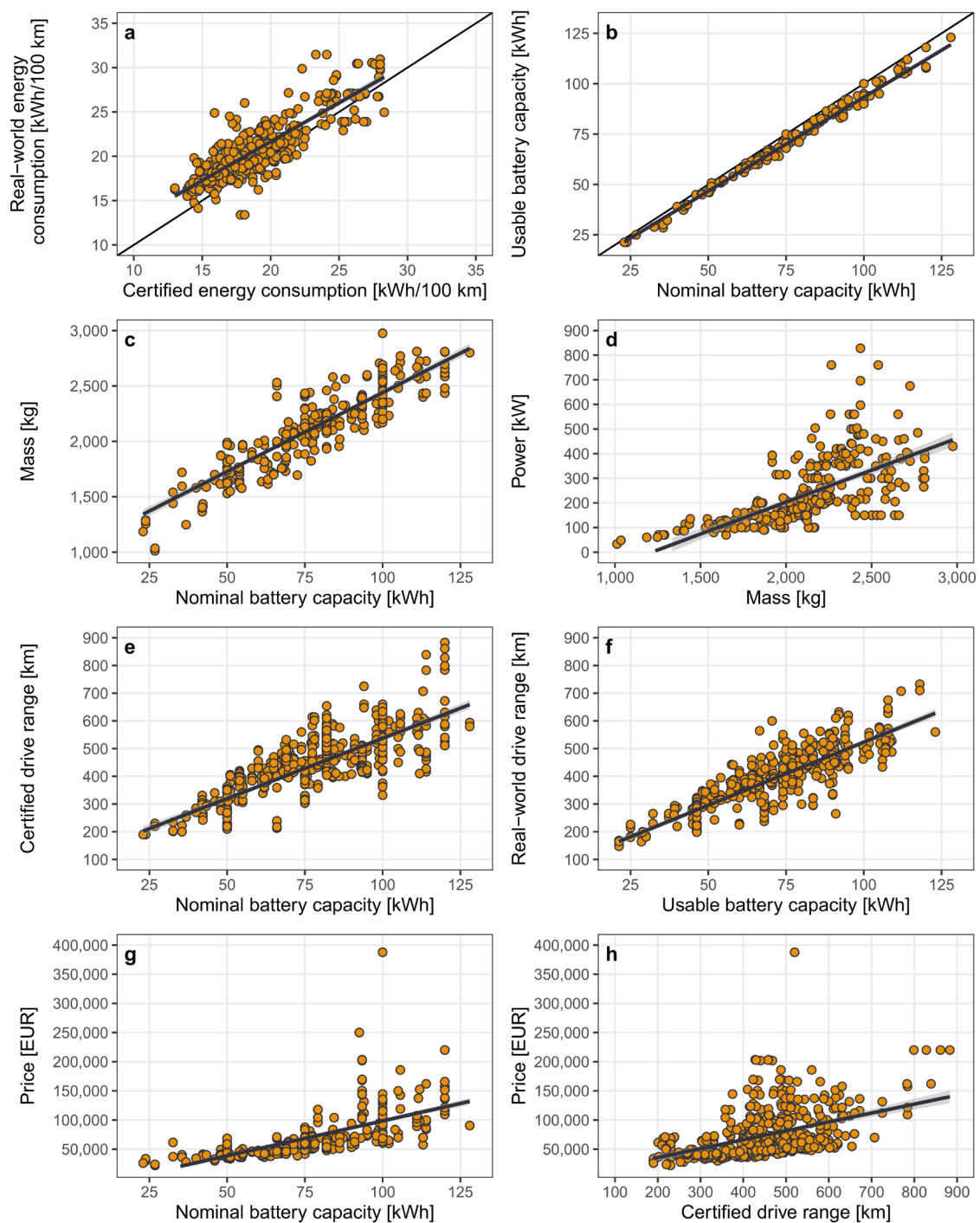
The results suggest that there are ample benefits of increasing the energy density of batteries, which would allow for a decrease in vehicle mass and energy consumption, thereby increasing drive range.

### 3.4. Energy Labeling of Electric Cars

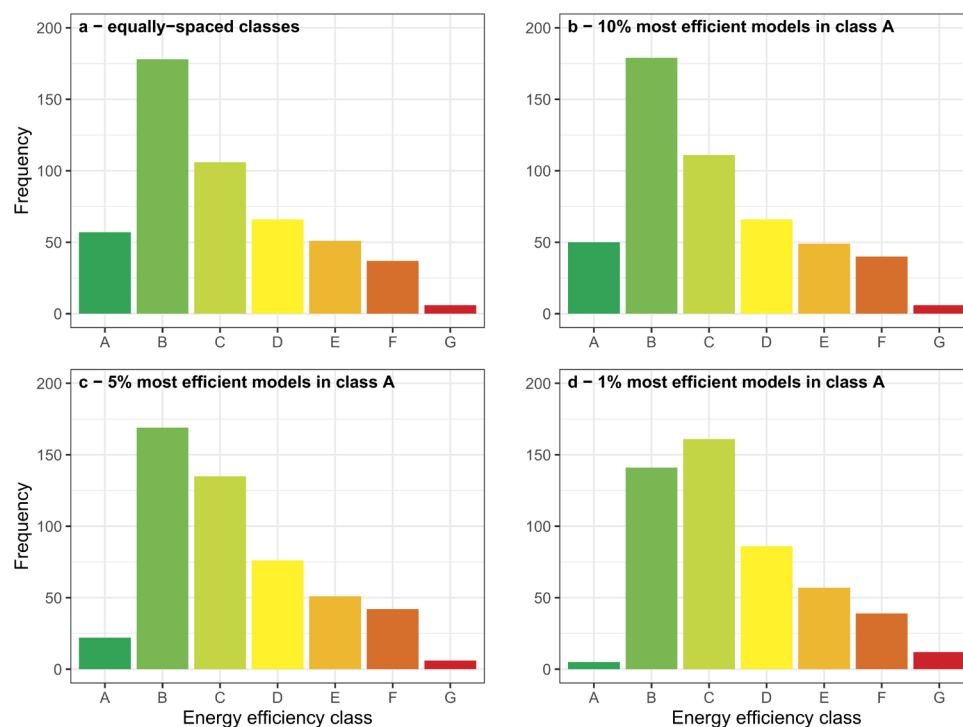
The collected data can be used to classify vehicles according to their energy consumption. However, such a classification is, to some extent, subjective, depending on the intended purpose. We think the classification criteria used for energy labeling should be the following:

- *Relevant*—to distinguish energy efficient from less energy efficient vehicles, thereby driving innovation and supporting informed consumer choices.
- *Accurate*—to correctly reflect the energy consumption experienced by consumers on the road under normal operating conditions.
- *Accessible*—to communicate information in a clear manner.
- *Long-lasting*—to remain relevant over time by being as technologically neutral and accommodating of innovation as possible.

In this way, vehicles should be classified, first and foremost, according to their certified energy consumption [kWh/100 km]. Certified energy consumption values are established through standardized type-approval testing; the information is, hence, readily available for all electric cars 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 entire 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 (Figure 5b–d). If such a classification was adopted, most vehicles would fall into classes B and C.



**Figure 4.** Complementary regression analyses; thin black lines in (a,b) depict a slope of one and a y-axis intercept of zero; thick black lines depict regression lines; shaded areas represent the 95% confidence interval of the regression line; certified energy consumption is based on TEL and TEH values; real-world energy consumption is based on mid-point values of data obtained from EVD [7] and mean values obtained from Spritmonitor [28]; letters (a–h) within the plot areas are used to identify plots for individual vehicle attributes in the main text.

