

Shared mobility may limit vehicle lifetimes – implications for the carbon footprint

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Abstract

Car sharing and ride sharing will likely increase the annual vehicle driving distance, which in turn may accelerate passenger car retirement. In this study, we develop a semi-empirical lifetime-driving intensity model. We integrate our model with a carbon footprint estimation model, which assesses future decarbonization of global, European, and Swedish energy systems. We calibrate the lifetime-driving intensity model using Swedish vehicle retirement statistics, which suggest that driving intensity strongly impacts vehicle lifetimes. Our combined model shows that use-phase emissions depend on driving intensity, while manufacturing emissions are distributed over the cumulative driving distance. Hence, the carbon footprint depends on both the calendar age and cumulative driving distance of the vehicle. The results of our study also show that higher driving intensities generally result in lower carbon footprints. However, empty travel by shared autonomous vehicles, i.e., the additional distance traveled to pick up passengers, may cause carbon footprints to increase.

Full Text

Decarbonizing road transportation is an important step in achieving the Paris Agreement¹, with battery electric vehicles (BEVs) one of the main strategies being considered^{2,3}. Transitioning towards a fully electrified passenger car fleet effectively eliminates tailpipe CO₂ emissions and has the potential to significantly reduce lifecycle CO₂ emissions⁴. Nevertheless, social and environmental sustainability concerns have been raised related to battery manufacturing and the mining of raw materials⁵.

Pathways with low resource exploitation and high energy efficiency are beneficial for decarbonization since they reduce the overall energy demand and material needs. Options for passenger cars include various on-demand mobility schemes (including ride sourcing and ride pooling) that could replace individual passenger car ownership⁶. Implementing such schemes on a large scale would probably depend on self-driving vehicles that are connected and autonomous^{7,8}. Each shared autonomous vehicle (shared AV) may replace on the order of ten individually owned cars⁹ and will likely be used more intensively during its lifetime as compared to individually owned cars¹⁰. The term “individually owned” is used to describe all types of arrangements where the car is primarily used by one household.

Carbon footprint estimates per vehicle-kilometer or person-kilometer are strongly dependent on the cumulative distance traveled over the vehicle’s lifetime due to the relatively large share of emissions in the manufacturing of the vehicle¹¹. This is especially relevant when comparing BEVs with internal combustion engine vehicles (ICEVs), since manufacturing emissions are usually considerably larger for BEVs than for ICEVs.

To estimate the carbon footprint of a car, we need to make assumptions on cumulative driving distance and calendar age, but these assumptions vary significantly among studies¹¹. These assumptions are even more uncertain for future mobility schemes including different aspects of car sharing or ride sharing¹². Nevertheless, carbon footprint studies tend to assume that shared AVs would travel at least as far as current taxis^{10,13}. Hence, considering a relationship between driving intensity and vehicle lifetime is critical when assessing the carbon footprint of shared AVs. Studies using survival analysis^{14,15} have determined that both calendar lifetime and cumulative driving distance are important for the decision to retire a vehicle. However, to our knowledge no study has yet attempted to establish a relationship between driving intensity and vehicle lifetime. Moreover, the carbon footprint related consequences of varying both vehicle lifetime and driving intensity have not yet been analyzed in situations where energy systems are decarbonized over time.

This study aims to bridge this gap by estimating the impact of vehicle lifetime and annual driving intensity on the carbon footprints of passenger cars. We use a prospective lifecycle assessment framework to capture the effects of climate change mitigation in global manufacturing and electricity generation. We also design a semi-empirical lifetime-intensity model for assessing the vehicle lifetime of cars with increasing annual driving intensity. Our insights will be useful when researching the environmental and resource impacts of implementing shared mobility in general, although this study focuses on the consequences for carbon footprint estimations. While the study is based on Swedish vehicle retirement statistics, the results are likely to be representative for many other industrialized countries, and the designed model could easily be recalibrated based on datasets for other countries.

Breakeven for electric cars depends on driving intensity

Carbon footprint comparisons are strongly dependent on several assumptions. For example, the breakeven lifetime distance in terms of greenhouse gas emissions for a BEV compared to an ICEV has been estimated at 17,000-310,000 kilometers (km)¹⁶. One key assumption is the carbon intensity of electricity used for charging, i.e., for the use phase of the vehicle.

Our modeling shows that carbon footprints for a vehicle manufactured in 2020 are on average smaller for BEVs than ICEVs already at relatively low annual driving intensities for the three levels of carbon intensity of electricity generation used for charging considered in this study (global, European, and Swedish electricity generation mix, see Supplementary Materials (SM) 1.1). If we assume the Swedish average annual driving intensity is 13.9 thousand km, see SM 2.2, the breakeven carbon footprint between ICEVs and BEVs occurs after 4 years, 3 years, and 2 years for the global, European, and Swedish electricity mix, respectively. This can be compared with the average lifetime of Swedish ICEVs of 17 years. Similarly, if we assume the Swedish average lifetime for a given car, the annual driving intensity must be less than 2,000 km for the global and European, and less than 1,000 km for Swedish electricity mix, for the BEV to have a higher carbon footprint than a comparable ICEV.

The reason behind these results is that the comparatively high upfront emissions related to battery manufacturing are compensated for by low emissions during the use phase of BEVs as compared to ICEVs even when assuming the global average electricity generation mix. Hence, for BEVs to have higher carbon footprints than ICEVs, annual driving intensity must be low or the lifetime short. Actually, BEVs have lower carbon footprints than ICEVs under most circumstances, including the average circumstances (i.e., lifetime of 17 years and an annual driving intensity of 13.9 thousand km). As expected, the carbon footprint continues to drop if the car is driven more intensely or has a longer lifetime, see Figure 1.

The role of the use phase of BEVs in the carbon footprint also points to the importance of the driving intensity. By combining driving intensity and lifetime, we can determine not only the total lifetime distance but also when in the future the driving would occur. The carbon intensity of electricity used for charging will gradually decrease as energy systems are decarbonized (assuming that the Paris Agreement's goals are met). Consider the example of a car manufactured in 2020 with a total lifetime driving distance of 240 thousand km and using global average electricity for charging. Its carbon footprint can vary between 108 and 151 g CO₂ per km depending on the annual driving intensity and lifetime assumptions (91-118 g CO₂ per km and 48-52 g CO₂ per km and for the European and Swedish electricity mix, respectively).

