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A Statistical Analysis of Trends in Light-duty Vehicle Scrappage and Survival: 2003-2020

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ABSTRACT

This report describes the results of statistical estimation of models of scrappage rates and survival probabilities as a function of vehicle age for U.S. light-duty vehicles. The data used are counts of vehicles in operation by vehicle type and model year for calendar years 2002-2020, which allows scrappage functions to be estimated for years 2003-2020. Models were estimated for three vehicle types: passenger cars, SUVs and vans, and pickup trucks. The models are structured to estimate trends in scrappage and survival rates over time for each vehicle type. Modified logistic functions were found to fit the data well, with R^2 values of 0.99 and statistically significant trends and fixed effects for each vehicle type. Results of estimation via nonlinear least squares indicate that life expectancies for all three vehicle types increased over the study period by 2-3 years for passenger cars, 3-4 years for SUVs and Vans, and 5-6 years for pickup trucks. By 2020, median expected lifetimes ranged from about 17 years for passenger cars, and 20 years for SUVs and vans, to about 25 years for pickup trucks.

INTRODUCTION

Statistical modeling of survival and "time-to-event" has an extensive literature and range of application from medicine to engineering (e.g., Hosmer et al., 2008). Economists and engineers have been modeling the scrappage rates and survival probabilities of motor vehicles for more than 50 years. Predicting the speed at which the stock of motor vehicles will turn over is important to analyzing the benefits and costs of policies such as promoting deep decarbonization, energy efficiency, reduced pollutant emissions and vehicle safety. Early studies were limited by the relatively small number of ages tracked in available data and the lack of detailed information about vehicle attributes. Today, fifty vehicle vintages are reported and individual vehicles can be identified. The remainder of this section presents a mathematical definition of survival and scrappage rate functions.

Survival times and failure rates (scrappage) of equipment are traditionally modeled by survival and hazard functions. Let $f_X(a)$ be the probability density function for failure at age a.[1] The probability of failure by age a is the integral of $f_X(a)$ from 0 to a:

$$F_X(a;\lambda,k) = p(X \le a) = \int_0^a f_X(x;\lambda,k)dx. \qquad (1)$$

The survival function, the probability of surviving to at least a-years old is $S_X(a) = 1-F_X(a)$. Note that $f_X(a)$ is not the probability of failure (scrappage) given that the equipment has survived to $a-1$ but rather the unconditional probability of failure at time a. The relative risk of scrappage in an infinitesimally small time interval after a, given (conditional on) survival to a is given by the hazard function which is the ratio of the pdf to the survival function, as shown in equation 2.

$$h_X(a) = \frac{f_X(a)}{S_X(a)} \qquad (2)$$

In discrete time, the hazard function is the probability of scrappage during the time interval a to $a+1$ divided by the probability of survival to age a. The hazard or conditional scrappage function is not a probability density function because, in general, it does not integrate to 1 over age, a.

Vehicle survival functions are cumulative probability density functions that represent the probability of surviving to a given age, x, for a new vehicle sold in year t:

$$p_t(x) \qquad (3)$$

The conditional survival probability function (csp f) represents the probability of a new vehicle surviving to age x+1, given that a vehicle has survived to age x. The scrappage rate function is 1 minus the cspf.

[1] The functions assume age is a continuous variable. In practice, data on vehicles in operation are assigned integer age values and models typically predict at discrete intervals. In such cases, the probability mass function can be substituted for the probability density function.

$$p(x+1 \mid x) \tag{4}$$

The cumulative survival function is therefore the cumulative product of the conditional survival probabilities.

$$p(x) = p(x|x-1)p(x-1|x-2) \dots p(1|0)1 \tag{5}$$

Scrappage rates are estimated by 1 minus the conditional probability of survival, i.e., one minus the ratio of the number of x-year-old vehicles in operation in year t to the number of x-1-year-old vehicles in operation in year t-1.

$$1 - p(x|x-1) = 1 - \frac{n(x,t)}{n(x-1,t-1)} = \frac{n(x-1,t-1) - n(x,t)}{n(x-1,t-1)} \tag{6}$$

The unconditional survival probability function (the cumulative survival function) is calculated from the conditional survival probabilities using equation 5.

This report presents the results of an analysis of recent trends in survival and scrappage rates for light-duty vehicles in the U.S. Models are estimated for three vehicle categories: passenger cars, SUVs and vans, and pickup trucks. Functions are estimated for calendar years 2003 to 2020, over which time the number of age groups increases from 33 to 50 years. Section II presents a review of the literature on vehicle scrappage and survival, focusing on functional forms and methodology. Section III presents the details of the modified logistic model used in this analysis. Section IV describes the vehicle population data, and Section V presents the results of the statistical estimation, focusing on trends in vehicle longevity. Section VI discusses the potential implications of the statistical analysis for public policy and possible directions for future research.

REVIEW OF VEHICLE SCRAPPAGE LITERATURE

Previous analyses of automobile scrappage have used several different functions to model scrappage as a function of vehicle age or cumulative mileage with a tendency to prefer Weibull or logistic functional forms (Engers et al, 2009). Zachariadis et al. (2001) proposed using the two parameter Weibull distribution as a function of vehicle age to model the effect of technological changes in vehicle emissions over time. Xu and Gao (2019) used three types of survival models (Kaplan-Meier, exponential and Weibull) to analyze the relationship between engine and transmission faults and vehicle survival. They concluded that vehicle lifetimes had been increasing due to improved reliability of engines and transmissions. Kolli et al. (2010) tested Beta, Gamma, Lognormal and Weibull distributions and concluded that the Beta and Weibull fit their data best. In a study of vehicle lifetimes in Japan, Kagawa et al. (2011) found that likelihood ratio tests supported use of the generalized gamma distribution of which the Weibull function is a special case. A study of vehicle lifetimes in 17 countries did not reject the hypothesis that lifetimes followed the Weibull distribution (Oguchi and Fuse, 2015).

"Mechanistic" scrappage models estimate scrappage solely as a function of age or cumulative miles while "economic" models add equations to estimate the effects of economic and other factors that vary over time and space. Mechanistic conditional scrappage rate (r^*) models were estimated by Walker (1968), Parks (1977) and Greene and Chen (1981). Walker (1968) was the first to specify a scrappage model comprised of separate mechanistic and economic equations. Mechanistic scrappage was estimated as a logistic function of vehicle age.

$$r^*(a) = \frac{1}{A + Be^{-\beta a}} \tag{7}$$

Year-to-year changes in the total number of vehicles scrapped, q, were estimated by a separate log-linear function of the price of used vehicles, P, the ratio of new vehicle sales to total stock (the turnover rate, R), and the aggregated mechanistic scrappage rate predicted using equation 7, r^*, multiplied by the total stock of vehicles, n.

$$q_t = AR_t^{\alpha} P_t^{\beta} r_t^* n_t \tag{8}$$

Parks (1977) imbedded economic factors (x_j) in a logistic scrappage equation, and estimated the logit of the scrappage rate as a linear function of the ratio of the price of an a-year-old used car, $P_u(a,t)$, to a price index of repair costs, $P_m(t)$, and the ratio of the scrappage price of an a-year-old vehicle, $P_s(a,t)$, to the repair cost index.

$$ln\left(\frac{r^*(a,t)}{1-r^*(a,t)}\right) = \sum_j \beta_j x_j(a,t) \rightarrow r^*(a,t) = \frac{1}{1+e^{-\sum_j \beta_j x_j(a,t)}} \quad (9)$$

Greene and Chen (1981) estimated mechanistic scrappage models for passenger cars and light trucks using a modification of Walker's (1968) logistic function that included an asymptotic scrappage rate (*A*).

$$r^*(a) = \frac{1}{A+Be^{-(\beta_0+\beta_1 a)}} \quad (10)$$

Based on 1966-77 data with only 12 age groups, they found significant differences in expected median lifetimes (9.9 years for cars and 16.4 for trucks) and asymptotic scrappage rates (cars, 0.29; trucks, 0.13). Using data on U.S. vehicles in operation from 1966-1992, Miaou (1995) estimated an expanded logistic model in which the exponential function in equation 10 was a function of socioeconomic variables, including new and used car prices, as well as age.

Manski and Golding's (1983) analysis of vehicle scrappage in Israel appears to be the earliest study of the combined effects of new and used vehicle prices on scrappage. Hamilton and Macauley (1999) divided scrappage effects into an "embodied" durability effect (similar to mechanistic scrappage) and a "dis-embodied" effect that included not only economic factors but also the effect of such things as reduced accident rates. Beginning with the model of Greene and Chen (1981) (equation 10), they added a linear equation that made the coefficient of age, β_1, a function of a set of "disembodied" variables and a set of "embodied" variables. The embodied variables consisted of model year indicator variables while the disembodied variables were calendar year indicators. After removing the first four years of a model year's life and any years that implied negative scrappage rates, they were left with 11 age groups for each of 42 calendar years from 1950 to 1991. Their overall conclusion was that dis-embodied (calendar year) factors had no effect until after 1970 but that subsequently vehicle life expectancy increased substantially. Vintage specific factors appeared to have little effect but, if anything, appeared to reduce life expectancy.

Greenspan and Cohen (1999) also modeled "engineering scrappage" (mechanistic) and "cyclical scrappage" (economic) separately. Engineering scrappage was modeled as a function of time and age. Cyclical scrappage, defined as actual total scrappage minus estimated engineering scrappage, was modeled as a linear function of the unemployment rate and price indexes for new vehicles, vehicle repairs and gasoline.

Citing an unpublished 2001 study by Schmoyer using Greenspan and Cohen's methodology, Davis et al. (2014) reported scrappage and survival rates for passenger cars and light trucks of model years 1970, 1980 and 1990. The estimates indicate that passenger car median survival times increased from 11.5 years for the 1970 model year to 16.9 years for 1990 model year cars. The study found a slight decline in light truck median lifetimes, from 16.2 years in 1970 to 15.5 years in 1990.

In early studies, scrappage models were estimated using aggregate survival rates of large numbers of vehicles as the dependent variable. Chen and Niemeier (2005) estimated Weibull scrappage functions based on individual vehicles randomly sampled from California's smog inspection program. Their model employed a mass point method that allowed them to estimate the effects of other variables, such as state of repair and make, on the probability of survival.