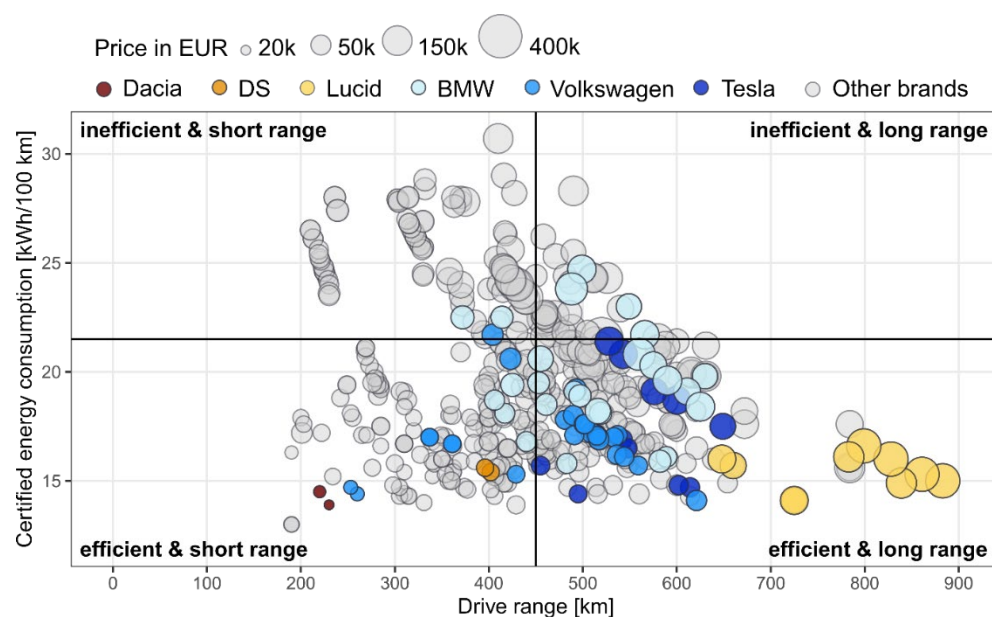


**Figure 5.** Distribution of vehicle models across efficiency classes A to G, based on certified TEL and TEH energy consumption values; panel (a) displays classes of equal size; in panels (b–d), class A represents the 10%, 5%, and 1% most efficient models, respectively, while classes B to G comprise the remaining data points dispersed over equally sized intervals.

Classifying vehicles according to their energy consumption avoids perverse incentives causing rebound effects or other undesirable market distortions. It leaves manufacturers any degree of freedom along which to improve efficiency, and it penalizes large and heavy vehicles that pose a sustainability challenge, specifically in urban areas. However, efficiency improvements could be achieved through diminishing vehicle utility, for example, by decreasing cabin space or drive range. It could, therefore, be desirable to include additional utility parameters in the classification of vehicles. Germany and Spain follow such an approach for conventional cars by considering the mass and footprint of vehicles [36]. 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.

Suitable utility factors could include battery capacity or drive range. Opting for drive range would address range anxiety, which is still a major market barrier for electric cars [37,38]. In fact, our data show that efficient vehicles are available at any price, but drive range has a cost—with the noteworthy exception of a few mid-priced cars that, e.g., consume less than 15 kWh/100 km and offer a drive range of more than 550 km (Figure 6).

Including such utility parameters could reveal important information to consumers and provide incentives 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.



**Figure 6.** Scatterplot of certified energy consumption and drive range, highlighting the three most popular brands (BMW, Volkswagen, and Tesla) and the three brands with the lowest average energy consumption (Dacia, DS, and Lucid); certified energy consumption is based on TEL and TEH values.

## 4. Discussion

### 4.1. Strengths and Limitations of the Research

We have compiled a comprehensive dataset of vehicle attributes for 342 fully electric cars sold in the Netherlands, Germany, and the United Kingdom (see Table S1 in the Supplementary Materials). We consider this dataset to be representative of mass-produced electric cars available in Europe in 2023 and 2024. The identified efficiency 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 detailed data for energy, transport, and economic modeling, and they offer policymakers an empirical basis from which to develop a dedicated energy label for electric cars. Additionally, our results could inspire similar analyses for other categories of electric vehicles, such as e-bikes, e-scooters, and light electric three- and four-wheelers, as well as electric heavy-duty vehicles and non-road machinery. Overall, this article supports the transition towards sustainable and climate-neutral road transportation. Nevertheless, it has noteworthy limitations:

- **Timeliness:** While our results may hold for the short-term future and vehicle markets outside Europe, they will become less accurate over time. Incremental innovation, technological breakthroughs, and pricing policy in a growing and increasingly diverse market will affect vehicle attributes and efficiency trade-offs.
- **Vehicle sales:** We capture models available on the market 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 our energy consumption data for fleet-wide energy and emissions modeling.
- **Vehicle models:** Drawing the boundary of what constitutes a model, rather than a variant or version of a model, is not straightforward. We consider vehicles to be individual models if they differ by name or battery capacity. This way, technically 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 similar but sold by several manufacturers. However, we consider this approach to be practical and justifiable given the challenges associated with implementing alternative system boundaries.

- *Energy consumption:* Real-world energy consumption values can vary greatly depending on, e.g., ambient temperature, drivers' behavior, or road profile. Furthermore, data samples in Spritmonitor [28] are still small for most models. Overall, we consider our data to be indicative of the real-world energy consumption and operating conditions, although they may not capture all specific conditions, such as very low winter temperatures.
- *System boundary:* We focus here on the energy consumption related to vehicle use. It is beyond the scope of this research to evaluate the overall energetic and environmental impacts of electric vehicles, which requires a holistic life-cycle assessment, including vehicle production, end-of-life treatment, and electricity generation (e.g., [39–42]).
- *Regression analysis:* The coefficients of determination suggest that both the linear and power-law regression models fit our data similarly well. However, the regression coefficients of both models are only robust if the underlying data meet certain criteria, such as normality, homogeneity, and independence [43]. Regression residuals should be uncorrelated with the independent variable. The diagnostic plots in Figures S1–S50 in the Supplementary Material suggest that this requirement may not always be met and that residuals can be heteroscedastic. We address the observed heteroscedasticity by estimating heteroscedasticity-robust standard errors for all regression coefficients [33].

#### 4.2. Comparison of Results

The average certified and real-world energy consumption values ( $19 \pm 4$  kWh/100 km and  $21 \pm 4$  kWh/100 km) are broadly consistent with the literature. For example, consumption values of 19 kWh/100 km were reported by Madziel and Campisi [44] 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 was found by Galvin [45]. Weiss et al. [46] reported certified and real-world energy consumption of  $16 \pm 4$  kWh/100 km and  $18 \pm 5$  kWh/100 km, albeit for a sample of 218 vehicles produced between 1989 and 2019. The deviation between these values and those documented here is caused by a market trend towards heavier and larger vehicles. In fact, the most efficient electric cars are mostly smaller vehicles that were already available a decade ago [47]. Considering all new car registrations in the European Union in 2022, EEA [1] 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. However, 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. [48] give an increase of 0.4 kWh/100 km and Weiss et al. [46] of 0.6 kWh/100 km with each 100 kg of vehicle mass.

Our study complements the analyses of Kozłowski et al. [49], who found a strong correlation between acceleration, vehicle speed, battery power, and the energy consumption of electric vehicles based on actual on-road driving data.

#### 4.3. Implications for Policymakers

##### 4.3.1. Deviation between Certified and Real-World Energy Consumption

We find that real-world energy consumption is around 7% higher than certified energy consumption (Figure 4a). This result is statistically significant and in line with the modelling of Komnos et al. [50], which likewise suggest the type-approval test underestimates the energy consumption of electric vehicles on the road. These findings demand attention from policymakers. If verified by more comprehensive data samples, the type-approval procedure may need to be adapted to ensure that consumers receive accurate information about the energy consumption of electric vehicles.