The higher the annual driving intensity and vehicle lifetime, the lower the carbon footprint – this is true for both ICEVs and BEVs. The carbon footprint for BEVs manufactured in 2020 using the global electricity mix can be as low as 78 g CO₂ per km (compared to 63 g CO₂ per km and 26 g CO₂ per km for EU and Swedish electricity mix, respectively), while it

never reaches below 182 g CO₂ per km for ICEVs. These estimates assume that the car is limited by a maximum lifetime driving distance of 500,000 km, see distribution of lifetime driving distances in SM 2.2.

Both manufacturing-related emissions and emissions related to the use phase could be significantly lower for a vehicle manufactured in 2050, see results in the bottom row of Figure 1. This is because we assume that the Paris Agreement's goals are met, and that global manufacturing and electricity generation are decarbonized accordingly. Results for a scenario where global manufacturing and electricity generation decarbonize in line with currently stated policies for 2050 are shown in SM 2.1. The carbon footprint of BEVs could reach between 8 and 13 g CO₂ per km depending on the electricity mix used for charging, while ICEVs could reach 157 g CO₂ per km. Hence, BEVs manufactured in 2050 would not need to reach old age to achieve a low carbon footprint compared to ICEVs due to the lower emissions assumed for 2050. Actually, a BEV does not even have to survive for one whole year at average annual driving intensity (13.9 thousand km) to have a lower carbon footprint compared to its ICEV counterpart fueled with fossil diesel or gasoline. Similarly, if we assume the average lifetime (17 years), no more than 500 km per year of driving is needed to achieve a lower carbon footprint than its ICEV counterpart.

To meet the goals of the Paris Agreement, shifts towards low-carbon manufacturing processes and electricity mixes used for charging would happen gradually over the course of the next 30 years⁴. Thus, the vehicle's lifetime, its annual driving intensity and its interaction with decarbonizing energy systems will play important roles in estimating the vehicle's carbon footprint over the coming decades. The relationship between annual driving intensities and vehicle lifetimes may also become more complex when the fleet is shared to a greater extent than today. The question is: How far can the car be pushed in terms of annual driving intensity before limiting the vehicle lifetime too much, resulting in a higher carbon footprint?

Vehicle lifetimes decrease with increased driving intensity

Statistics on vehicle retirement can provide insights into how vehicle lifetimes vary with driving intensity. Most Swedish vehicles retired in 2014-2018 had a lifetime between 7 and 27 years and lifetime driving distances between 42 and 402 thousand km (95% interval —assuming Normal-distributed data). Calculating the average annual driving intensity for these vehicles results in a range between 1 and 27 thousand km per year (95% interval). All vehicles analyzed are ICEVs, since we are interested in capturing the behavior of mature vehicle technologies; very few BEVs have been retired so far.

The statistics show an average lifetime of 17 years, average lifetime driving distance of 222 thousand km, and an average annual driving intensity of 13.9 thousand km per year. Note that while a Normal distribution can approximate vehicle lifetimes well, lifetime distances may be better approximated by a Weibull distribution, see SM 2.2, confirming previous research¹⁴. Since the sample is unevenly distributed over driving intensities with a bias towards the mean, stratification is used as a starting point for characterizing how the vehicle lifetimes vary with average annual driving intensity, see Figure 2 and details on the stratified samples in SM 1.3.

The results of the stratification reveal that the mean vehicle lifetime decreases with each higher driving intensity class, from 21 years for average driving intensities of 0-5,000 km per year to 4 years for average driving intensities of 70,001-100,000 km per year. The standard deviation of the distributions also indicates that the range of probable lifetimes becomes narrower with increasing annual driving intensity (although the standard deviation increases in relative terms). The standard deviation decreases from 6 years for driving intensities of 0-5,000 km per year to 2 years for driving intensities of 70,001-100,000 km per year (assuming Normal-distributed data). All in all, the results suggest that the annual driving intensity indeed has a strong influence on vehicle lifetimes.

Sensitivity to driving intensity determines carbon footprint

This section presents carbon footprint estimates for BEVs for different average annual driving intensities based on the developed semi-empirical lifetime-intensity model, see Methods section for full description and discussion of the design. The model estimates the expected lifetime of a vehicle given a certain assumed average annual driving intensity. Hence, we assume that the lifetime-intensity model is representative for BEVs despite being calibrated on data for ICEVs. BEVs are a relatively new technology on the market. To date, only very few BEVs have been retired and may not be representative of technologically mature BEVs sold in the future. This assumption is discussed in greater depth in SM 3.

We assume the *elasticity design* with Normal distribution, see equation (4) in Methods, and an elasticity ($\epsilon \approx -0.59$) based on empirical data (i.e., Swedish vehicle retirement statistics described in the previous section) and maximum likelihood estimation, see SM 2.3. A lifetime-intensity elasticity of -0.59 implies that the lifetime is reduced by about -0.59% if annual driving intensity is increased by 1%. Consequently, the cumulative lifetime driving distance increases by about 0.41% if annual driving intensity is increased by 1%.

Carbon footprints are also estimated for two extreme cases, $\epsilon = 0$ and $\epsilon = -1$, representing no influence of driving intensity on lifetime and full influence of driving intensity, respectively. Figure 3 shows the results for BEVs using the global average electricity mix, assuming that global electricity generation decarbonizes in line with the goals of the Paris Agreement. Results for European and Swedish average electricity mixes are available in SM 2.5. We assume that global electricity generation decarbonizes in line with the Paris Agreement's goals here, since it shows the interaction between manufacturing phase and use phase, and the large influence that the mitigation scenario has on the use phase. Although these aspects are true for all analyzed cases, manufacturing-phase emissions tend to drive the trend of the total carbon footprint in cases where use-phase emissions are low and/or constant, see SM 2.5.

Emissions per km related to vehicle manufacturing decrease with increasing driving intensity when using the elasticity based on empirical evidence, see solid line in Figure 3 and SM 2.5. This can be compared to when the lifetime is only determined by driving intensity, i.e., $\epsilon = -1$, which implies that the expected cumulative driving distance over the whole lifetime of the vehicle is fixed. In that case, manufacturing emissions per km are constant and independent of driving intensity, see dashed line in Figure 3. For the elasticity based on empirical evidence, i.e., $\epsilon = -0.59$, a greater cumulative lifetime driving distance is obtained as the driving intensity increases (on average). In the third case, $\epsilon = 0$, the lifetime is constant since it is not at all influenced by the driving intensity, i.e., the expected cumulative driving distance increases with the same percentage increase as the driving intensity. This results in manufacturing emissions per km approaching zero with increased driving intensity, see dotted lines in Figure 3.

