Shared mobility may limit vehicle lifetimes but could still reduce carbon footprints

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Supplementary Materials

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1 Method and assumptions

1.1 Carbon intensity of electricity generation

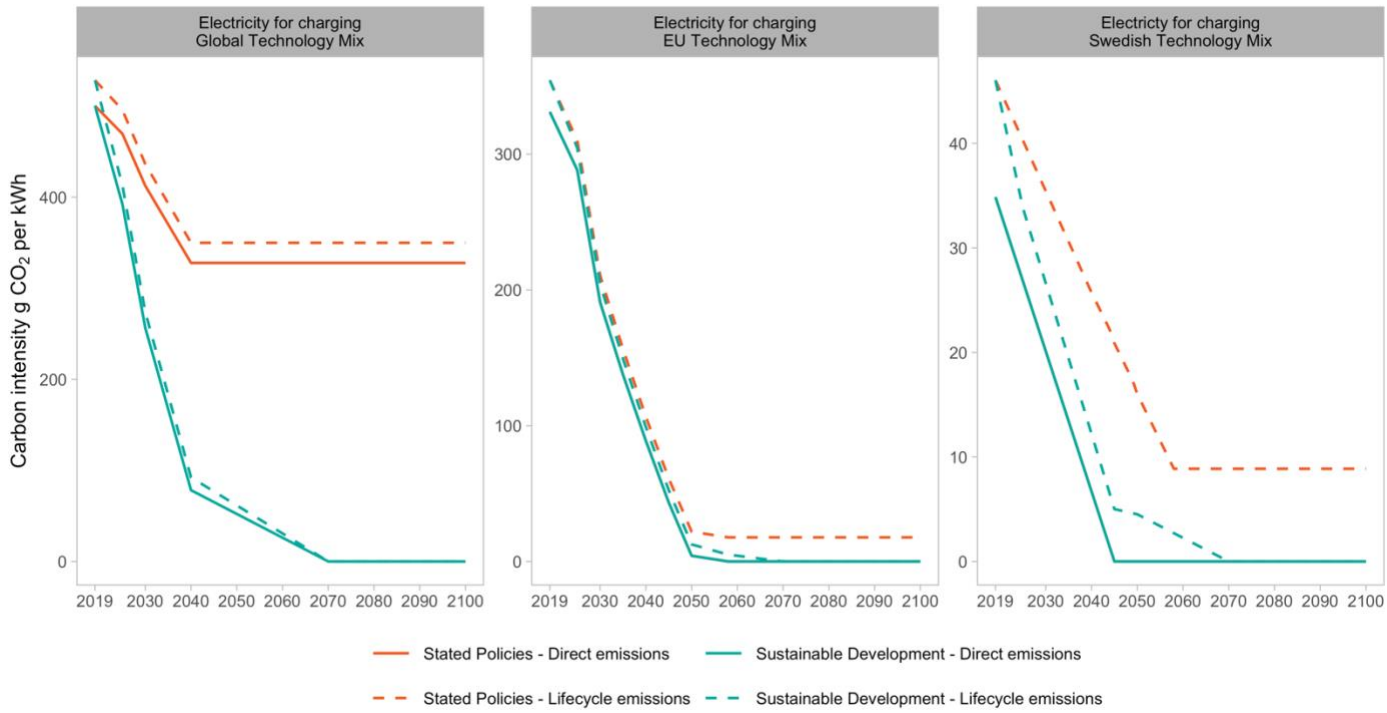

Figure SM 1: Carbon intensity of electricity generation based on global, EU and Swedish average technology mix. Note that in the cases of European and Swedish electricity mix, direct emissions are equal between the two climate change mitigation scenarios.

1.2 Cleaning of the dataset for Swedish vehicle retirement statistics

Table SM 1: Criteria for cleaning of the dataset, the reasoning behind each criterium and the number of observations removed. Note that some observations may be removed due to not fulfilling several of the criteria. Hence, the sum of observations removed will not be equal to the actual number of observations removed when considering all criteria.

Criteria	*No. of observations removed*	*Reasoning*
Age or distance travelled must not be missing, equal to zero or equal to 999999	59,159	
Time between last inspection and date of deregistration must not be longer than 14 months	360,110	This criterion aims to ensure that the vehicle has not been sitting unused for a longer time than 14 months before scrapping. The duration was chosen since vehicles older than five years need to be inspected annually and each inspection needs to happen within 14 months of the previous inspection[1]. Hence, if the duration between the last inspection is longer than 14 months, the car has most likely been sitting unused for some time.
Time between first registration of the vehicle and the model year must not be larger than one year	180,814	This criterion aims to ensure that the vehicle was not registered in Sweden late in its lifetime, indicating that it may have been driven somewhere else. This could influence the results since driving patterns may differ between countries.
Average distance travelled must not be larger than 400 km per day	255	This criterion aims to avoid vehicles with an unreasonably high mileage compared to age, probably due to errors in the dataset. The limit of 400 km is equivalent to driving 5 h continuously at 80 km/h on any given day.
Average distance travelled must not be smaller than 1 km per day	22,959	This criterion aims to avoid vehicles that are not used regularly, such as vintage cars that are only driven a few times per year.
Mass in running order must not be larger than 3,000 kg	235	Maximum total weight for a passenger car is 3,500 kg in Sweden. The mass in running order does not cover passengers or payload. Hence, the criterion is set at 3,000 kg to account for four passengers (75 kg each) and 200 kg payload.
Engine type is gasoline or diesel without hybridization	18,080	Other engine types are either emerging technologies (cars using electric engines) or niche market vehicles (ethanol flexifuel and natural gas / biogas). In both cases, the samples are limited and may be biased by issues with immature technologies or circumstances of the niche markets.