The National Highway Traffic Safety Administration (NHTSA, 2006) estimated survival functions for passenger cars and light trucks as a function of age for use in regulatory analyses. Survival was defined as the ratio of the number of model year *y* vehicles in operation in a given year, t=y+*a*, where *a* is vehicle age, divided by the number in operation in the year in which that cohort of vehicles was new, *t*=*y*. Thus, NHTSA's function is an unconditional survival function. NHTSA (2006) estimated two-piece survival functions for passenger cars and light trucks as a function of age. In equation 9, A and B are constants to be estimated for cars ten years old or less (i = 1) and older than ten years (i = 2). For light trucks the breakpoint was put at 12 years.

$$r_v(a) = 1 - e^{-e^{A_i+B_i a}}; i = 1,2 \quad (11)$$

Li et al. (2009) estimated a logistic scrappage model using data for 20 U.S. metropolitan areas that is model and vintage specific for the years 1997-2000 but only market segment specific for 2001-2005. The model and model year detail permitted the inclusion of seven sets of indicator variables in addition to gasoline price, fuel economy, median household income and household size. The results indicated that when gasoline prices increased, scrappage rates decreased for the most efficient 20% of vehicles and increased for the lower 80% of vehicles.

Scrappage models have been used extensively to estimate the impacts of accelerated scrappage policies on vehicle fuel use and emissions. A review of early studies is provided by Van Wee et al. (2011). Li and Wei (2013) used a discrete choice framework to analyze the impacts of the U.S. Cash for Clunkers program on vehicle scrappage, new vehicle demand and emissions. Three variables were included in the model, vehicle age, fuel consumption per mile and vehicle type (car vs. light truck), as well as fixed effects for make of vehicle. Separate regressions were estimated for the 5-year scrappage rate from 2001-2005 and the 3-year scrappage rate from 2006-2008.

Jacobsen and Van Bentham (2015) analyzed scrappage rates for U.S. vehicles up to 19 years of age over the period 1999-2009, at the make, model and trim level. They regressed the logarithms of scrappage rates on the logarithms of used car prices and indicator variables comprised of make-model interacted with age and calendar year interacted with age. Recognizing the endogeneity of used car scrappage rates and used car prices, they substituted an instrumental variables estimate of used car prices for the actual prices.

Both new and used car prices have been included among the economic factors affecting scrappage rates. Recent studies indicate that scrappage is inelastic with respect to new and used vehicle prices (Jacobsen et al., 2021) Elasticities of vehicle scrappage with respect to used car values estimated by Jacobsen and van Bentham (2015) ranged from -0.36 for pickups to -0.77 for vans. Combining all classes together produced an elasticity estimate of -0.7. Considering only vehicles aged 10-19, the estimate for all classes combined was -0.60[2], with a range of -0.19 (pickups) to -0.92 (vans) across vehicle classes. A somewhat lower elasticity, -0.36, was found by Bento et al. (2018) for U.S. light-duty vehicles over the period 1969-2014.

Alberini et al. (2018) used a Weibull hazard function to estimate the effects of emissions taxes on the scrappage of used vehicles aged 4 to 14 years in Switzerland. They chose a Weibull hazard function with λ =1 and a proportional hazard model. The proportional hazard function is convenient for introducing additional variables, ***Z***, that can affect scrappage rates besides age or cumulative miles because it is separable in the influencing variables.

$$h(x, Z) = h_0(x)e^{\mathbf{Z}\beta} = kx^{k-1}e^{\mathbf{Z}\beta} \qquad (12)$$

Bento et al. (2018) fitted a logistic function to U.S. vehicle conditional scrappage rates for vehicles up to 14 years old (e.g., Bento et al., 2018; Greene and Chen, 1981). Unlike the Weibull hazard function, the logistic hazard function approaches an asymptotic scrappage rate (*1/L*) as age, *x*, increases.

$$F(x) = \frac{1}{L+Be^{-\beta x}} \qquad (13)$$

Bento et al. (2018) assumed that *F*(*x*) represented an “engineering” scrappage rate and that “cyclical” factors such as used car prices, *P*, rate of turnover of vehicle ownership, *r*, and the number of vehicles in operation, *n*, would proportionately affect scrappage rates.

$$h_t(x, Z) = \alpha_0 r_t^{\alpha} p_t^{\beta} n_t F_t(x) \qquad (14)$$

Zheng et al. (2019) estimated the logistic scrappage model used by Greene and Chen (1981) to quantify the effects of a change in China’s mandatory scrappage regulations on the expected median lifetime of four types of light-duty vehicles. Lu et al. (2018) used a two-parameter logistic function to model the survival and scrappage rates

[2] The similarity of newer and older vehicles’ price elasticities may be due to the much lower prices of older vehicles. The elasticities still imply that older vehicles’ scrappage rates will respond more than newer vehicles’ scrappage rates to an equal dollar reduction in price.

of eight types of vehicles in China. The authors note that although vehicle scrappage and survival rates are normally affected by a number of parameters, including vehicle age, new vehicle prices, repair costs, cumulative distance traveled, fuel prices, emissions regulations, fuel economy and subsidies, vehicle survival rates in China were mainly affected by China's mandatory scrappage standards. Their analysis is similar to the seminal work on Chinese vehicle scrappage by Hao et al. (2011) which employed a Weibull function to model the evolution of private passenger vehicles, business passenger vehicles and taxis in China.

Nakamoto et al. (2019) employed Weibull distributions to represent the cumulative scrappage functions of 15 countries in an assessment of lifecycle CO_2 emissions. The parameters of the Weibull functions were taken from an analysis by Oguchi and Fuse (2015) of data spanning the years 2000-2009. Rith et al. (2020) developed a simplified method for estimating Weibull survival functions for developing countries with limited data on vehicles in operation.

Zaman and Zacour (2020) simulated consumers' new vehicle purchase and scrappage decisions under varying incentives to accelerate scrappage by means of a dynamic programming model[3] similar to the optimal replacement model of Baltas and Xepapadeas (1999). Laborda and Moral (2020) used a logistic scrappage function to estimate the effects of accelerated scrappage programs in Spain. Variables included in the scrappage function in addition to vehicle age were gross domestic product, the volume of used sales, roadway fatalities and injuries, and (0,1) variables representing different scrappage incentives.

Gohlke and Cribioli (2021) estimated survival probabilities for light-duty vehicles as a whole and by powertrain, by comparing new vehicle sales data by model year to the numbers of vehicles in operation in calendar year 2021, estimating a median survival time of 17.6 years. Looking at individual models, they found that pickup trucks like the Ford F150 had expected survival times substantially longer (about 22 years) than sedans like the Honda Civic (about 18 years). Although were more limited, they found that hybrid vehicles' expected median survival times were comparable to those of all light-duty vehicles (18.3 vs. 17.6 years). With ten or fewer model years of data, definitive estimates of survival curves for plug-in and full battery electric vehicles could not be estimated.

NHTSA (2022) updated a previous (NHTSA, 2008) logistic model of scrappage as a function of vehicle age, new and used car prices, fuel prices, fuel economy, GDP, and other variables.

$$r_t(a, \boldsymbol{x}) = \frac{\sum_j \beta_j x_j}{1+\sum_j \beta_j x_j} \qquad (15)$$

Using data on vehicles in operation from 1975-2017, NHTSA (2022) estimated separate equations for passenger cars, SUVs and vans and pickup trucks. Fixed effects were included for model years to represent trends in vehicle technology, and for calendar years 2009 and 2010 to represent the effects of the Great Recession and policies implemented during those years to accelerate the retirement of used vehicles. The analysis detected a trend of increasing vehicle longevity, but noted that the trend might be affected by the fact that the number of age categories included in the data steadily increased over time. The logistic scrappage function was used for ages up to 30 years. Beyond thirty years of age an "accelerated decay function" was used to reduce the number of older vehicles and insure that the total vehicle counts predicted by the model matched the historical data.

Despite intense interest in modeling the future evolution of the stocks of zero emission vehicles, empirical research has been limited by the lack of data on modern electric vehicles of sufficient age to experience significant scrappage. Spangher et al. (2019) used an agent-based model to simulate the impact of electric vehicles sales on CO_2 emissions. Lacking data on electric vehicles, their model used logistic scrappage probabilities as a function of age for five types of light-duty vehicles based on

[3] The model assumed a constant maximum vehicle lifetime and divided consumers into high and low income groups with different propensities to purchase new and used vehicles. They calibrated the model using plausible assumptions rather than historical data and conducted sensitivity tests on parameter values.

conventional internal combustion engine vehicles. Nakamoto et al. (2019) were also unable to estimate cumulative scrappage functions for different vehicle types and propulsion systems. They concluded that "…expanded analysis with a focus of wide variety of vehicle models is an important and challenging future work." (p. 1043)

LOGISTIC SCRAPPAGE MODEL

Review of the literature reveals four general issues relevant to this analysis of trends in light-duty vehicle scrappage and survival.

1. The conceptual distinction between mechanistic vs. economic models
2. Choice of functional form between Weibull and logistic functions
3. Changes in scrappage and survival rates over time
4. Differences in scrappage rates among vehicle types

Vehicle scrappage analyses have long recognized that although scrappage patterns are most strongly related to vehicle age and use, economic and other factors are also important. The concept of mechanistic scrappage includes wear and tear with cumulative use and exposure, as well as inherent durability due to technology embodied in the vehicle (materials and the quality of design and manufacture). Economic factors include supply, demand and prices, design and technological obsolescence, economic determinants of vehicle use, maintenance and repair, and public policies. Because our primary interest is in trends in vehicle longevity regardless of cause, and trends toward increased longevity that may continue into the future, we represent the combined mechanistic and economic effects with time trend variables and calendar year and vintage fixed effects. We also estimate separate functions for three vehicle types: 1) passenger cars, 2) SUVs and vans, and 3) pickup trucks. Differences among the three vehicle types found by NHTSA (2022) are clearly evident in the graphs shown below.

Both Weibull and logistic functional forms have been widely used in the literature to model conditional scrappage rates. We estimate both forms, and both produce statistically highly significant coefficient estimates and R^2 values of 0.98 or better. However, we decided in favor of the logistic function based on analysis of residuals from the fitted models, as explained in appendix A.