Intuitively, average use-phase emissions depend on the vehicle-specific energy use and the carbon intensity of the electricity mix used for charging in each specific year, see SM 2.5. However, it also depends on the driving intensity in a changing energy system, provided that the lifetime of the vehicle is affected by the driving intensity. In the case where the vehicle lifetime is fully determined by driving intensity, i.e., $\epsilon = -1$, an increased driving intensity implies a shorter lifetime, leading to the cumulative lifetime driving distance occurring in the more near-term when the carbon intensity is higher. Therefore, the average use-phase emissions increase with driving intensity since the carbon intensity decreases over time. In the case with an empirically estimated elasticity, i.e., $\epsilon = -0.59$, a greater driving intensity also implies a shorter lifetime, but to a smaller extent compared to when $\epsilon = -1$. Hence, the average use-phase emissions increase with driving intensity. In the third case, $\epsilon = 0$, the lifetime is independent of driving intensity, and consequently so are the average use-phase emissions.

Empty travel by autonomous vehicles may increase emissions

For a large-scale expansion of car sharing and ride sharing to take place at a significant scale, the vehicles likely need to be self-driving. Self-driving vehicles could decrease the cost and convenience of such schemes and thus render it preferable over individually owned cars⁷. Sharing is often raised as an argument for increasing resource efficiency and reducing the environmental load of a system. However, shared AVs may to a large extent travel around idle (“empty travel” or “deadhead travel”). Simulation studies of shared autonomous taxis have found that in urban areas empty travel could increase the total travel distance by 10–100% compared to the intended travel distance^{9,17}. Empirical studies show a level of around 60% for taxi rides¹⁸ and 40% for ride-sourcing services¹⁹ on top of the intended travel distance. This aspect, together with the fact that the lifetime of the vehicle is likely to decrease with increased driving intensity, is likely to reduce the resource and environmental efficiency of sharing. With this in mind, we therefore ask: How much empty travel can there be without the carbon footprint of a shared vehicle exceeding that of an individually owned vehicle?

The breakeven share of empty travel (i.e., the point where the carbon footprints of the shared autonomous vehicle and the individually owned vehicle are equal) depends on the assumed elasticity for the lifetime-intensity model. A simplified equation, see SM 1.5, shows that when the elasticity is equal to zero (i.e., when vehicle retirement only depends on calendar age), the breakeven share of empty travel increases with the increased ratio between manufacturing emissions and total use-phase emissions and with the increase in driving intensity. If $\epsilon = -1$ and the lifetime is determined solely by cumulative driving distance, the breakeven share of empty travel approaches zero since any empty travel would lead to an increase in the carbon footprint.

For estimating the breakeven share of empty travel based on the lifetime-intensity model with elasticity based on empirical evidence, we assume that two electric vehicles are manufactured in 2020. The first is used as a shared autonomous vehicle with annual useful travel distance 5 times the current average driving intensity (i.e., the travel distance for transporting passengers). The second is used as an individually owned vehicle with current average driving intensity. The breakeven share of empty travel can be estimated numerically showing that it is 0% for a vehicle manufactured in 2020 when assuming the global electricity mix for charging and that global electricity generation decarbonizes in line with the Paris Agreement’s goals. This means that, in this example, a shared AV using the global electricity mix currently has a higher carbon footprint than the individually owned alternative regardless of the share of empty travel. This can also be seen in Figure 3, where the carbon footprint slightly increases with increasing driving intensity. However, if the carbon intensity of the electricity mix were smaller, the outcome would be different.

The breakeven point is at 6% and 90% of empty travel, see Figure 4, when using the European and Swedish electricity mix, respectively. If instead we assume that the vehicle is manufactured in 2050, the breakeven share of empty travel is 32% for the global electricity mix, while reaching 100% for the European and Swedish electricity mixes. This range indicates the influence of climate change mitigation in global manufacturing and electricity generation, see the visualization in SM 2.6. Hence, a shared AV manufactured in 2050 using the European or Swedish electricity mix for charging could double its traveling distance due to empty travel and still have a lower carbon footprint.

Discussion

Our analysis suggests that the relationship between vehicle lifetime and driving intensity is an important factor when estimating the carbon footprint of car sharing and ride sharing. Some analysts argue that passenger cars in today’s fleets are not being used enough to compensate for material use and emissions during the manufacturing phase²⁰. Therefore, increasing the driving intensity, for example through car sharing, may be an option for reducing lifecycle emissions from passenger car travel. However, if increasing driving intensity also results in shortened vehicle lifetimes, as suggested by the statistics, the carbon footprint could increase for the trips made by those vehicles. However, this

aspect becomes less important as vehicle and battery manufacturing industries decarbonize, as well as when the carbon intensity of use-phase emissions drops.

The statistical analysis and the results from the designed semi-empirical lifetime-intensity model suggest that increased intensity of vehicle use tends to increase the cumulative lifetime distance, where a 1% increase in intensity decreases the lifetime by 0.59% on average, resulting in an average increase in cumulative driving distance of 0.41%. Hence, the results indicate that car sharing could reduce the carbon footprint if it results in higher driving intensity of each individual vehicle. However, this assumes a level of zero empty travel. Existing studies^{9,17} point to substantial levels of empty travel that could erase any potential benefits of sharing through ride-sourcing or autonomous taxis. On the other hand, the emissions reduction potential of car sharing services could be further improved if ride sharing were also implemented, since each traveler sharing the ride in that case would bear part of the carbon footprint, by effectively increasing the occupancy ratio. Finally, in addition to the empty travel that could occur for car and ride sharing of connected and automated vehicles, these services may also result in induced travel demand. The induced travel demand is due to the lower perceived cost of traveling by car when the passenger can do something other than drive while traveling²¹.

Methods

Prospective lifecycle assessment of carbon footprints. Carbon footprints (reported in g CO₂ per vehicle-km) are estimated using a prospective lifecycle assessment framework based on GREET® 2 - Version 2019²² adapted for scenario analysis⁴. The framework enables estimations of future carbon footprints of passenger cars depending on climate change mitigation efforts in global manufacturing. Two scenarios for this mitigation are analyzed: Stated Policies and Sustainable Development; the results for Sustainable Development are presented in the main paper, with the results for the Stated Policies in the SM. The Stated Policies Scenario is based on currently implemented and stated climate policies by 2019 and the Sustainable Development Scenario is designed to limit global mean temperature increase to below 1.8°C, which is assumed to be in line with the Paris Agreement’s goals. The two scenarios are based on the IEA²³ scenarios with the same names.