#### 4.3.2. Energy Labeling

The range of energy consumption values (Figure 1) suggests that consumers would benefit from the introduction 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 [5]. By that time, the overall electricity consumption of electric cars will likely exceed that of any other labeled product. Although the European Commission currently has no plans to implement an energy label for electric vehicles [51], the Commission is asked to review the car labeling directive by 31 December 2024 [52]. Our analysis offers a timely contribution to this review.

Regarding *labeling metrics*, certified energy consumption [kWh/100 km; km/kWh] is an obvious choice. Standardized data are readily available from type approval; the information is 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 tend to follow linear scaling (see [53]). Such scaling is intuitive and could also be applied to electric vehicles. Non-linear scaling based on percentiles or ranks could be considered but may need to be explained to consumers. Also, behavioral aspects are relevant in this context. Labeling too few or too many models as class A suggests efficient vehicles are unattainable or common. Both types of mislabeling would discourage 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 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.

#### 4.3.3. Efficiency Improvements

The wide range of energy consumption values (Figure 1a,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 to their increasing size and mass. If we compare our findings with data for electric vehicles built between 1988 and 2019 [46], it appears that electric cars available in Europe have become 24% heavier (from  $1690 \pm 470$  kg to  $2100 \pm 350$  kg) and 53% more powerful (from  $150 \pm 127$  kW to  $230 \pm 140$  kW). Nominal battery capacity has increased by 65% (from  $46 \pm 26$  kWh to  $76 \pm 22$  kWh), whereas certified energy consumption has increased by 21% (from  $16.0 \pm 3.7$  kWh/100 km to  $19.4 \pm 3.8$  kWh/100 km).

These findings are troublesome because the recent technical efficiency improvements [9,11] appear to have triggered rebound effects like those observed for conventional cars in the past [31,35]. Yet, they also highlight 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 [46]). As the electric vehicle fleet grows, rising electricity demand will challenge green electricity production and network transmission capacity [54,55]. Reducing the size of vehicles decreases electricity consumption and, in combination with smart charging, can help manage peak electricity demand [56]. Downsizing also reduces resource consumption of rare earth metals [57], for example, thereby contributing to more resilient and sustainable transportation.

## 5. Conclusions

This paper analyzes the energy consumption and efficiency trade-offs across electric vehicles in Europe. We draw the following conclusions:

- As of 2023, a large variety of electric cars and vans is available on the market; their certified and real-world energy consumption ranges from 13 to 30 kWh/100 km and averages  $19 \pm 4$  kWh/100 km and  $21 \pm 4$  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 and vehicle price; energy consumption is negatively correlated with drive range, indicating that improved powertrain efficiency is an important factor for extending the drive range of electric vehicles.
- The electric battery accounts for half of the vehicle mass and is thereby an important driver of energy consumption; our regression analysis confirms that increasing the energy density of batteries would indeed benefit both the energy consumption and the drive range of vehicles.
- Real-world energy consumption tends to be higher than certified energy consumption, suggesting that the type approval test systematically underestimates the energy consumption of electric vehicles on the road; policymakers should monitor the situation and adapt the test procedure if needed.
- Efficient vehicles are available at any price, but drive range has a cost; this finding points to important price-range trade-offs, which should be made transparent to consumers when purchasing electric vehicles.
- The large variability in energy consumption values suggests there is a need to inform consumers about the energy use, energy-related costs, and efficiency trade-offs of electric cars through a dedicated energy label.

With a firm commitment to energy efficiency [20], it is only a matter of time before electric cars receive their own energy label in the European Union and elsewhere. Our findings support policy efforts in that direction and could inspire similar analyses for other electric vehicles such as e-bikes, e-scooters, 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: <https://www.mdpi.com/article/10.3390/su16177529/s1>. Reference [58] is cited in Supplementary Materials.

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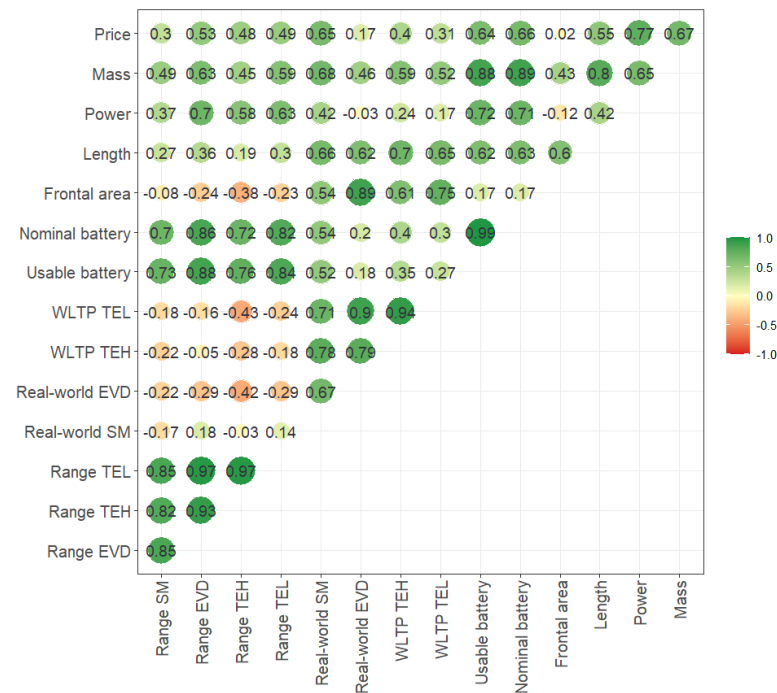
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## Abbreviations

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 average real-world energy consumption as given by Spritmonitor [28]; Range EVD—drive range based on average real-world energy consumption as given by EVD [7]; 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 [28]; Real-world EVD—real-world energy consumption as given by EVD [7]; WLTP TEH—certified TEH energy consumption; WLTP TEL—certified TEL energy consumption; Usable battery—usable battery capacity; Nominal battery—nominal battery capacity.

**Table A1.** Regression analyses of certified and real-world energy consumption as a function of vehicle attributes; coefficients are significant at 1% level (\*\*\*) and 5% level (\*\*); certified energy consumption is based on TEL and TEH values; real-world energy consumption is based on mid-point values of data obtained from EVD [7] and mean values obtained from Spritmonitor [28].

Energy Consumption	Coefficient	Value	Standard Error	t Value	Pr (>abs t)	p Value	Adjusted R <sup>2</sup>
Model 1a: energy consumption = $\alpha + \beta \times \text{mass}$							
Certified	(Intercept) ***	7.11	0.65	10.98	$2.97 \times 10^{-25}$	< $2.2 \times 10^{-16}$	0.30
	Mass ***	$5.80 \times 10^{-3}$	$3.21 \times 10^{-4}$	18.07	$1.56 \times 10^{-56}$		
Real-world	(Intercept) ***	9.47	0.61	15.42	$4.40 \times 10^{-44}$	< $2.2 \times 10^{-16}$	0.26
	Mass ***	$5.44 \times 10^{-3}$	$3.19 \times 10^{-4}$	17.03	$1.63 \times 10^{-51}$		
Model 1b: energy consumption = $\alpha + \beta \times \text{power}$							
Certified	(Intercept) ***	18.12	0.37	48.73	$7.69 \times 10^{-192}$	$6.41 \times 10^{-5}$	0.04
	Power ***	$5.33 \times 10^{-3}$	$1.32 \times 10^{-3}$	4.03	$6.41 \times 10^{-5}$		
Real-world	(Intercept) ***	20.13	0.34	59.24	$1.35 \times 10^{-226}$	$2.36 \times 10^{-2}$	<0.01
	Power **	$2.70 \times 10^{-3}$	$1.19 \times 10^{-3}$	2.27	$2.36 \times 10^{-2}$		
Model 1c: energy consumption = $\alpha + \beta \times \text{frontal area}$							
Certified	(Intercept) ***	−4.24	1.23	−3.46	$5.82 \times 10^{-4}$	< $2.2 \times 10^{-16}$	0.45
	Frontal area ***	9.15	0.47	19.36	$1.05 \times 10^{-62}$		
Real-world	(Intercept) ***	−5.30	0.99	−5.35	$1.38 \times 10^{-7}$	< $2.2 \times 10^{-16}$	0.56
	Frontal area ***	10.08	0.38	26.62	$1.65 \times 10^{-97}$		
Model 1d: energy consumption = $\alpha + \beta \times \text{all-wheel drive}$							
Certified	(Intercept) ***	18.75	0.24	78.77	$1.20 \times 10^{-283}$	$5.90 \times 10^{-6}$	0.04
	All-wheel drive ***	1.45	0.32	4.58	$5.90 \times 10^{-6}$		
Real-world	(Intercept) ***	20.25	0.23	88.68	$1.43 \times 10^{-305}$	$1.11 \times 10^{-4}$	0.02
	All-wheel drive ***	1.23	0.32	3.90	$1.11 \times 10^{-4}$		
Model 1e: energy consumption = $\alpha + \beta \times \text{nominal battery capacity}$							
Certified	(Intercept) ***	14.78	0.57	25.84	$4.65 \times 10^{-94}$	$1.50 \times 10^{-15}$	0.12
	Nominal battery capacity ***	$5.94 \times 10^{-2}$	$7.21 \times 10^{-3}$	8.24	$1.50 \times 10^{-15}$		