The logistic probability density function (pdf) provides a flexible basis for constructing a conditional survival probability function. As noted above, the conditional survival probability function (cspf) is not a probability density function and does not integrate to 1 over the range of ages. Instead, it describes the probability that a vehicle that has survived to age x, will also survive to age x+1. The logistic pdf is shown in equation 1, in which μ is the mean, median and mode of the pdf and σ scales the effect of increasing age on the probability of survival.

$$f(x;\mu,\sigma) = \frac{e^{-(x-\mu)/\sigma}}{\sigma(1+e^{-(x-\mu)/\sigma})^2} \qquad (16)$$

The pdf can be readily modified to become a cspf by including a scaling factor, K, (since the cspf does not integrate to 1) and an asymptotic scrappage rate, A, to allow the cspf to be asymmetric, and to allow the possibility that the probability of survival may not converge toward 0 within the range of ages in the data. The modified cspf is shown in equation 17, which has been rearranged by multiplying numerator and denominator by $e^{(x-\mu)/\sigma}$.

$$g(x;\mu,\sigma,K,A) = \frac{K}{(e^{(x-\mu)/2\sigma}+e^{-(x-\mu)/2\sigma})^2+A} \qquad (17)$$

Equation 17 is static and does not include the fact that technological advances and economic factors may change the coefficients of the cspf over time. To include the effects of changes in economic factors over time, K is replaced by annual fixed effects, $\exp(a_t d_t)$, where a_t is a year-specific constant and d_t a year-specific indicator variable, for t = 2003 to 2020. The possibility of a linear trend in average age is included by replacing μ by $\mu_0 + \mu_1 t$, and σ is replace by $\sigma_0 + \sigma_1 t$. Technological change, on the other hand, is expected to be incorporated in vehicles predominantly by model year rather than affecting all ages of vehicles in a calendar year. This possibility is included by multiplying centered age, x-μ, by exp(βy), where y increases from 0 to 70 as model year increases from 1950 to 2020.

DATA

The data used in this analysis are proprietary counts of light-duty vehicles in operation on January 1 of each year, in the United States. Use of the data was purchased from IHS Markit Insight™, which requires nondisclosure of the data but permits publication of statistical inferences derived from it that do not disclose the original counts. The data were aggregated to make, model, body style and trim levels by calendar year and model year. These data were further aggregated into three vehicle types within each age group, 1) passenger cars, 2) SUVs, minivans and passenger vans, 3) pickup trucks. Vehicle age is calculated by subtracting a vehicle's model year from the current calendar year.[4] For calendar year 2003 there are 33 age groups, and the number of age groups increases by one each year to 50 age groups in 2020.

When vehicles are new or 1 to 2 years old, it is common for vehicles in operation data to show negative scrappage, i.e., an increase in vehicles in operation. Frequently, the entire production of a model year is not sold within the first or even second calendar year. In addition, a new model year is typically introduced before its corresponding calendar year. For this reason, the scrappage functions are estimated using ages 3 and older.

ESTIMATION AND RESULTS

The full cspf model was estimated using the Stata™ statistical software's nonlinear least square routine with the robust standard errors option to correct for heteroscedasticity and certain types of misspecification. Models were estimated for three vehicle types: passenger cars, SUVs and vans, and pickup trucks, without weighted observations and with weighting of observations by the number of vehicles in operation for the respective vehicle type, age and calendar year. All models achieved adjusted R^2 values of 0.99[5] and all coefficient estimates of all models were statistically significant at the 0.0001 level, using the robust standard error estimates. The detailed results are shown in Appendix B. Despite the high R^2 values, patterns in the residual plots indicate a small remaining lack of fit for the logistic functional form or possible misspecification due to omission of explanatory variables other than age and vintage. There is also clear evidence of heteroscedasticity, confirming the appropriateness of using the robust estimation method (Figures 1-3). As expected, residuals from the regressions weighted by vehicles in operation show smaller variance for vehicles up to about 20 years of age, but increased variance for older vehicles. The residual plots also suggest there may be a few outliers in the data. Unweighted scrappage models for passenger cars and pickups were re-estimated, respectively deleting 2 and 4 seeming outliers. There were small differences in some estimated coefficients. The results shown in graphs below and the regression results reported in Appendix B do not exclude potential outliers, but include all data points.

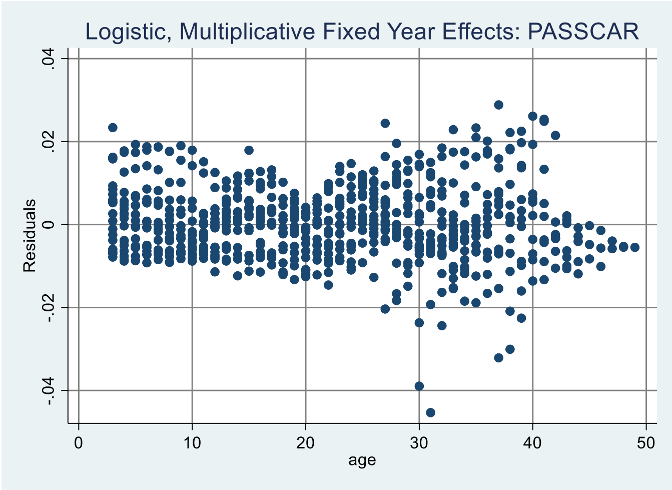


Figure 1a. Residuals from the Full Logistic Scrappage Model for Passenger Cars

[4] In a few cases of new vehicle registrations, a vehicle's model year exceeds the calendar year. We code these observations as having an age of 0, representing a new vehicle.

[5] R-squared values in nonlinear models can be misleading. Mean squared error (MSE) is an alternative measure of model fit that can be more meaningful. Similarly parameterized Weibull models had MSE values that were 7% larger than the logistic model MSEs for pickups, 46% larger for SUVs and vans, and 51% larger for passenger cars.

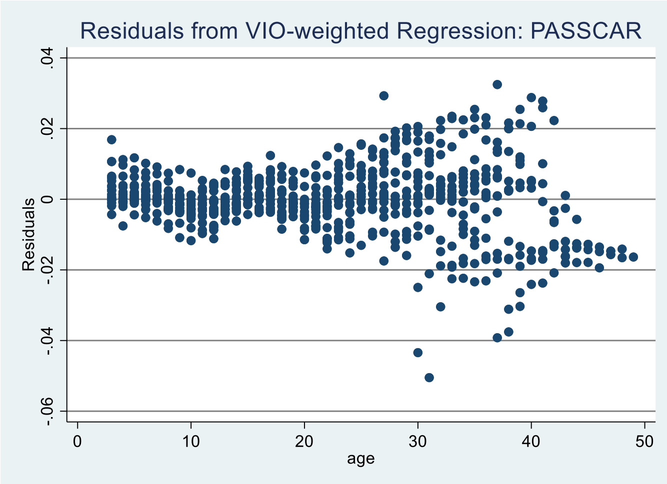


Figure 1b. Residuals from Scrappage Model with VIO-Weighted Observations: Passenger Cars.

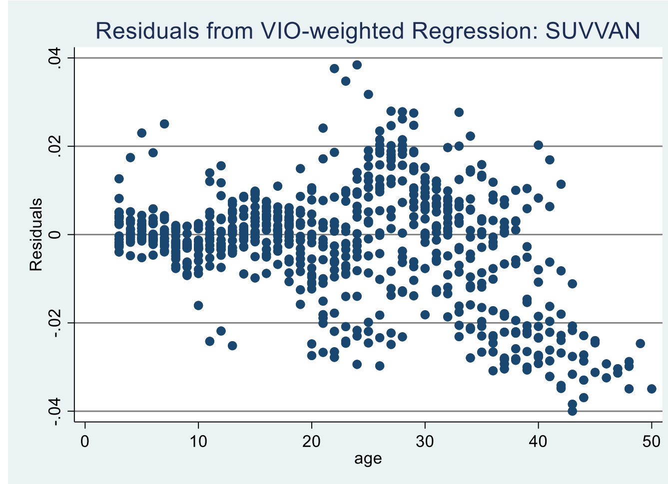


Figure 2b. Residuals from Scrappage Model with VIO-Weighted Observations: SUVs and Vans.