Carbon footprints per km are estimated based on

$$\text{Carbonfootprint}(t_0, \tau, D) = \frac{\text{Vehiclecycle}(t_0, \tau) + \sum_{t=t_0}^{\tau} (\text{Fuelcycle}(t, d(t, \tau, D)) + \text{Tailpipe}(t, d(t, \tau, D)))}{\sum_{t=t_0}^{\tau} d(t, \tau, D)}$$

1

For different combinations of vehicle lifetimes (2-40 years), annual average driving intensities (5,000-100,000 km per year), and the manufacturing year, t_0 , between 2020 and 2050. The average annual driving intensity, D , corresponds to the distance traveled over the whole lifetime of the vehicle, τ . The annual driving distance, d , for year t , is assumed to decrease by $b = 4.4\%$ per year, following this equation:

$$d(t, \tau, D) = \frac{D \cdot \tau}{\sum_{t=t_0}^{\tau} (1 - b)^{t-t_0-1}} (1 - b)^{t-t_0-1}$$

2

Vehicle cycle CO₂ emissions are estimated based on manufacturing processes as implemented in GREET® for the Stated Policies Scenario, while new and innovative processes are phased in over time for the Sustainable Development

Scenario based on a literature review⁴.

Fuel cycle as well as tailpipe CO₂ are use-phase emissions related to the distance traveled each year. The specific energy use of the car is determined depending on the type of car and its manufacturing year. ICEVs are assumed to use 669 Wh per km in 2020, decreasing to 492 Wh per km in 2030 and beyond, following energy efficiency improvements⁴. Similarly, BEVs are assumed to use 223 Wh per km in 2020, decreasing to 201 Wh per km in 2030 and beyond. ICEVs are assumed to use 100% fossil fuels acquired on average global markets, and BEVs are assumed to charge with electricity produced using average global, European, or Swedish technology mixes. Fuel cycle and tailpipe CO₂ are estimated annually based on traveled distance, vehicle energy use, and appropriate carbon intensities.

The carbon intensity of electricity is based on estimates of average direct emissions for future electricity mixes of each respective geographic area, see description of sources for scenario data below. 2019 is used as a base year to avoid influence of the Covid-pandemic on the carbon intensities. Upstream emissions occurring in production of fuels and power stations are accounted for by adding a weighted factor for future electricity mixes based on estimates by Pehl et al.²⁴. We assume that Pehl et al.'s estimates of upstream emissions for each electricity generation technology can be applied regardless of geographic area and that their baseline and climate policy scenarios resemble the Stated Policies and Sustainable Development scenarios used in this study. Note that emissions for construction of water and nuclear power stations are assumed to be zero for Sweden and the European Union due to their long lifetime, the fact that they were mainly constructed several decades ago, and that few new stations are planned. Hence, we assume that the emissions from the construction of these stations are only attributed to electricity production prior to 2019. Continuing to account for these construction-related emissions in the carbon intensity of electricity after 2019 would not have any significant impact on the results.

For the global electricity mix used in manufacturing and for charging, future direct emissions and adjustments to account for transmission and distribution losses (based on the difference between estimated supply and demand) are based on estimates by the IEA²³ for the two decarbonization pathways, Stated Policies and Sustainable Development. For the European electricity mix used for charging, direct emissions and adjustments to account for transmission and distribution losses are based on European Commission scenarios²⁵ combined with the cap of the European Union emissions trading system reaching zero in 2058²⁶ for both decarbonization pathways. For the Swedish electricity mix used for charging, direct emissions for 2019 are calculated based on the total emissions for electricity generation divided by the end-use of electricity^{27,28}. Direct emissions are assumed to decrease linearly to zero by 2045 for both decarbonization pathways, in line with the adopted net-zero emission target and the Swedish government's intention to reach zero for electricity generation²⁹. Upstream emissions are based on estimates by Pehl et al.²⁴ and projections for the future electricity generation mix by the IEA²³, European Commission²⁵, and Swedish Energy Agency³⁰.

Swedish vehicle retirement statistics. Statistics on Swedish passenger cars retired between 2014 and 2018 are used to understand how changes in annual average driving intensity could influence vehicle lifetimes. The statistics are collected from the Swedish registry for road transport vehicles, regulated by Swedish law³¹. The excerpt, provided by the Swedish government agency Transport Analysis³², includes information on manufacturing year, date of registration, car manufacturer, engine type, mass in running order, total distance traveled at last inspection, date of last inspection, and date of deregistration. The excerpt only includes vehicles that were indeed retired at the date of deregistration. Hence, vehicles that were deregistered for administrative reasons or exported are excluded.

The cleaned dataset includes 365,575 observations. The cleaning performed by the authors aims to reduce bias in the results and applies the following criteria: (i) age or distance traveled must not be missing, equal to zero, or equal to 999,999, (ii) time between last inspection and date of deregistration must not be longer than 14 months, (iii) time

between first registration of the vehicle and the manufacturing year must not be longer than one year, (iv) average distance traveled must not be greater than 400 km per day, (v) average distance traveled must not be less than 1 km per day, (vi) mass in running order must not be greater than 3,000 kg, and (vii) engine type is gasoline or diesel without hybridization. Details and rationale for these criteria are provided in SM 1.2.

Stratified random sampling is used to create a new dataset for analyzing the influence of increasing driving intensity since only a small share of total current vehicle retirement represents cars with high average annual driving intensity, such as taxis or other commercial vehicles. The strata and random sample size are set to maximize the amount of information about vehicles with high driving intensity while also ensuring high enough sample size to enable further statistical analysis. This results in strata for average annual driving intensity classes of 5,000 km/year increments from 0 km/year to 40,000 km/year, and three additional classes with larger increments (40,001-50,000 km/year, 50,001-70,000 km/year, and 70,001-100,000 km/year) due to limited data availability. The random sample size in each stratum is 300 observations, except for the highest intensity class where the whole sample of 287 observations is used, see SM 1.3 and 1.4.

