Supplementary Information 1 for Beyond the Tailpipe: Market-Wide Analysis of All US Vehicles Shows the Climate Benefits of Electrification

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Other Supplementary Materials for this manuscript include the following:

Dataset 1: The file *Supplementay data tables_Market-wide CF of LDVs.xlsx* contains data for every figure in the main article and supplementary information.

Supplementary Text S1: Extended Methods

Life cycle carbon footprint model

The carbon footprint model characterizes the ln footprint for each of the 1434 vehicle variants. The individual carbon footprints are aggregated into the 459 vehicles models using production-weighted averages for each variant.

The life cycle is broken into (non-battery) materials, traction battery, assembly and logistics, vehicle operation, and service and decommissioning. The EPA ATR is the primary source for vehicle characteristics, including vehicle mass, battery capacity, and operating efficiency. Most carbon intensity factors are drawn from the Sphera Managed Life Cycle (MLC) Database, including materials (e.g., steel, aluminum) and the traction battery. Cambium is used for all electricity emission factors. GREET2 is used for the energy demand during assembly and decommissioning, as well as service schedules. A more complete review of the data is described in the following sections.

A2Mac1

A2Mac1 is the source of material compositions for the vehicles in this study. There are several limitations to the A2Mac1 approach. First, not every vehicle is available in the database, as automakers need to subscribe to the service and a physical teardown needs to occur. Second, vehicle models are not refreshed every year, nor is information available for all variants. Third, the material categorization and precision vary from vehicle to vehicle. However, even with these limitations, leveraging A2Mac1 offers the unique ability to develop an abundance of vehicle-specific material breakdowns, thus allowing for a more detailed and bespoke understanding of material composition.

Table S1 shows a summary of material composition binned into four major material categories. This data is reflected graphically in Figure 7 and broken down into individual vehicles.

Table S1. Average mass breakdown of sampled vehicles. Excludes high-voltage battery cells.

Powertrain	Vehicles	Steel	Aluminum	Polymers	Other
BEV	Sedans and small SUVs	39%	17%	34%	9%
	Pickups, vans, and large SUVs	40%	15%	33%	12%
non-BEV	Cars and small SUVs	49%	11%	26%	13%
	Pickups, vans, and large SUVs	49%	11%	25%	16%

Material carbon factors

Carbon intensity factors (kg CO_2e/kg) are taken from the Sphera Managed LCA Content (MLC) database and supplemented with literature or industry expertise when necessary. Standard manufacturing processes are included for each material type. This study also accounted for both unplanned and planned for scrap by applying estimates for part yield (assumed to be 95%) and material utilization (varies by material). Combining all of these factors with the material breakdown in the BOMs allows for an estimate of the carbon footprint of the materials comprising each vehicle.

Table SI2 shows the datasets or assumptions made for each material type.

Table S2. Information on materials datasets, manufacturing methods, recycled content, material utilization, and yields