Table A1. Cont.

Energy Consumption	Coefficient	Value	Standard Error	t Value	Pr (>abs t)	p Value	Adjusted R <sup>2</sup>
Real-world	(Intercept) ***	16.94	0.55	31.04	$3.72 \times 10^{-118}$	$2.07 \times 10^{-12}$	0.09
	Nominal battery capacity ***	$5.08 \times 10^{-2}$	$7.04 \times 10^{-3}$	7.21	$2.07 \times 10^{-12}$		
Model 1f: energy consumption = $\alpha + \beta \times \text{drive range}$							
Certified	(Intercept) ***	23.14	0.68	33.83	$3.82 \times 10^{-131}$	$3.03 \times 10^{-10}$	0.08
	Drive range ***	$-8.55 \times 10^{-3}$	$1.33 \times 10^{-3}$	-6.43	$3.03 \times 10^{-10}$		
Real-world	(Intercept) ***	24.07	0.72	33.26	$3.72 \times 10^{-128}$	$9.49 \times 10^{-8}$	0.06
	Drive range ***	$-8.77 \times 10^{-3}$	$1.62 \times 10^{-3}$	-5.42	$9.49 \times 10^{-8}$		
Model 1g: energy consumption = $\alpha + \beta \times \text{price}$							
Certified	(Intercept) ***	16.99	0.39	43.42	$6.50 \times 10^{-171}$	$1.41 \times 10^{-9}$	0.13
	Price ***	$3.29 \times 10^{-5}$	$5.33 \times 10^{-6}$	6.17	$1.41 \times 10^{-9}$		
Real-world	(Intercept) ***	18.98	0.38	49.71	$9.38 \times 10^{-194}$	$4.02 \times 10^{-6}$	0.06
	Price ***	$2.63 \times 10^{-5}$	$5.65 \times 10^{-6}$	4.66	$4.02 \times 10^{-6}$		
Model 2: energy consumption = $\alpha + \beta \times \text{mass} + \beta \times \text{power} + \beta \times \text{frontal area} + \beta \times \text{all-wheel drive}$							
Certified	(Intercept) ***	-7.96	1.21	-6.59	$1.10 \times 10^{-10}$	< $2.2 \times 10^{-16}$	0.55
	Mass ***	$2.03 \times 10^{-3}$	$5.76 \times 10^{-4}$	3.53	$4.60 \times 10^{-4}$		
	Power **	$4.16 \times 10^{-3}$	$1.83 \times 10^{-3}$	2.27	$2.35 \times 10^{-2}$		
	Frontal area ***	8.52	0.59	14.35	$2.63 \times 10^{-39}$		
	All-wheel drive	0.16	0.36	0.44	0.66		
Real-world	(Intercept) ***	-6.43	0.95	-6.78	$3.37 \times 10^{-11}$	< $2.2 \times 10^{-16}$	0.60
	Mass ***	$1.65 \times 10^{-3}$	$5.17 \times 10^{-4}$	3.19	$1.49 \times 10^{-3}$		
	Power	$-1.34 \times 10^{-3}$	$1.47 \times 10^{-3}$	-0.91	0.36		
	Frontal area ***	9.16	0.50	18.48	$2.74 \times 10^{-58}$		
	All-wheel drive ***	1.02	0.34	3.01	$2.74 \times 10^{-3}$		



Table A1. Cont.

Energy Consumption	Coefficient	Value	Standard Error	t Value	Pr (>abs t)	p Value	Adjusted R <sup>2</sup>
Model 3a: $\log(\text{energy consumption}) = \alpha + \beta \times \log(\text{mass})$							
log(Certified)	(Intercept) ***	−1.61	0.23	−6.89	$1.66 \times 10^{-11}$	< $2.2 \times 10^{-16}$	0.32
	log(Mass) ***	0.60	$3.07 \times 10^{-2}$	19.42	$5.80 \times 10^{-63}$		
log(Real-world)	(Intercept) ***	−0.96	0.20	−4.83	$1.86 \times 10^{-6}$	< $2.2 \times 10^{-16}$	0.30
	log(Mass) ***	0.52	$2.65 \times 10^{-2}$	19.75	$2.12 \times 10^{-64}$		
Model 3b: $\log(\text{energy consumption}) = \alpha + \beta \times \log(\text{power})$							
log(Certified)	(Intercept) ***	2.57	$8.47 \times 10^{-2}$	30.35	$2.19 \times 10^{-115}$	$5.76 \times 10^{-6}$	0.05
	log(Power) ***	$7.11 \times 10^{-2}$	$1.55 \times 10^{-2}$	4.58	$5.76 \times 10^{-6}$		
log(Real-world)	(Intercept) ***	2.78	$7.69 \times 10^{-2}$	36.17	$5.84 \times 10^{-141}$	$1.73 \times 10^{-3}$	0.02
	log(Power) ***	$4.47 \times 10^{-2}$	$1.42 \times 10^{-2}$	3.15	$1.73 \times 10^{-3}$		
Model 3c: $\log(\text{energy consumption}) = \alpha + \beta \times \log(\text{frontal area})$							
log(Certified)	(Intercept) ***	1.83	$5.72 \times 10^{-2}$	32.01	$4.60 \times 10^{-123}$	< $2.2 \times 10^{-16}$	0.43
	log(Frontal area) ***	1.18	$5.93 \times 10^{-2}$	19.93	$1.84 \times 10^{-65}$		
log(Real-world)	(Intercept) ***	1.85	$4.19 \times 10^{-2}$	44.21	$8.20 \times 10^{-174}$	< $2.2 \times 10^{-16}$	0.57
	log(Frontal area) ***	1.23	$4.31 \times 10^{-2}$	28.62	$6.06 \times 10^{-107}$		
Model 3d: $\log(\text{energy consumption}) = \alpha + \beta \times \text{all-wheel drive}$							
log(Certified)	(Intercept) ***	2.91	$1.17 \times 10^{-2}$	248.07	0.00	$9.35 \times 10^{-8}$	0.05
	All-wheel drive ***	$8.44 \times 10^{-2}$	$1.56 \times 10^{-2}$	5.42	$9.35 \times 10^{-8}$		
log(Real-world)	(Intercept) ***	2.99	$1.06 \times 10^{-2}$	281.06	0.00	$1.90 \times 10^{-6}$	0.04
	All-wheel drive ***	$6.83 \times 10^{-2}$	$1.42 \times 10^{-2}$	4.82	$1.90 \times 10^{-6}$		
Model 3e: $\log(\text{energy consumption}) = \alpha + \beta \times \log(\text{nominal battery capacity})$							
log(Certified)	(Intercept) ***	1.98	0.10	19.77	$1.18 \times 10^{-64}$	< $2.2 \times 10^{-16}$	0.14
	log(Nominal battery capacity) ***	0.22	$2.33 \times 10^{-2}$	9.63	$3.04 \times 10^{-20}$		
log(Real-world)	(Intercept) ***	2.23	$8.61 \times 10^{-2}$	25.94	$3.12 \times 10^{-94}$	< $2.2 \times 10^{-16}$	0.12
	log(Nominal battery capacity) ***	0.18	$2.01 \times 10^{-2}$	9.17	$1.23 \times 10^{-18}$		

Table A1. Cont.

