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

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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.

Keywords:

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Decarbonizing road transportation is an important step in achieving the Paris Agreement[1], 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 CO_2 emissions and has the potential to significantly reduce lifecycle CO_2 emissions[4]. Nevertheless, social and environmental sustainability concerns have been raised related to battery manufacturing and the mining of raw materials[5].

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 ownership[6]. 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 cars[9] and will likely be used more intensively during its lifetime as compared to individually owned cars[10]. 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 commonly used[11] and can provide useful insights to lifecycle CO_2 emissions impacts of strategies for decarbonizing passenger car travel. The indicators 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 vehicle[11]. 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. However, the indicators do not capture impacts on overall travel activity and the impact a changed travel cost budget may have on consumption in other sector, such as direct and indirect rebound effects of passenger car electrification[12] in general as well as carsharing and ridesharing schemes[13] in particular.

To estimate the carbon footprint of a car, we need to make assumptions on cumulative driving distance, but these assumptions vary significantly among studies[11] and have large impacts on the results[14]. These assumptions are even more uncertain for future mobility schemes including different aspects of car sharing or ride sharing[13,15]. Nevertheless, carbon footprint studies tend to assume that shared AVs would travel at least as far as current taxis over the course of their lifetimes[10,16]. Hence, considering a relationship between driving intensity and vehicle lifetime is critical when assessing the carbon footprint of shared AVs. Studies using survival analysis[17,18] have determined that both calendar lifetime and cumulative driving distance are important for the decision to retire a vehicle. Studies using statistical analyses of historical data have also shown that changes in driving intensity over the lifetime of the vehicle can have impacts on CO_2 emissions[19] and that vehicle lifetime extensions can result in lower carbon footprints[20].

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 changes in driving intensity have not yet been analyzed in situations where energy systems are decarbonized over time. 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 years[4]. 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. This study aims to bridge this research gap by estimating the impact of vehicle lifetime and annual driving intensity on the carbon footprints per vehicle-kilometer of passenger cars used for car sharing and ride sharing.

We design a semi-empirical lifetime-intensity model for assessing the vehicle lifetime of cars with increasing annual driving intensity. The model is used together with a prospective lifecycle assessment framework to capture the effects of climate change mitigation in global manufacturing for specific manufacturing years and for electricity used for charging during the use phase of the vehicles, while retaining current vehicle sizes and travel patterns. 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.

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 Supplementary Materials (SM) 2.1, confirming previous research[14]. 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 1 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.