MATERIAL TYPE	DATASET OR ASSUMPTION	ADDITIONAL MANUFACTURING	RC %	MU %	YIELD %
ABS	DE: Acrylonitrile-butadiene-styrene granulate (ABS) mix	Plastic compounding + injection moulding	0%	95%	95%
ALUMINUM	Assume 67% aluminum casting, 17% aluminum extrusion, and 17% aluminum sheet		41%	84%	95%
ALUMINUM EXTRUSION	RNA: Aluminum automotive extrusion AA <p-agg>		70%	75%	95%
ALUMINUM SHEET	RNA: Aluminum automotive sheet AA <p-agg>	Aluminum sheet deep drawing	17%	50%	95%
ALUMINUM CASTING	RNA: Aluminum die-cast product AA <p-agg>, with 40% recycled content plan		40%	95%	95%
EPDM	DE: Ethylene Propylene Diene Elastomer (EPDM)	Plastic compounding + injection moulding	0%	95%	95%
FLUID	DE: Rinsing-agent (100% solvents)		0%	100%	95%
GLASS	RER: Float flat glass		0%	75%	95%
MAGNET	GLO: market for permanent magnet, for electric motor ecoinvent 3.8		0%	100%	95%
OTHER ELASTOMER	DE: Silicone rubber (RTV-2, condensation)	Plastic compounding + injection moulding	0%	95%	95%
OTHER METAL	GLO: Copper cathode, 99.99% Cu ICA	Copper wire (0.6 mm) process	0%	95%	95%
OTHER PLASTIC	Calculated - 50% PP, 25% PC, 25% PA	Plastic compounding + injection moulding	0%	95%	95%
PA	DE: Polyamide 6 granulate (PA 6) mix	Plastic compounding + injection moulding	0%	95%	95%
PC	DE: Polycarbonate granulate (PC)	Plastic compounding + injection moulding	0%	95%	95%
PC/ABS	Assume average of PC and ABS	Plastic compounding + injection moulding	0%	95%	95%
PE	DE: Polyethylene high density granulate (HDPE/PE-HD) mix	Plastic compounding + injection moulding	0%	95%	95%
PET/PBT	DE: Polybutylene terephthalate granulate (PBT) mix	Plastic compounding + injection moulding	0%	95%	95%
PP	DE: Polypropylene granulate (PP) mix	Plastic compounding + injection moulding	0%	95%	95%
PUR	RER: Polyurethane rigid foam (PU) PlasticsEurope	Plastic compounding + injection moulding	0%	95%	95%
PVC	DE: Polyvinyl chloride granulate (S-PVC) mix	Plastic compounding + injection moulding	0%	95%	95%
STEEL	GLO: Steel hot dip galvanised Worldsteel 2022	US: Steel sheet deep drawing <LC>	15%	60%	95%

TIRE	https://www.epa.gov/sites/default/files/2019-06/documents/warm_v15_tires.pdf	0%	100%	95%
WIRE HARNESS	Assume 50% copper and 50% plastic			
OTHER MATERIAL	Weighted average of categorized materials			

Aluminum

Aluminum constitutes a significant portion of a vehicle's carbon footprint. However, the GHG emissions from an aluminum part vary significantly based on the aluminum sub-type (e.g., aluminum casting or aluminum sheet). Different aluminum sub-types have different manufacturing processes, material utilizations, and generally recycled content.

While A2Mac1 categorizes many parts as 'Aluminum' or an aluminum alloy, the sub-type of aluminum cannot be easily discerned. To accurately reflect automotive aluminum, without a clear breakdown of aluminum sub-types, this study employed a weighted average carbon factor based on a 2:1 ratio of cast and wrought aluminum. Wrought aluminum was further split in a 1:1 ratio into aluminum extrusions and aluminum sheets. The final carbon factor for the material type, 'Aluminum' is a 4:1:1 ratio of aluminum castings, aluminum extrusions, and aluminum sheets. The datasets and assumptions for each sub-type can be found in Table SI2.

Assembly

Assembly and logistics include the inbound logistics to the assembly facility, the assembly operations (paint, onsite manufacturing, general assembly, etc.) and outbound logistics to the customer. The energy from assembly operations are taken from the GREET model, which sum to roughly 5,600 megajoules of natural gas and 770 kilowatt-hours of electricity per vehicle. The Sphera MLC database is used to determine emissions for natural gas supply chain and combustion; the National Renewable Energy Laboratory's (NREL) Cambium 2023 model is used for the electricity.

Inbound and Outbound Logistics

Inbound and outbound logistics cover the transportation of parts and materials to the general assembly location (inbound) and delivery of the final vehicle to the customer (outbound). Upstream transportation within the supply chain is captured in the material emission factors.

In practice, logistics can vary significantly based on current supply chains, production locations, and automotive manufacturers. This study uses a simplified logistics model that assumes an inbound route of 8,000 miles by ocean ship and 1,000 miles by heavy duty truck. Outbound logistics are assumed to be 1,000 miles by auto carrier. The transportation factors are multiplied against the mass of the vehicle; for inbound logistics, a 50% adder is included on the mass to account for material utilization, part yield, and dunnage.