Semi-empirical lifetime-intensity model. The semi-empirical lifetime-intensity model enables estimations of vehicle lifetime probabilities for a given annual average driving intensity. The model should easily be updated with new parameters on average vehicle retirement lifetime, its standard deviation, and the average annual driving distance, as new statistics become available. The model should also easily be recalibrated based on new stratified random sampling datasets to enable use for other geographical regions. Two model designs are considered together with two assumptions on the probability distribution of the lifetime data as a result of these prerequisites.

If the data follow a **Normal distribution**, we assume that the probability of a vehicle manufactured at year t_0 , with average annual driving intensity D , being retired at year t is

$$\phi_n(t, t_0, D) = \int_{t_0}^t \frac{1}{\sigma(D)\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{t-\mu(D)}{\sigma(D)}\right)^2} dt. \quad (3)$$

In the **elasticity design**, we introduce a factor dependent on the quota between the driving intensity of the vehicle and the average annual driving intensity of current vehicle retirements, D_0 , as part of the mean,

$$\mu(D) = \tau_0 \left(\frac{D}{D_0} \right)^\epsilon$$

4

that adjusts the expected vehicle lifetime of current retirements, τ_0 , dependent on the elasticity, ϵ , that decides the level of influence of the driving intensity. An elasticity of -1 implies that the vehicle lifetime is fully determined by the driving intensity (e.g., if driving intensity is doubled, lifetime is halved), 0 indicates no influence and the lifetime is only determined by calendar age, while an elasticity above 0 would imply that the vehicle lifetime increases with driving intensity. This design benefits from easy interpretation, but it only applies for driving intensities equal to or greater than the current average.

The standard deviation,

$$\sigma(D) = \alpha \tau_0 \left(\frac{D}{D_0} \right)^{\epsilon\beta}$$

is designed in a similar way to the design for the mean, where the constant $\alpha = \frac{\sigma_0}{\tau_0}$ is determined based on a fit of a Normal distribution to current vehicle retirement statistics. An additional elasticity, β , is introduced in the standard deviation to account for the distributions becoming increasingly narrow with higher driving intensity classes, see Figure 2.

In the **logistic design**, we instead assume that the distribution is governed by a function inspired by the logistic curve to better capture the form of the stratified random sampling. The logistic curve function is slightly altered to reduce the number of parameters to fit to the data. Hence, $\mu(D)$ and $\sigma(D)$ are defined as follows in this design.

$$\mu(D) = L_0 - \frac{L}{1 + e^{(1-D/D_0)}} \text{ and (6)}$$

$$\sigma(D) = \alpha \left(L_0 - \frac{L}{1 + e^{(1-D/D_0)}} \right)$$

7

where L and L_0 are the parameters that would be calibrated based on the stratified random sampling. This design applies for all driving intensities greater than zero.

If the data are assumed to follow a **Weibull distribution**, we assume that the probability of a vehicle manufactured in year t_0 , with average annual driving intensity D , being retired at year t , is

$$\Phi_W(t, t_0, D) = \int_{t_0}^t \frac{k(D)}{\lambda(D)} \left(\frac{t}{\lambda(D)} \right)^{(k(D)-1)} e^{-(t/\lambda(D))^{k(D)}} dt, \quad (8)$$

where the scale, $\lambda(D)$, and shape, $k(D)$, are defined in the same way as the mean, $\mu(D)$, and standard deviation, $\sigma(D)$, for the two model designs (see equations 4-7 above). Note that the average vehicle lifetime of current retirements, τ_0 , in this case represent the scale of current vehicle retirement statistics and that the constant, $\alpha = \frac{k_0}{\tau_0}$, is determined by fitting a Weibull distribution. The fact that the median is lower than the mean for higher driving intensity classes, see SM 2.2, indicates that the distribution is more positively skewed for higher driving intensity classes. This suggests that a Weibull distribution with a longer tail towards higher vehicle lifetimes would be a better fit, confirming previous research^{14,33}.

The parameters for the different model designs are estimated using *maximum likelihood estimation*, see SM 1.4 and 2.3. A comparison of modeled vehicle lifetimes with the stratified random samples for different driving intensity classes is presented in Figure 5. The contour lines in Figure 5, also known as isodensity lines³⁴, show how the points of equal probability density for a given vehicle lifetime shift depending on the assumed driving intensity (y-axis) and on the model design (panel and line type). The highest probability density level is shown around the mean of the distribution, and the distance indicates the rate of change, implying that a larger distance between the lines indicates a more spread-out distribution, analogously to on a topographic map.

The left panel clearly shows that the elasticity design deviates from the statistics at the average current driving intensity of 13,900 km/year and approaches an infinite lifetime as driving intensities decrease. The proposed correction of this issue is to use the *logistic design*, as demonstrated in the right panel. However, a limitation of the *logistic design* is that the distribution of vehicle lifetimes is assumed to be kept constant for driving intensities higher than the stratum with

highest driving intensity (i.e., higher than 100,000 km/year in this study), see SM 2.4. The *elasticity design* instead results in vehicle lifetimes that approach zero for very high driving intensities. Regarding the choice of distribution, the Weibull distribution benefits from better reflecting the skewness of the statistics. However, it overcompensates for higher driving intensities when applied with the *logistic design*, resulting in longer tails of vehicle lifetimes than the statistics indicate, see the greater distance between lines in the right panel of Figure 5 and SM 2.4. This difference between Normal- and Weibull-based model designs is close to negligible for the *elasticity design*. Benefits and drawbacks for the choice of distribution and for the model design are summarized in Table 1.

Table 1
Benefits and drawbacks with design different aspects of the semi-empirical model

Design	Benefits	Drawbacks
Elasticity model	<ul style="list-style-type: none"> • Simple formulation • Easy to interpret 	<ul style="list-style-type: none"> • Applies to driving intensities equal to or greater than current average
Logistic model	<ul style="list-style-type: none"> • Applies for all driving intensities 	<ul style="list-style-type: none"> • Less intuitive model design
Normal distribution	<ul style="list-style-type: none"> • Simple implementation 	<ul style="list-style-type: none"> • Does not capture the skewness of the data
Weibull distribution	<ul style="list-style-type: none"> • Captures the skewness of the data and accounts for longer tails 	<ul style="list-style-type: none"> • Shape parameter of Weibull more difficult to interpret • May overestimate longer tails

Data availability

Data for all figures and additional data used in the analyses are available from the corresponding author upon request. Note that the detailed data on vehicle retirement are treated as confidential since data that could be traced back to individuals or companies are protection under the Swedish Public Access to Information and Secrecy Act (SFS 2009:400). Hence, requests for access to these detailed data should be made directed to the Swedish governmental agency Transport Analysis.