Table SM 2: Number of observations before and after cleaning, per engine type

Engine type	Before cleaning	After cleaning
Gasoline	794,608	334,846
Diesel	79,332	30,729
Battery electric	171	
Mild hybrid electric	2,405	
Plug-in hybrid electric	163	
Ethanol flexifuel	12,221	
Natural gas / Biogas	3,047	
Others	73	

Table SM 3: Number of observations before and after cleaning, per year of deregistration

	Before cleaning	After cleaning
2014	173,611	74,892
2015	176,175	73,874
2016	173,291	71,048
2017	179,047	72,416
2018	189,896	73,345
Total	**892,020**	**365,575**

1.3 Details on the stratified random sampling of Swedish vehicle retirement statistics

Table SM 4: Number of observations for each stratum and the random sample size used for each stratum

Average annual driving intensity class	No. observations	Random sample size
0-5,000 km/year	16,170	300
5,001-10,000 km/year	72,180	300
10,001-15,000 km/year	142,713	300
15,001-20,000 km/year	90,565	300
20,001-25,000 km/year	29,241	300
25,001-30,000 km/year	8,993	300
30,001-35,000 km/year	2,938	300
35,001-40,000 km/year	1,129	300
40,001-50,000 km/year	800	300
50,001-70,000 km/year	480	300
70,001-100,000 km/year	287	287
100,001+ km/year	79	-

1.4 R-packages used for the statistical analyses

Table SM 5: R-packages used for the statistical analyses

Section of methodology	Purpose	Function (R-package)
Swedish vehicle retirement statistics.	Stratified random sampling	stratified (splitstackshape v.1.4.8)
	Fit distributions to datasets	fitdist (fitdistrplus v.1.1-3)
Semi-empirical lifetime-intensity model.	Optimizer for maximum likelihood estimation.	optimx (optimx v.2020-4.2)
Self-reported data on remaining battery capacity (SM 3).	Extrapolation of data.	stat_smooth (ggplot2 v.3.3.3) lm (stats v.4.1.2)
	Significance in difference of the mean between strata.	t.test (stats v.4.1.2)

1.5 Breakeven for empty travel

We derive a simplified formula for finding the empty travel level for shared AVs which leads to a breakeven with respect to the carbon footprint to that of an individually owned car. We state the carbon footprint for the individually owned car on the left side of the equation and the carbon footprint for the shared vehicle on the right side, as shown below.

$$\frac{C + \sum_{\tilde{t}=t}^{\tilde{t}=t+\tau_0} k(\tilde{t}) \cdot D_0 \cdot \tau_0}{D_0 \cdot \tau_0} = \frac{C + \sum_{\tilde{t}=t}^{\tilde{t}=t+\tau_0 \cdot \left(\frac{(1+e)\cdot D}{D_0}\right)^{\varepsilon}} k(\tilde{t}) \cdot (1+e) \cdot D}{D \cdot \tau_0 \cdot \left(\frac{(1+e)\cdot D}{D_0}\right)^{\varepsilon}}$$

C is manufacturing emissions, $k(t)$ is use-phase emissions per unit distance, D is the average annual distance for a shared AV, D_0 is the average annual distance for the individually owned passenger car, τ_0 is the average lifetime for the individually owned passenger car, e is additional empty traveling when the passenger car is used as a shared autonomous vehicle, ε is the intensity-lifetime elasticity and $i = \frac{D}{D_0}$ is the ratio of intended travel distance by shared vehicle to average travel by an individually owned passenger car.

If we assume that $k(t) = k$, i.e., use-phase emissions are constant over time, we can simplify the expression to

$$\frac{C + k \cdot D_0 \cdot \tau_0}{D_0 \cdot \tau_0} = \frac{C + k \cdot (1+e) \cdot D \cdot \tau_0 \cdot \left(\frac{(1+e)\cdot D}{D_0}\right)^{\varepsilon}}{D \cdot \tau_0 \cdot \left(\frac{(1+e)\cdot D}{D_0}\right)^{\varepsilon}}$$

If $\varepsilon = 0$, this implies that

$$e = \frac{C}{k \cdot D \cdot \tau_0} \cdot \left(\frac{D}{D_0} - 1\right) = \frac{C}{k \cdot D \cdot \tau_0} \cdot (i - 1)$$

or in words:

$$e = \frac{Manufacturing\ emissions}{Total\ use\ phase\ emissions} \cdot (\%\ increase\ in\ intended\ driving\ intensity).$$

This says that the larger the ratio of manufacturing-related emission to total use phase emissions, the larger is the breakeven level of empty travel. Also, the larger the increase in intended driving intensity (i.e., the served travel distance) is, the larger is the breakeven level of empty travel.

If $\varepsilon \to -1$, this implies that

$$e \to 0.$$

Hence, no empty traveling is possible without increasing emissions in this case. This occurs since the cumulative driving distance is constrained $\tau \cdot D = \tau_0 \cdot D_0$, which can easily be found by applying $\varepsilon = -1$ in equation (4) in the manuscript. Hence, any empty travel would just increase carbon footprints per unit of intended travel distance.