Energy Consumption	Coefficient	Value	Standard Error	t Value	Pr (>abs t)	p Value	Adjusted R <sup>2</sup>
Model 3f: $\log(\text{energy consumption}) = \alpha + \beta \times \log(\text{drive range})$							
log(Certified)	(Intercept) ***	3.85	0.20	19.56	$1.27 \times 10^{-63}$	$3.83 \times 10^{-6}$	0.05
	log(Certified drive range) ***	−0.15	$3.20 \times 10^{-2}$	−4.63	$3.83 \times 10^{-6}$		
log(Real-world)	(Intercept) ***	3.70	0.18	20.27	$6.07 \times 10^{-67}$	$1.46 \times 10^{-4}$	0.04
	log(Real-world drive range) ***	−0.12	$3.03 \times 10^{-2}$	−3.83	$1.46 \times 10^{-4}$		
Model 3g: $\log(\text{energy consumption}) = \alpha + \beta \times \log(\text{price})$							
log(Certified)	(Intercept) ***	0.79	0.18	4.29	$2.18 \times 10^{-5}$	$<2.2 \times 10^{-16}$	0.23
	log(Price) ***	0.19	$1.68 \times 10^{-2}$	11.55	$1.69 \times 10^{-27}$		
log(Real-world)	(Intercept) ***	1.22	0.19	6.28	$7.35 \times 10^{-10}$	$<2.2 \times 10^{-16}$	0.16
	log(Price) ***	0.16	$1.78 \times 10^{-2}$	9.18	$1.21 \times 10^{-18}$		
Model 4: $\log(\text{energy consumption}) = \alpha + \beta \times \log(\text{mass}) + \beta \times \log(\text{power}) + \beta \times \log(\text{frontal area}) + \beta \times \text{all-wheel drive}$							
log(Certified)	(Intercept)	$2.96 \times 10^{-2}$	0.38	$7.85 \times 10^{-2}$	0.94	$<2.2 \times 10^{-16}$	0.54
	log(Mass) ***	0.24	$6.51 \times 10^{-2}$	3.73	$2.10 \times 10^{-4}$		
	log(Power)	$1.29 \times 10^{-2}$	$2.37 \times 10^{-2}$	0.54	0.59		
	log(Frontal area) ***	1.03	$7.71 \times 10^{-2}$	13.41	$3.28 \times 10^{-35}$		
	All-wheel drive **	$3.99 \times 10^{-2}$	$1.90 \times 10^{-2}$	2.10	$3.59 \times 10^{-2}$		
log(Real-world)	(Intercept)	0.45	0.33	1.36	0.18	$<2.2 \times 10^{-16}$	0.63
	log(Mass) ***	0.24	$6.04 \times 10^{-2}$	4.04	$6.25 \times 10^{-5}$		
	log(Power) ***	$-5.49 \times 10^{-2}$	$1.96 \times 10^{-2}$	−2.80	$5.38 \times 10^{-3}$		
	log(Frontal area) ***	1.02	$6.93 \times 10^{-2}$	14.75	$5.21 \times 10^{-41}$		
	All-wheel drive ***	$7.19 \times 10^{-2}$	$1.48 \times 10^{-2}$	4.86	$1.59 \times 10^{-6}$		

**Table A2.** Complementary regression analyses; coefficients are significant at 1% level (\*\*\*) and 5% level (\*\*); certified energy consumption is based on TEL and TEH values; real-world energy consumption is based on mid-point values of data obtained from EVD [7] and mean values obtained from Spritmonitor [28].

	Coefficient	Value	Standard Error	t Value	Pr (>abs t)	p Value	Adjusted R <sup>2</sup>
Real-world vs. Certified energy consumption	Model 1g: real-world energy consumption = $\alpha + \beta \times$ certified energy consumption						
	(Intercept) ***	4.11	0.48	8.63	$1.44 \times 10^{-16}$	<2.2 $\times 10^{-16}$	0.75
	Certified energy consumption ***	0.88	$2.65 \times 10^{-2}$	33.14	$8.93 \times 10^{-118}$		
Usable vs. Nominal battery capacity	Model 1h: usable battery capacity = $\alpha + \beta \times$ nominal battery capacity						
	(Intercept)	$6.41 \times 10^{-2}$	0.41	0.16	0.88	<2.2 $\times 10^{-16}$	0.99
	Nominal battery capacity ***	0.93	$6.18 \times 10^{-3}$	150.85	$1.56 \times 10^{-313}$		
Mass vs. Nominal battery capacity	Model 1i: mass = $\alpha + \beta \times$ nominal battery capacity						
	(Intercept) ***	1015	34	29.83	$6.28 \times 10^{-97}$	<2.2 $\times 10^{-16}$	0.79
	Nominal battery capacity ***	14.25	0.41	34.41	$8.42 \times 10^{-113}$		
Mass vs. Frontal area	Model 1j: mass = $\alpha + \beta \times$ frontal area						
	(Intercept) ***	697	184	3.79	$1.79 \times 10^{-4}$	$1.44 \times 10^{-13}$	0.18
	Frontal area ***	460	60	7.71	$1.44 \times 10^{-13}$		
Power vs. Mass	Model 1k: power = $\alpha + \beta \times$ mass						
	(Intercept) ***	−315	29	−11.05	$1.90 \times 10^{-24}$	<2.2 $\times 10^{-16}$	0.43
	Mass ***	0.26	$1.52 \times 10^{-2}$	17.10	$9.77 \times 10^{-48}$		
Certified drive range vs. Nominal battery capacity	Model 1l: certified drive range = $\alpha + \beta \times$ nominal battery capacity						
	(Intercept) ***	102	12	8.86	$1.14 \times 10^{-17}$	<2.2 $\times 10^{-16}$	0.60
	Nominal battery capacity ***	4.35	0.16	27.13	$1.60 \times 10^{-103}$		
Real-world drive range vs. Usable battery capacity	Model 1m: real-world drive range = $\alpha + \beta \times$ usable battery capacity						
	(Intercept) ***	68	8	8.37	$6.10 \times 10^{-16}$	<2.2 $\times 10^{-16}$	0.71
	Usable battery capacity ***	4.56	0.12	36.99	$1.82 \times 10^{-144}$		
Price vs. Nominal battery capacity	Model 1n: price = $\alpha + \beta \times$ nominal battery capacity						
	(Intercept) ***	−21,119	3681	−5.74	$1.45 \times 10^{-8}$	<2.2 $\times 10^{-16}$	0.43
	Nominal battery capacity ***	1196	59	20.23	$1.57 \times 10^{-71}$		

Table A2. Cont.