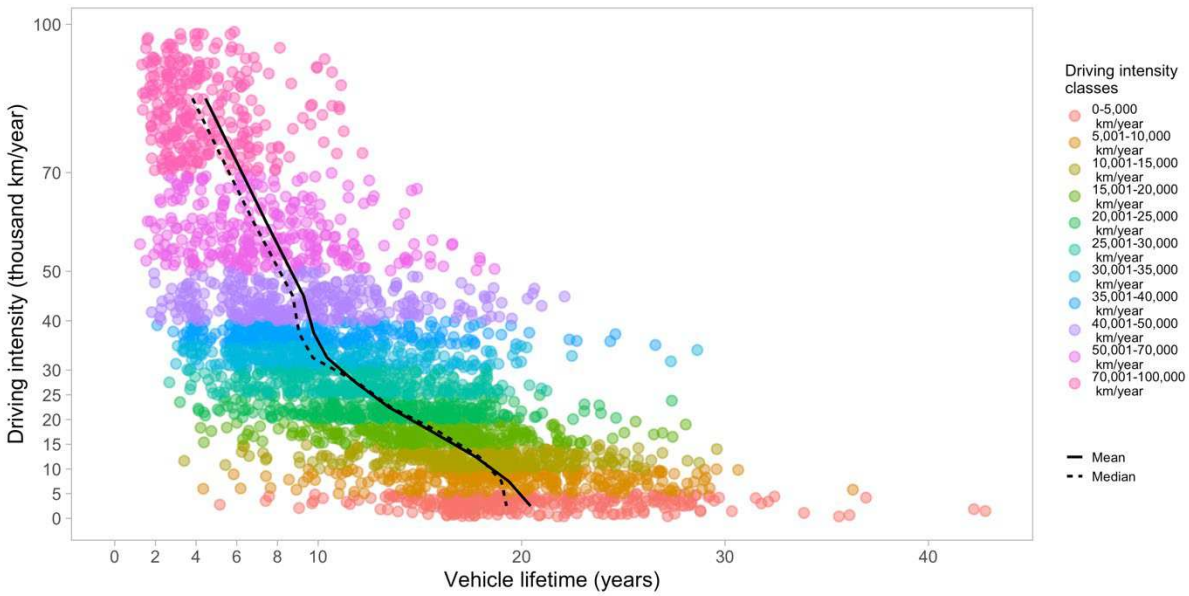

Figure 1: Statistical data on lifetime and average driving intensity for stratified samples based on average driving intensity class (right-side panels) of Swedish ICEVs retired between 2014-2018.

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 ($\varepsilon \approx -0.59$) based on empirical data (i.e., Swedish vehicle retirement statistics described in the previous section) and maximum likelihood estimation, see SM 2.2. 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, $\varepsilon = 0$ and $\varepsilon = -1$, representing no influence of driving intensity on lifetime and full influence of driving intensity, respectively.

Figure 2 shows the results for BEVs using the global average electricity mix. . 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. Additional results for global average electricity mix pathways that decarbonize in line with current policies and for European and Swedish average electricity mixes are available in SM 2.4.

Assumed pathways for carbon intensities of electricity generation used for charging are shown in SM 1.1.

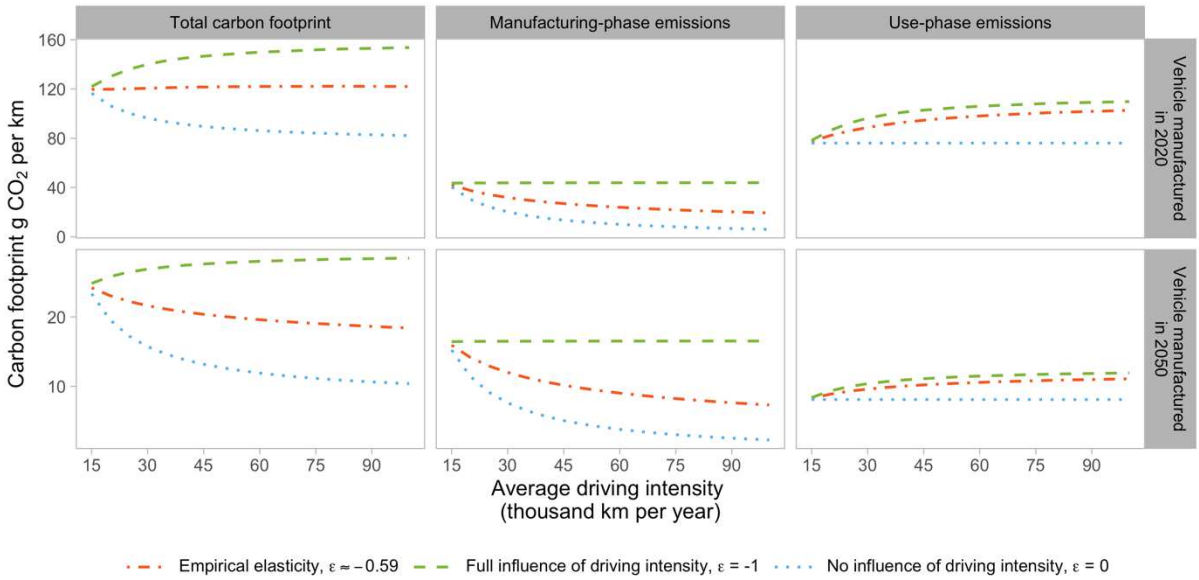

Figure 2: Carbon footprint for BEVs depending on the elasticity of the semi-empirical lifetime-intensity model, assuming global electricity technology mix and that global manufacturing and electricity generation follow climate change mitigation in line with the Sustainable Development Scenario.

