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Added mass offset half of the efficiency gains in Europe's electric vehicles

Christopher Knittel

knittel@mit.edu

Massachusetts Institute of Technology https://orcid.org/0000-0002-7654-8641

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Added mass offset half of the efficiency gains in Europe's electric vehicles

Christopher R. Knittel[1,2,3,4]

[1]MIT Sloan School of Management, Cambridge, MA, USA
[2]MIT Center for Energy and Environmental Policy Research, Cambridge, MA, USA
[3]MIT Climate Policy Center, Cambridge, MA, USA
[4]National Bureau of Economic Research, Cambridge, MA, USA

Correspondence: knittel@mit.edu

Abstract

I estimate technological progress in battery-electric vehicles from every battery-electric vehicle registered in the European Union, Iceland, and Norway from 2019 to 2025. The trade-off between energy consumption and vehicle attributes takes the functional form implied by the physics of energy consumption, and the estimated mass and drag coefficients are close to the values implied by the test cycle. At fixed attributes, technological progress reduced consumption by 14.3 percent. Fleet-average consumption fell by only 7.5 percent, because the average new vehicle became 271 kilograms heavier. The added mass offset 53 percent of the technological progress, and the mass of larger batteries alone offset 29 percent. Range rose 45 percent, mainly because battery capacity became cheaper. The longer range likely raised electric vehicle sales enough to offset the emissions from the added electricity. Motor power, which carries a large energy cost in internal combustion vehicles, does not affect electric vehicle consumption.

The electrification of passenger transportation is central to most decarbonization pathways, and the energy consumption of electric vehicles per kilometer determines the electricity generation, the battery materials, and the charging infrastructure that a given level of electrified mobility requires[1,2]. Over the past six years, the attributes of new battery-electric vehicles sold in Europe have changed considerably (Fig. 1). The average new battery-electric vehicle registered in Europe in 2025 was 17 percent heavier than the average vehicle registered in 2019 and had a 33 percent larger battery. Its time from 0 to 100 km/h was a full second shorter. Over the same period, its rated energy consumption fell by 7 percent. These changes represent both movements along and shifts in the frontier that relates energy consumption to vehicle attributes. The policy implications of these changes depend on how much of each occurred.

In this paper, I estimate the technological progress that has occurred in battery-electric vehicles since 2019 and the trade-offs that manufacturers and consumers face between energy consumption,

mass, drag, power, and range. I use the European Environment Agency registry of new vehicles, which records the type-approval consumption of 7.9 million battery-electric passenger vehicles, including SUVs, registered from 2019 to 2025[3]. I merge it with variant-level battery capacities, list prices, and dimensions[4,5], and with drag coefficients that I collected for the variants that account for 95 percent of registrations. I then decompose the observed change in consumption into a shift of the frontier and a movement along it. The approach builds on Knittel[6], which found that the fuel economy of new vehicles in the United States rose only 15 percent between 1980 and 2006, while fuel economy at 1980 attributes would have risen by nearly 60 percent. The bulk of that progress went into weight and horsepower, and similar results hold for Sweden and Great Britain[7,8].

I make two changes to that framework. The first comes from a key difference between internal combustion and electric vehicles. Range is a choice variable for an electric vehicle, and, in contrast to internal combustion vehicles, its choice has real implications for efficiency, since the battery accounts for roughly a quarter of the vehicle's mass. The trade-offs are therefore a system of equations rather than a single equation. Electricity consumption depends on mass and drag. Mass depends on battery capacity and size. Range is battery capacity divided by consumption. The second change is to base the empirical model on physics. The energy balance of a vehicle on a fixed test cycle dictates the functional form of the frontier, predicts the magnitudes of the mass and drag coefficients, and identifies attributes that should not affect consumption.

I find that, holding attributes fixed, technological progress reduced consumption by 25 Wh/km, or 14.3 percent, between 2019 and 2025. In contrast, fleet-average consumption fell by only 13 Wh/km. This is due to changes in vehicle attributes. The average new vehicle was 271 kilograms heavier, and the estimates imply that the added mass increased consumption by 13 Wh/km, of which 7 Wh/km came from larger batteries. Mass therefore absorbed 53 percent of the technological progress, and the mass of larger batteries absorbed 29 percent. I also find that this absorption was concentrated between 2020 and 2022, and since 2022 nearly all of the technological progress has gone to lower consumption. I find no evidence that vehicles became lighter at a given battery capacity. Finally, I find that range rose 45 percent, and most of the increase came from cheaper batteries rather than from a more efficient drivetrain. The longer range likely raised electric vehicle sales. Estimates of the value of range imply that the larger batteries raised sales by about 12 percent, more than four times the 2.8 percent increase needed to offset the emissions from the

added electricity.

The physics of electric vehicle energy consumption

On a fixed test cycle, the electricity a vehicle draws from the charging point per kilometer is the sum of four terms, divided by the efficiencies of the charger and the drivetrain[9,10]. Rolling resistance is proportional to mass. The kinetic energy that is not recovered during braking is also proportional to mass. Aerodynamic drag is proportional to the drag area, which is the drag coefficient times the frontal area. Auxiliary loads are fixed per unit of time and therefore per kilometer at a given average speed:

$$E = \frac{1}{\eta_c \, \eta_d} \left[C_{rr} \, m \, g \; + \; \tfrac{1}{2} \rho \, C_d A \, \overline{v^2} \; + \; (1 - \eta_r) \, m \, \kappa \; + \; \frac{P_{aux}}{\bar{v}} \right], \tag{1}$$

where E is consumption in Wh/km, m is mass, C_{rr} is the tire rolling resistance coefficient, $C_d A$ is the drag area, η_r is the share of braking energy recovered through regeneration, P_{aux} is auxiliary power, and η_c and η_d are the charging and drivetrain efficiencies (Methods).

This energy balance has three implications for the empirical model. First, it dictates the functional form. Consumption in Wh/km is linear in mass and in drag area, and progress in the drivetrain and the charger scales the whole expression. I therefore estimate the frontier as Wh/km equal to a year-specific technology factor times a load function that is linear in mass, drag area, frontal area, length, and an indicator for all-wheel drive. A second motor and inverter lower the drivetrain efficiency, which is why all-wheel drive enters the load function. Frontal area and length absorb the error in the published drag coefficients (Methods).

Second, the energy balance predicts the size of two coefficients. On the WLTP test cycle, an additional kilogram should add 0.037 to 0.045 Wh/km with current tires and regenerative braking, and 0.054 Wh/km with older tires and weaker regeneration. An additional square meter of drag area should add 104 Wh/km (Extended Data Table 1).

Third, motor power, torque, and battery chemistry do not appear in the energy balance. An electric motor operates near its peak efficiency over most of its speed and torque map, so a 300 kW motor uses about the same energy on the test cycle as a 150 kW motor. These attributes should

therefore not affect consumption once mass, drag, and drive configuration are held fixed. This is the sharpest contrast with the internal combustion engine, whose efficiency falls as displacement rises relative to the energy demanded[6].

The estimates agree with the physics

Fig. 2 shows the estimated frontier in 2019 and 2025, Fig. 3 compares the estimates with the physics, and Extended Data Table 2 reports the full estimates. In the preferred specification, the drag-area coefficient is 113 Wh/km per square meter, which is not statistically different from the 104 implied by the test cycle. The mass coefficient is 0.057 Wh/km per kilogram. This is above the range for current tires, but it is not statistically different from its upper end, and it is close to the value of 0.054 for older tires and weaker regeneration. All-wheel drive adds 11 Wh/km, or about 7 percent, which is consistent with the spinning and inverter losses of a second motor.

The attributes that the physics excludes behave as predicted (Extended Data Table 3). The coefficients on motor power, torque, and lithium iron phosphate chemistry are not statistically different from zero. In every test, the 2025 year effect is within one log point of its value without the added attribute. In the internal combustion fleet, horsepower carried an elasticity of about -0.3 (ref.[6]). The average 0 to 100 km/h time of new electric vehicles fell by a second over the period, and the estimates imply that this improvement did not raise consumption.

Technological progress at fixed attributes

The technology factor in the preferred specification is 0.857. At fixed mass, drag, and drive configuration, a 2025 vehicle therefore uses 14.3 percent less energy per kilometer than a 2019 vehicle, or roughly 2 percent less per year. Conditioning on the vehicle's real list price, as in Knittel[6], lowers the 2019 to 2025 shift to 11.8 percent, so most of the progress is not a shift toward more expensive vehicles (Methods).

Where the technological progress went

Because the load function is linear, the change in fleet-average consumption separates exactly into a technology effect, evaluated at 2019 attributes, and an attribute effect, evaluated at 2025 technology (Methods). Fig. 4 reports the decomposition, and Extended Data Table 4 reports it for each specification. Fleet-average consumption in the decomposition sample fell from 175 to 161 Wh/km between 2019 and 2025. The technology factor applied to the 2019 fleet would have taken consumption to 149 Wh/km, a reduction of 25 Wh/km. The changes in attributes added 12 Wh/km back.

Mass added 13.3 Wh/km. I split the mass effect with a second frontier that relates mass to battery capacity, power, size, and drive configuration (Extended Data Table 5). Usable capacity rose from 54.2 to 70.7 kWh. At 8.9 kilograms of vehicle per usable kWh, these 16.5 kWh added 7.3 Wh/km. The shift in the mass frontier added 2.6 Wh/km, and the mass that came with higher power and larger bodies added 3.5 Wh/km. The drag area rose as the fleet moved toward SUVs, but the larger frontal area and length that came with it offset the increase, and the three terms together reduced consumption by 1.1 Wh/km. Mass therefore absorbed 53 percent of the technological progress, the mass of larger batteries 29 percent, and all attributes together 47 percent.

These shares are ratios of estimated quantities. I compute their standard errors with a cluster bootstrap by make-model that re-estimates all three frontiers in each draw (Methods and Extended Data Table 6). The standard error is 13 percentage points for the share absorbed by mass, 8 for the mass of larger batteries, and 10 for all attributes. Most of this uncertainty comes from the technology effect in the denominator, whose standard error is 3.2 Wh/km. The share absorbed by attributes is positive in every draw.

Nearly all of the added mass came from changes in which models were sold (Extended Data Fig. 1). Across all WLTP registrations, fleet-average mass rose by 280 kilograms between 2019 and 2025, and only 11 kilograms of the increase occurred within continuing models.