2 Detailed results

2.1 Distributions of main variables analyzed in Swedish vehicle retirement statistics

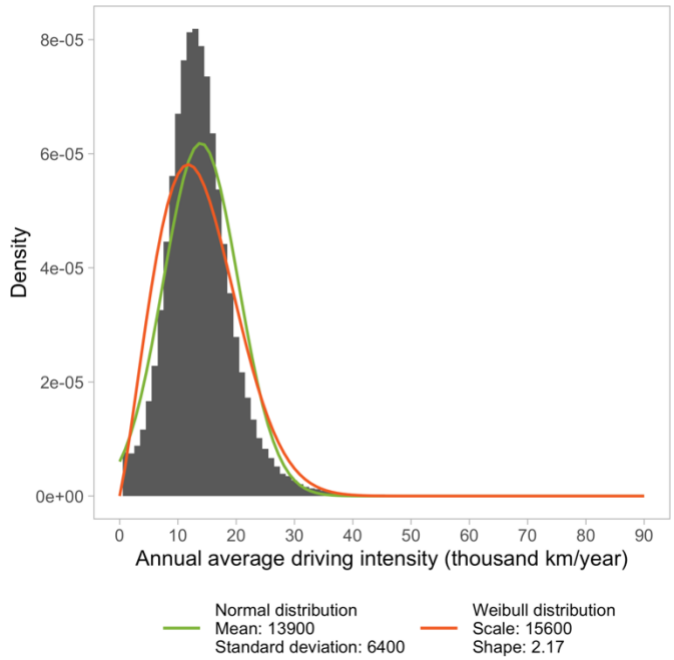

Figure SM 2: Distribution of annual average driving intensities for Swedish passenger cars retired during 2014-2018 (histogram) and fitted normal and Weibull distributions (lines).

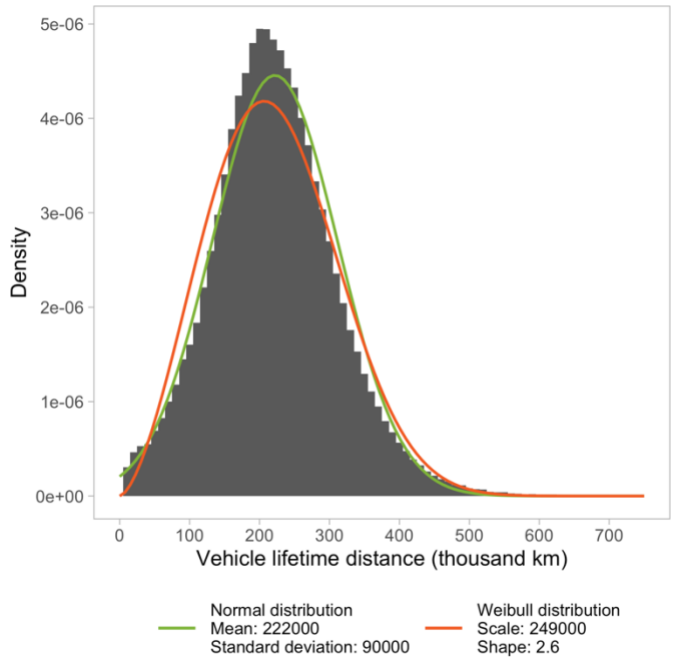

Figure SM 3: Distribution of total lifetime distance for Swedish passenger cars retired during 2014-2018 (histogram) and fitted normal and Weibull distributions (lines).

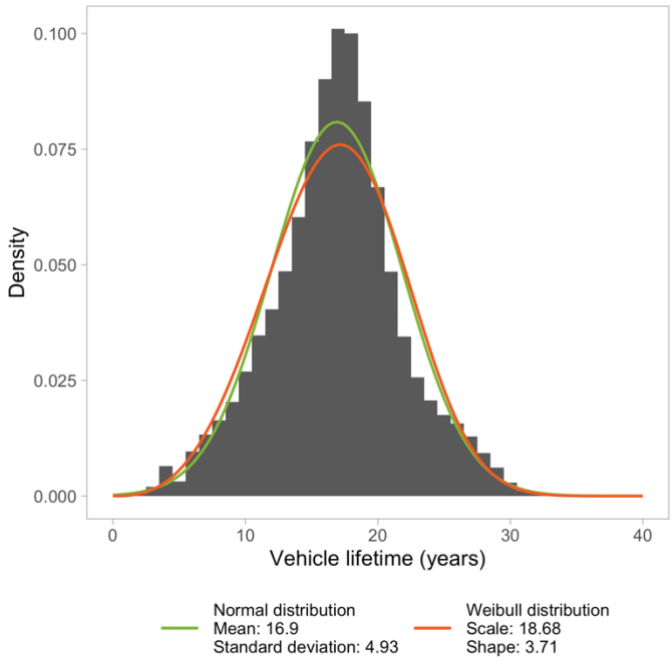

Figure SM 4: Distribution of vehicle lifetimes for Swedish passenger cars retired during 2014-2018 (histogram) and fitted normal and Weibull distributions (lines).

2.2 Maximum likelihood estimation of semi-empirical model designs

Table SM 6: Parameters estimated based on the full dataset.

	Normal distribution	Weibull distribution
D_0	13912	13912
τ_0	16.901	18.676
α	0.29180	0.19842

Table SM 7: Parameters estimated using maximum likelihood

	Normal distribution	Weibull distribution
Elasticity model		
ε	-0.58691	-0.56931
β	0.46667	0.59151
Logistic model		
L_0	28.153	31.152
L	22.299	23.992