Code availability

The computer code used to generate the results reported in this study are available from the corresponding author upon request.

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Figures

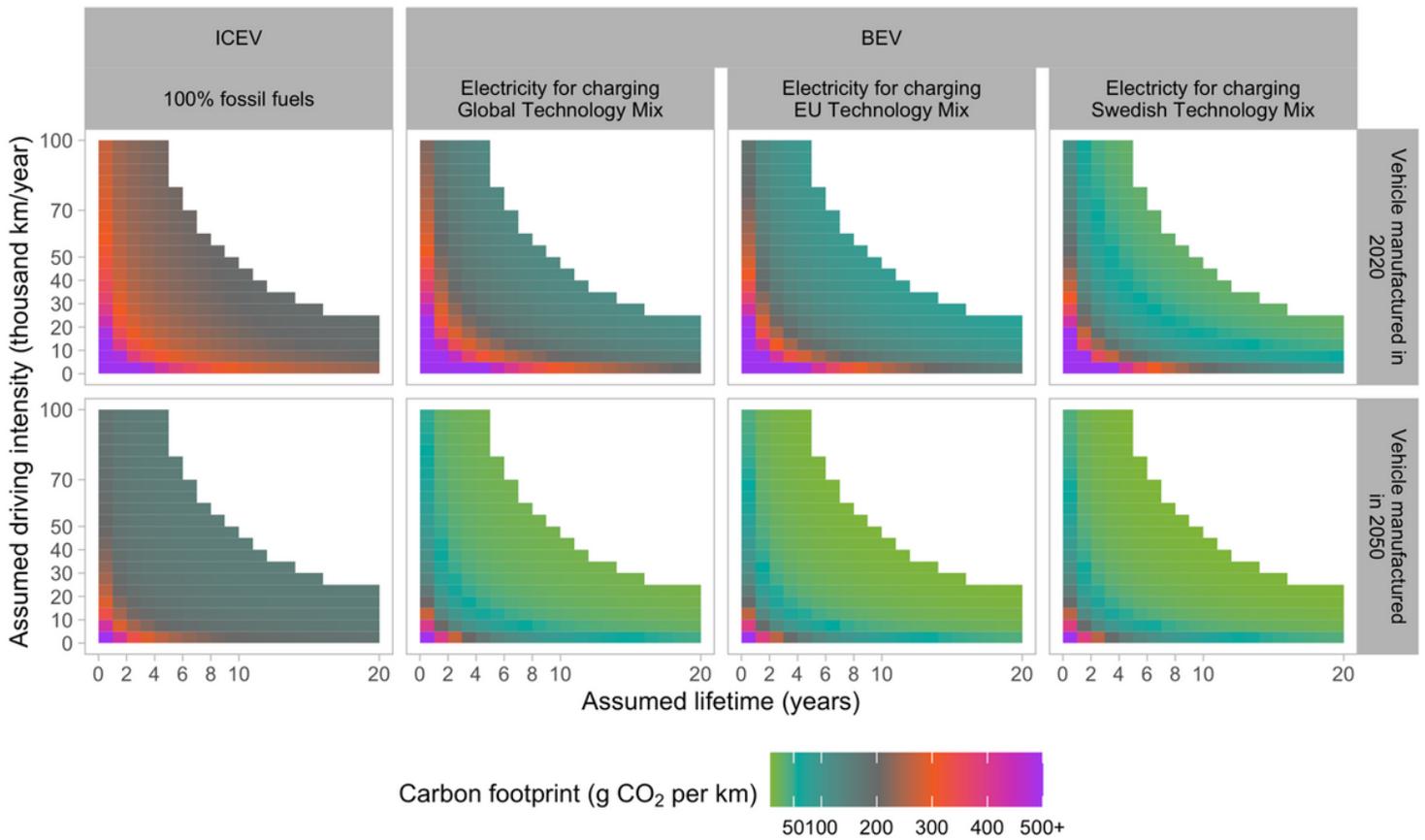


Figure 1

Estimated carbon footprints depending on average driving intensity (y-axis) and lifetime (x-axis) over the lifecycle of a passenger car manufactured in 2020 or 2050 (vertical panels) assuming global manufacturing and electricity generation decarbonize in line with the Paris Agreement's goals and electricity for charging is generated using three different technology mixes (horizontal panels - global average, EU, and Swedish). Results are only shown for vehicles with a lifetime driving distance of up to 500,000 km since almost no vehicles drive farther than that, see SM 2.2.