The mass frontier shows no evidence that vehicles became lighter at a given battery capacity. Each additional usable kWh adds 8.9 kilograms of vehicle at a given power, size, and drive configuration. This implies an effective energy density of about 110 Wh per kilogram for the marginal pack and the structure that carries it. The year-specific coefficient is 9.6 kilograms per kWh in

2019 and 8.6 in 2025, and the decline is not statistically significant (Extended Data Fig. 2). A 2025 vehicle of given battery capacity, power, size, and drive configuration is 53 kilograms heavier than a 2019 vehicle, a difference that is statistically significant only at the 10 percent level. Cell-level gravimetric energy density improved over this period[11,12], but the improvement has not reduced vehicle mass. This is consistent with the shift of the volume segment toward lithium iron phosphate cells, which are heavier per kWh.

When the progress was absorbed

The absorption through more mass was concentrated in two years (Fig. 4c and Supplementary Table 1). In the decomposition sample, the average new vehicle gained 188 kilograms and 9.0 kWh of usable capacity between 2020 and 2022. These changes increased consumption by 10.2 Wh/km. Technology reduced consumption by 8.5 Wh/km over the same two years, so fleet-average consumption rose.

After 2022, attributes absorbed almost none of the progress. Between 2022 and 2024, technology lowered consumption at fixed attributes by 7.4 Wh/km. The average vehicle still gained 65 kilograms, which added 3.3 Wh/km, but lower drag and changes in body size and drive configuration reduced consumption by 3.2 Wh/km. Fleet-average consumption fell by 6.9 Wh/km over the two years, nearly the full technology effect. The share absorbed therefore depends on the base year. From 2019 to 2020, technology lowered consumption by 6 Wh/km, and attributes changed little. Measured from 2020, attributes absorbed 56 percent of the progress (Supplementary Table 2). The technology effect from 2020 is smaller, so this share is less precisely estimated. Three years is a short window, however, and the data cannot yet say whether the absorption has stopped or paused.

Where the added range came from

Mean log range, computed as usable capacity divided by consumption, rose by 38 log points between 2019 and 2025, or about 45 percent. Because the efficiency frontier is linear in mass, log range is a nonlinear function of the attributes. I therefore apply the changes one at a time to every vehicle registered in 2019 (Methods and Extended Data Table 7). Larger batteries account for 25 log points, net of the efficiency lost to their mass, with a bootstrap standard error of 1.1. The

shift in the efficiency frontier accounts for 15 log points, with a standard error of 1.8. The battery component is larger than the efficiency component in every one of the 999 bootstrap draws. The mass frontier, the other attributes, and the residuals together reduced mean log range by 3 log points (Fig. 5a). Had battery capacity stayed at its 2019 level, range would have risen by 15 log points, or 16 percent.

For the battery component to represent technological progress, the larger batteries must come from cheaper capacity rather than from higher spending. I test this with a third frontier that relates log usable capacity to power, size, and the log of the real list price (Extended Data Table 8). Between 2019 and 2025, usable kWh per euro rose 27 percent at given power and size, and the change is statistically significant at the 1 percent level. The timing broadly follows the BloombergNEF pack-price series, including the large changes between 2019 and 2020 and in 2024 (Fig. 5b). The increase is smaller than the 45 to 81 percent that the pack-price decline would imply if every saving went to capacity[13,14]. Part of the saving went to lower vehicle prices, which fell 6 percent in real terms on this sample. European pack prices were also well above the global average[14]. In the system conditional on price, the shift of the battery frontier accounts for 22 log points of the increase in range, with a standard error of 4.4. The shift of the efficiency frontier accounts for 13, with a standard error of 2.3. The increase in range therefore came from technological progress, and mainly from progress in battery cost rather than in drivetrain efficiency.

Electricity and battery materials

The 2025 cohort of 1.9 million battery-electric vehicles carried about 31 GWh more battery capacity than it would have at the 2019 mean. Its attributes raise its consumption by 12 Wh/km at 2025 technology, and its added mass alone by 13 Wh/km. At 15,000 km per vehicle per year, these figures imply 0.3 to 0.4 TWh of additional electricity each year the cohort is on the road. Summed over the cohorts since 2019, the additional draw is about 1.13 TWh per year. At the EU average carbon intensity of electricity generation in 2024, 213 grams of CO_2 per kWh[15], the added consumption of the 2025 cohort emits 71,000 to 81,000 tonnes of CO_2 a year. Per kilometer, the 12 Wh/km of added consumption is 2.5 grams of CO_2, about 2.7 percent of the 93.6 g/km fleet-average target that applies to new vehicles from 2025. This capacity contains about 3,100 tonnes of lithium and

14,000 to 19,000 tonnes of nickel (Methods).

Discussion

Technological progress in electric vehicles has proceeded at about the same rate as in internal combustion vehicles, roughly 2 percent per year. The share of that progress absorbed by other attributes is smaller for electric vehicles, 47 percent measured from 2019 and 56 percent from 2020, against roughly two-thirds for internal combustion vehicles over a much longer period[6,7]. The attributes doing the absorbing are also different. In the internal combustion fleet, weight and horsepower each absorbed a substantial share. In the electric fleet, power has no energy cost, and the added mass came mainly from larger batteries.

The flat efficiency map of an electric motor removes the power trade-off that drove much of the internal combustion result. The battery introduces a trade-off that the internal combustion vehicle did not have, since a larger fuel tank weighs a few kilograms and a larger battery weighs hundreds. This is in stark contrast to internal combustion vehicles and has important policy implications. Leard et al.[16] find that the performance manufacturers forgo when fuel economy standards tighten is worth roughly as much to buyers as the fuel they save. That cost arises because performance and fuel economy compete for the same engine technology. For electric vehicles, they do not compete, so an efficiency requirement would not carry a performance cost. However, current European policies do not incentivize reduction in electricity consumption among electric vehicles. Under the European Union's CO_2 standards for new passenger cars, a battery-electric vehicle counts as a zero-emission vehicle whatever its consumption, so the standards give manufacturers no reason to trade range or mass for efficiency.

It is important to note that the shift toward heavier vehicles with longer range does not necessarily increase emissions from the transportation sector. Buyers place a high value on range, and limited range has been one of the main barriers to the adoption of electric vehicles[17,18]. The longer range therefore likely raised sales of electric vehicles. Each internal combustion vehicle that an electric vehicle replaces saves about 90 grams of CO_2 per kilometer, while the change in attributes added 2.5 grams per kilometer to the average electric vehicle. The added range therefore offsets the emissions from its added electricity if it raised electric vehicle sales by about 2.8 percent, or about

52,000 vehicles in the 2025 cohort. Estimates of the value of range from Norwegian vehicle sales[19] imply that the larger batteries raised the value of the average 2025 electric vehicle by about 7,000 euros and raised electric vehicle sales by about 12 percent, more than four times the break-even increase (Methods). On these estimates, the demand effect of the added range more than offsets the lost efficiency.

The estimates use type-approval consumption on the WLTP cycle, and the gap between type-approval and real-world ratings has grown for conventional vehicles in Europe[20]. EV Database reports a real-world consumption figure for variants that account for 44 percent of the decomposition sample. On these registrations, the technology effect is 22 Wh/km with the WLTP rating and 24 Wh/km with the real-world figure, and mass accounts for 40 and 45 percent of the progress (Supplementary Table 6). The real-world figure is modeled by EV Database rather than measured, however. Agreement with the physics is a useful specification check, but it cannot rule out all omitted vehicle characteristics. If the frontier omitted an important determinant of consumption, the year effects could reflect changes in that omitted factor rather than technological progress. In that case, the coefficients on mass and drag area would be unlikely to match their physical values.

Methods

Vehicle registrations

The core data are from the European Environment Agency's vehicle-level registry of new passenger cars, collected under Regulation (EU) 2019/631 and its predecessor for the calculation of manufacturers' fleet-average CO_2 emissions[3]. Member states report every new registration with the vehicle's make, commercial name, manufacturer, type-approval identifiers, mass in running order, wheelbase, track width, fuel type, power, electric energy consumption in Wh/km, and, from 2020, electric range. The data cover the 27 member states plus Iceland and Norway, and the United Kingdom through 2019. I use the final data for each year through 2024 and the provisional data for 2025.

I retain registrations with fuel type electric and vehicle category M1. Category M1 covers vehicles designed to carry passengers, including SUVs and passenger vans, and excludes light commercial vehicles. I then aggregate records with identical make, commercial name, manufacturer,

mass, test mass, power, consumption, range, wheelbase, and track within a year, and I weight each cell by its number of registrations. I screen out implausible values (mass outside 800 to 3,500 kg, consumption outside 80 to 450 Wh/km, power outside 20 to 800 kW, and range outside 60 to 900 km). I also drop cells whose consumption differs by more than a factor of 1.5 from the registration-weighted median of the same make-model and test cycle, and, after matching to EV Database variants, from the median of the same matched variant. The second screen catches cells filed under a different commercial name. Together the two screens drop about 34,000 registrations, 27,000 of them in 2025, the most recent and still provisional year of the registry, where some cells of common models report consumption about 2.5 times that of every other cell of the same vehicle. After these screens, 8.4 million battery-electric registrations from 2010 to 2025 remain, of which 7.9 million were rated on the WLTP cycle from 2019 to 2025. Consumption was measured on the New European Driving Cycle through 2017 and on the Worldwide Harmonized Light Vehicles Test Procedure (WLTP) from 2019, with 2018 mixing the two. The two cycles are not comparable, so I estimate on the WLTP data for 2019 to 2025. Member states reported power inconsistently, and over the period many changed from reporting the 30-minute rated power to peak power. Wherever power enters the estimation, I measure it as the peak power reported in the specification data. I use the registry's figure only for the 18 percent of registrations for which the specification data do not report it.

Variant specifications, prices, and matching

The registry does not record battery capacity, acceleration, dimensions other than wheelbase and track, battery chemistry, or price. EV Database[4] lists 1,549 battery-electric variants sold in Europe, with usable battery capacity, EU unladen weight, 0 to 100 km/h acceleration time, list price in euros, market segment, and the dates the variant was available to order. The open-ev-data project[5] provides 1,189 variant records for model years 2023 to 2025 with dimensions, power, torque, battery capacity, and chemistry. Where the two sources report dimensions for the same model, they agree to the millimeter.

I match each registry cell to an EV Database variant within make by model name and by proximity in mass and implied usable capacity. A match requires mass within 8 percent and capacity within 18 percent, among variants on sale in that calendar year or the adjacent years.