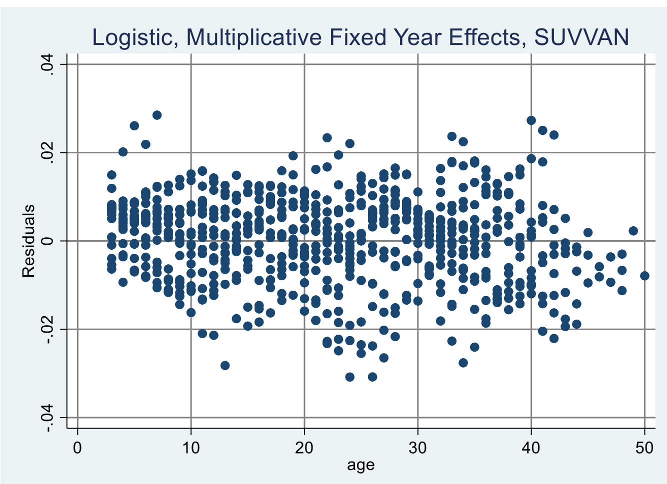


Figure 2a. Residuals from the Full Logistic Scrappage Model for SUVs and Vans

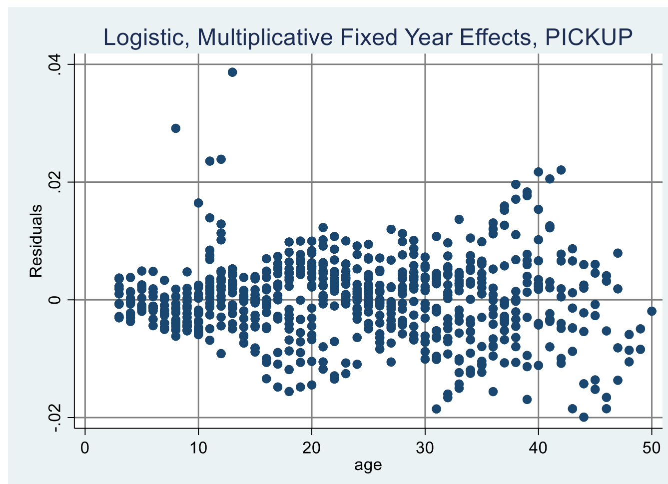


Figure 3a. Residuals from the Full Logistic Scrappage Model for Pickup Trucks

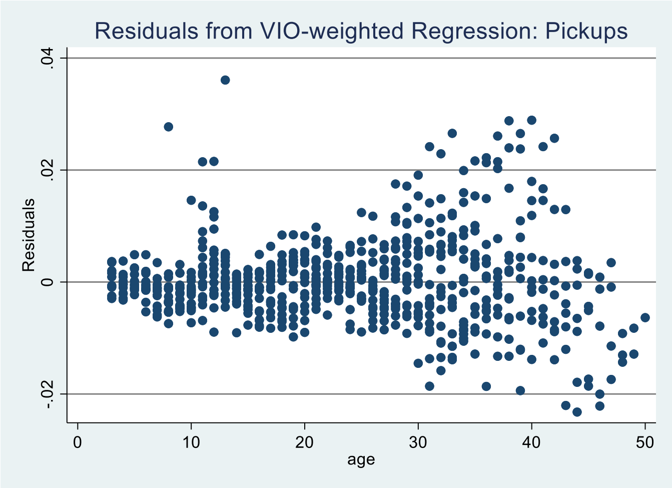


Figure 3b. Residuals from Scrappage Model with VIO-Weighted Observations: Pickups.

The conditional survival probability functions for passenger cars, SUVs and Vans and Pickups for calendar years 2003, 2011 and 2019 (8-year intervals) are shown in Figures 4-6.[6] In the legend, “W” indicates that the estimates are based on observations weighted by vehicles in operation. The weighted estimates are represented by open squares while the unweighted estimates are represented by filled circles. Graphs showing all years can be found in Appendix C. The functions are strikingly different across the vehicle types. The passenger car functions are narrower, peak at conditional scrappage probabilities of 0.16 to 0.21. The ages at which scrappage probability peaks have shifted over time towards longer lifetimes. For passenger cars, the age of maximum scrappage shifts from μ = 19.4 years in 2003 to μ = 22.4 in 2020, based on the calendar year logistic scrappage model coefficients fitted to weighted data. For SUVs and vans, the increase is from 19.5 years in 2003 to 22.1 years, while pickups show the largest shift, from 24.4 years in 2003 to 28.2 years in 2020. Weighting the data by the numbers of vehicles in operation by model year and calendar year increased conditional scrappage rates for newer vehicles in 2019 and decreased scrappage rates for older vehicles in 2003.

[6] The years were chosen to be at equal time intervals, but also because the 2020 scrappage and survival functions deviate from the general trend, as can be seen in Appendix C. The reason for the change in 2020 is not obvious and suggests the importance of further analysis to explore the impacts of economic factors.

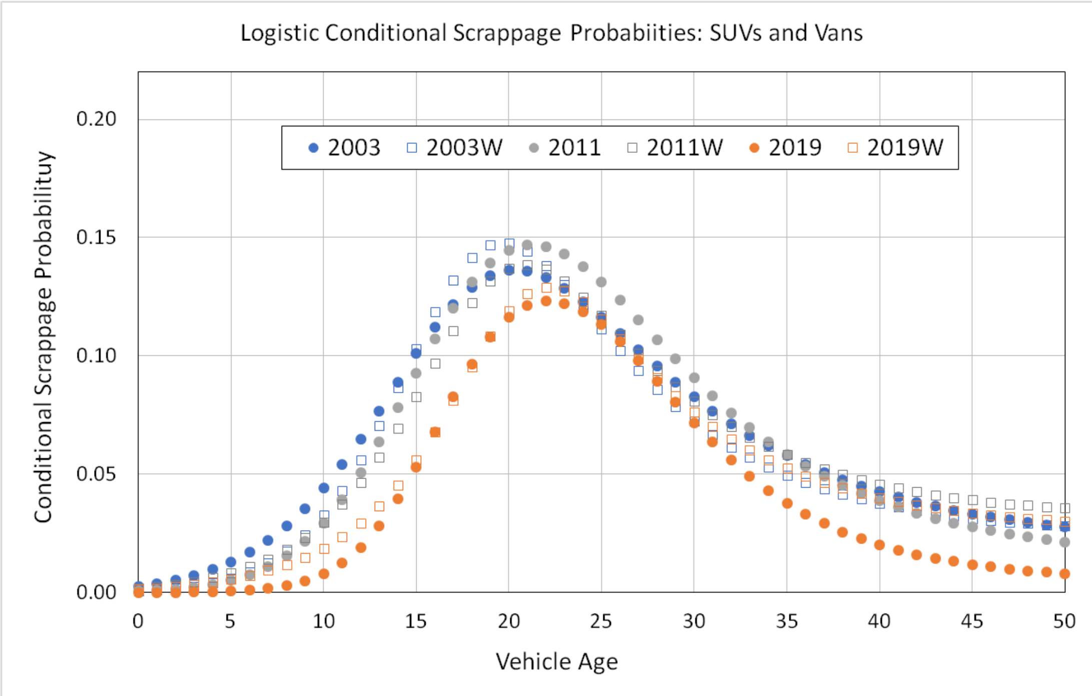


Figure 5. Conditional Scrappage Probability Functions for 2003, 2011 and 2019: SUVs and Vans.

The conditional scrappage functions for pickups are broader still, with even lower peak scrappage rates of approximately 0.07 to 0.12. Weighting the data caused only minor changes in scrappage probabilities.

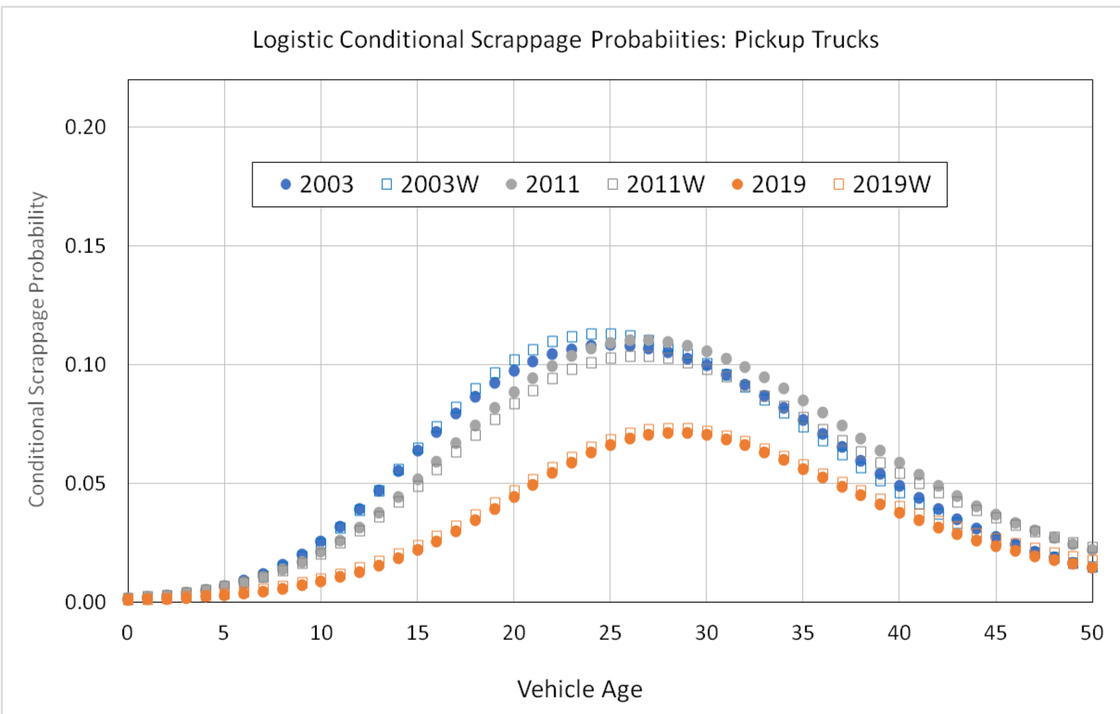


Figure 6. Conditional Scrappage Probability Functions for 2003, 2011 and 2019: Pickup Trucks.

The trend toward increasing vehicle lifetimes is also evident in the cumulative survival probability functions (Figures 7-9). Over the 17-year period from 2003 to 2020, the median expected lifetimes of all vehicle types increased by several years. For all three vehicle types, functions based on weighted and unweighted data are very similar, but the 2019 functions for cars and SUVs indicate lower survival rates.

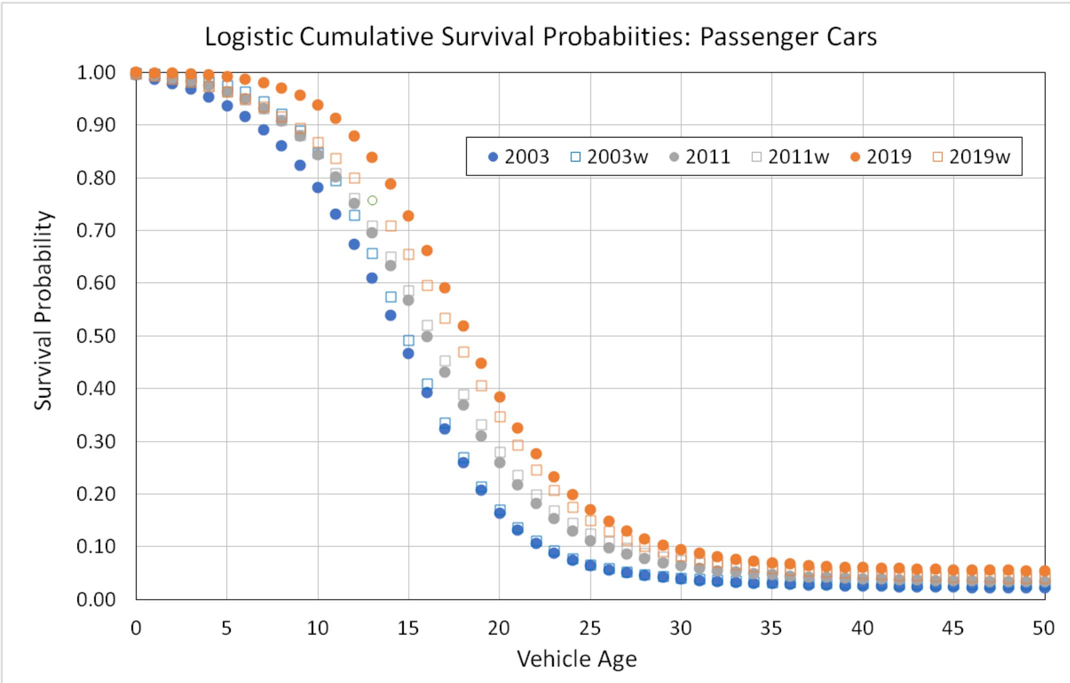


Figure 7. Cumulative Survival Probability Distributions, 2003, 2011 and 2019: Passenger Cars.