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 2 and SM 2.4. This can be compared to when the lifetime is only determined by driving intensity, i.e., $\varepsilon = -1$, 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 2. For the elasticity based on empirical evidence, i.e., $\varepsilon = -0.59$, a greater cumulative lifetime driving distance is obtained as the driving intensity increases (on average). In the third case, $\varepsilon = 0$, 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 2.

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 2.4. 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., $\varepsilon = -1$, 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., $\varepsilon = -0.59$, a greater driving intensity also implies a shorter lifetime, but to a smaller extent compared to when $\varepsilon = -1$. Hence, the average use-phase emissions increase with driving intensity. In the third case, $\varepsilon = 0$, 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 cars[7]. 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% to 100% compared to the intended travel distance[9,22]. Empirical studies show a level of around 60% for taxi rides[23] and 40% for ride-sourcing services[24] 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.

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, see intersection between solid and dot-dashed lines in upper left panel of Figure 3. 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 2, 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.

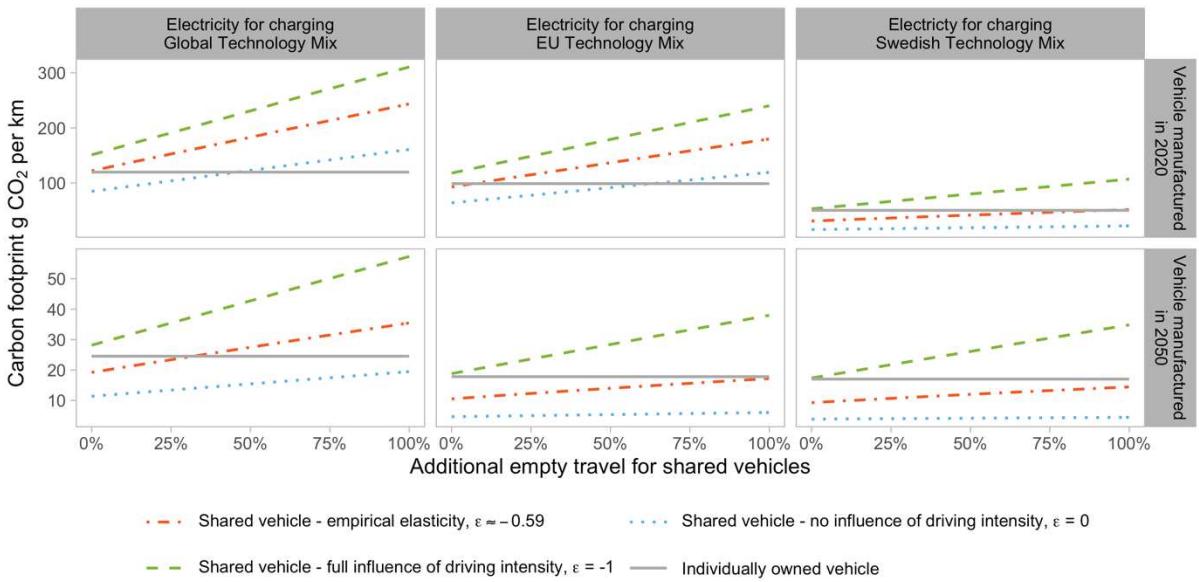

Figure 3: Breakeven point for the carbon footprint between individually owned BEVs and shared BEVs depending on the elasticity of the semi-empirical lifetime-intensity model (line types), electricity used for charging (horizontal panels) and manufacturing year (vertical panels), and assuming global manufacturing and electricity generation decarbonize in line with the Paris Agreement's goals.

The breakeven point is at 6% and 90% of empty travel, see intersection between solid and dot-dashed lines in upper middle and right panels of Figure 3, 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.