Implied capacity is the registry's range times its consumption, scaled by 0.85 to account for the charging losses included in the consumption figure. The scaling matters only for matching, since the capacity used in estimation is the EV Database figure. Because the implied capacity is built from range and consumption, I also repeat the matching with mass alone and with mass and power (Supplementary Table 8). The match covers 98.7 percent of registrations from 2019 to 2025 and at least 96 percent in every year. In the large majority of cells, the EV Database weight equals the registry mass exactly. The price is the list price of the matched variant. EV Database keeps a single list price for each variant: the current price for a variant still on sale and the last list price for a discontinued one. I deflate each price to 2019 euros with the euro-area harmonized index of consumer prices of the year to which the price refers. A variant registered in several years therefore has the same real price in each of them, and the change in mean real prices over time comes from the change in which variants were sold.

Drag coefficients, drive configuration, and dimensions

Neither the registry nor the specification sources record the drag coefficient. I collected the drag coefficient, the drive configuration, the heat pump fitment, and the cathode chemistry for the 388 variants that account for 95 percent of registrations from 2019 to 2025. The sources are manufacturer press kits and technical specifications, the ADAC catalog, and the automotive press. For the drag coefficient, I give priority to the manufacturer's own press releases and technical data sheets, then to the ADAC catalog, and then to press reports that attribute the figure to the manufacturer. Renault publishes only the drag area of the Renault 5 E-Tech, 0.746 square meters, so I use the drag coefficient of 0.32 reported in a published road test[21], which is consistent with that drag area. A sourcing audit re-collected the drag coefficients of 62 variants, covering 15 percent of registrations, from documents that state the value. Eight of the 62 values changed, by at most 0.04. The drive configuration is used as an indicator for all-wheel drive. Where a collected value is missing, I use the EV Database value. Where both values are available, they agree on the chemistry for 97 percent of variants and on the drive configuration for all of them. The drag area is the drag coefficient times the frontal area, measured as width times height. The registration-weighted mean drag coefficient is 0.27, and the mean drag area is 0.78 square meters. The registrations without a published drag coefficient are concentrated in a few inexpensive models, such as the Dacia Spring

and the Fiat 500e. The preferred sample contains the 6.7 million registrations with a drag coefficient, a drive configuration, and a heat pump status.

The two specification sources report dimensions for 85 percent of registrations. I extended the coverage in two steps. First, I collected length, width, and height from manufacturer specifications and the ADAC catalog for 48 further make-models, which account for 10 percent of registrations. Second, I assigned the within-make-model median to the remaining variants of models with at least one measured variant, which account for 5 percent. Together, the sources cover 99.8 percent of registrations. Supplementary Table 3 reports registration-weighted means by year.

The energy balance and its calibration

Equation (1) writes the energy balance of a vehicle on a fixed test cycle[9] in the cycle-averaged form of Sovran and Bohn[10], with the regenerative braking term of Sovran and Blaser[22]. In it, m is mass, C_{rr} is the tire rolling resistance coefficient, g is gravitational acceleration, ρ is air density, C_d is the drag coefficient, A is frontal area, $\overline{v^2}$ is the distance-weighted mean of squared speed over the cycle, κ is the cycle's positive kinetic energy per unit mass and distance, η_r is the share of braking energy recovered through regeneration, P_{aux} is auxiliary power, $\bar{v}$ is average speed, and η_d and η_c are the drivetrain and charging efficiencies. The registry's consumption figure is measured at the charging point after the vehicle has been recharged, so it includes η_c, and the energy recovered during the cycle's decelerations is netted out through η_r.

The inputs to the calibration are of two kinds (Extended Data Table 1). The first is the test cycle. The WLTC class 3b speed trace is a second-by-second speed profile of 1,800 seconds and 23.27 km, fixed by UN Global Technical Regulation No. 15. From it, I compute the mean speed of 46.5 km/h, the distance-weighted mean of squared speed of 515 $\mathrm{m^2/s^2}$, and the positive kinetic energy per unit mass and distance of 0.154 $\mathrm{m/s^2}$. The second kind is a set of engineering parameters, each within a narrow published range. Air density at the test temperature is 1.2 $\mathrm{kg/m^3}$. The tire rolling resistance coefficient is 0.008 to 0.009, the B and C classes of the EU tire label. Regeneration recovers 70 to 80 percent of braking energy. The cycle-average drivetrain efficiency is 0.90, and the charging efficiency is 0.92.

The computation has three steps. The first step computes the energy that each term requires at the wheels per unit of distance. The second converts that energy into Wh/km. The third divides

by the efficiencies of the drivetrain and the charger.

Consider first the drag term. Aerodynamic drag is a force equal to $\frac{1}{2}\rho C_d A\, v^2$, and the energy needed to push a vehicle through a meter of air is equal to that force. Averaging over the test cycle therefore requires the mean of v^2 weighted by distance, which is 515 $\mathrm{m}^2/\mathrm{s}^2$. With an air density of 1.2 kg/m^3, each square meter of drag area requires $0.5 \times 1.2 \times 515 = 309$ joules per meter. One joule per meter is 1/3.6 Wh/km, so the requirement is 86 Wh/km per square meter at the wheels. Dividing by $0.90 \times 0.92 = 0.828$ gives 104 Wh/km per square meter at the charging point.

The mass term has two parts. The first is rolling resistance. The tires resist rolling with a force equal to C_{rr} times the vehicle's weight, so each kilogram requires $C_{rr} g$ joules per meter. With a rolling resistance coefficient of 0.008 to 0.009, this is 0.022 to 0.025 Wh/km per kilogram at the wheels. The second part is the kinetic energy lost in braking. The WLTP cycle requires 0.154 joules of kinetic energy per meter for each kilogram. Only the share that regeneration does not recover, $1 - \eta_r$, is lost. With regeneration recovering 70 to 80 percent, the loss is 0.009 to 0.013 Wh/km per kilogram at the wheels. Adding the two parts and dividing by 0.828 gives a mass term of 0.037 to 0.045 Wh/km per kilogram at the charging point. With a rolling resistance coefficient of 0.010 and regeneration of 60 percent, the mass term is 0.054 Wh/km per kilogram.

The efficiency frontier

The efficiency frontier is

$$E_{it} = e^{a_t} \left(b_0 + b_m\, m_{it} + b_{C_dA}\, C_d A_{it} + b_A\, A_{it} + b_L\, L_{it} + b_{AWD}\, AWD_{it} \right) + \varepsilon_{it}, \tag{2}$$

where E_{it} is consumption in Wh/km of specification i registered in year t, m is mass in running order, C_dA is the drag area, A is frontal area, L is length, and AWD is one for all-wheel drive. I refer to the bracketed term as the load function. The year effects a_t enter as Hicks-neutral technical change. They scale the whole load function, which is what progress in η_d and η_c does in equation (1).

Frontal area and length enter the load function because the drag area is measured with error. Manufacturers usually publish the drag coefficient of the most aerodynamic wheel and trim combination of a model. In addition, width times height overstates the projected frontal area by a factor

that is larger for long, rounded bodies than for short, boxy ones. My measure of C_dA therefore differs from the true drag area by an amount that is correlated with the size of the body. Consistent with this, both size terms enter negatively in the preferred specification. All-wheel drive in the European fleet is equivalent to a second motor, apart from a few thousand three- and four-motor registrations.

I estimate equation (2) by weighted nonlinear least squares with registrations as weights. Extended Data Table 2 reports six specifications. Column (1) uses frontal area and length without the drag coefficient on all 7.9 million WLTP registrations with dimensions. Column (2) repeats it on the 6.7 million registrations of the preferred sample. Column (3) adds the drag area alone, column (4) adds all-wheel drive, and column (5), the preferred specification, adds frontal area and length. Column (6) adds the log of real price to the technology factor. To test the exclusions implied by the physics, I add power, torque, and an indicator for lithium iron phosphate chemistry to the preferred load function one at a time (Extended Data Table 3). For comparison with Knittel[6], I also estimate the log-linear specification of that paper, in which log km per kWh depends on log mass, log power, log frontal area, log length, and year effects (Supplementary Note 3). The log-linear frontier shifts by 13 to 14 log points between 2019 and 2025, close to the 15 log points of the physics form.

The mass frontier

The mass frontier is

$$m_{it} = c_t + \kappa\, K_{it} + \gamma_p\, p_{it} + \gamma_A\, A_{it} + \gamma_L\, L_{it} + \gamma_{AWD}\, AWD_{it} + u_{it}, \tag{3}$$

where K is usable battery capacity, p is power, and κ is kilograms of vehicle per usable kWh. A battery pack's mass is its capacity divided by its gravimetric energy density, and the rest of the vehicle scales with size and with the number of motors. The coefficient κ is therefore the inverse of an effective pack-level energy density that includes the structure that carries the pack. The year effects c_t measure how much lighter or heavier a vehicle of given battery capacity, power, size, and drive configuration has become, in kilograms. The mass frontier conditions on frontal area and length rather than on the drag area, because the body's mass scales with its size. I estimate it by

weighted least squares, and I also estimate a version with κ specific to each year (Extended Data Fig. 2).

Range connects the two frontiers. Range in kilometers is usable capacity divided by consumption:

$$R = \frac{1000\,K}{E}. \tag{4}$$

Because E is measured at the charging point, this R is the range the vehicle would have if no energy were lost in charging, and the WLTP range in the registry is about 15 percent above it.

The battery frontier

A fleet can carry larger batteries because battery capacity became cheaper, because buyers spent more on batteries, or because models with larger batteries gained sales. The efficiency and mass frontiers cannot distinguish these, because neither contains the price of the vehicle. I therefore add a third frontier:

$$\ln K_{it} = d_t + \delta_p \ln p_{it} + \delta_s' \ln s_{it} + \delta_P \ln P_{it} + \nu_{it}, \tag{5}$$

where s denotes the frontal area and length, and P is the real list price. Holding power, size, and price fixed, $e^{d_{2025}-d_{2019}}$ is the ratio of usable kWh per euro in 2025 to that in 2019. Because each variant has a single price in these data, the shift is identified by the prices and capacities of the variants sold in each year, that is, by entry, exit, and the changing mix of variants, and not by changes in the price of a variant while it was on sale. The year effects can be compared with pack prices through a simple benchmark. Suppose a manufacturer spends a fixed amount B on the battery, so that $K = B/c_b$, where c_b is the pack price per kWh. If the pack price falls and the manufacturer keeps the vehicle price and the battery budget fixed, then

$$\Delta \ln(K/P) = -\Delta \ln c_b. \tag{6}$$

The estimated shift is below this benchmark if part of the pack-price decline went to a lower vehicle price, and it is above it if manufacturers raised the battery budget. BloombergNEF reports a nominal decline in global average pack prices of 31 percent and a real decline of about 45 percent between 2019 and 2025 (refs.[13,14]). The benchmark therefore implies an increase in kWh per euro

of 45 to 81 percent.