	Coefficient	Value	Standard Error	<i>t</i> Value	Pr (>abs <i>t</i> )	<i>p</i> Value	Adjusted <i>R</i> <sup>2</sup>
Price vs. Certified drive range	<i>Model 1o: price = α + β × certified drive range</i>						
	(Intercept)	5105	4880	1.05	0.30	<2.2 × 10 <sup>−16</sup>	0.22
	Certified drive range ***	153	12	12.39	2.99 × 10 <sup>−31</sup>		
log(Real-world energy consumption) vs. log(Certified energy consumption)	<i>Model 3g: log(real-world energy consumption) = α + β × log(certified energy consumption)</i>						
	(Intercept) ***	0.70	6.22 × 10 <sup>−2</sup>	11.20	1.41 × 10 <sup>−25</sup>	<2.2 × 10 <sup>−16</sup>	0.73
	log(Certified energy consumption) ***	0.79	2.14 × 10 <sup>−2</sup>	37.03	1.47 × 10 <sup>−132</sup>		
log(Usable battery capacity) vs. log(Nominal battery capacity)	<i>Model 3h: log(usable battery capacity) = α + β × log(nominal battery capacity)</i>						
	(Intercept) ***	−0.12	2.54 × 10 <sup>−2</sup>	−4.55	7.65 × 10 <sup>−6</sup>	<2.2 × 10 <sup>−16</sup>	0.99
	log(Nominal battery capacity) ***	1.01	5.91 × 10 <sup>−3</sup>	170.98	0.00		
log(Mass) vs. log(Nominal battery capacity)	<i>Model 3i: log(mass) = α + β × log(nominal battery capacity)</i>						
	(Intercept) ***	5.51	6.95 × 10 <sup>−2</sup>	79.36	1.82 × 10 <sup>−221</sup>	<2.2 × 10 <sup>−16</sup>	0.80
	log(Nominal battery capacity) ***	0.50	1.58 × 10 <sup>−2</sup>	31.41	1.54 × 10 <sup>−102</sup>		
log(Mass) vs. log(Frontal area)	<i>Model 3j: log(mass) = α + β × log(frontal area)</i>						
	(Intercept) ***	6.76	0.11	60.32	1.14 × 10 <sup>−183</sup>	2.17 × 10 <sup>−14</sup>	0.22
	log(Frontal area) ***	0.79	9.89 × 10 <sup>−2</sup>	7.99	2.17 × 10 <sup>−14</sup>		
log(Power) vs. log(Mass)	<i>Model 3k: log(power) = α + β × log(mass)</i>						
	(Intercept) ***	−13.06	0.69	−18.97	3.01 × 10 <sup>−55</sup>	<2.2 × 10 <sup>−16</sup>	0.54
	log(Power) ***	2.40	9.13 × 10 <sup>−2</sup>	26.29	6.36 × 10 <sup>−84</sup>		
log(Certified drive range) vs. log(Nominal battery capacity)	<i>Model 3l: log(certified drive range) = α + β × log(nominal battery capacity)</i>						
	(Intercept) ***	2.75	9.91 × 10 <sup>−2</sup>	27.79	7.68 × 10 <sup>−107</sup>	<2.2 × 10 <sup>−16</sup>	0.63
	log(Nominal battery capacity) ***	0.76	2.29 × 10 <sup>−2</sup>	33.43	1.37 × 10 <sup>−134</sup>		
log(Real-world drive range) vs. log(Usable battery capacity)	<i>Model 3m: log(real-world drive range) = α + β × log(usable battery capacity)</i>						
	(Intercept) ***	2.57	8.30 × 10 <sup>−2</sup>	30.94	1.13 × 10 <sup>−117</sup>	<2.2 × 10 <sup>−16</sup>	0.73
	log(Usable battery capacity) ***	0.80	1.96 × 10 <sup>−2</sup>	40.66	9.56 × 10 <sup>−160</sup>		

Table A2. Cont.

	Coefficient	Value	Standard Error	t Value	Pr (>abs t)	p Value	Adjusted R <sup>2</sup>
	Model 3n: $\log(\text{price}) = \alpha + \beta \times \log(\text{nominal battery capacity})$						
log(Price) vs. log(Nominal battery capacity)	(Intercept) ***	6.51	0.17	38.80	$4.10 \times 10^{-174}$	<2.2 × 10 <sup>-16</sup>	0.59
	log(Nominal battery capacity) ***	1.06	$3.97 \times 10^{-2}$	26.66	$1.52 \times 10^{-107}$		
	Model 3o: $\log(\text{price}) = \alpha + \beta \times \log(\text{certified drive range})$						
log(Price) vs. log(Certified drive range)	(Intercept) ***	6.52	0.31	20.95	$5.66 \times 10^{-72}$	<2.2 × 10 <sup>-16</sup>	0.25
	log(Certified drive range) ***	0.75	$5.19 \times 10^{-2}$	14.54	$1.06 \times 10^{-40}$		

Table A3. Class sizes and value ranges for several alternative labeling schemes; based on 501 data points for certified energy consumption (TEL and TEH 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	18.1–20.5	20.6–23.0	23.1–25.5	25.6–28.1	$\geq 28.2$
	10% vehicles in A; B–G equal class size	2.55	<15.4	15.4–17.9	18.0–20.4	20.5–23.0	23.1–25.5	25.6–28.1	$\geq 28.2$
	5% in A; B–G equal class size	2.67	<14.7	14.7–17.3	17.4–19.9	20.0–22.6	22.7–25.3	25.4–28.0	$\geq 28.1$
	1% in A; B–G equal class size	2.78	<14.0	14.0–16.7	16.8–19.5	19.6–22.3	22.4–25.0	25.1–27.8	$\geq 27.9$
Certified energy consumption per 100 kWh nominal battery capacity [1/km]	Equal class size over the entire data range	8.34	<20.8	20.8–29.1	29.2–37.4	37.5–45.8	45.9–54.1	54.2–62.4	$\geq 62.5$
	10% vehicles in A; B–G equal class size	8.67	<18.8	18.8–27.4	27.5–36.1	36.2–44.8	44.9–53.4	53.5–62.1	$\geq 62.2$
	5% in A; B–G equal class size	8.95	<17.2	17.2–26.0	26.1–35.0	35.1–43.9	44.0–52.9	53.0–61.8	$\geq 61.9$
	1% in A; B–G equal class size	9.59	<13.3	13.3–22.8	22.9–32.4	32.5–42.0	42.1–51.6	51.7–61.2	$\geq 61.3$
Certified energy consumption per 100 km drive range [kWh/km <sup>2</sup> ]	Equal class size over the entire data range	1.56	<3.26	3.26–4.81	4.82–6.37	6.38–7.93	7.94–9.49	9.50–11.05	$\geq 11.06$
	10% vehicles in A; B–G equal class size	1.61	<2.96	2.96–4.56	4.57–6.17	6.18–7.78	7.79–9.39	9.40–11.00	$\geq 11.01$
	5% in A; B–G equal class size	1.66	<2.66	2.66–4.31	4.32–5.97	5.98–7.63	7.64–9.29	9.30–10.95	$\geq 10.96$
	1% in A; B–G equal class size	1.78	<1.94	1.94–3.71	3.72–5.49	5.50–7.27	7.28–9.05	9.06–10.83	$\geq 10.84$