Note that no influence of driving intensity on vehicle lifetime ($\varepsilon = 0$) would result in a higher breakeven point of empty travel for shared AVs manufactured in 2020 and a breakeven point greatly exceeding 100% for shared AVs manufactured in 2050, see dotted lines in Figure 3. Conversely, full influence of driving intensity on vehicle lifetime ($\varepsilon = -1$) would result in the breakeven point being below 0% in all cases, see dashed lines in Figure 3, indicating that the carbon footprints of shared AVs always exceed that of an individually owned vehicle in those cases. The reason why the breakeven point reaches below 0% even when there is no empty travel is due to the shorter lifetime of the vehicle and that the electricity system decarbonizes over time. All in all, this points to the importance of designing future shared AVs for durability.

Discussion

The passenger transport systems are likely to go through several changes during the coming decades. The most prominent changes include increased use of electrified and autonomous vehicles as well as on-demand mobility schemes, including car sharing and ride sharing. These trends will affect the pathways towards decarbonization of passenger car travel, including changes in cost structures[7] and the value of travel time[25–27], which may induce

additional travel activity[28] and cause modal shifts[29,30]. These trends may also cause changes in vehicle design, including materials used in manufacturing[31] and changes to facilitate material recycling[32], but many of these aspects are yet to materialize.

Our analysis shows 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 phase[32,33]. 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 the use-phase 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[9,22] 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, our conclusions rely on that the relationship between driving intensity and vehicle lifetime established in the semi-empirical model will hold also for future BEVs and shared AVs. The intention here is not to suggest that this will necessarily be true, but rather to highlight potential consequences based on a semi-empirical model trained with currently available data. The analysis shows that the carbon footprint may be substantially reduced if the driving intensity and vehicle lifetime relationship is weakened, pointing to the importance of designing future BEVs and shared AVs for durability.

Methods

Prospective lifecycle assessment of carbon footprints. Carbon footprints (reported in g CO_2 per vehicle-km) are estimated using a prospective lifecycle assessment framework based on GREET® 2 - Version 2019[34] adapted for scenario analysis[4]. 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 IEA[35] scenarios with the same names.

Carbon footprints per km are estimated based on

$$\text{Carbon footprint}(t_0, \tau, D) = \frac{\text{Vehicle cycle}(t_0,\tau)+\sum_{t=t_0}^{\tau}\left(\text{Fuel cycle}\left(t,d(t,\tau,D)\right)+\text{Tailpipe}\left(t,d(t,\tau,D)\right)\right)}{\sum_{t=t_0}^{\tau} d(t,\tau,D)} \quad (1)$$

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:

$$d(t, \tau, D) = \frac{D \cdot \tau}{\sum_{t=t_0}^{\tau}(1-b)^{t-t_0-1}}(1-b)^{t-t_0-1} \quad (2)$$

Vehicle cycle CO_2 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 review[4].

Fuel cycle as well as tailpipe CO_2 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 improvements[4]. 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 CO_2 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.[36]. 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 IEA[35] 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 scenarios[37] combined with the cap of the European Union emissions trading system reaching zero in 2058[38] 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[39,40]. 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 generation[41]. Upstream emissions are based on estimates by Pehl et al.[36] and projections for the future electricity generation mix by the IEA[35], European Commission[37], and Swedish Energy Agency[42].

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 law[43]. The excerpt, provided by the Swedish government agency Transport Analysis[44], 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

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

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,

$$\mu(D) = \tau_0 \left(\frac{D}{D_0}\right)^{\varepsilon} \tag{4}$$

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,

$$\sigma(\mathrm{D}) = \alpha\tau_0 \left(\frac{D}{D_0}\right)^{\varepsilon\beta} \tag{5}$$

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 1.

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.

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

$$\sigma(D) = \alpha\left(L_0 - \frac{L}{1+e^{(1-D/D_0)}}\right), \tag{7}$$

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

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

where the scale, $\lambda(\mathrm{D})$, and shape, $\mathrm{k}(\mathrm{D})$, 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 2.1, 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[17,45].

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 4. The contour lines in Figure 4, also known as isodensity lines[46], 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.