Decomposition of consumption

Because the load function in equation (2) is linear in attributes, the registration-weighted mean of predicted consumption in year t is e^{a_t} times the load function evaluated at that year's mean attributes. The change in fleet-average consumption between years t_0 and t_1 therefore separates exactly into two parts:

$$\begin{aligned}\Delta\overline{E} = &\underbrace{\left(e^{a_{t_1}} - e^{a_{t_0}}\right)\left(b_0 + b_m\overline{m}_{t_0} + b_{C_dA}\overline{C_dA}_{t_0} + b_A\overline{A}_{t_0} + b_L\overline{L}_{t_0} + b_{AWD}\overline{AWD}_{t_0}\right)}_{\text{technology, at } t_0 \text{ attributes}} \\ &+ \underbrace{e^{a_{t_1}}\left(b_m\Delta\overline{m} + b_{C_dA}\Delta\overline{C_dA} + b_A\Delta\overline{A} + b_L\Delta\overline{L} + b_{AWD}\Delta\overline{AWD}\right)}_{\text{attributes, at } t_1 \text{ technology}}.\end{aligned} \tag{7}$$

The first term is what consumption would have done had the fleet's attributes stayed at their t_0 values. The second is what the change in each attribute costs at t_1 technology. I split the mass term with the mass frontier into three parts. The first is κ times the change in mean battery capacity, which is the mass of larger batteries. The second is the shift in the mass frontier intercept. The third is the mass that came with changes in power, size, and drive configuration, together with the residual. The decomposition sample is the preferred sample with usable capacity and power, 6.7 million registrations.

The chained decomposition in Extended Data Fig. 1 borrows from price index methods. For each pair of adjacent years, I take the models sold in both, which cover 71 to 90 percent of the later year's registrations. I split the change in the fleet mean into the change within continuing models at the earlier year's shares, the reallocation of sales among continuing models at the later year's means, and the remainder, which is entry and exit. I then sum the links from 2019 to 2025.

Decomposition of range

The physics form does not allow an additive decomposition of range, because log range is a nonlinear function of the attributes when the efficiency frontier is linear in mass. I therefore start with observed vehicles and compute the components one step at a time. I start with every specification registered in 2019, weighted by its registrations. For each one, I compute log range from the system:

its battery capacity, its mass, the consumption that the efficiency frontier implies for that mass and its other attributes, and range from equation (4). The registration-weighted average is the starting value of mean log range. I then change one thing at a time and recompute.

First, I raise every vehicle's battery capacity by the change in mean log capacity. Each added kWh raises the vehicle's mass by κ kilograms. Each added kilogram raises its consumption by $e^{a_t} b_m$ Wh/km. Range therefore rises by less than capacity. Second, I replace the 2019 technology factor with the 2025 factor. Third, I replace the 2019 intercept of the mass frontier with the 2025 intercept, so that every vehicle gets heavier or lighter by the amount the mass frontier shifted. Fourth, I move the drag area, frontal area, length, and the share of all-wheel drive to their 2025 means, one at a time. These steps do not take the 2019 fleet all the way to the 2025 fleet, because power and size also enter mass directly and each frontier has a residual. I report the gap as a separate row. The sum of all the steps after the first is the change in range that would have occurred had battery capacity stayed at its 2019 level. The share of a proportional increase in capacity that reaches range after the mass penalty is

$$\frac{d \ln R}{d \ln K} = 1 - \frac{e^{a_t} \, b_m \, \kappa \, K}{E}, \tag{8}$$

which is 0.84 at the 2019 means.

In the system conditional on price, I split the first step with the battery frontier. The change in mean log capacity has four parts. The first is the shift in d_t, which is the capacity from cheaper batteries at a given price. The second is δ_p times the change in mean log power, which is the capacity bundled with higher power. The third is δ_P times the change in mean log real price, which is the capacity gained or given up with the change in real spending. The fourth is the size terms and the residual. I apply each piece to the 2019 fleet in turn, with the same mass and consumption penalties.

Holding cost constant

Knittel[6] conditioned on the vehicle's real price, which proxies for the quantity of technology and materials embodied in the vehicle, so that the year effects measure the shift in an iso-cost frontier. I add $\theta \ln P_{it}$ to the technology factor in equation (2) and $\gamma_P \ln P_{it}$ to equation (3). Conditional

on price, a_t, c_t, and d_t measure the shifts in the three frontiers at constant cost. Adding price moves the technology factor from 0.857 to 0.882. It also moves the mass coefficient of the efficiency frontier from 0.057 to 0.040 Wh/km per kilogram and the kilograms per kWh of the mass frontier from 8.9 to 5.6. The second figure is barely above the mass of the cells alone, about 5 kilograms per usable kWh, before the pack enclosure, the cooling, and the structure that carries them. I read both declines as the result of collinearity between price and the battery, and I use the unconditional coefficients in the decompositions of consumption. I use the price-conditioned system to separate the sources of the increase in battery capacity.

Electricity, emissions, and battery materials

The added electricity follows from the decomposition of equation (7) in five steps. First, for each registration year t from 2019 to 2025, I compute the registration-weighted means of mass, drag area, frontal area, length, the all-wheel-drive indicator, and usable battery capacity on the decomposition sample. Second, for each cohort t from 2020 to 2025, the added consumption per vehicle is the attribute term of equation (7) between 2019 and t, evaluated at the technology of year t:

$$\Delta E_t = e^{a_t} \left(b_m \Delta \overline{m}_t + b_{C_d A} \Delta \overline{C_d A}_t + b_A \Delta \overline{A}_t + b_L \Delta \overline{L}_t + b_{AWD} \Delta \overline{AWD}_t \right), \tag{9}$$

where Δ is the change in the mean from 2019 to year t. This gives 1.1, 5.2, 11.2, 10.8, 10.8, and 11.8 Wh/km for the 2020 to 2025 cohorts. The mass term alone gives -0.2, 3.0, 9.7, 11.1, 12.6, and 13.3 Wh/km, and the two give the range reported for the 2025 cohort. Third, the added electricity of cohort t in a year on the road is $N_t \times 15{,}000 \times \Delta E_t$, where N_t is the number of battery-electric registrations in year t and 15,000 km is the annual distance per vehicle. This applies the per-vehicle effect estimated on the decomposition sample to all registrations of the year. It gives 0.010, 0.071, 0.207, 0.259, 0.249, and 0.335 TWh a year for the 2020 to 2025 cohorts. Fourth, the total across cohorts is the sum of these figures, 1.13 TWh a year. The sum assumes that every vehicle registered since 2020 is still on the road and is driven the same distance, which is reasonable for vehicles at most six years old. Fifth, the added battery capacity of cohort t is N_t times the change in mean usable capacity from 2019 to t: 0.5, 3.2, 11.9, 18.3, 21.6, and 31.3 GWh, for a total of 87 GWh.

The CO_2 figures multiply the added electricity by the EU average carbon intensity of electricity

generation in 2024, 213 grams per kWh[15]. The carbon intensity of EU electricity has been falling, by 11 percent between 2023 and 2024 alone[23], so the vehicles will be charged on a cleaner grid in later years than in their first. The 93.6 g/km target is the fleet-average CO_2 target for new vehicles from 2025 under Regulation (EU) 2019/631.

The break-even increase in electric vehicle sales compares two emission rates per kilometer. First, in 2024, new vehicles in the EU, Iceland, and Norway averaged 106.8 grams of CO_2 per kilometer on the WLTP cycle, and battery-electric vehicles, which count as zero, were 14.5 percent of registrations[24]. The other new vehicles therefore averaged $106.8/0.855 = 125$ g/km. Second, a 2025 battery-electric vehicle at the decomposition-sample mean of 161 Wh/km emits 34 g/km at 213 grams per kWh. An electric vehicle that replaces an internal combustion vehicle therefore saves about 90 g/km. The change in attributes added 12 Wh/km, or 2.5 g/km, to the average 2025 electric vehicle. These added emissions are offset if electric vehicle sales rise by 2.5/90, or 2.8 percent. With the mass effect alone, 13 Wh/km, the break-even increase is 3.1 percent. The calculation compares emissions per kilometer only. It leaves out the emissions from manufacturing batteries, which raise the break-even increase, and the gap between real-world and WLTP emissions of internal combustion vehicles, which lowers it. The 125 g/km average includes plug-in hybrids, whose low test-cycle emissions make it a conservative figure for the vehicle an electric vehicle replaces.

I compare the break-even increase with the increase in sales implied by estimates of the value of range. First, the range decomposition implies that larger batteries raised mean log range by 22.8 log points relative to the counterfactual with 2019 batteries (Extended Data Table 7). At the 2025 mean WLTP range of 508 km in the decomposition sample, the counterfactual range is 404 km. Second, Fridstrøm and Østli[19] estimate a discrete choice model of all new vehicle sales in Norway from 2003 to 2019, in which the range of a battery-electric vehicle enters utility through a Box-Cox transformation with an exponent of -0.5. Their marginal willingness to pay is 354 euros per km at a range of 150 km and 59 euros per km at 500 km. Integrating their marginal willingness to pay from 404 to 508 km gives 7,000 euros per vehicle. Third, I convert this value into a change in sales with their price coefficient, which implies a change in utility of 2.0×10^{-5} per euro. In a logit model in which every electric vehicle gains the same utility, the change in log electric vehicle sales is this utility gain times one minus the electric vehicle share. With a 2025 battery-electric share of

19 percent[25], the added range raises electric vehicle sales by 12 percent. The break-even increase of 2.8 percent would require buyers to value the added 104 km at only about 1,700 euros, or 16 euros per km. Stated-preference estimates for Italian buyers range from 37 to 106 euros per km[26], and the Norwegian estimate at 500 km is 59 euros per km.

The calculation has four limitations. First, the price coefficient implies an elasticity of electric vehicle sales with respect to price of only about -0.7 at a price of 40,000 euros. Remmy[27] finds that a purchase subsidy of 2,000 euros per battery-electric vehicle, together with support for charging stations, nearly doubled electric vehicle sales in Germany, which suggests a more elastic demand and a larger sales response to range. Second, the Norwegian estimates come from a market with large incentives for electric vehicles and from years in which ranges were shorter. Third, the Norwegian ranges are likely rated on the NEDC cycle, which rates range higher than WLTP. Scaling the ranges by 1.2, roughly the ratio of the two ratings, lowers the value of the added range to 6,400 euros and the sales increase to 11 percent. Fourth, the calculation holds vehicle prices fixed. The larger batteries came mainly from cheaper capacity at a given price, but manufacturers could instead have passed the lower battery costs to buyers as lower prices, which would also have raised sales.