Temperature effects

Temperature variations have a reduction effect on efficiency due to cabin heating or air conditioning usage[1,2]. Temperature has a higher relative effect on increasing energy consumption for BEVs, according to empirical regressions derived by Wu[1]. The vehicle energy consumption data source in our model corresponds to the EPA fuel economy 5-cycle test data, which already reflects real-world driving conditions by including national weighted representative driving cycles for high-speed, cold start, and air conditioning[3]. We use the 5-cycle data for our aggregated results at national level, to avoid the modelling and parameter uncertainty derived from additional equations: (i) fleet average empirical equations to convert 2-cycle consumption to on-road with no temperature, and (ii) powertrain equations to adjust the temperature at state level based on historical temperature measurements[1]. To conduct our sensitivity analysis for temperature effects, we follow a simplified approach based on the temperature adjustment factors by US county level estimated by Woody et al.[4]. These factors were calculated from monthly temperature data from 2016 to 2020, to capture the seasonal variability of hot and cold weather, and are differentiated by ICE, HEV and BEV. To extend it to PHEV we follow their same method: we combine the temperature deviations provided by Woody with the temperature coefficients by powertrain derived by Wu et al. We average the temperature adjustment factors (by powertrain) to state level by using county population as weights and estimated the ratio of each state factor to the national average. We then use the most extreme relative variation (North Dakota) as our sensitivity test for cold-weather conditions.

Service

Service includes replacement of consumables over the life of the vehicle. Depending on the vehicle powertrain, these may include fluids, tires, and batteries. Service intervals and masses for fluids and low-voltage batteries are matched to the GREET database[5] and vary based on vehicle type and powertrain.

Tire replacement occurs every 40,000 miles for vehicles with internal combustion engines, which matches information in the GREET model. EVs may use more tires over their life due to higher torques and vehicle masses. This study assumes that EVs have a 25% reduction in tread life compared to ICE vehicles.

Replacement of high-voltage batteries is not expected over the life of the vehicle. This assumption is tested in the sensitivity analysis.

Decommissioning

The GREET model is used to estimate the energy for decommissioning the vehicle and materials at the end of its life. Electricity emission factors is taken from the Cambium-based predictions at the last year of operation. Vehicles are assumed to travel 500 miles to the decommissioning facility.

Supplementary Text S2: High-Voltage Traction Batteries

To simplify and match the robustness of the data, the carbon intensity of high-voltage traction battery cells is assigned based on whether chemistries are nickel-based or LFP. Cell-level carbon intensity factors (as measure in units of kg CO_2e/kWh of battery capacity) are derived from the lithium-ion battery model available in the Sphera MLC database[6]. Nickel chemistries are represented by an NCA cell manufactured in China with a cell-level carbon intensity of 83.0 kg CO_2e/kWh. Non-nickel chemistries are represented by an LFP cell manufactured in China with a cell-level carbon intensity of 84.6 kg CO_2e/kWh.

Carbon intensity of cells varies between data sources. The ecoinvent database (version 3.9) publishes values of 40-50 kg CO_2e/kWh, depending on the cathode chemistry. A recent study by Peiseler et al.[7] publishes a range between 59-115 kg CO_2e/kWh (50th percentile = 74) for NMC811 and 54-69 kg CO_2e/kWh (50th percentile = 62) for LFP. Many factors contribute to the wide ranges of factors, including assumptions on cell energy manufacturing (total consumption, electricity source, ratio of thermal versus electricity); anode graphite source amount, and type (synthetic vs. natural); and active material sources.

This study uses Sphera as the data source, which represents values on the higher side of the carbon intensity scale. If ecoinvent values were used instead, the production-weighted life cycle carbon footprint for BEVs would be reduced by approximately 10% (reduced from 173 to 156 g CO_2e/mi). While this is a large effect for BEVs themselves, the delta between other powertrains is incremental: the production-weighted footprint for BEVs is 67% lower than ICE vehicles using the Sphera battery carbon intensities and 70% lower using ecoinvent battery carbon intensities. Overall, battery carbon intensities are important in determining the carbon footprint of a given BEV but are only marginally influential when considering the differences between powertrains.