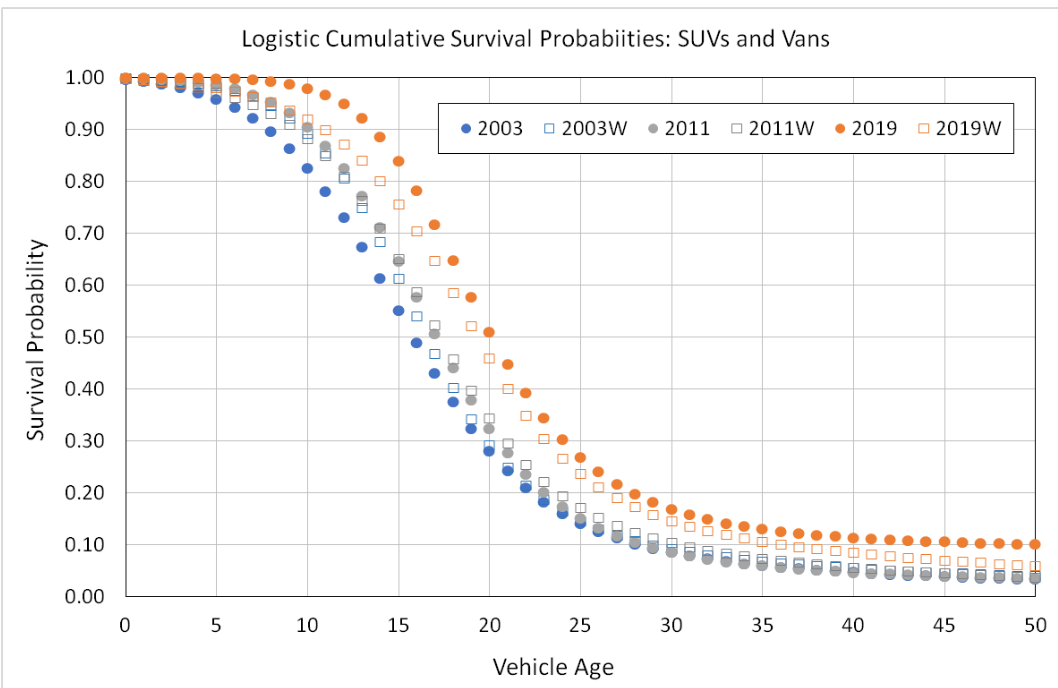


Figure 8. Cumulative Survival Probability Distributions, 2003, 2011 and 2019: SUVs and Vans.

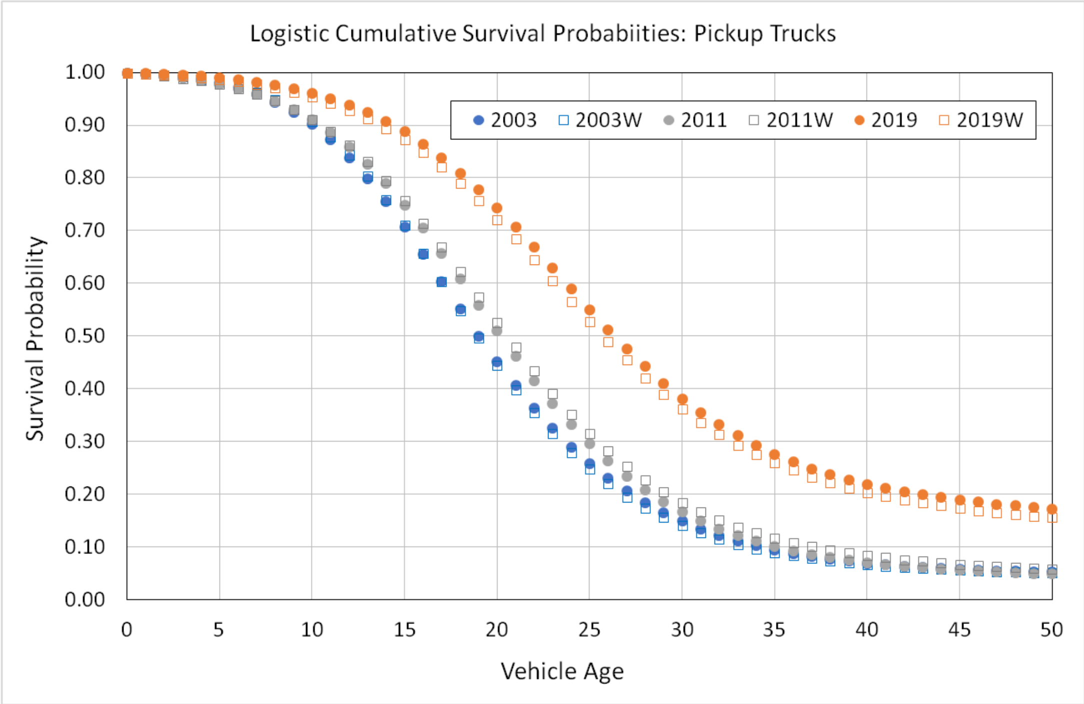
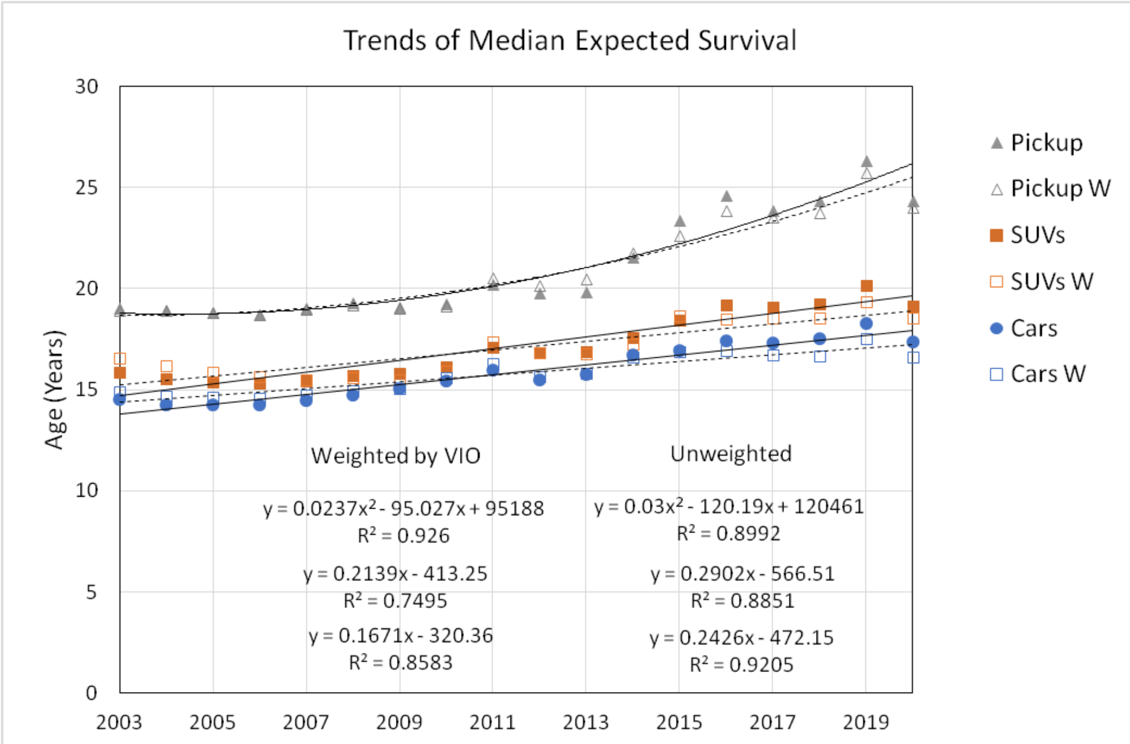


Figure 9. Cumulative Survival Probability Distributions, 2003, 2011 and 2019: Pickup Trucks.

The graphs in Figures 4-9 suggest that there has been a steady increase in longevity, year after year. However, the individual calendar year functions tell a more nuanced story. Changes in the calendar year fixed effects cause ups and downs in maximum scrappage rates and some deviations from the trend of increasing longevity, indicating that temporal factors shift the scrappage schedules from one year to the next (Figure 10). The year-by-year estimates show relatively little change in median expected lifetimes from 2003-2012, with greater increases from 2013-2020. The full set of cspf curves are shown in Appendix C.

The cumulative survival probability curves for each vehicle type were used to calculate median expected survival ages by calendar year (Figure 10). The results indicate a period of constant or slowly increasing median expected lifetimes through about 2010, followed by a more rapid increase through 2020. The data again indicate that pickup trucks have experienced the greatest increase in life expectancy. However, the data also reflect notable variation by calendar year, suggesting an important influence of economic factors.



DISCUSSION

The enhanced logistic function with calendar year fixed effects, linear trends in k, μ, σ and the asymptote, and exponential trends by model year describes the data well, despite some patterns that appear in the residuals. However, these patterns are far less pronounced than those in the residuals from the Weibull function. Weighting observations by the numbers of vehicles in operation by vehicle type, age and calendar year yields a small improvements in mean square errors of the logistic models, with the noticeable improvements in fits for younger vehicles at a cost of somewhat poorer fits to vehicles more than 25 years old.