To convert capacity into minerals, I use the mineral content per kWh of cells reported by Transport & Environment[28]. A kWh of NMC811 cells contains about 0.10 kilograms of lithium, 0.65 kilograms of nickel, 0.08 kilograms each of cobalt and manganese, and 0.75 kilograms of graphite. The average nickel-based cell of 2020 contained about 0.48 kilograms of nickel, 0.13 kilograms of cobalt, 0.17 kilograms of manganese, and 0.87 kilograms of graphite per kWh. A kWh of lithium iron phosphate cells contains about the same lithium and about 1.1 kilograms of graphite. The mix of nickel-based cathodes is not observed, so I use the 2020 average and NMC811 to bound the nickel-based cells. I apply the share of lithium iron phosphate in each cohort's capacity, 7.2 percent in 2025. The intensities are for cells and exclude the aluminum, copper, and steel in housings, current collectors, and pack enclosures. At these intensities, the 31 GWh of added capacity in the 2025 cohort contains about 3,100 tonnes of lithium, 14,000 to 19,000 tonnes of nickel, 2,300 to 3,800 tonnes of cobalt, and 24,000 to 28,000 tonnes of graphite.

Robustness

Supplementary Notes 1 to 5 report the robustness checks. Dropping the drag coefficient and estimating on all 7.9 million registrations gives a technology effect of 24 to 26 Wh/km and a mass effect of 11 to 15 Wh/km (Supplementary Table 4). Using 2020 as the base year lowers the technology effect to 19 Wh/km and raises the share absorbed by attributes to 56 percent (Supplementary Table 2). Letting the mass coefficient vary by year lowers the share absorbed by mass from 53 to 52 percent. The drift in the mass coefficient is not statistically significant, with a p-value of 0.79 against no drift (Supplementary Note 2). With brand fixed effects in the technology factor, the drag-area coefficient falls to 50 Wh/km per square meter, so it is identified mostly across brands. The mass coefficient, the all-wheel-drive coefficient, and the technology factor are unchanged (Supplementary Table 5). A standard heat pump enters the load function positively across models and negatively within make-model-year, so I treat it as a brand marker and exclude it from the preferred specification (Supplementary Table 5). Body-type indicators improve the fit but do not change the technology effect (Supplementary Note 5). The range decompositions use the implied range of equation (4) rather than the WLTP range in the registry, which is reported from 2020. On the 89 percent of the decomposition sample that has both, the implied range rose 33 log points between 2020 and 2025 and the reported range rose 29 (Supplementary Table 7). Within a variant, the ratio of the two hardly changed, so the gap comes from newer models that lose less energy in charging. Lower charging losses are part of the shift of the efficiency frontier, but they do not add range on a charge. Measured as range per charge, the efficiency frontier would account for about 11 log points of the increase in range rather than 15, which strengthens the conclusion that larger batteries contributed more. Matching registrations to variants on mass alone, rather than on mass and implied capacity, leaves the results nearly unchanged: mass offsets 52 percent of the technological progress, the mass of larger batteries 30 percent, and larger batteries account for 26 log points of the increase in range against 16 for the efficiency frontier (Supplementary Table 8). Matching on mass and power raises the shares offset by mass to 63 and 38 percent. The registry reports most power in 2020 and 2021 on a 30-minute basis, which makes power a poor guide to the variant, and registrations matched to variants without a collected drag coefficient drop out of the sample. Even so, larger batteries account for more of the increase in range than the efficiency

frontier, 33 log points against 16.

The last check concerns the test cycle. EV Database reports a real-world consumption figure for 82 of the matched variants, which account for 3.0 million registrations of the decomposition sample. The figure has three limitations. First, it is modeled for mild weather and mixed driving rather than measured. Second, it is consumption drawn from the battery, so it excludes the charging losses that the WLTP figure includes. Third, it is a single value per variant that does not vary across registration years. I re-estimate the preferred frontier and the decompositions on these registrations twice, once with the WLTP rating and once with the real-world figure, so that the two estimates differ only in the measure of consumption (Supplementary Table 6). With the WLTP rating, the technology factor is 0.874, and mass accounts for 40 percent of the progress. With the real-world figure, the technology factor is 0.855, and mass accounts for 45 percent. In the range decomposition, larger batteries account for 28 log points with the WLTP rating and 26 with the real-world figure.

Statistics

All regressions weight specification-year cells by registrations. Standard errors are clustered by make-model. I estimate equation (2) by nonlinear least squares and equations (3) and (5) by least squares. Error bars in the figures are 95 percent confidence intervals.

The decompositions combine estimates from three frontiers, and their shares are ratios of estimated quantities, so they have no analytic standard error. I compute standard errors with a cluster bootstrap by make-model with 999 draws. Each draw resamples the 1,455 make-models of the preferred sample with replacement, keeping all of a model's registrations in every year. It then re-estimates the efficiency frontier and the mass frontier, each with and without price, and the battery frontier. Finally, it recomputes every decomposition on the observed fleet. I hold the fleet means fixed because they are the population of registrations rather than a sample from it, so the standard errors measure the uncertainty in the estimated frontiers. Extended Data Table 6 reports the standard errors and the 2.5th and 97.5th percentiles of the draws. If the fleet means are also resampled, the share of progress absorbed by attributes is positive in 99 percent of draws. Larger batteries then contribute more to the increase in range than the efficiency frontier in 88 percent of draws.

Data availability

The vehicle registration data are publicly available from the European Environment Agency[3]. Variant specifications and list prices are from EV Database[4], which provides them under license, and from the open-ev-data project[5]. The drag coefficients, drive configurations, heat pump fitment, and cathode chemistries collected for this study, with their sources, will be deposited in GitHub on publication.

Code availability

The code that reproduces the estimates, tables, and figures will be deposited in [repository] on publication.

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Author contributions

C.R.K. designed the study, collected the data, performed the analysis, and wrote the paper.

Competing interests

The author declares no competing interests.

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Figures

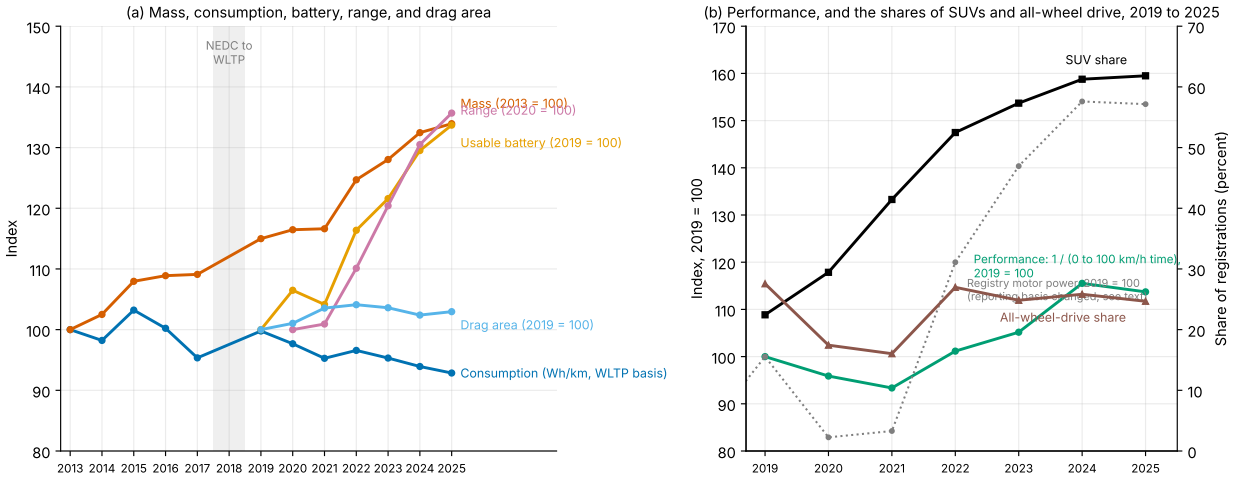


Fig. 1. Attributes of new battery-electric vehicles in the EU, Iceland, and Norway, 2013 to 2025. a, Registration-weighted mean mass and type-approval consumption, indexed to 2013; usable battery capacity and drag area, indexed to 2019; and electric range, indexed to 2020, the first year the registry reports it. Consumption was rated on the NEDC cycle through 2017 and on the WLTP cycle from 2019. For this panel only, NEDC-era ratings are converted to a WLTP basis with the 19 models sold with unchanged mass in both 2017 and 2019. The year 2018, in which member states reported a mixture of the two cycles, is shaded. **b**, Performance, measured as the inverse of the mean 0 to 100 km/h time, and the registry's rated motor power, indexed to 2019 (left axis), and the shares of registrations that are SUVs and that have all-wheel drive (right axis). The power series is dotted because member states changed from reporting 30-minute rated power to peak power over the period.

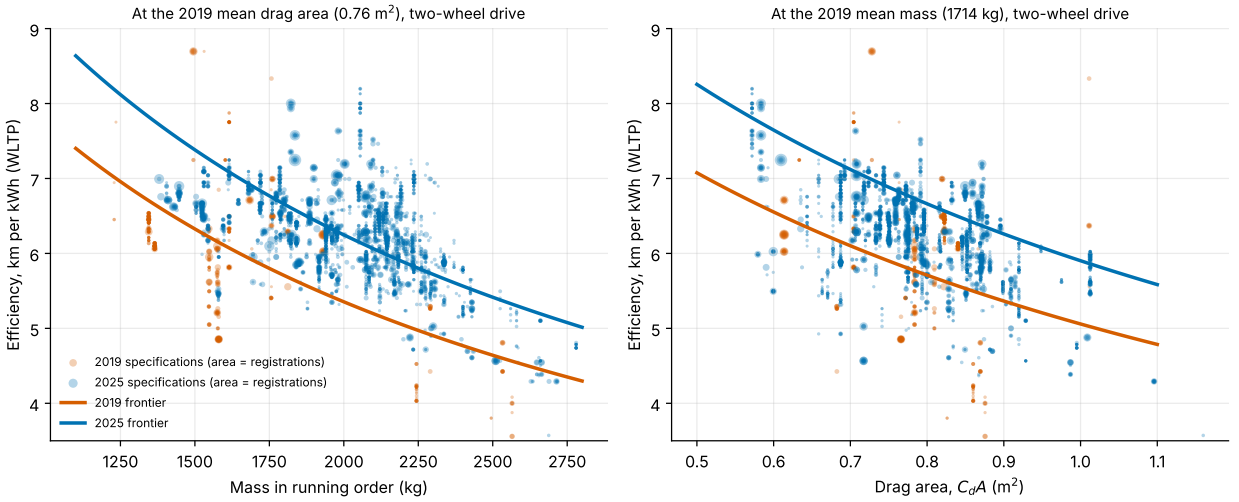


Fig. 2. The efficiency frontier in 2019 and 2025. Points are specifications registered in 2019 or 2025 with at least 50 registrations, sized by registrations. Curves are the preferred frontier (Extended Data Table 2, column 5) for two-wheel-drive vehicles at the 2019 mean frontal area and length. **a**, Efficiency against mass at the 2019 mean drag area of 0.76 m^2. **b**, Efficiency against drag area at the 2019 mean mass of 1,714 kg.