References

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Figures S1 to S2

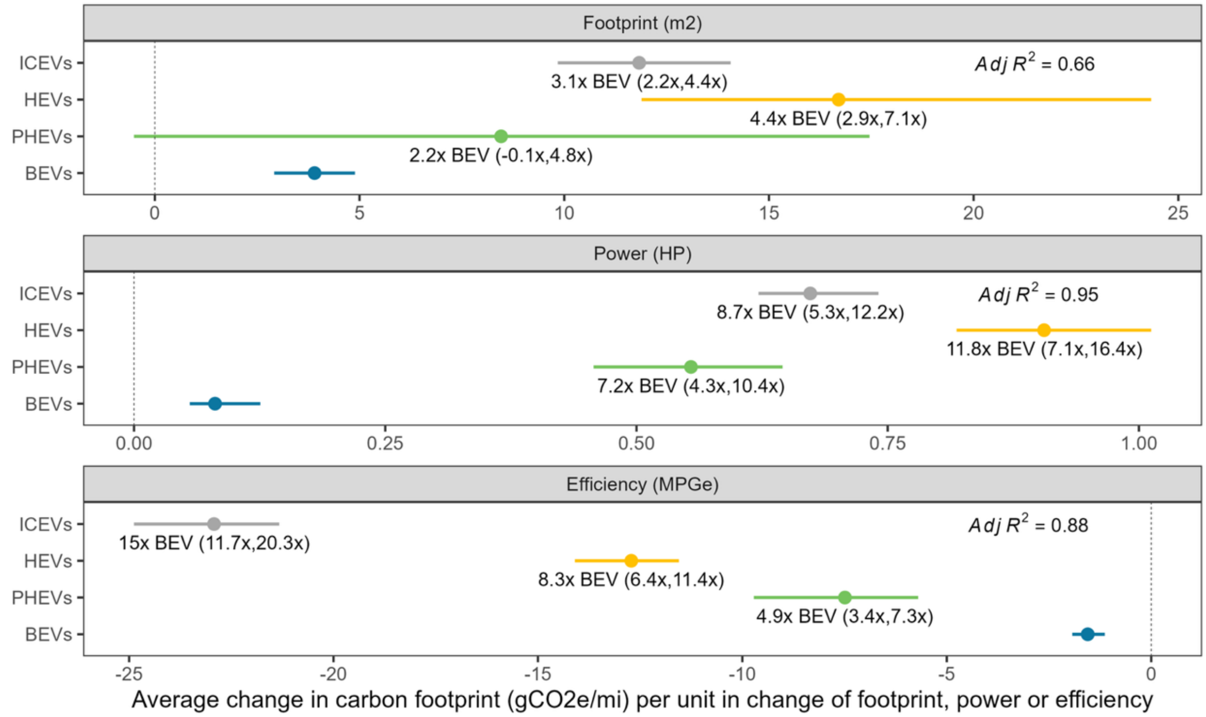

Figure S1. Marginal (linear) effect of footprint (m^2), power (hp) or efficiency (MPGe) on the vehicle carbon footprint (g CO_2e/mile) by powertrain. *For each panel (footprint, power or efficiency), a multiple linear regression model (n=459, unique vehicle model results) was fitted, using carbon footprint as the dependent variable, and the interaction between powertrain and the characteristic (e.g., power) as explanatory variables, thus predicting a different intercept and slope per powertrain. The adjusted R^2 is* *presented for each model. On text below each slope estimate, the ratio with respect to BEVs slope is shown. All confidence intervals are at 95% and estimated through bootstrapping (1000 runs per model).*