2.3 Semi-empirical model designs compared to the distribution of each individual class of driving intensity

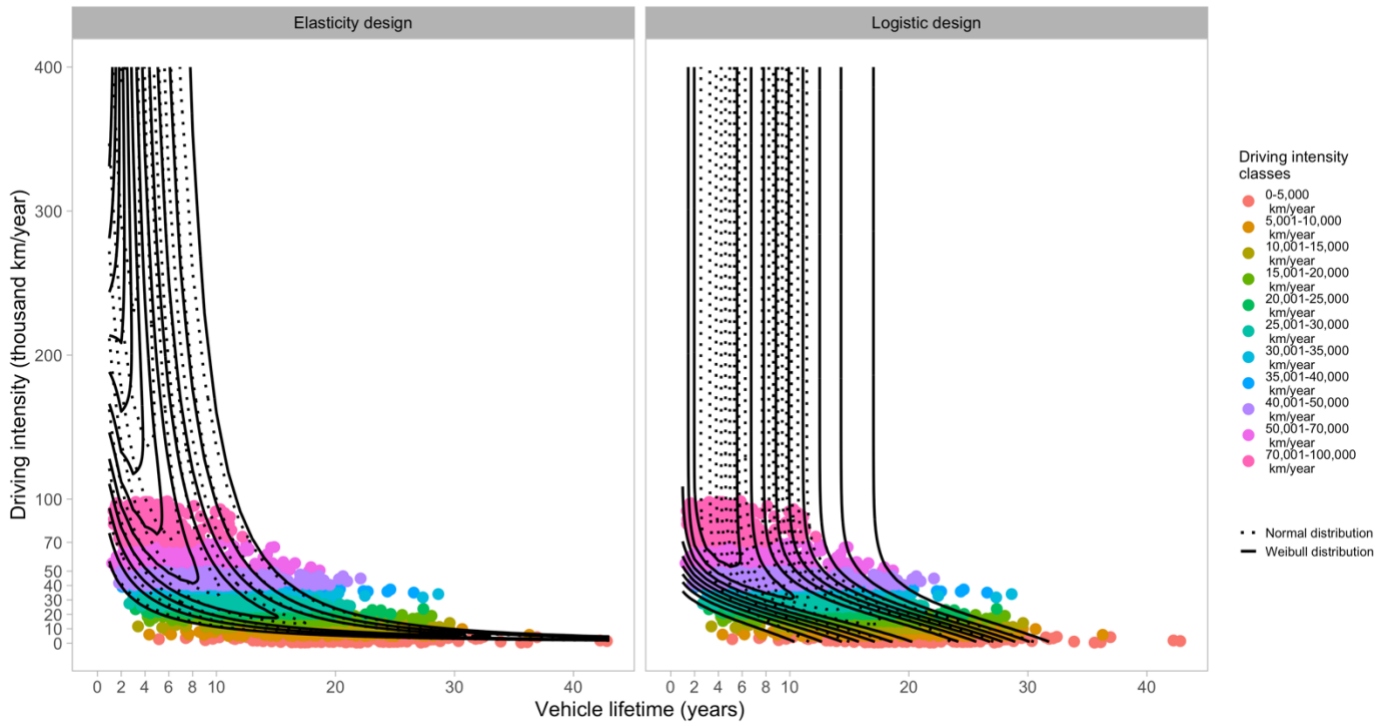

Figure SM 5: Semi-empirical model results for the elasticity and logistic models (see panels) and for normal or weibull distributions (see line type). Stratified samples of Swedish vehicle retirement statistics for 2014-2018 are provided in the background for comparison together with their respective means and medians.

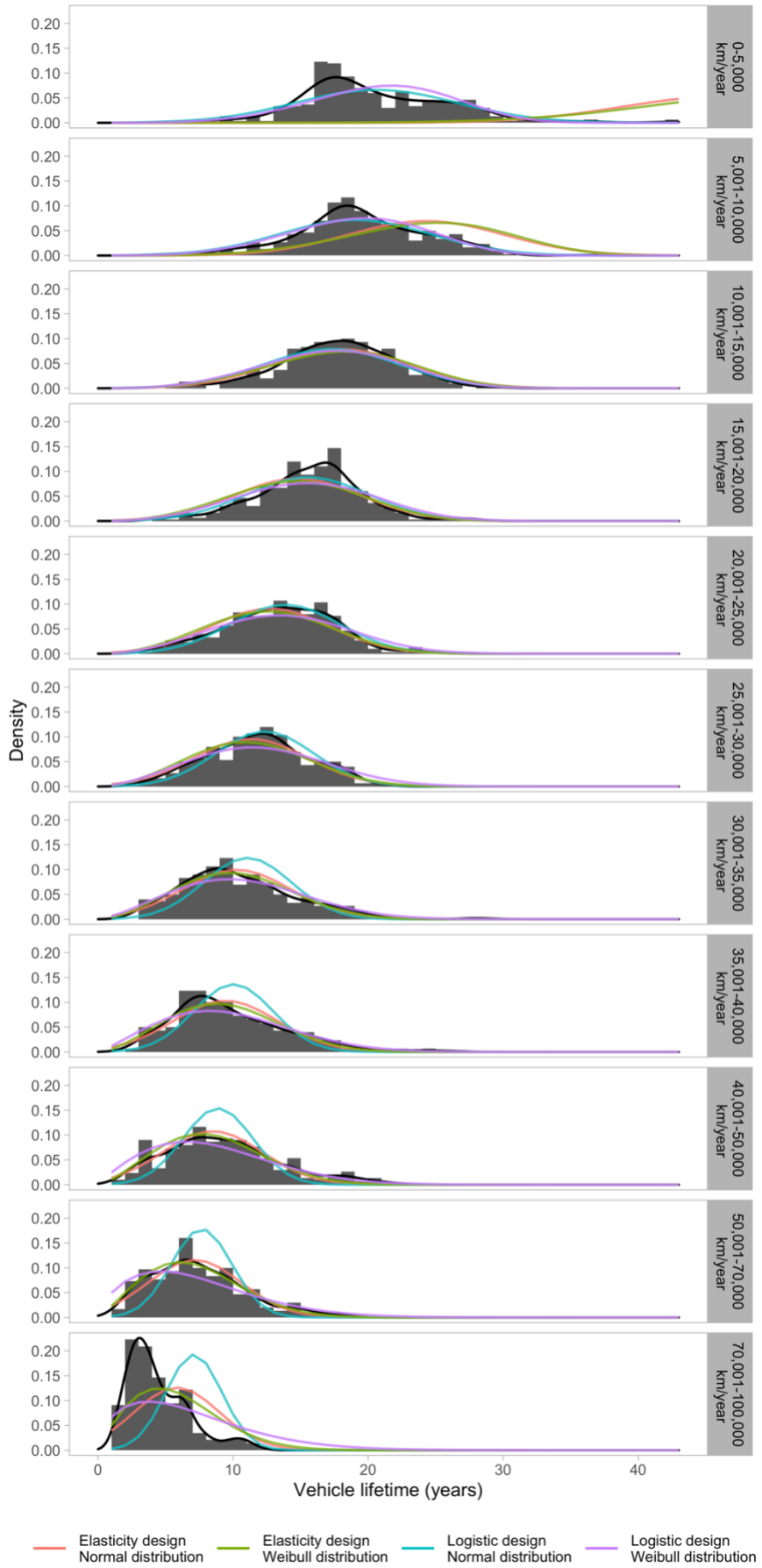

Figure SM 6: Semi-empirical model results for each respective driving intensity class and modelling approach, compared to the distribution of the stratified sample of the same class.