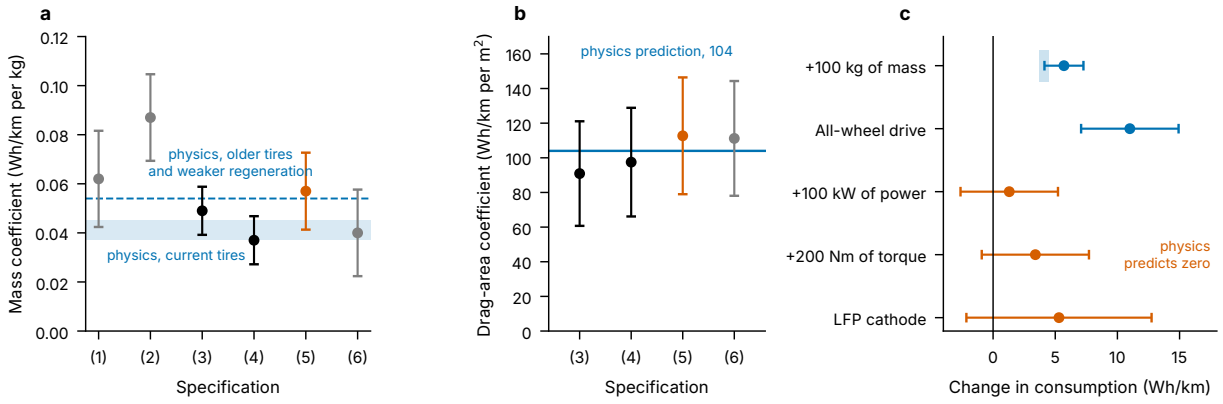


Fig. 3. Estimated coefficients against the values implied by the physics. **a**, The mass coefficient of the efficiency frontier in the six specifications of Extended Data Table 2: (1) frontal area and length, all registrations; (2) the same on the drag-coefficient sample; (3) drag area; (4) drag area and all-wheel drive; (5) the preferred specification, which adds frontal area and length; and (6) the preferred specification with the log of real price. The shaded band is the value implied by equation (1) for current tires and regeneration, and the dashed line the value for older tires and weaker regeneration. **b**, The drag-area coefficient in specifications (3) to (6), against the 104 Wh/km per m^2 implied by the WLTP cycle. **c**, The change in consumption implied by the preferred specification for 100 kg of mass and for all-wheel drive, and by the specifications of Extended Data Table 3 for 100 kW of power, 200 Nm of torque, and a lithium iron phosphate cathode. The physics predicts zero for the last three. The shaded band is the physics prediction for 100 kg. Error bars are 95 percent confidence intervals from standard errors clustered by make-model.

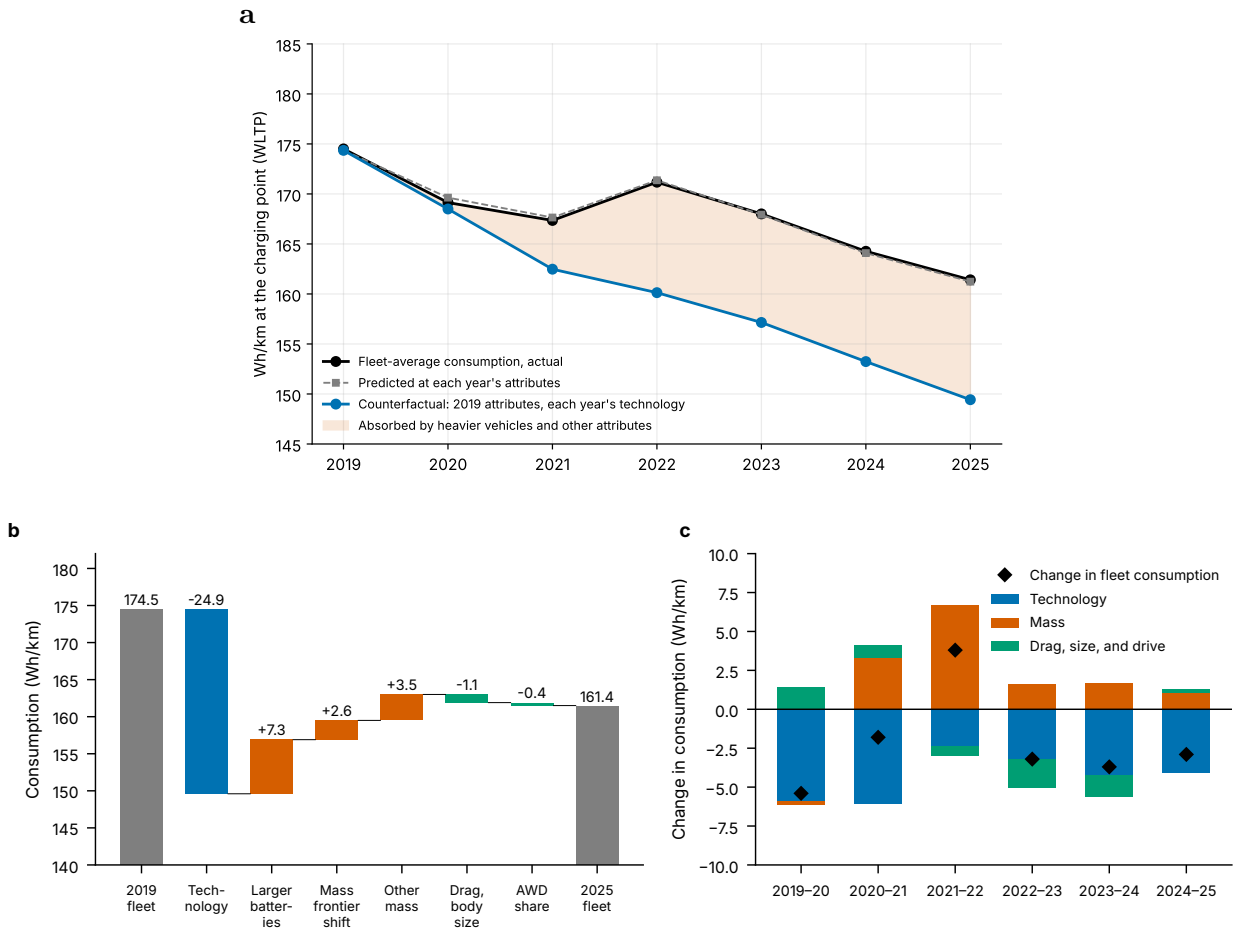


Fig. 4. Where the technological progress went. **a**, Fleet-average consumption on the decomposition sample, the consumption the preferred frontier predicts at each year's mean attributes, and the counterfactual at 2019 attributes, e^{a_t} times the 2019 load function. The shaded area is the consumption added by the change in attributes at each year's technology. **b**, Decomposition of the change in fleet-average consumption between 2019 and 2025 with equation (7). Mass effects are split with the mass frontier into the mass of larger batteries, the shift in the mass frontier, and the mass that came with changes in power, size, and drive configuration. The bars sum to the change in predicted consumption, which differs from the actual change by less than 0.1 Wh/km. **c**, The same decomposition for each pair of adjacent years. Diamonds are the change in fleet-average consumption.

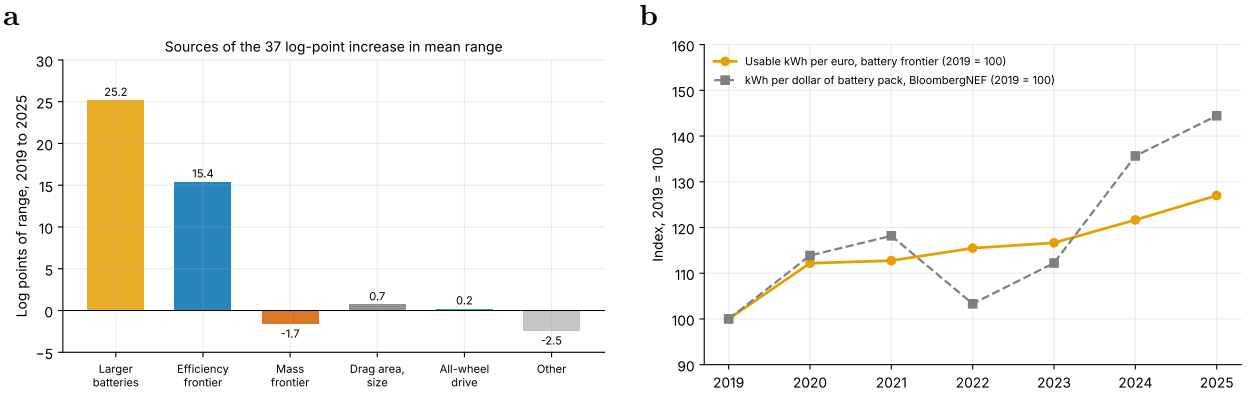
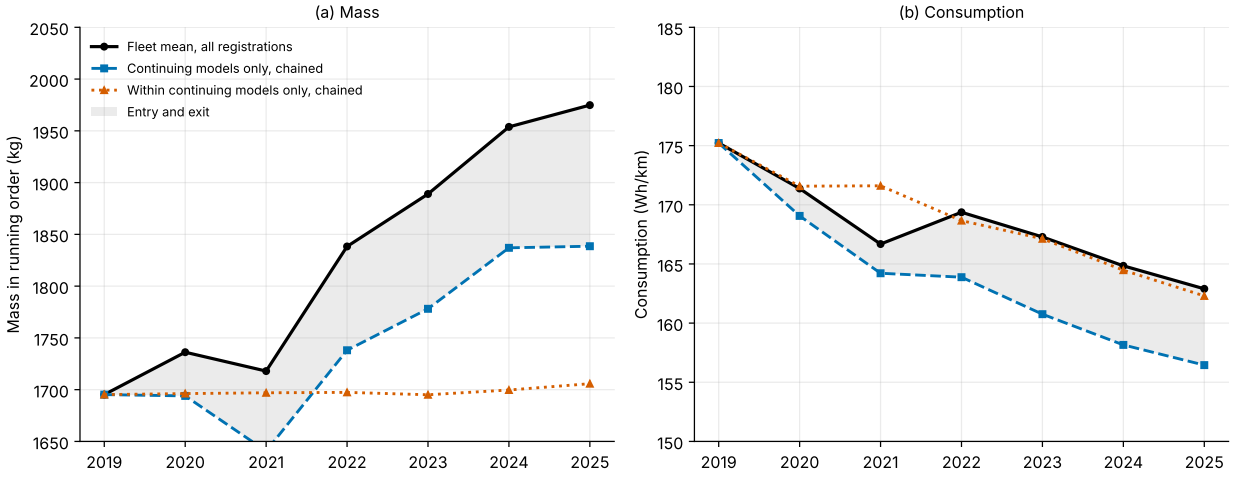
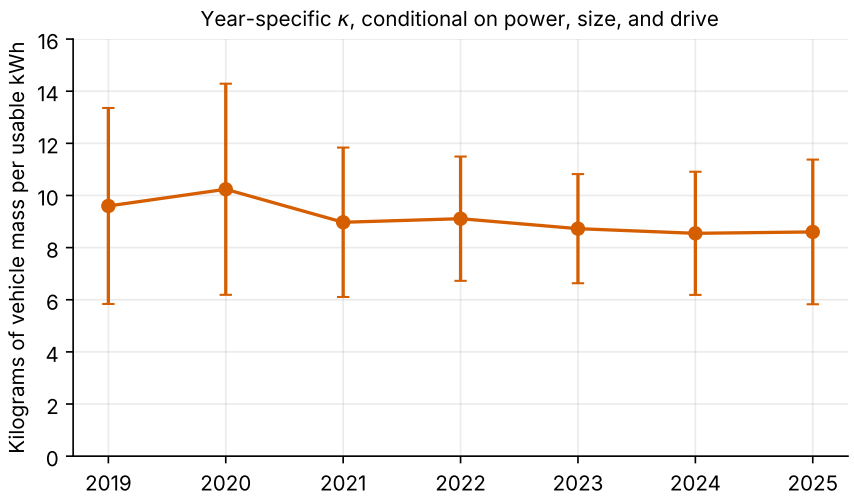