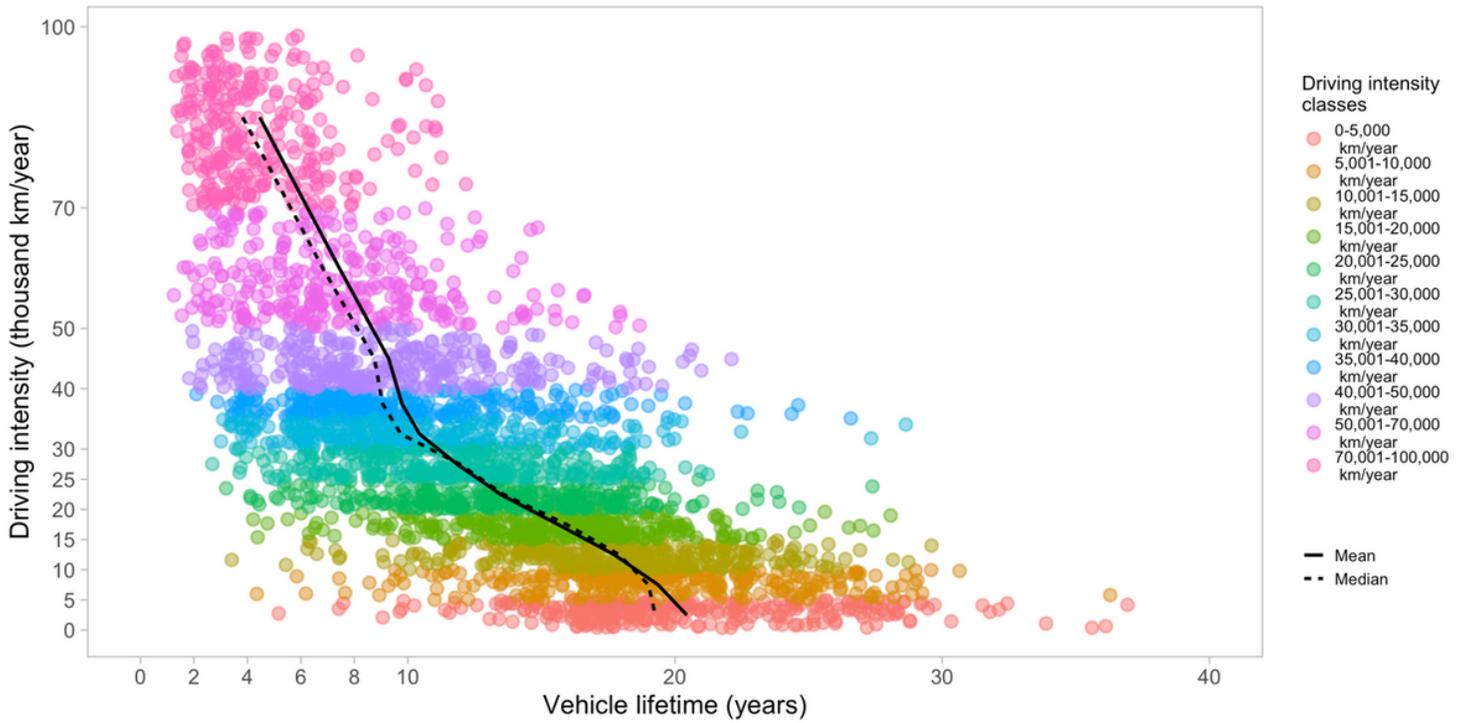


Figure 2

Statistical data on lifetime and average driving intensity for stratified samples based on average driving intensity class (right-side panels) of Swedish ICEVs retired between 2014-2018.

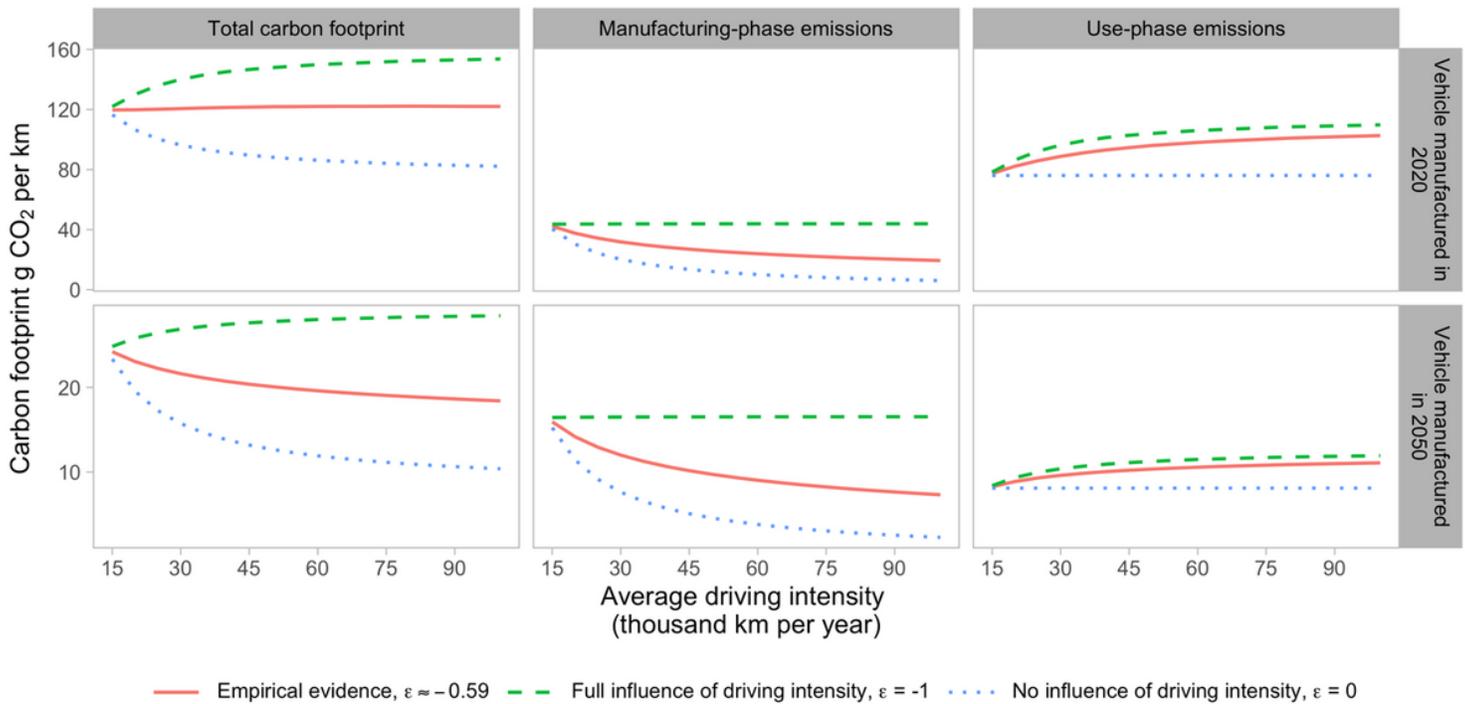


Figure 3

Carbon footprint for BEVs depending on the elasticity of the semi-empirical lifetime-intensity model, assuming global electricity technology mix and that global manufacturing and electricity generation follow climate change mitigation in

line with the Sustainable Development Scenario.