2.4 Semi-empirical model results for carbon footprint

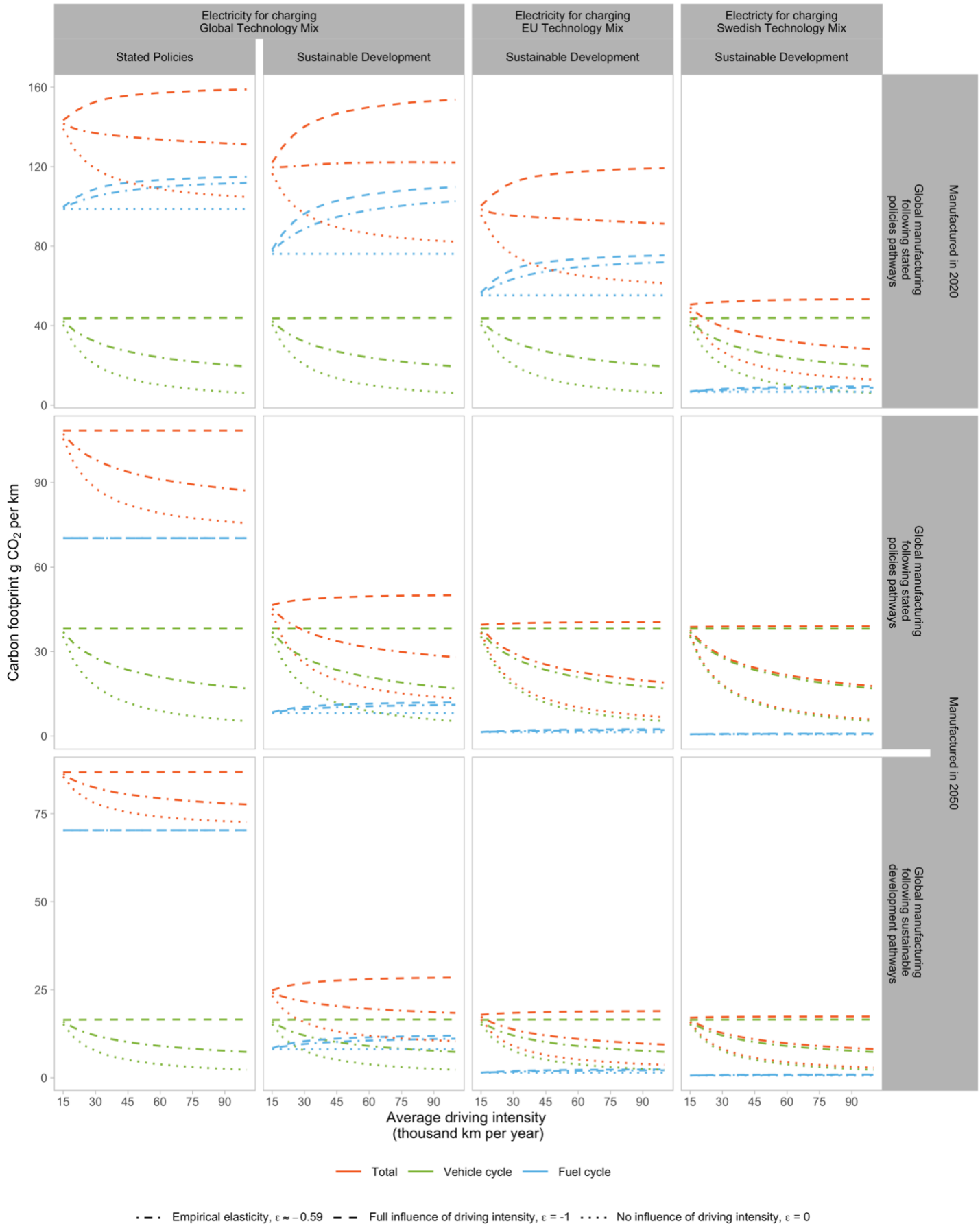

Figure SM 7: Carbon footprint, estimated in total and for vehicle and fuel cycles (color), for BEVs with different elasticity for the influence of driving intensity on vehicle lifetime (line type), depending on electricity used for charging (horizontal panels), climate change mitigation in global manufacturing (vertical panels)