The results strongly support the following descriptive findings:

1. Conditional scrappage rates are different for passenger cars, SUVs and vans, and pickup trucks, with pickups having the lowest scrappage rates and longest survival times.
2. Over the 2003-2020 period, expected lifetimes increased by several years for all three vehicle types, although the increase is not constant and uniform from one year to the next.
3. Light duty vehicles now have expected lifetimes of 18-27 years, with potentially important implications for public policies that regulate new vehicles and rely on stock turnover to achieve their full effect. The effect of increasing vehicle age for all vehicle types has been amplified by the increased market share of light trucks.
4. In addition to the trends towards increasing life expectancies, scrappage and survival rates vary from year to year, indicating that factors such as new vehicle prices, macroeconomic variables and other secular shocks have important effects on vehicle scrappage.

It is tempting to assume that the calendar year effects and trends incorporated in the statistical scrappage models represent secular changes in prices and economic factors, while the model year variables reflect technological changes in vehicle durability embodied in the vehicles manufactured in a given year. However, vehicle prices may also vary by model year for various reasons, including content such as luxury accessories that would not affect technical durability. Likewise, technological change over time might also affect the maintenance and repair of vehicles across model years. This study has not attempted to identify the causes of changes in vehicle scrappage and survival over time but only to describe them.

Increased vehicle survival rates imply that it will take more time to turn over the stock of light duty vehicles. From a public policy perspective, it will take longer for the benefits of increased fuel economy, reduced pollutant emissions and improved safety features to achieve their full impact. The changes in scrappage rates over the past two decades suggest that nearly complete replacement of the existing light-duty vehicle stock may take 10% to 20% longer today than it would have twenty years ago. Whether these trends will continue remains is not known, and whether policy intervention to accelerate stock turnover would be beneficial is an open question. Answering such questions will require a better understanding of the causes of increased vehicle longevity.

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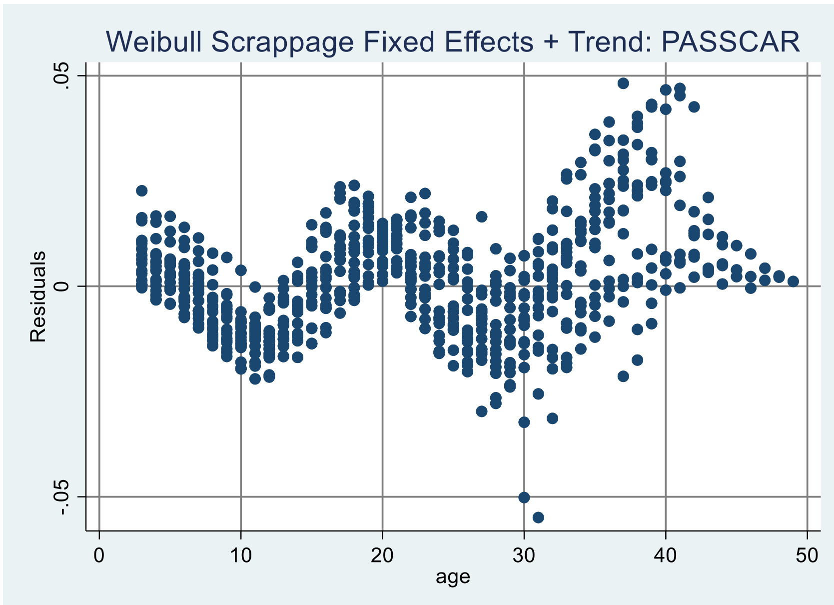
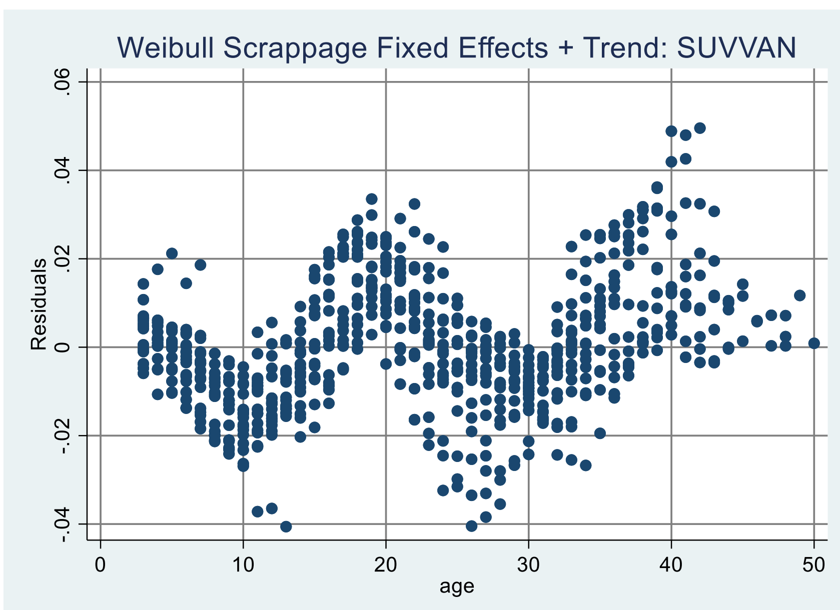
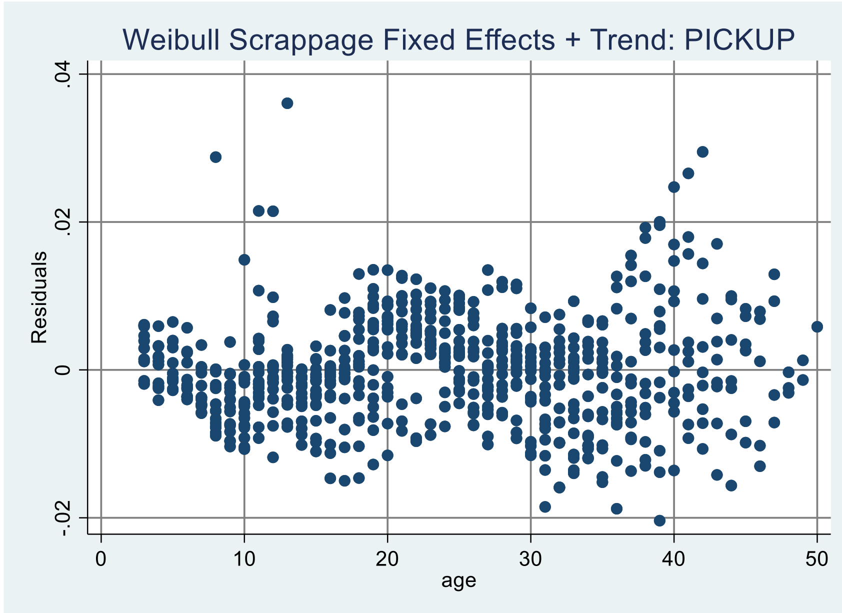
APPENDIX A. RESIDUALS FROM WEIBULL MODELS

Although the estimated Weibull conditional scrappage models produced high adjusted R^2 values and generally, highly statistically significant coefficient estimates, examination of their residuals plotted against vehicle age revealed much more pronounced systematic patterns than are evident in the residuals from the logistic models (see Figs. 1-3, above). The patterns clearly indicate that the curvature of the Weibull function periodically under- and over-predicts scrappage rates for all three vehicle types. This effect persisted whether or not calendar year fixed effects and model year trends were included, and could not be corrected by weighting the data, for example by number of vehicles in operation. The residuals from logistic models show far less pronounced systematic lack of fit and have slightly higher R^2 values, lower mean squared errors, and improved significance levels for estimated coefficients.







Figures A1, A2, A3. Residuals vs. Vehicle Age for Weibull Conditional Scrappage Functions with Fixed Calendar Year Effects and Calendar Year and Model Year Coefficient Trends.

APPENDIX B. RESULTS OF STATISTICAL ESTIMATION OF LOGISTIC MODELS

Passenger Cars

Nonlinear regression

Unweighted

Number of obs	=	695
R-squared	=	0.9924
Adj R-squared	=	0.9922
Root MSE	=	.0091439
Res. dev.	=	-4578.722

scraprate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
/y3	.7474401	.0724918	10.31	0.000	.6051017	.8897785
/y4	.8471639	.066361	12.77	0.000	.7168632	.9774645
/y5	.8981347	.0602479	14.91	0.000	.7798372	1.016432
/y6	.9516125	.0558864	17.03	0.000	.841879	1.061346
/y7	.9526714	.052076	18.29	0.000	.8504196	1.054923
/y8	.9497712	.0493528	19.24	0.000	.8528664	1.046676
/y9	.9315229	.0480847	19.37	0.000	.8371081	1.025938
/y10	.8841581	.0434515	20.35	0.000	.7988405	.9694756
/y11	.7770678	.0459965	16.89	0.000	.686753	.8673825
/y12	1.063917	.0414582	25.66	0.000	.982513	1.14532
/y13	1.077441	.0420741	25.61	0.000	.9948276	1.160054
/y14	.7953055	.0512984	15.50	0.000	.6945806	.8960304
/y15	.834278	.0455144	18.33	0.000	.74491	.9236459
/y16	.7467465	.0551897	13.53	0.000	.638381	.855112
/y17	.9615449	.0383093	25.10	0.000	.8863241	1.036766
/y18	1.01145	.0630766	16.04	0.000	.8875988	1.135302
/y19	.8083632	.	.	.	.	.
/y20	1.436527	.0511343	28.09	0.000	1.336124	1.53693
/kt	.239925	.0248421	9.66	0.000	.1911474	.2887027
/s	10.5565	.6168027	17.11	0.000	9.345399	11.7676
/st	-.217161	.0266951	-8.13	0.000	-.2695772	-.1647448
/sy	.0126159	.0006005	21.01	0.000	.0114367	.0137951
/mu	19.5912	.0620159	315.91	0.000	19.46943	19.71297
/mut	.1573961	.0065728	23.95	0.000	.1444904	.1703018
/a	-32.70332	3.114514	-10.50	0.000	-38.8187	-26.58793
/at	2.723116	.2057155	13.24	0.000	2.319191	3.12704