Fig. 5. Where the added range came from. a, Decomposition of the 2019 to 2025 change in mean log range (Extended Data Table 7, unconditional column). The battery component is net of the efficiency lost because of the battery's mass. **b**, Usable kWh per euro from the battery frontier with price, e^{d_t} (Extended Data Table 8, column 2), against kWh per dollar of battery pack from the BloombergNEF survey[13,14], both indexed to 2019.

Extended Data



Extended Data Fig. 1. Chained decomposition of the change in fleet-average mass and consumption, 2019 to 2025. **a**, Mass. **b**, Consumption. All WLTP registrations. For each pair of adjacent years, the models sold in both years are the continuing models, which account for 71 to 90 percent of the later year's registrations. The within-model path cumulates the registration-weighted change in each continuing model's mean at the earlier year's shares. The continuing-models path adds the reallocation of sales among continuing models. The gap to the fleet mean is entry and exit.



Extended Data Fig. 2. Kilograms of vehicle mass per usable kWh by year. Estimates from the mass frontier of Extended Data Table 5, column (3), conditional on power, frontal area, length, and drive configuration, with κ estimated separately for each year. Error bars are 95 percent confidence intervals from standard errors clustered by make-model.

Extended Data Table 1. Calibration of equation (1) on the WLTP test cycle

	Value	Source or calculation
Panel A: cycle statistics, from the WLTC class 3b speed trace		
Duration (s); distance D (km)	1,800; 23.27	UN GTR No. 15, Annex 1
Mean speed $\bar{v}$ (km/h)	46.5	D divided by duration
Distance-weighted mean squared speed $\overline{v^2}$ (m^2/s^2)	515	$\sum_i v_i^3 \Delta t / D$ over the 1 Hz trace
Positive kinetic energy per unit mass and distance κ (m/s^2)	0.154	$\sum_i (v_{i+1}^2 - v_i^2)^+ / (2D)$
Panel B: parameters		
Air density ρ (kg/m^3)	1.20	Test at 23°C, near sea level
Tire rolling resistance coefficient C_{rr}	0.008 to 0.009	EU tire label classes B and C, Regulation (EU) 2020/740
Share of braking energy recovered η_r	0.70 to 0.80	Sovran and Blaser [22]; Guzzella and Sciarretta [9]
Drivetrain efficiency η_d (battery to wheels, cycle average)	0.90	Guzzella and Sciarretta [9]
Charging efficiency η_c (mains to battery)	0.92	WLTP measures energy recharged from the mains, Regulation (EU) 2017/1151
Panel C: implied coefficients		
Drag term at the wheels (Wh/km per m^2 of $C_d A$)	86	$\frac{1}{2}\rho\,\overline{v^2} = 309$ J/m, divided by 3.6
Drag term at the charging point (Wh/km per m^2)	104	86 divided by $\eta_c \eta_d = 0.828$
Rolling resistance at the wheels (Wh/km per kg)	0.022 to 0.025	$C_{rr}\, g / 3.6$
Unrecovered kinetic energy at the wheels (Wh/km per kg)	0.009 to 0.013	$(1 - \eta_r)\, \kappa / 3.6$
Mass term at the charging point (Wh/km per kg)	0.037 to 0.045	Sum of the two, divided by 0.828
Mass term with C_{rr} of 0.010 and η_r of 0.60 (Wh/km per kg)	0.054	Same calculation
Auxiliary load at the charging point (Wh/km per 100 W)	2.6	$P_{aux}/\bar{v}$, divided by 0.828

Notes: The speed trace is the Worldwide Harmonized Light Vehicles Test Cycle for class 3b vehicles, the cycle on which every battery-electric vehicle in the sample was certified, taken from the European Commission Joint Research Centre's `wltp` reference implementation. One J/m equals 1/3.6 Wh/km. The ranges in Panel B are the values for current tires and drivetrains; the last row of Panel C shows the mass term for older tires and weaker regeneration. The coefficients are what equation (1) implies for a vehicle whose energy is measured at the charging point, as the registry's consumption figure is.

Extended Data Table 2. The efficiency frontier in the physics form, 2019 to 2025

	(1) Mass, A, L all registrations	(2) Mass, A, L C_d sample	(3) Mass, C_dA	(4) Mass, C_dA, AWD	(5) Mass, C_dA, A, L, AWD	(6) (5) + ln real price
b_m, mass (kg)	0.062***	0.087***	0.049***	0.037***	0.057***	0.040***
	(0.010)	(0.009)	(0.005)	(0.005)	(0.008)	(0.009)
b_A, frontal area (m^2)	24.4**	7.5			−26.3***	−21.0**
	(11.0)	(9.8)			(9.0)	(8.4)
b_L, length (m)	−27.4***	−39.0***			−5.9	−8.5
	(8.8)	(8.0)			(7.5)	(7.8)
b_{C_dA}, drag area (m^2)			90.9***	97.5***	112.7***	111.2***
			(15.4)	(16.0)	(17.2)	(16.9)
b_{AWD}, all-wheel drive (0/1)				12.0***	11.0***	8.6***
				(2.0)	(2.0)	(2.2)
θ, ln real price						0.113***
						(0.036)
a_{2020}	−0.032	−0.043**	−0.033*	−0.025	−0.034**	−0.023
	(0.020)	(0.020)	(0.018)	(0.018)	(0.017)	(0.018)
a_{2021}	−0.070***	−0.085***	−0.073***	−0.062***	−0.071***	−0.059***
	(0.019)	(0.018)	(0.018)	(0.018)	(0.015)	(0.018)
a_{2022}	−0.084***	−0.099***	−0.087***	−0.077***	−0.085***	−0.070***
	(0.019)	(0.016)	(0.017)	(0.018)	(0.015)	(0.018)
a_{2023}	−0.111***	−0.125***	−0.113***	−0.099***	−0.104***	−0.086***
	(0.020)	(0.017)	(0.018)	(0.019)	(0.017)	(0.020)
a_{2024}	−0.140***	−0.157***	−0.140***	−0.124***	−0.129***	−0.105***
	(0.019)	(0.018)	(0.019)	(0.020)	(0.018)	(0.022)
a_{2025}	−0.163***	−0.186***	−0.166***	−0.148***	−0.154***	−0.126***
	(0.021)	(0.019)	(0.020)	(0.021)	(0.018)	(0.022)
Technology factor, $e^{a_{2025}}$	0.850	0.830	0.847	0.862	0.857	0.882
Registrations (millions)	7.93	6.71	6.71	6.71	6.71	6.65
R^2	0.463	0.524	0.556	0.591	0.619	0.630

Notes: Nonlinear least squares estimates of $\text{Wh/km}_{it} = \exp(a_t + \theta \ln P_{it})(b_0 + \sum_k b_k x_{kit})$; coefficients inside the load function are in Wh/km per unit of the attribute in parentheses and the year effects are relative to 2019. Column (1) uses all WLTP registrations from 2019 to 2025 with dimensions; columns (2) to (5) use the registrations whose variant has a manufacturer-stated drag coefficient, drive configuration, and heat pump status, 84 percent of column (1); column (6) adds the log of the real list price, centered at 45,000 euros, to the technology factor on the registrations of that sample with a matched price. The drag area C_dA is the drag coefficient times the frontal area (width times height). The technology factor is the proportional change in consumption at fixed attributes between 2019 and 2025. Weights are registrations; standard errors clustered by make-model in parentheses. *, **, ***: significant at 10, 5, and 1 percent.

Extended Data Table 3. Attributes that should not shift the efficiency frontier conditional on mass, drag, and drive configuration

Added attribute	(1) Power	(2) Torque	(3) LFP chemistry
b_m, mass (kg)	0.056^{***}	0.053^{***}	0.059^{***}
	(0.009)	(0.013)	(0.008)
b_{C_dA}, drag area (m^2)	115.6^{***}	142.8^{***}	117.6^{***}
	(16.7)	(22.8)	(16.8)
b_A, frontal area (m^2)	-25.7^{***}	-39.3^{***}	-28.3^{***}
	(8.7)	(15.1)	(9.6)
b_L, length (m)	−6.6	−5.0	−7.0
	(7.3)	(11.1)	(7.4)
b_{AWD}, all-wheel drive (0/1)	10.2^{***}	10.6^{***}	11.7^{***}
	(1.9)	(2.9)	(2.2)
Power (kW)	0.013		
	(0.020)		
Torque (Nm)		0.017	
		(0.011)	
LFP cathode (0/1)			5.3
			(3.8)
a_{2025}, with the added attribute	-0.156^{***}	-0.151^{***}	-0.157^{***}
	(0.019)	(0.020)	(0.018)
a_{2025}, same sample without it	-0.154^{***}	-0.155^{***}	-0.154^{***}
	(0.018)	(0.021)	(0.018)
Registrations (millions)	6.65	4.79	6.71
R^2	0.619	0.609	0.622

Notes: Each column adds one attribute to the load function of the preferred specification, column (5) of Extended Data Table 2, so its coefficient is in Wh/km per unit of the attribute in parentheses. Torque is available for part of the sample. The last two rows report the 2025 year effect with and without the added attribute on the same registrations. Weights are registrations; standard errors clustered by make-model in parentheses. *, **, ***: significant at 10, 5, and 1 percent.