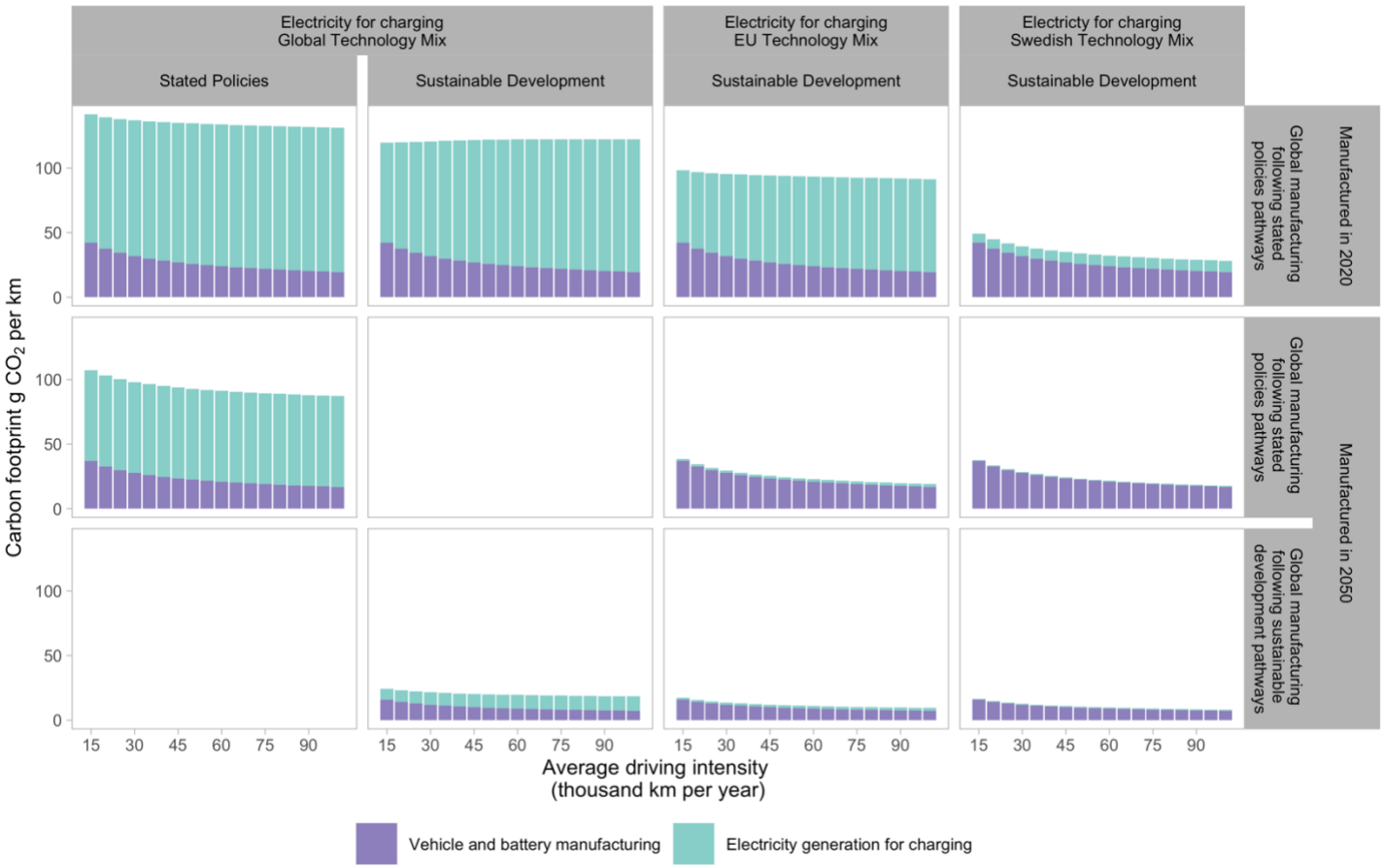

Figure SM 8: Carbon footprint for a battery electric passenger car divided between fuel and vehicle cycles (colors in bars), depending on electricity used for charging (horizontal panels), climate change mitigation in global manufacturing (vertical panels).