## References

- EEA. New Registrations of Electric Vehicles in Europe. EEA–European Environmental Agency, 2023. Available online: <https://www.eea.europa.eu/en/analysis/indicators/new-registrations-of-electric-vehicles> (accessed on 1 February 2024).
- IEA. Executive Summary. Global EV Outlook 2023. IEA–International Energy Agency, 2023. Available online: <https://www.iea.org/reports/global-ev-outlook-2023/executive-summary> (accessed on 21 March 2024).
- ICCT. Electric Vehicles Market Monitor for Light-Duty Vehicles: China, Europe, United States, and India, 2022. 2023. Available online: [https://theicct.org/wp-content/uploads/2023/06/Major-Mkts\\_briefing\\_FINAL.pdf](https://theicct.org/wp-content/uploads/2023/06/Major-Mkts_briefing_FINAL.pdf) (accessed on 27 September 2023).
- ACEA. Vehicles on European Roads. ACEA–European Automobile Manufacturers Association, 2024. Available online: <https://www.acea.auto/files/ACEA-Report-Vehicles-on-European-roads-.pdf> (accessed on 27 April 2024).
- EC. Regulation (EU) 2023/851 of the European Parliament and of the Council of 19 April 2023 amending Regulation (EU) 2019/631 as regards strengthening the CO<sub>2</sub> emission performance standards for new passenger cars and new light commercial vehicles in line with the union’s increased climate ambition. EC–European Commission. *Off. J. Eur. Union* **2023**, L110, 5–20.
- EEA. Electric vehicles in Europe. Report No 20/2016. EEA–European Environmental Agency No 20/2016. 2016. Available online: <https://op.europa.eu/en/publication-detail/-/publication/1a4a941c-9a8d-11e6-9bca-01aa75ed71a1/language-en> (accessed on 28 April 2024). [CrossRef]
- EVD. Electric Vehicle Database. EV Database (9-Five-9 Ventures BV). 2023. Available online: <https://ev-database.org> (accessed on 5 August 2023).
- Weiss, M.; Zeffass, A.; Helmers, E. Fully electric and plug-in hybrid cars–An analysis of learning rates, user costs, and costs for mitigating CO<sub>2</sub> and air pollutant emissions. *J. Clean. Prod.* **2019**, *212*, 1478–1489. [CrossRef] [PubMed]
- Xu, J.; Cai, X.; Cai, S.; Shao, X.; Hu, C.; Lu, S.; Ding, S. High-energy lithium-ion batteries: Recent progress and a promising future in applications. *Energy Environ. Mater.* **2023**, *6*, 12450. [CrossRef]
- Helmers, E.; Marx, P. Electric cars: Technical characteristics and environmental impacts. *Environ. Sci. Eur.* **2012**, *24*, 14. [CrossRef]
- Yadlapalli, R.T.; Kotapati, A.; Kandipati, R.; Koritala, C.S. A review of energy efficient technologies for electric vehicle applications. *J. Energy Storage* **2022**, *50*, 104212. [CrossRef]
- EC. Directive 1999/94/EC of the European Parliament and of the Council of 13 December 1999 relating to the availability of consumer information on fuel economy and CO<sub>2</sub> emissions in respect of the marketing of new passenger cars. EU–European Commission. *Off. J. Eur. Union* **1999**, L012, 16.
- EC. Regulation (EC) No 715/2007 of the European Parliament and of the Council of 20 June 2007 on type approval of motor vehicles with respect to emissions from light passenger cars and commercial vehicles (Euro 5 and Euro 6). EC–European Commission. *Off. J. Eur. Union* **2007**, L171, 1–16. Available online: <https://eur-lex.europa.eu/eli/reg/2007/715/oj> (accessed on 8 January 2024).
- EC. Directive 2007/46/EC establishing a framework for the approval of motor vehicles and their trailers, and of systems, components and separate technical units intended for such vehicles. EC–European Commission. *Off. J. Eur. Union* **2007**, L263, 1–160.
- EC. Transition Pathway for a Green, Digital, and Resilient EU Mobility Industrial Ecosystem. News Article, 29 January 2024. EC–European Commission, Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs, 2024. Available online: [https://single-market-economy.ec.europa.eu/news/transition-pathway-green-digital-and-resilient-eu-mobility-industrial-ecosystem-2024-01-29\\_en](https://single-market-economy.ec.europa.eu/news/transition-pathway-green-digital-and-resilient-eu-mobility-industrial-ecosystem-2024-01-29_en) (accessed on 27 April 2024).
- EC. Sustainable and Smart Mobility Strategy–Putting European Transport on Track for the Future. Document SWD(2020) 331 Final. EC–European Commission, 2020. Available online: [https://eur-lex.europa.eu/resource.html?uri=cellar:5e601657-3b06-11eb-b27b-01aa75ed71a1.0001.02/DOC\\_1&format=PDF](https://eur-lex.europa.eu/resource.html?uri=cellar:5e601657-3b06-11eb-b27b-01aa75ed71a1.0001.02/DOC_1&format=PDF) (accessed on 28 April 2024).
- E-CUBE. 2030 peak power demand in North-West Europe. Report (Final version)–September 2020. E-CUBE Strategy Consultants and the Institute of Energy Economics at the University of Cologne gGmbH (EWI), 2020. Available online: <https://www.ewi.uni-koeln.de/cms/wp-content/uploads/2020/09/E-CUBE-EWI-2030-Peak-Power-Demand-in-North-West-Europe-vf3.pdf> (accessed on 28 April 2024).
- Prognos. Entwicklung des Bruttostromverbrauchs Bis 2030. Prognos AG Berlin, 2021. Available online: <https://www.prognos.com/de/projekt/entwicklung-des-bruttostromverbrauchs-bis-2030> (accessed on 28 April 2024).
- EC. Commission Regulation (EU) 2017/1151 supplementing Regulation (EC) No 715/2007 of the European Parliament and of the Council on type-approval of motor vehicles with respect to emissions from light passenger and commercial vehicles (Euro 5 and Euro 6) and on access to vehicle repair and maintenance information, amending Directive 2007/46/EC of the European Parliament and of the Council, Commission Regulation (EC) No 692/2008 and Commission Regulation (EU) No 1230/2012 and repealing Commission Regulation (EC) No 692/2008. EC–European Commission. *Off. J. Eur. Union* **2017**, L175, 1–839.
- EC. Directive (EU) 2023/1791 of the European Parliament and of the Council of 13 September 2023 on energy efficiency and amending Regulation (EU) 2023/955 (recast). EC–European Commission. *Off. J. Eur. Union* **2023**, L231, 1–111. Available online: [https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:JOL\\_2023\\_231\\_R\\_0001&qid=1695186598766](https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:JOL_2023_231_R_0001&qid=1695186598766) (accessed on 24 April 2024).
- EEC. Council Directive 92/75/EEC of 22 September 1992 on the indication by labelling and standard product information of the consumption of energy and other resources by household appliances. EEC–European Economic Community. *Off. J. Eur. Communities* **1992**, L297, 6–19.