Extended Data Table 4. Decomposition of the change in fleet-average consumption, 2019 to 2025 (Wh/km)

	(3) Mass, C_dA	(4) Mass, C_dA, AWD	(5) Mass, C_dA, A, L, AWD	(6) (5), at constant price
Fleet-average consumption, 2019	174.5	174.5	174.5	174.5
Fleet-average consumption, 2025	161.4	161.4	161.4	161.4
Technology, at 2019 attributes	−26.6	−24.0	−24.9	−20.6
Counterfactual 2025 consumption at 2019 attributes	147.7	150.2	149.4	153.5
Mass, at 2025 technology	11.1	8.7	13.3	9.5
of which larger batteries ($\kappa\,\Delta K$)	6.3	4.8	7.3	3.3
of which mass frontier shift	1.5	1.7	2.6	5.3
of which power, size, drive, residual	3.3	2.3	3.5	1.0
Drag area	2.4	2.7	3.1	3.1
Frontal area			−3.6	−2.9
Length			−0.6	−0.9
All-wheel drive		−0.4	−0.4	−0.3
Real price				−1.2
Attributes, total	13.6	11.0	11.8	7.4
Technology factor	0.847	0.862	0.857	0.882
Share of the technology effect absorbed by mass	0.42	0.36	0.53	0.46
by the mass of larger batteries	0.24	0.20	0.29	0.16
Kilograms per usable kWh, κ	9.3	8.9	8.9	5.6
Change in mean usable capacity (kWh)	16.5	16.5	16.5	16.5

Notes: The technology effect is $(e^{a_{2025}} - 1)$ times the 2019 load function at the 2019 registration-weighted mean attributes; each attribute effect is $e^{a_{2025}}$ times the coefficient times the change in the attribute mean, so the rows sum to the change in predicted consumption. The mass effect is split with the mass frontier of Extended Data Table 5: κ times the change in mean usable capacity, the shift in the mass frontier intercept, and the remainder. Columns (3) to (5) use the efficiency frontiers of the same columns of Extended Data Table 2 with mass frontier (2) for column (3) and (3) otherwise; column (6) holds the real price at its 2019 mean in the technology effect and reports the effect of the fall in real prices separately, with mass frontier (4). Sums may differ from the actual change by the residual.

Extended Data Table 5. The mass frontier in levels, 2019 to 2025

	(1) kWh, power	(2) kWh, power, A, L	(3) kWh, power, A, L, AWD	(4) (3) + ln real price
κ, usable battery (kWh)	15.6***	9.3***	8.9***	5.6***
	(0.9)	(1.3)	(1.2)	(0.7)
Power (kW)	0.21	0.11	−0.12	−0.34***
	(0.27)	(0.22)	(0.17)	(0.11)
Frontal area (m^2)		297***	273***	272***
		(100)	(91)	(61)
Length (m)		254***	263***	150***
		(47)	(43)	(32)
All-wheel drive (0/1)			85***	34
			(29)	(27)
ln real price				437***
				(58)
Year 2020	−11	19	24	62**
	(32)	(33)	(32)	(29)
Year 2021	8	38	45	75***
	(30)	(29)	(28)	(26)
Year 2022	32	52*	57**	100***
	(30)	(28)	(27)	(26)
Year 2023	35	43	54*	107***
	(30)	(28)	(28)	(27)
Year 2024	26	39	52*	129***
	(29)	(29)	(29)	(26)
Year 2025	9	37	53*	151***
	(30)	(28)	(28)	(25)
Registrations (millions)	6.65	6.65	6.65	6.65
R^2	0.800	0.883	0.893	0.925

Notes: Weighted least squares estimates of $m_{it} = c_t + \kappa K_{it} + \gamma' z_{it} + u_{it}$ on the drag-coefficient sample, so that κ is the kilograms of vehicle mass that accompany a usable kWh conditional on the controls z; year effects are kilograms relative to 2019. Column (4) uses the registrations with a matched price. Weights are registrations; standard errors clustered by make-model in parentheses. *, **, ***: significant at 10, 5, and 1 percent.

Extended Data Table 6. Cluster bootstrap standard errors and intervals for the decompositions

	Estimate	Bootstrap standard error	95 percent interval
Panel A: consumption, 2019 to 2025 (Wh/km)			
Technology, at 2019 attributes	−24.9	3.2	[−31.2, −18.9]
Mass, at 2025 technology	13.3	2.3	[8.7, 18.0]
of which larger batteries	7.3	1.5	[3.7, 9.7]
Attributes, total	11.8	1.6	[8.3, 14.3]
Share of the technology effect absorbed by mass	53	13	[33, 85]
by the mass of larger batteries	29	8	[14, 44]
by all attributes	47	10	[30, 67]
Technology at constant real price	−20.6	4.0	[−28.1, −12.6]
share absorbed by mass, at constant price	46	17	[22, 90]
Panel B: consumption, 2020 to 2025 (Wh/km)			
Technology, at 2020 attributes	−19.2	3.5	[−25.6, −12.1]
Share absorbed by mass	71	22	[41, 125]
by the mass of larger batteries	36	11	[16, 59]
by all attributes	56	14	[38, 89]
Panel C: range, 2019 to 2025 (log points)			
Larger batteries, net of their mass penalty	25.2	1.1	[23.4, 27.8]
Efficiency frontier shift	15.4	1.8	[11.9, 19.0]
Mass frontier shift	−1.7	1.1	[−4.3, 0.0]
Change with 2019 batteries	14.7	2.2	[10.8, 19.4]
At constant price: battery frontier shift	22.1	4.4	[13.9, 31.2]
lower real spending	−1.9	0.6	[−3.0, −0.8]
efficiency frontier shift	12.6	2.3	[7.8, 16.8]
Panel D: frontier parameters			
b_m, Wh/km per kilogram	0.057	0.010	[0.037, 0.077]
κ, kilograms per usable kWh	8.9	1.3	[5.6, 10.7]
Mass frontier shift, 2019 to 2025 (kg)	53	31	[−1, 121]
Battery frontier shift, 2019 to 2025 (log points)	23.9	4.9	[14.7, 34.1]

Notes: 999 bootstrap draws. Each draw resamples make-models with replacement, keeping all of a model's registrations in every year, and re-estimates the efficiency frontier (columns 5 and 6 of Extended Data Table 2), the mass frontier (columns 3 and 4 of Extended Data Table 5), and the battery frontier (column 2 of Extended Data Table 8), and then recomputes the decompositions of Extended Data Tables 4 and 7 and Supplementary Table 2 on the observed fleet, so that the intervals reflect the uncertainty in the estimated frontiers and not variation in the fleet means. The interval is the 2.5th to 97.5th percentile of the draws. Shares are in percent.

Extended Data Table 7. Decomposition of the change in mean log range, 2019 to 2025

	Unconditional (5)	At constant real price (6)
Change in mean log range	0.375	0.375
Larger batteries, net of their mass penalty	0.252	0.224
battery frontier shift (more kWh per euro)		0.221
batteries bundled with higher power		0.023
lower real spending		−0.019
Efficiency frontier shift	0.154	0.126
Mass frontier shift	−0.017	−0.034
Drag area	−0.019	−0.019
Frontal area	0.022	0.018
Length	0.004	0.006
All-wheel drive	0.002	0.002
Other	−0.025	0.051
Change in mean log usable capacity	0.306	0.306
Change in mean log real price		−0.063
Counterfactual change in log range with 2019 batteries	0.147	0.103
Pass-through of capacity to range, $1 - b_m \kappa K e^a / E$	0.841	0.930
Registrations (millions)	6.65	6.65

Notes: Sequential counterfactuals applied to every specification registered in 2019 and averaged with registration weights, using efficiency frontier (5) or (6) of Extended Data Table 2 and mass frontier (3) or (4) of Extended Data Table 5. In column (5) every 2019 vehicle's usable capacity is raised by the change in mean log capacity, its mass by κ kilograms per added kWh, and its consumption by b_m per added kilogram; the efficiency frontier is then moved to 2025, the mass frontier intercept to 2025, and the drag area, frontal area, length, and drive means to 2025, in that order. In column (6) the capacity step is split with the battery frontier, $\ln K = d_t + \delta_p \ln p + \delta_s' \ln s + \delta_P \ln P$, into its shift at constant cost, the capacity bundled with higher power, and the capacity given up to lower real spending, and the price effect on the efficiency frontier is held at the 2019 price. Other collects the direct effects of power, size, and price on mass and consumption and the residuals of each frontier.

Extended Data Table 8. The battery frontier with and without price, 2019 to 2025

Dependent variable: ln usable capacity	(1) Power, size	(2) Power, size, price
ln power	0.191***	0.100**
	(0.042)	(0.044)
ln frontal area	0.812**	0.610**
	(0.338)	(0.294)
ln length	1.518***	1.072**
	(0.342)	(0.476)
ln real price		0.336***
		(0.096)
Year 2020	0.089**	0.115***
	(0.036)	(0.034)
Year 2021	0.103**	0.120***
	(0.048)	(0.041)
Year 2022	0.117**	0.144***
	(0.050)	(0.043)
Year 2023	0.114**	0.154***
	(0.053)	(0.045)
Year 2024	0.139***	0.196***
	(0.052)	(0.045)
Year 2025	0.171***	0.239***
	(0.051)	(0.048)
Registrations (millions)	6.65	6.65
R^2	0.725	0.758

Notes: Weighted least squares on the drag-coefficient sample with a matched price, 2019 to 2025. Year effects are log points relative to 2019; with price included, they measure the change in the usable capacity that a given real expenditure buys, conditional on power and size. Weights are registrations; standard errors clustered by make-model in parentheses. *, **, ***: significant at 10, 5, and 1 percent.

Supplementary Files

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- EVSteroidsNESI.pdf