2.5 Breakeven for share of empty travel

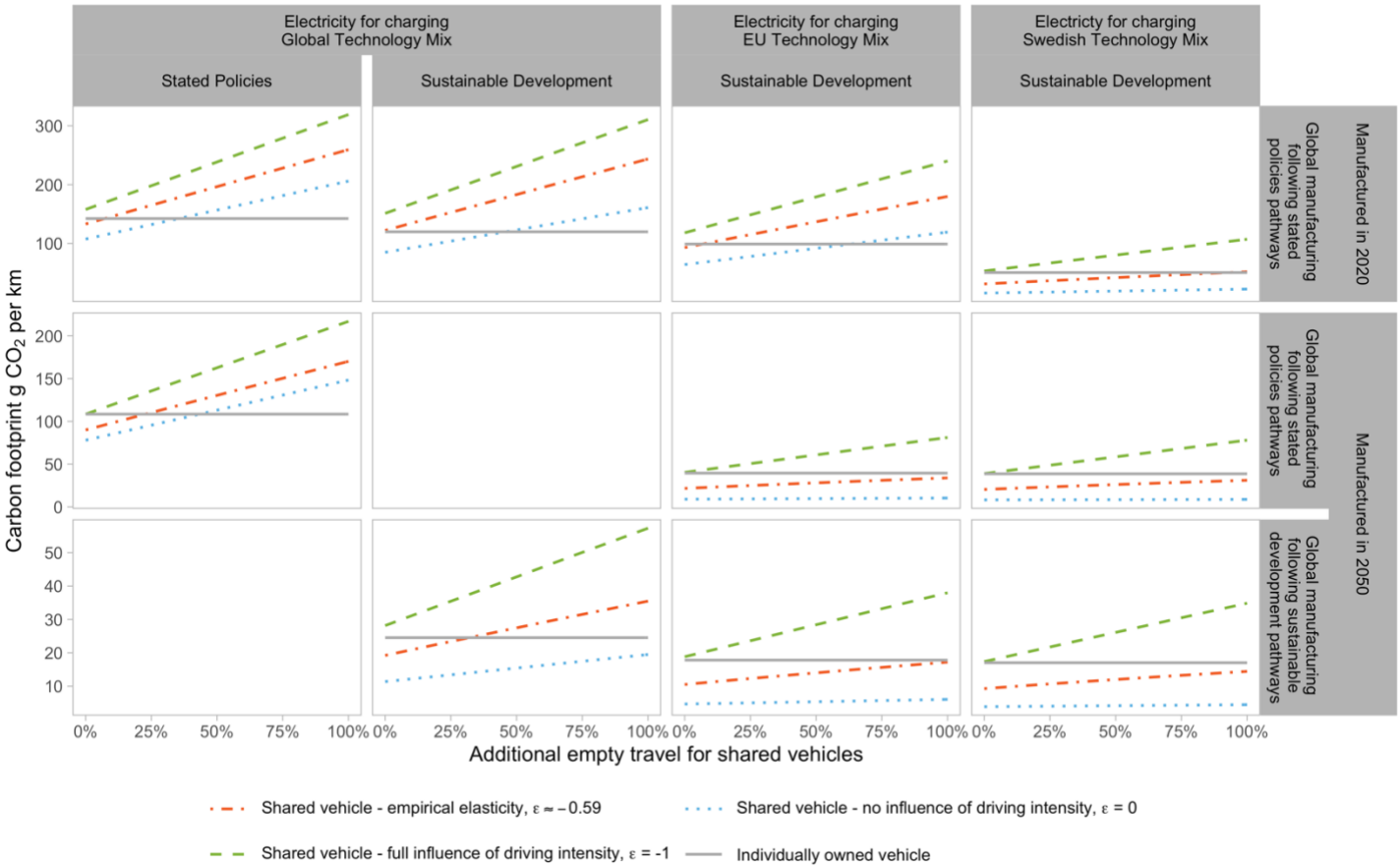

Figure SM 9: Breakeven for the carbon footprint between individually owned and shared BEVs depending on electricity used for charging (horizontal panels), climate change mitigation in global manufacturing (vertical panels).

3 How representative are the results for BEVs?

A key assumption in the study is that lifetime-driving intensity relationship for retired ICEVs during 2014-2018 could be used as a proxy for the lifetime-driving intensity relationship for electrified shared cars. The degradation behavior of an electric powertrain may be very different from the degradation of an ICE powertrain. The battery lifetime is often pointed out as an important constraining factor[2,3].

3.1 Batteries may outlive vehicles

Battery degradation occurs over time and may be amplified by extreme ambient temperatures, storing it at high states of charge, high cycling rates (i.e., the rate of completed full charging and discharging cycles), bad thermal management and high depth of discharge (i.e., almost fully discharging the battery before connecting to a charger) [2–4]. Retirement standards are used to determine when a battery should be taken out of use, which currently is set to when the actual battery capacity reaches below 80% of the original capacity or when power output is lower than the power demand. While the battery may very well provide sufficient power and range for the driver's needs below a battery capacity of 80%, safety related concerns may also limit how long the battery can be used with only partial battery capacity remaining [5].

Mathematical models for assessing battery degradation are typically using physical and chemical aspects of the battery cells and are empirically calibrated and verified based on data from laboratory experiments [4]. For example, assumptions must be made on how the temperature of the battery cells depends on the battery management system and on ambient temperature, or on how and when the driver choses to charge the vehicle. Two recent studies have concluded that the battery capacity should not decrease below 80% regardless of charging strategy for a car that is driven 12,000 km per year[4,6].

Statistics on battery lifetimes from real-world driving are scarce due to the recent large-scale introduction of electric vehicles in the passenger car market. The number of electric vehicles on the roads in 2010 were in the thousands while it reached over 10 million by 2020. Since then there has also been a shift towards the nickel manganese cobalt oxide (NMC) battery chemistry with relatively lower cobalt use[7,8]. If enough retirement statistics for electric vehicles were available to make thorough statistical analyses, most vehicles would only be less than 10 years old. Also, future battery chemistries may differ from the ones used today. Hence, it would be hard to draw any distinct conclusions that could be expected to be valid also for future electric vehicles.

3.2 Statistical analysis of self-reported data on Tesla cars

Nevertheless, one statistics source with relatively homogenous battery technology that is available is self-reported data on the remaining battery capacity of Tesla cars over ca. 10 years of driving[9]. As per 23 January 2021, the dataset includes 1,649 entries for cars manufactured between 2012 and 2020. Each entry includes information on the Tesla model, manufacturing date, total driving distance, reporting date, frequency of supercharging and remaining battery capacity (as reported by the car computer system). Entries without manufacturing date, with age estimated to less than one year or with reported remaining battery capacity above 100% are excluded, leaving 1,008 entries in the cleaned dataset.

Table SM 8: Number of entries after cleaning divided in three average annual driving intensity classes

a) Average annual driving intensity class	*No. of entries*	*b) Completed cycles class*	*No. of entries*
0-30,000 km/year	441	*0-85 cycles/year*	515
30,001+ km/year	567	*86+ cycles/year*	493
(of which 60,000+ km/year	55)	*Total*	1,008
Total	1,008		

The data was stratified into two classes either based on average annual driving intensity, 0-30,000 km/year, 30,001+ km/year, or on completed number of charging cycles, 0-85 cycles/year and 86+ cycles/year, see Table SM 5. The number of charging cycles are estimated based on each observations cumulative driving distance, the average specific energy use of 220 Wh per km, and each models battery

capacity. Random samples containing 400 observations of each class are used in the following analysis. The data is extrapolated by fitting a linear function or a square root function to the data, see SM 1.4 for details on the statistical package used. Note that Tesla cars and their battery management systems have been further developed since this database was founded and that the results therefore should be interpreted with great care.

The stratification of the dataset based on average annual driving intensity shows that more intensive driving habits slightly affects the remaining battery capacity (mean: 95.1% to 94.4%, considered statistically significant based on a Welch Two Sample t-test, and median: 95.7% to 94.7%). It is also interesting to note that the difference is even higher for cars older than 5 years (mean: 92.2% to 85.9%), although that sample only covers 28 cars. Linear and square root extrapolations[2,10,11] of the datasets illustrate that the cars could reach a remaining battery capacity below 80% by a 15-year lifetime for high annual driving intensity and a 20-year lifetime for low annual driving intensity (linear extrapolation) or a lifetime that exceeds 25 years (square root extrapolation), see left panel of Figure SM 10. Neither of the extrapolations can be seen as predictions and are provided only for illustrative purposes given that several additional aspects likely influence battery degradation that are not taken into account here.