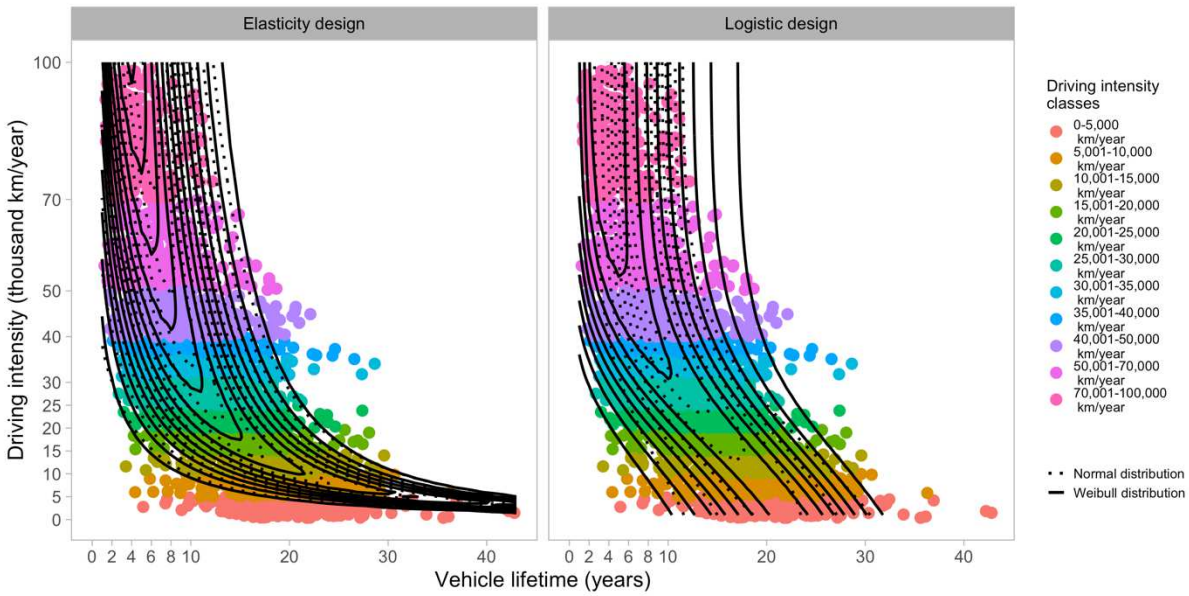

Figure 4: Semi-empirical model results for the elasticity and logistic models (see panels) and for Normal or Weibull distributions (see line type). Stratified samples of Swedish vehicle retirement statistics for 2014-2018 are provided in the background for comparison. The contours show probability density levels.

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 2.3. 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 4 and SM 2.3. 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	• Simple formulation • Easy to interpret	• Applies to driving intensities equal to or greater than current average
Logistic model	• Applies for all driving intensities	• Less intuitive model design
Normal distribution	• Simple implementation	• Does not capture the skewness of the data
Weibull distribution	• Captures the skewness of the data and accounts for longer tails	• *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.

References

1. United Nations Environment Programme. *Emissions Gap Report 2020*. https://www.unenvironment.org/emissions-gap-report-2020 (2020).

2. de Coninck, H. *et al.* Strengthening and Implementing the Global Response. in *Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,* (eds. Masson-Delmotte, V. et al.) (IPCC, 2018).

3. MIT Energy Initiative. *Insights into Future Mobility*. http://energy.mit.edu/insightsintofuturemobility (2019).

4. Morfeldt, J., Davidsson Kurland, S. & Johansson, D. J. A. Carbon footprint impacts of banning cars with internal combustion engines. *Transportation Research Part D: Transport and Environment* **95**, 102807 (2021).

5. International Energy Agency (IEA). *Global EV Outlook 2019 - Scaling-up the transition to electric mobility*. https://www.iea.org/reports/global-ev-outlook-2019 (2019).

6. Grubler, A. *et al.* A low energy demand scenario for meeting the 1.5 °C target and sustainable development goals without negative emission technologies. *Nature Energy* **3**, 515–527 (2018).

7. Compostella, J. *et al.* Travel time costs in the near- (circa 2020) and long-term (2030–2035) for automated, electrified, and shared mobility in the United States. *Transport Policy* **105**, 153–165 (2021).