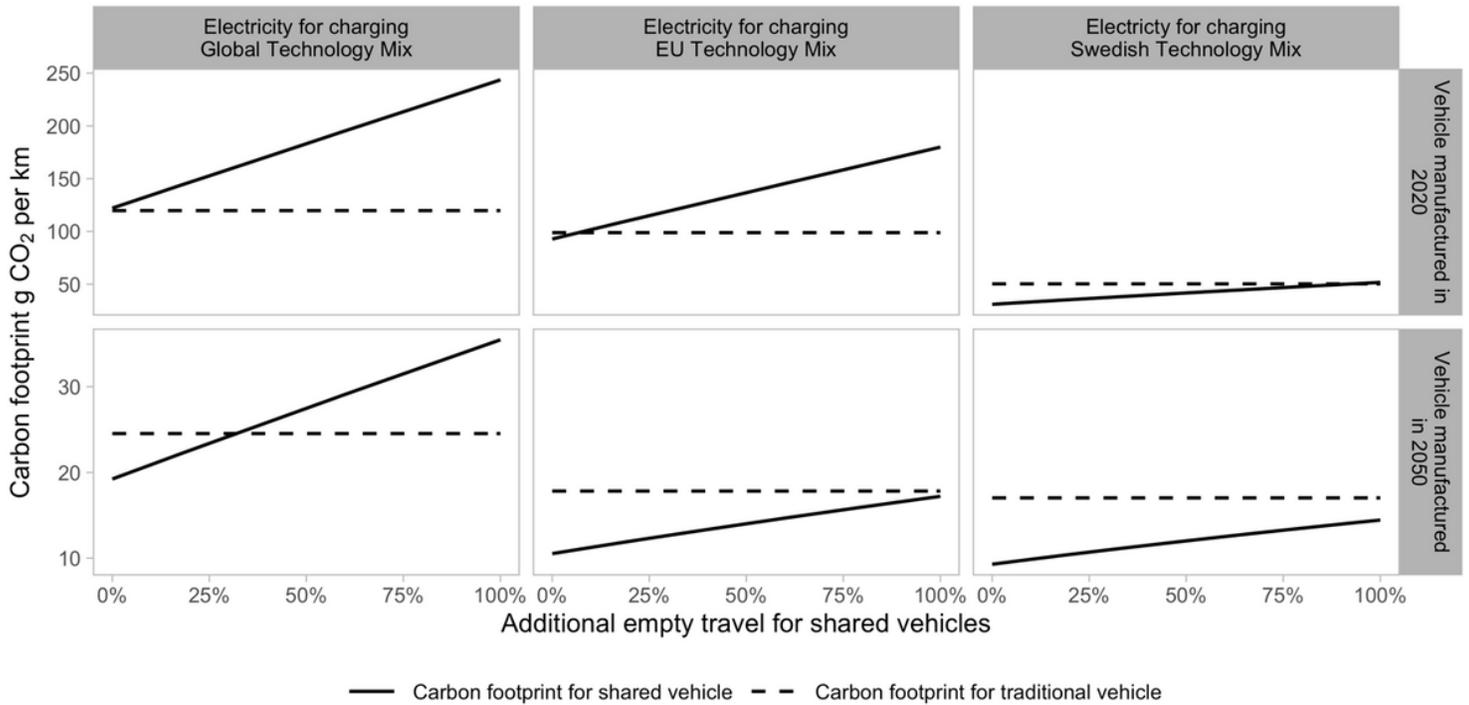


Figure 4

Breakeven point for the carbon footprint between individually owned BEVs and shared BEVs depending on electricity used for charging (horizontal panels) and manufacturing year (vertical panels), and assuming global manufacturing and electricity generation decarbonize in line with the Paris Agreement's goals.

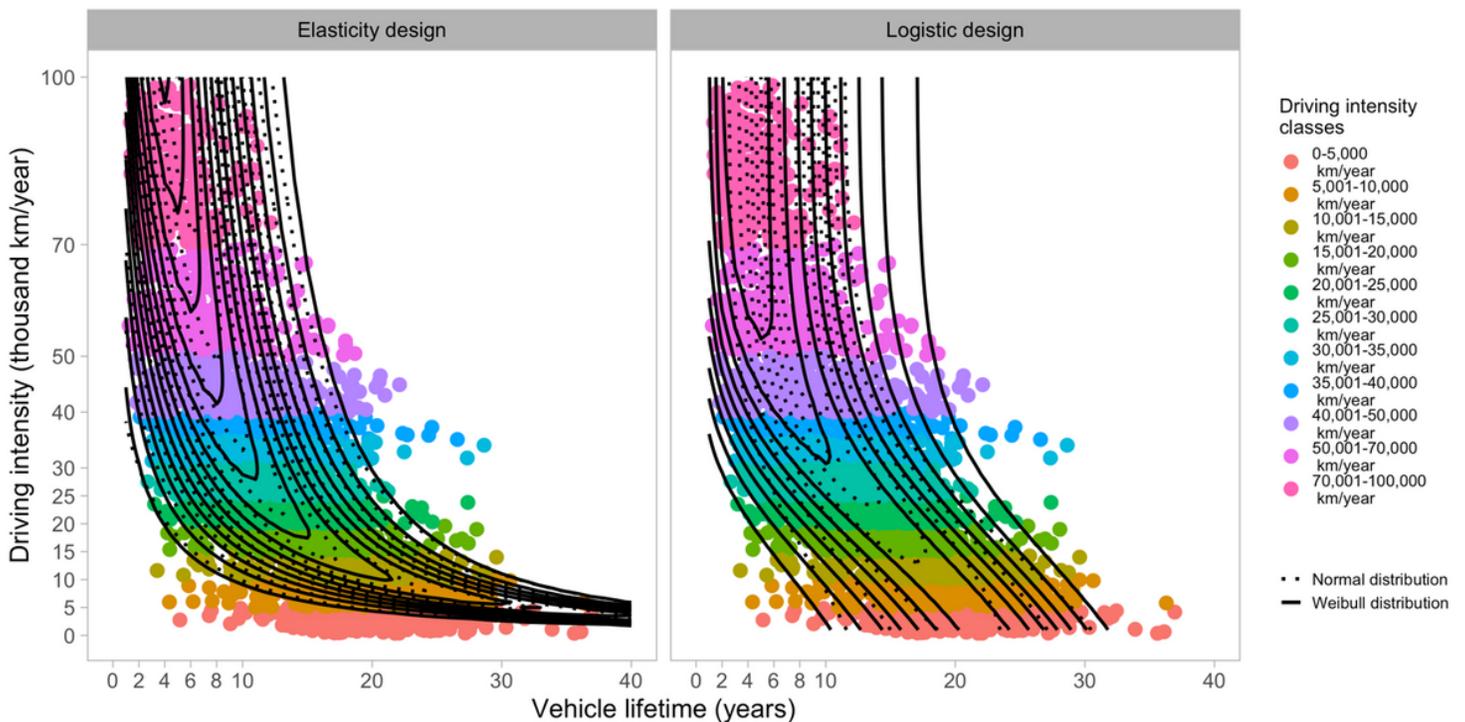


Figure 5

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. The contours show probability density levels.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryMaterialsLifetimeintensityLCAv.5.1.pdf](#)