22. EC. Regulation (EC) No 1222/2009 of the European Parliament and of the Council of 25 November 2009 on the labelling of tires with respect to fuel efficiency and other essential parameters. EU–European Commission. *Off. J. Eur. Union* **2009**, L342, 46.
23. EC. Commission Delegated Regulation (EU) 2015/1186 of 24 April 2015 supplementing Directive 2010/30/EU of the European Parliament and of the Council with regard to the energy labelling of local space heaters. EU–European Commission. *Off. J. Eur. Union* **2015**, L193, 20–42.
24. EC. Commission Delegated Regulation (EU) 2019/1369 of 11 March 2019 supplementing Regulation (EU) 2017/1369 of the European Parliament and of the Council with regard to energy labelling of electronic displays and repealing Commission Delegated Regulation (EU) No 1062/2010. EC–European Commission. *Off. J. Eur. Union* **2019**, L315, 1–28.
25. EC. Commission Delegated Regulation (EU) 2023/1669 of 16 June 2023 supplementing Regulation (EU) 2017/1369 of the European Parliament and of the Council with regard to the energy labelling of smartphones and slate tablets. EC–European Commission. *Off. J. Eur. Union* **2023**, L214, 9–49.
26. UNECE. Addendum 153–UN Regulation No. 154. 2021. Available online: <https://unece.org/sites/default/files/2021-08/R154e.pdf> (accessed on 5 June 2024).
27. BEV. BEV-Database. Eberhard Droege Consulting, 2023. Available online: <https://bev-database.de> (accessed on 5 August 2023).
28. Spritmonitor. *Verbrauchswerte Real Erfahren*; Fisch und Fischl GmbH: Thyrnau, Germany, 2023; Available online: <https://www.spritmonitor.de/> (accessed on 31 August 2023).
29. Bowling, B. Air Drag Coefficients and Frontal Area Calculation. 2010. Available online: <http://www.bgsoflex.com/airdragchart.html> (accessed on 30 May 2024).
30. Hucho, W.-H.; Sovran, G. Aerodynamics of road vehicles. *Annu. Rev. Fluid Mech.* **1993**, *25*, 485–537. [CrossRef]
31. Knittel, C. Automobiles on steroids. Product attribute trade-offs and technological progress in the automobile sector. *Am. Econ. Rev.* **2011**, *101*, 3368–3399. [CrossRef]
32. Tietge, U.; Mock, P.; Franco, V.; Zacharof, N. From laboratory to road: Modeling the divergence between official and real-world fuel consumption and CO<sub>2</sub> emission values in the German passenger car market for the years 2001–2014. *Energy Policy* **2017**, *103*, 212–222. [CrossRef]
33. Blair, G.; Cooper, J.; Coppock, A.; Humphreys, M.; Sonnet, L.; Fultz, N. *Package 'estimatr'*; R Foundation for Statistical Computing: Vienna, Austria, 2018; Available online: <https://cran.r-project.org/web/packages/estimatr/estimatr.pdf> (accessed on 23 April 2018).
34. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2024; Available online: <https://www.R-project.org/> (accessed on 25 January 2024).
35. Weiss, M.; Irrgang, L.; Kiefer, A.T.; Roth, J.R.; Helmers, E. Mass- and power-related efficiency trade-offs and CO<sub>2</sub> emissions of compact passenger cars. *J. Clean. Prod.* **2020**, *243*, 118326. [CrossRef]
36. Haq, G.; Weiss, M. CO<sub>2</sub> labelling of passenger cars in Europe: Status, challenges, and future prospects. *Energy Policy* **2016**, *95*, 324–335. [CrossRef]
37. She, Z.-Y.; Sun, Q.; Ma, J.-J.; Xie, B.-C. What are the barriers to widespread adoption of battery electric vehicles? A survey of public perception in Tianjin, China. *Transp. Policy* **2017**, *56*, 29–40. [CrossRef]
38. Pamidimukkala, A.; Kermanshachi, S.; Rosenberger, J.M.; Hladik, G. Barriers and motivators to the adoption of electric vehicles: A global review. *Green Energy Intell. Transp.* **2024**, *3*, 100153. [CrossRef]
39. Moro, A.; Lonza, L. Electricity carbon intensity in European Member States: Impacts on GHG emissions of electric vehicles. *Transp. Res. Part D Transp. Environ.* **2018**, *64*, 5–14. [CrossRef]
40. Skráčány, T.; Kendra, M.; Stopka, O.; Milojević, S.; Figlus, T.; Csiszár, C. Impact of the electric mobility implementation on the greenhouse gases production in Central European countries. *Sustainability* **2019**, *11*, 4948. [CrossRef]
41. Helmers, E.; Dietz, J.; Weiss, M. Sensitivity analysis in the life-cycle assessment of electric vs. combustion engine cars under approximate real-world conditions. *Sustainability* **2020**, *12*, 1241. [CrossRef]
42. Das, P.K.; Bhat, M.Y.; Sajith, S. Life cycle assessment of electric vehicles: A systematic review of literature. *Environ. Sci. Pollut. Res.* **2024**, *31*, 73–89. [CrossRef] [PubMed]
43. Zuur, A.F.; Ieno, E.N.; Walker, N.J.; Saveliev, A.A.; Smith, G.M. *Mixed Effects Models and Extensions in Ecology with R*; Springer: New York, NY, USA, 2009.
44. Madziel, M.; Campisi, T. Energy consumption of electric vehicles: Analysis of selected parameters based on created database. *Energies* **2023**, *16*, 1437. [CrossRef]
45. Galvin, R. Are electric vehicles getting too big and heavy? Modelling future vehicle journeying demand on a decarbonized US electricity grid. *Energy Policy* **2022**, *161*, 112746. [CrossRef]
46. Weiss, M.; Cloos, K.C.; Helmers, E. Energy efficiency trade-offs in small to large electric vehicles. *Environ. Sci. Eur.* **2020**, *32*, 46. [CrossRef]
47. Spritmonitor. *Sparsame Elektrofahrzeuge-E-Autos Mit Wenig Stromverbrauch*; Fisch und Fischl GmbH: Thyrnau, Germany, 2024; Available online: [https://www.spritmonitor.de/de/sparsame\\_elektrofahrzeuge.html](https://www.spritmonitor.de/de/sparsame_elektrofahrzeuge.html) (accessed on 18 April 2024).
48. Redelbach, M.; Klötzke, M.; Friedrich, H.E. Impact of Lightweight Design on Energy Consumption and Cost Effectiveness of Alternative Powertrain Concepts. In Proceedings of the European Electric Vehicle Congress, Brussels, Belgium, 19–22 November 2012.
49. Kozłowski, E.; Wiśniowski, P.; Gis, M.; Zimakowska-Laskowska, M.; Borucka, A. Vehicle acceleration and speed as factors determining energy consumption in electric vehicles. *Energies* **2024**, *17*, 4051. [CrossRef]

50. Komnos, D.; Tsiakmakis, S.; Pavlovic, J.; Ntziachristos, L.; Fontaras, G. Analysing the real-world fuel and energy consumption of conventional and electric cars in Europe. *Energy Convers. Manag.* **2022**, *270*, 116161. [\[CrossRef\]](#)
51. EC. Ecodesign and energy labelling working plan 2022–2024. EC–European Commission. *Off. J. Eur. Union* **2022**, *C 182*, 1–12.
52. EC. Regulation (EU) 2019/631 of 17 April 2019 setting CO<sub>2</sub> emission performance standards for new passenger cars and for new light commercial vehicles, and repealing Regulations (EC) No 443/2009 and (EU) No 510/2011. EC–European Commission. *Off. J. Eur. Union* **2019**, *L111*, 13.
53. Wikipedia. European Union Energy Label. 2024. Available online: [https://en.wikipedia.org/wiki/European\\_Union\\_energy\\_label](https://en.wikipedia.org/wiki/European_Union_energy_label) (accessed on 17 April 2024).
54. Lauvergne, R.; Perez, Y.; Françon, M.; De La Cruz, A.T. Integration of electric vehicles into transmission grids: A case study on generation adequacy in Europe in 2040. *Appl. Energy* **2022**, *326*, 120030. [\[CrossRef\]](#)
55. Garcia, B.B.; Ferraz, B.; Vidor, F.F.; Gazzana, D.S.; Ferraz, R.G. Chapter Eleven-Power Loss Analysis in Distribution Systems Considering the Massive Penetration of Electric Vehicles. In *Advanced Technologies in Electric Vehicles*; Gali, V., Canha, L.N., Resener, M., Ferraz, B., Varaprasad, M.V.G., Eds.; Academic Press: Cambridge, MA, USA, 2024; pp. 279–297, ISBN 9780443189999. [\[CrossRef\]](#)
56. Anastasiadis, A.G.; Kondylis, G.P.; Polyzakis, A.; Vokas, G. Effects of increased electric vehicles into a distribution network. *Energy Procedia* **2019**, *157*, 586–593. [\[CrossRef\]](#)
57. Gielen, D.; Lyons, M. Critical Materials for the Energy Transition: Rare Earth Elements. International Renewable Energy Agency, Abu Dhabi. Technical paper 2/2022. 2022. Available online: [https://www.irena.org/-/media/Irena/Files/Technical-papers/IRENA\\_Rare\\_Earth\\_Elements\\_2022.pdf?rev=6b1d592393f245f193b08eed6512abc](https://www.irena.org/-/media/Irena/Files/Technical-papers/IRENA_Rare_Earth_Elements_2022.pdf?rev=6b1d592393f245f193b08eed6512abc) (accessed on 14 June 2024).
58. STHDA. Linear Regression Assumption and Diagnostics in R: Essentials. STHDA–Statistical Tools for High-throughput Data Analysis. 2018. Available online: <http://www.sthda.com/english/articles/39-regression-model-diagnostics/161-linear-regression-assumptions-and-diagnostics-in-r-essentials/> (accessed on 1 February 2024).

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