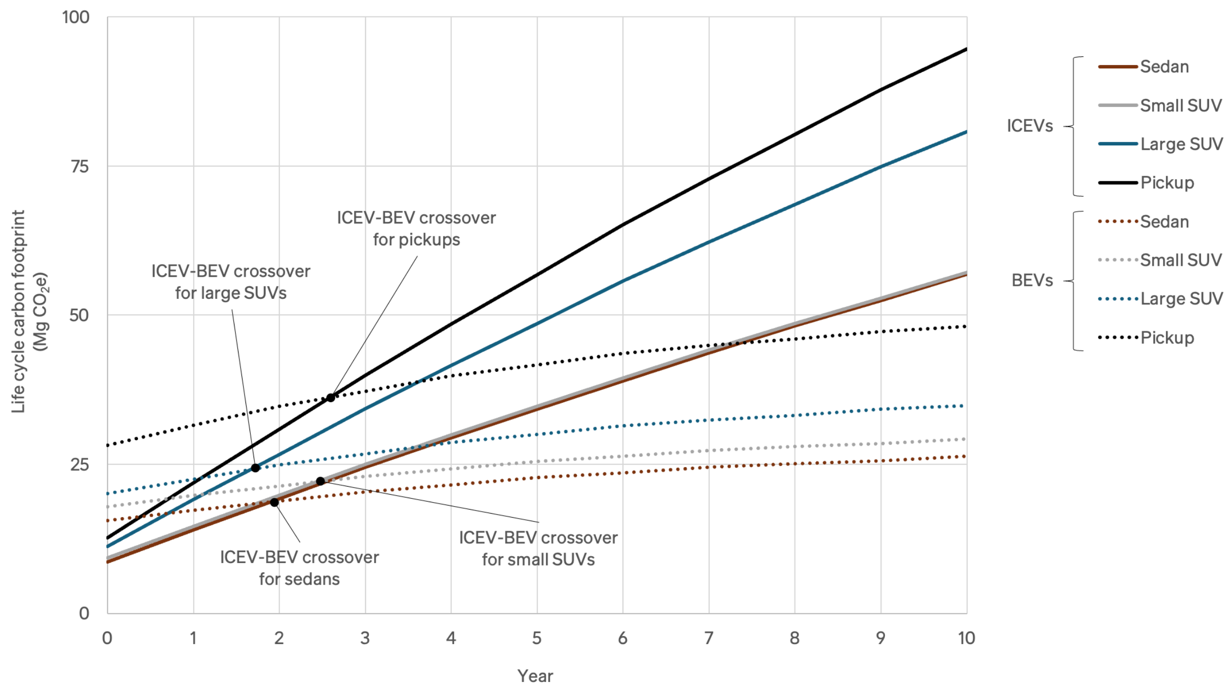

Figure S2. Carbon footprint crossover years for BEV relative to ICEVs. Sedans and large SUVs crossover between 1-2 years, meaning that after two years, the production-weighted average BEV will have a lower carbon footprint. Small SUVs and pickups crossover between 2-3 years.

Tables S3 to S4

Table S3. Vehicle models by powertrain and segment

Powertrain	Sedans	Small SUVs	Large SUVs	Pickups	Vans	Total
ICEVs	119	31	111	18	6	276
HEVs	35	6	37	4	3	85
PHEVs	14	3	19	-	1	37
BEVs	23	15	12	2	-	52
total	*191*	*55*	*179*	*24*	*10*	459

Table S4. Vehicle production volume by powertrain and segment

Powertrain	Sedans	Small SUVs	Large SUVs	Pickups	Vans	Total
ICEVs	2,586,020	1,074,863	518,3890	1,739,356	25,4944	10,839,073
HEVs	419,254	52,776	890,547	287,388	69,651	1,719,616
PHEVs	27,441	9,580	180,110	0	26,049	243,180
BEVs	519,851	633,810	182,329	55,871	0	1,391,861
total	3,552,566	1,771,029	6,436,876	2,082,615	350,644	14,193,730

Table S5. Electricity emission rates from Cambium 2023. *Data represents the load (including combustion and non-combustion emissions) for the midcase scenario for the US. Values in black represent data directly from the model, which are provided every five years. Grey values are linearly interpolated between known years. Values for 2023 and 2024 are linearly extrapolated using the annual change between 2025 and 2030.*

YEAR	AVERAGE EMISSION RATES	LONg-RUN EMISSION RATES	SHORT-RUN EMISSION RATES
2023	391.3	611.6	825.6
2024	357.5	554.4	779.4
2025	323.8	497.3	733.2
2026	290.1	440.2	687.0
2027	256.3	383.0	640.8
2028	222.6	325.9	594.7
2029	188.8	268.7	548.5
2030	155.1	211.6	502.3
2031	147.3	200.1	488.0
2032	139.5	188.5	473.8
2033	131.6	177.0	459.5
2034	123.8	165.4	445.3
2035	116.0	153.9	431.0

2036	112.7	152.7	422.6
2037	109.4	151.5	414.2
2038	106.1	150.4	405.8
2039	102.8	149.2	397.4
2040	99.5	148.0	389.0
2041	97.6	142.1	383.2
2042	95.7	136.1	377.4
2043	93.8	130.2	371.7
2044	91.9	124.2	365.9
2045	90.0	118.3	360.1
2046	91.4	126.9	360.5
2047	92.8	135.4	360.8
2048	94.1	144.0	361.2
2049	95.5	152.5	361.5
2050	96.9	161.1	361.9