Nonlinear regression

Weighted

Number of obs	=	1903428123
R-squared	=	0.9963
Adj R-squared	=	0.9963
Root MSE	=	.0050882
Res. dev.	=	-1.30e+10

scraprate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
/y3	1.723377	.0000282	61150.25	0.000	1.723322	1.723433
/y4	1.728226	.0000272	63574.53	0.000	1.728173	1.72828
/y5	1.699431	.0000256	66265.97	0.000	1.69938	1.699481
/y6	1.678074	.0000244	68767.16	0.000	1.678026	1.678122
/y7	1.613923	.0000236	68245.60	0.000	1.613877	1.61397
/y8	1.551444	.0000233	66685.71	0.000	1.551399	1.55149
/y9	1.496722	.0000222	67324.67	0.000	1.496679	1.496766
/y10	1.372929	.0000197	69740.53	0.000	1.37289	1.372968
/y11	1.214388	.0000191	63676.04	0.000	1.214351	1.214425
/y12	1.325392	.0000179	73997.77	0.000	1.325357	1.325427
/y13	1.279557	.0000172	74437.84	0.000	1.279523	1.279591
/y14	1.110202	.0000173	64208.36	0.000	1.110168	1.110236
/y15	1.039957	.0000167	62329.46	0.000	1.039924	1.03999
/y16	1.020316	.0000134	76360.97	0.000	1.02029	1.020342
/y17	1.052066	.0000118	89162.60	0.000	1.052043	1.052089
/y18	1.04712	.0000158	66298.79	0.000	1.047089	1.047151
/y19	.8691812	.	.	.	.	.
/y20	1.051771	.0000173	60711.62	0.000	1.051737	1.051805
/kt	.0193807	7.66e-06	2528.62	0.000	.0193657	.0193958
/s	5.060083	.0003084	16405.78	0.000	5.059479	5.060688
/st	.4112844	.0000489	8402.40	0.000	.4111885	.4113804
/sy	.0119387	1.12e-06	10652.87	0.000	.0119365	.0119409
/mu	19.39584	.0000816	2.4e+05	0.000	19.39568	19.396
/mut	.1785366	8.44e-06	21155.32	0.000	.1785201	.1785532
/a	8.098507	.0018011	4496.40	0.000	8.094976	8.102037
/at	-2.314201	.0001752	-1.3e+04	0.000	-2.314545	-2.313858

SUVs and Vans

Nonlinear regression

Unweighted

Number of obs =	695
R-squared =	0.9885
Adj R-squared =	0.9881
Root MSE =	.0099907
Res. dev. =	-4455.61

scraprate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
/y3	1.459542	.1242361	11.75	0.000	1.215602	1.703481
/y4	1.538914	.1190646	12.93	0.000	1.305129	1.772698
/y5	1.6012	.1140365	14.04	0.000	1.377288	1.825112
/y6	1.66069	.1085145	15.30	0.000	1.447621	1.87376
/y7	1.681655	.1048964	16.03	0.000	1.47569	1.887621
/y8	1.672065	.0994333	16.82	0.000	1.476826	1.867303
/y9	1.707217	.0897381	19.02	0.000	1.531015	1.883418
/y10	1.686505	.0836057	20.17	0.000	1.522345	1.850666
/y11	1.441016	.0847186	17.01	0.000	1.27467	1.607362
/y12	1.624748	.0753656	21.56	0.000	1.476767	1.772729
/y13	1.684859	.070334	23.96	0.000	1.546757	1.82296
/y14	1.530989	.0650894	23.52	0.000	1.403186	1.658793
/y15	1.260872	.0861958	14.63	0.000	1.091626	1.430118
/y16	.9866428	.0799999	12.33	0.000	.8295621	1.143724
/y17	1.15322	.0545879	21.13	0.000	1.046036	1.260404
/y18	1.186866	.0585304	20.28	0.000	1.071941	1.301791
/y19	.7541264	.	.	.	.	.
/y20	1.515797	.0822062	18.44	0.000	1.354384	1.677209
/kt	.3814183	.048468	7.87	0.000	.2862508	.4765859
/s	12.61918	.9694549	13.02	0.000	10.71564	14.52272
/st	-.2338635	.0517069	-4.52	0.000	-.3353905	-.1323365
/sy	.0207183	.00081	25.58	0.000	.0191278	.0223088
/mu	20.2309	.1275655	158.59	0.000	19.98042	20.48137
/mut	.1131327	.0088358	12.80	0.000	.0957834	.1304819
/a	-18.31887	8.166898	-2.24	0.025	-34.35467	-2.283081
/at	3.148626	.6732575	4.68	0.000	1.826678	4.470575

Nonlinear regression

Weighted

Number of obs =	1087328600
R-squared =	0.9874
Adj R-squared =	0.9874
Root MSE =	.0065042
Res. dev. =	-6.28e+09

scraprate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
/y3	1.567183	.0001146	13675.87	0.000	1.566959	1.567408
/y4	1.604066	.0001084	14801.93	0.000	1.603854	1.604279
/y5	1.64475	.0001007	16328.82	0.000	1.644553	1.644948
/y6	1.665856	.0000934	17830.64	0.000	1.665673	1.666039
/y7	1.680504	.0000889	18902.86	0.000	1.68033	1.680678
/y8	1.643548	.0000825	19917.30	0.000	1.643386	1.64371
/y9	1.660675	.0000727	22858.48	0.000	1.660533	1.660817
/y10	1.566659	.0000694	22578.07	0.000	1.566523	1.566795
/y11	1.276221	.000066	19346.11	0.000	1.276091	1.27635
/y12	1.371517	.0000593	23144.74	0.000	1.371401	1.371633
/y13	1.38552	.0000532	26045.82	0.000	1.385416	1.385624
/y14	1.296408	.0000464	27959.50	0.000	1.296318	1.296499
/y15	1.030941	.0000616	16726.68	0.000	1.03082	1.031062
/y16	1.062431	.0000314	33806.57	0.000	1.062369	1.062493
/y17	1.055204	.0000246	42957.18	0.000	1.055155	1.055252
/y18	1.059512	.0000227	46773.27	0.000	1.059468	1.059556
/y19	.9037876	.	.	.	.	.
/y20	1.077017	.0000295	36511.96	0.000	1.076959	1.077074
/kt	.017388	.000018	963.84	0.000	.0173526	.0174233
/s	11.62954	.002601	4471.11	0.000	11.62444	11.63464
/st	1.418073	.0005633	2517.46	0.000	1.416969	1.419177
/sy	.0270405	3.89e-06	6958.27	0.000	.0270329	.0270481
/mu	19.50744	.0003395	57454.61	0.000	19.50677	19.5081
/mut	.1536904	.0000232	6632.33	0.000	.153645	.1537358
/a	-13.30347	.012537	-1061.13	0.000	-13.32804	-13.2789
/at	-6.368423	.0021059	-3024.13	0.000	-6.372551	-6.364296

Pickup Trucks

```
Nonlinear regression                              Number of obs =        676
                                                  R-squared     =     0.9914
                                                  Adj R-squared =     0.9911
                                                  Root MSE      =   .0068325
                                                  Res. dev.     =  -4848.221
```

Unweighted

scraprate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
/y3	2.164713	.0823989	26.27	0.000	2.002914	2.326513
/y4	2.154402	.0790963	27.24	0.000	1.999088	2.309717
/y5	2.144987	.0765365	28.03	0.000	1.994699	2.295275
/y6	2.13458	.0743228	28.72	0.000	1.988639	2.280521
/y7	2.070868	.0717375	28.87	0.000	1.930003	2.211733
/y8	2.008856	.0687382	29.22	0.000	1.87388	2.143831
/y9	2.016209	.0665991	30.27	0.000	1.885434	2.146984
/y10	1.967523	.063448	31.01	0.000	1.842936	2.092111
/y11	1.805697	.0634204	28.47	0.000	1.681164	1.93023
/y12	1.845434	.0635089	29.06	0.000	1.720727	1.970142
/y13	1.80931	.06495	27.86	0.000	1.681773	1.936846
/y14	1.532381	.0525168	29.18	0.000	1.429258	1.635504
/y15	1.250057	.0480244	26.03	0.000	1.155755	1.344358
/y16	1.047578	.0408177	25.66	0.000	.9674276	1.127728
/y17	1.1015	.0365407	30.14	0.000	1.029748	1.173252
/y18	.9853766	.0359148	27.44	0.000	.9148537	1.0559
/y19	.6411712	.	.	.	.	.
/y20	.8271541	.0424905	19.47	0.000	.7437192	.910589
/kt	.0380161	.0150688	2.52	0.012	.0084268	.0676055
/s	5.432334	.4731866	11.48	0.000	4.503178	6.36149
/st	.2026306	.0417862	4.85	0.000	.1205787	.2846825
/sy	.0086276	.001288	6.70	0.000	.0060984	.0111569
/mu	24.87408	.1881148	132.23	0.000	24.50469	25.24346
/mut	.2053818	.016225	12.66	0.000	.1735221	.2372416
/a	61.95143	8.214492	7.54	0.000	45.82133	78.08153
/at	-3.638056	.4771206	-7.63	0.000	-4.574937	-2.701175

```
Nonlinear regression                              Number of obs =  703144375
                                                  R-squared     =     0.9891
                                                  Adj R-squared =     0.9891
                                                  Root MSE      =   .0054594
                                                  Res. dev.     =  -4.89e+09
```