8. Fulton, L. M. Three Revolutions in Urban Passenger Travel. *Joule* **2**, 575–578 (2018).

9. Pernestål, A. & Kristoffersson, I. Effects of driverless vehicles – Comparing simulations to get a broader picture. *European Journal of Transport and Infrastructure Research* **19**, 1–23 (2019).

10. Greenblatt, J. B. & Saxena, S. Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. *Nature Climate Change* **5**, 860–863 (2015).

11. Nordelöf, A., Messagie, M., Tillman, A. M., Ljunggren Söderman, M. & Van Mierlo, J. Environmental impacts of hybrid, plug-in hybrid, and battery electric vehicles—what can we learn from life cycle assessment? *International Journal of Life Cycle Assessment* **19**, 1866–1890 (2014).

12. Font Vivanco, D., Nechifor, V., Freire-González, J. & Calzadilla, A. Economy-wide rebound makes UK's electric car subsidy fall short of expectations. *Applied Energy* **297**, (2021).

13. Amatuni, L., Ottelin, J., Steubing, B. & Mogollón, J. M. Does car sharing reduce greenhouse gas emissions? Assessing the modal shift and lifetime shift rebound effects from a life cycle perspective. *Journal of Cleaner Production* **266**, (2020).

14. Hawkins, T. R., Singh, B., Majeau-Bettez, G. & Strømman, A. H. Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *Journal of Industrial Ecology* **17**, 53–64 (2013).

15. Vilaça, M., Santos, G., Oliveira, M. S. A., Coelho, M. C. & Correia, G. H. A. Life cycle assessment of shared and private use of automated and electric vehicles on interurban mobility. *Applied Energy* **310**, 118589 (2022).

16. Fernando, C. *et al.* Life cycle environmental assessment of a transition to mobility servitization. *Procedia CIRP* **90**, 238–243 (2020).

17. Kolli, Z., Hivert, L. & Dupont-Kieffer, A. Car survival in a national fleet : a non-parametric approach based on French data. *12th World Conference on Transport Research* 1–17 (2010).

18. Chen, C. & Niemeier, D. A mass point vehicle scrappage model. *Transportation Research Part B: Methodological* **39**, 401–415 (2005).

19. Kaneko, M. & Kagawa, S. Driving propensity and vehicle lifetime mileage: A quantile regression approach. *Journal of Environmental Management* **278**, 111499 (2021).

20. Nakamoto, Y. & Kagawa, S. A generalized framework for analyzing car lifetime effects on stock, flow, and carbon footprint. *Journal of Industrial Ecology* jiec.13190 (2021) doi:10.1111/jiec.13190.

21. Helmers, E., Dietz, J. & Weiss, M. Sensitivity Analysis in the Life-Cycle Assessment of Electric vs. Combustion Engine Cars under Approximate Real-World Conditions - Supplementary Materials. *Sustainability* **12**, 1241 (2020).

22. Schäfer, A. W. & Yeh, S. A holistic analysis of passenger travel energy and greenhouse gas intensities. *Nature Sustainability* **3**, 459–462 (2020).

23. Cramer, J. & Krueger, A. B. Disruptive Change in the Taxi Business: The Case of Uber. *American Economic Review* **106**, 177–182 (2016).

24. Henao, A. Impacts of Ridesourcing – Lyft and Uber – on Transportation including VMT, Mode Replacement, Parking, and Travel Behavior. (University of Colorado, 2017).

25. Rebalski, E. Are We There Yet? Combining qualitative and quantitative methods to study the introduction of CAVs in Sweden, and potential travel demand effects. (Chalmers University of Technology, 2021).

26. Steck, F., Kolarova, V., Bahamonde-Birke, F., Trommer, S. & Lenz, B. How Autonomous Driving May Affect the Value of Travel Time Savings for Commuting. *Transportation Research Record* **2672**, 11–20 (2018).

27. Correia, G. H. de A., Looff, E., van Cranenburgh, S., Snelder, M. & van Arem, B. On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. *Transportation Research Part A: Policy and Practice* **119**, 359–382 (2019).