The stratification of the dataset based on completed cycles shows also shows similar tendencies that more intensive driving habits in terms of completed charging cycles per year slightly affects the remaining battery capacity (mean: 95.3% to 94.5%, considered statistically significant based on a Welch Two Sample t-test, and median: 95.7% to 94.7%). The linear extrapolations of the datasets show similar results as for stratification on driving intensity (a 15-year lifetime for high number of cycles per year and a 20-year lifetime for low number of cycles per year), see right panel of Figure SM 10. However, the square root extrapolation shows slightly shorter lifetime for the high cycles per year stratum as compared with the high driving intensity stratum.

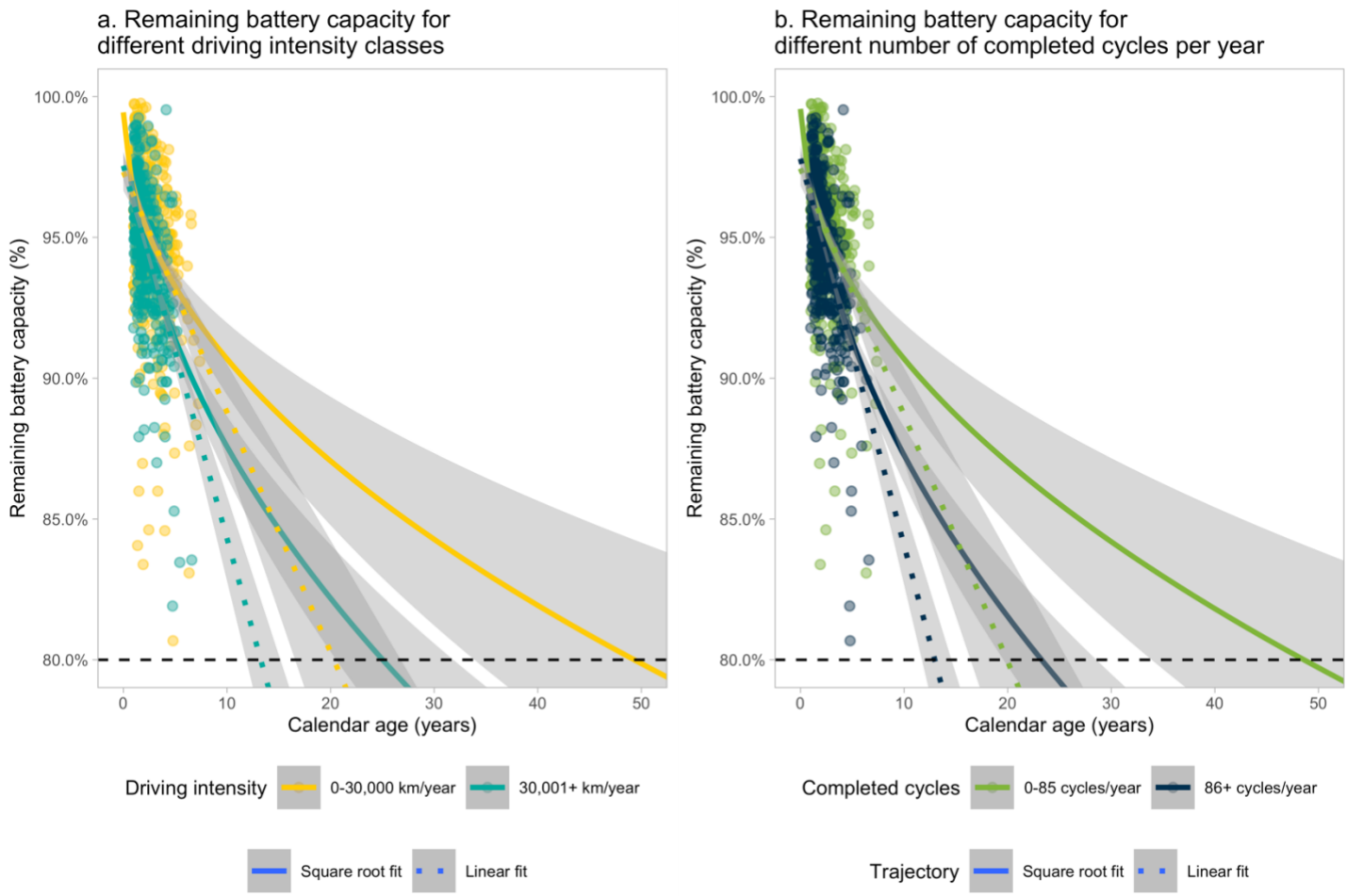

Figure SM 10: Self-reported data on remaining battery capacity from Tesla users, divided into two classes of driving intensity, and extrapolations based on square root fit or linear fit to the data.

Results using battery degradation models of current battery chemistries have been verified using real-world test vehicles[4] and the self-reported data for Tesla can provide some insight to the expected lifetime of current batteries. However, the question is how representative current estimates are for future electric vehicles given the on-going research and development of batteries. One example is the potential effects of a recent study[12] on a thermally modulated iron phosphate battery that could enable faster charging times, less influence of ambient temperature on battery capacity and output power. Such a battery is expected to have a lifetime of 51 years, covering over 900,000 km lifetime distance before reaching a capacity loss of 20%. Although promising, this technology is still in the design stage and far from dominating the market. However, technologies overcoming such barriers could very well be representing a large share of the market in the future, when carsharing is introduced at large scale.

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