28. Wadud, Z., MacKenzie, D. & Leiby, P. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy and Practice* **86**, 1–18 (2016).

29. Meyer, J., Becker, H., Bösch, P. M. & Axhausen, K. W. Autonomous vehicles: The next jump in accessibilities? *Research in Transportation Economics* **62**, 80–91 (2017).

30. Wadud, Z. & Chintakayala, P. K. To own or not to own – That is the question: The value of owning a (fully automated) vehicle. *Transportation Research Part C:*

Emerging Technologies **123**, 102978 (2021).

31. Taiebat, M., Brown, A. L., Safford, H. R., Qu, S. & Xu, M. A review on energy, environmental, and sustainability implications of connected and automated vehicles. *Environmental Science and Technology* **52**, 11449–11465 (2018).

32. Richter, J. L. A circular economy approach is needed for electric vehicles. *Nature Electronics* **5**, 5–7 (2022).

33. Hertwich, E. G. *et al.* Material efficiency strategies to reducing greenhouse gas emissions associated with buildings, vehicles, and electronics—a review. *Environmental Research Letters* **14**, 043004 (2019).

34. Argonne National Laboratory. The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET®) Model - GREET 2, Version 2019. https://greet.es.anl.gov/ (2020).

35. International Energy Agency (IEA). *World Energy Outlook 2020*. www.iea.org/weo (2020).

36. Pehl, M. *et al.* Understanding future emissions from low-carbon power systems by integration of life-cycle assessment and integrated energy modelling. *Nature Energy* **2**, 939–945 (2017).

37. European Commission. *In-depth analysis in support of the Commission communication COM(2018) 773 - A Clean Planet for all - A European long-term strategic vision for a prosperous, modern, competitive and climate neutral economy*. https://ec.europa.eu/clima/policies/strategies/2050_en (2018).

38. Zetterberg, L. & Elkerbout, M. *Policy Brief: The Future of the EU Emissions Trading System - Responding to the EU Green Deal Proposals*. https://www.mistracarbonexit.com/s/Policy-Brief_MCE_dec2019_3.pdf (2019).

39. Swedish Energy Agency. *Energiläget i siffror 2021 (Energy in Sweden in numbers 2021)*. https://www.energimyndigheten.se/statistik/energilaget/ (2021).

40. Swedish Environmental Protection Agency. *Fördjupad analys av den svenska klimatomställningen 2020 - Klimat och luft i fokus (In-depth analysis of the Swedish climate transition 2019 - Climate and air pollution in focus)*. *Rapport* vol. 6945 http://www.naturvardsverket.se/978-91-620-6945-2 (2020).

41. Swedish Government. *Regeringens proposition 2019/20:65 En samlad politik för klimatet – klimatpolitisk handlingsplan (Governmental bill 2019/20:65 Joint policy for climate change - climate policy action plan)*. https://www.regeringen.se/rattsliga-dokument/proposition/2019/12/prop.-20192065/ (2020).

42. Swedish Energy Agency. *Scenarier över Sveriges energisystem 2020 (Scenarios for Sweden's energy system 2020) ER 2021:6*. (2021).

43. Swedish Parliament. *Lag (2001:558) om vägtrafikregister (Law on road traffic*

registry). (2001).

44. Transport Analysis. *Detailed excerpt on scrappage of vehicles from the statistics 'Fordon på väg' (Road vehicles) for the years 2014-2018*. https://www.trafa.se/vagtrafik/fordon/ (2020).

45. Kızılersü, A., Kreer, M. & Thomas, A. W. The Weibull distribution. *Significance* **15**, 10–11 (2018).

46. Fernández, A. & Vázquez, M. A generalized regression methodology for bivariate heteroscedastic data. *Communications in Statistics - Theory and Methods* **40**, 598–621 (2011).

Figures

Figure 1

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 2

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 3

Breakeven point for the carbon footprint between individually owned BEVs and shared BEVs depending on the elasticity of the semi-empirical lifetime-intensity model (line types), 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 4

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

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- SupplementaryMaterials.pdf