Weighted

scraprate	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
/y3	2.057575	.0001119	18393.19	0.000	2.057356	2.057794
/y4	2.028291	.0001073	18901.02	0.000	2.02808	2.028501
/y5	2.022907	.0001039	19472.16	0.000	2.022704	2.023111
/y6	2.014601	.0001003	20084.65	0.000	2.014405	2.014798
/y7	1.95658	.0000965	20281.81	0.000	1.956391	1.95677
/y8	1.898603	.0000926	20503.73	0.000	1.898421	1.898784
/y9	1.908201	.0000891	21416.13	0.000	1.908026	1.908375
/y10	1.872373	.0000845	22166.71	0.000	1.872207	1.872538
/y11	1.651375	.0000813	20316.02	0.000	1.651216	1.651535
/y12	1.685252	.0000794	21232.36	0.000	1.685096	1.685408
/y13	1.623292	.0000799	20308.07	0.000	1.623135	1.623448
/y14	1.428288	.0000619	23090.84	0.000	1.428167	1.428409
/y15	1.289957	.0000637	20250.94	0.000	1.289832	1.290082
/y16	1.109349	.0000441	25162.62	0.000	1.109263	1.109435
/y17	1.120451	.0000379	29572.69	0.000	1.120377	1.120525
/y18	1.065883	.000033	32283.42	0.000	1.065818	1.065948
/y19	.7821686	.	.	.	.	.
/y20	.9723553	.0000364	26691.74	0.000	.9722839	.9724267
/kt	.020252	.0000142	1425.54	0.000	.0202241	.0202798
/s	5.720173	.0012878	4441.85	0.000	5.717649	5.722698
/st	.2897582	.0001265	2289.98	0.000	.2895102	.2900062
/sy	.0101763	4.01e-06	2535.30	0.000	.0101685	.0101842
/mu	24.3616	.0003699	65853.60	0.000	24.36088	24.36233
/mut	.2256228	.0000299	7535.47	0.000	.2255641	.2256815
/a	48.6662	.0119904	4058.77	0.000	48.6427	48.6897
/at	-3.337898	.0004649	-7179.84	0.000	-3.33881	-3.336987

APPENDIX C. SCRAPPAGE AND SURVIVAL CURVES BY CALENDAR YEAR

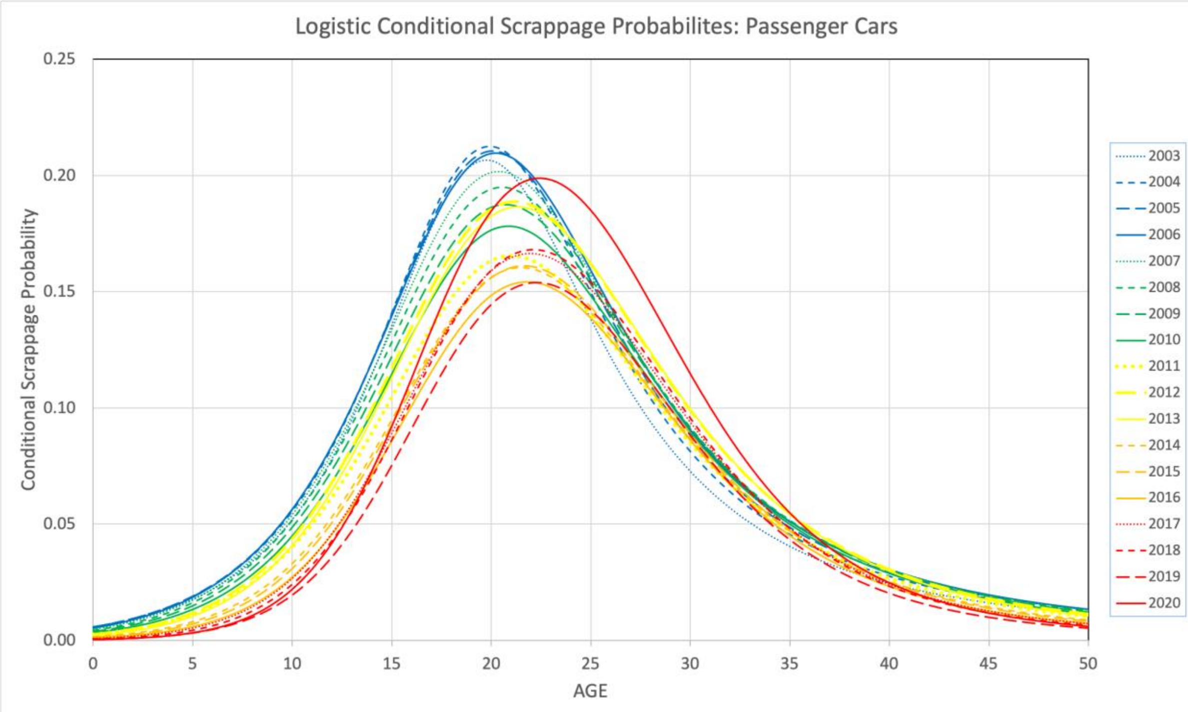


Figure C1a. Passenger Car Scrappage Rates vs. Age: Unweighted Data

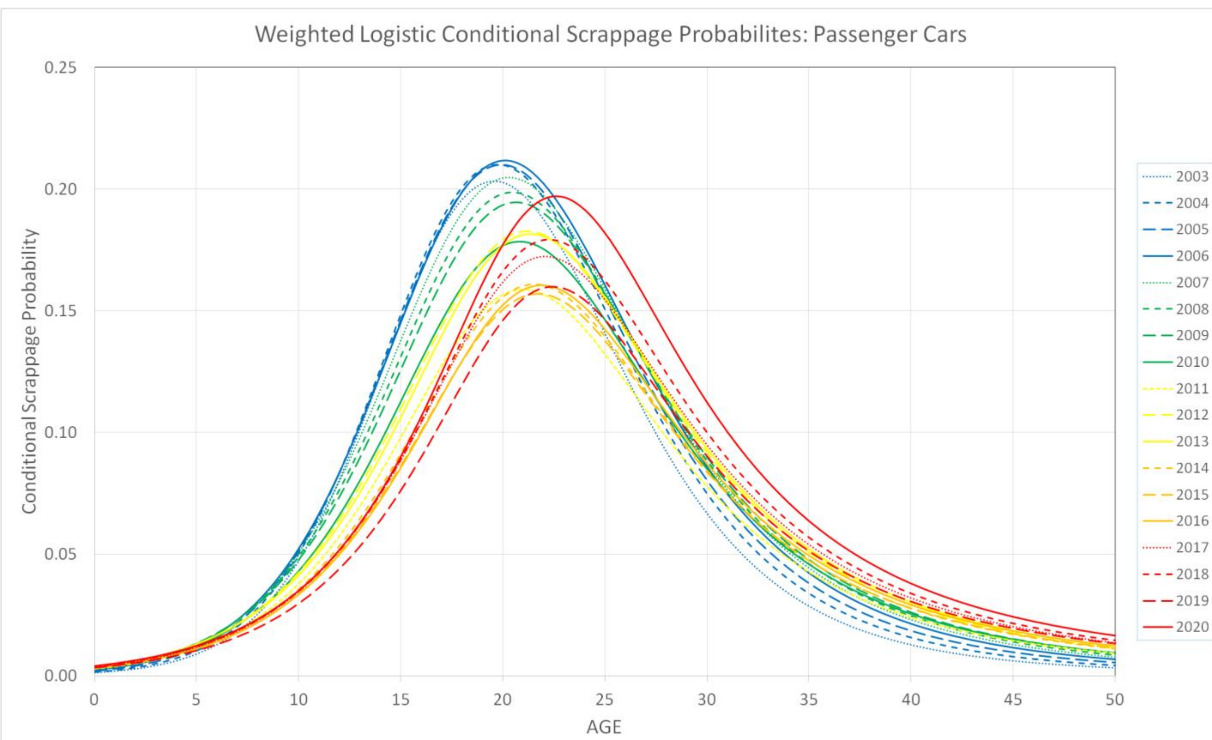


Figure C1b. Passenger Car Scrappage Rates vs. Age: Data Weighted by Vehicles in Operation.

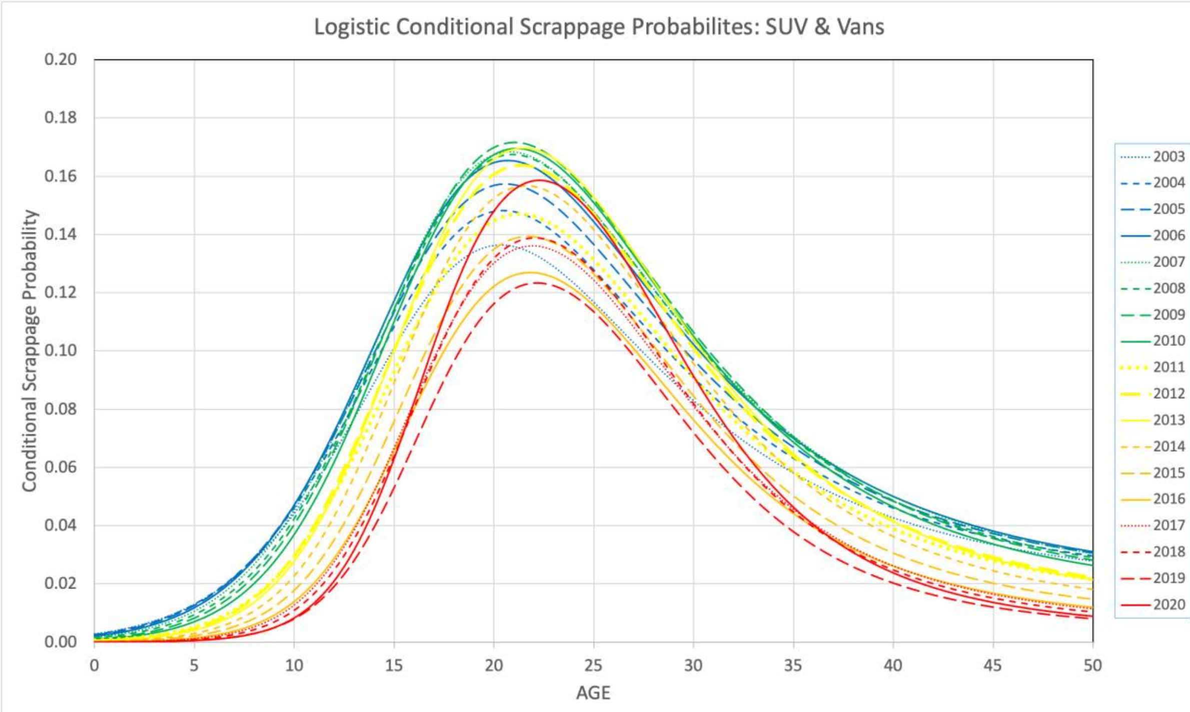


Figure C2a. SUV and Van Scrappage Rates vs. Age: Unweighted Data

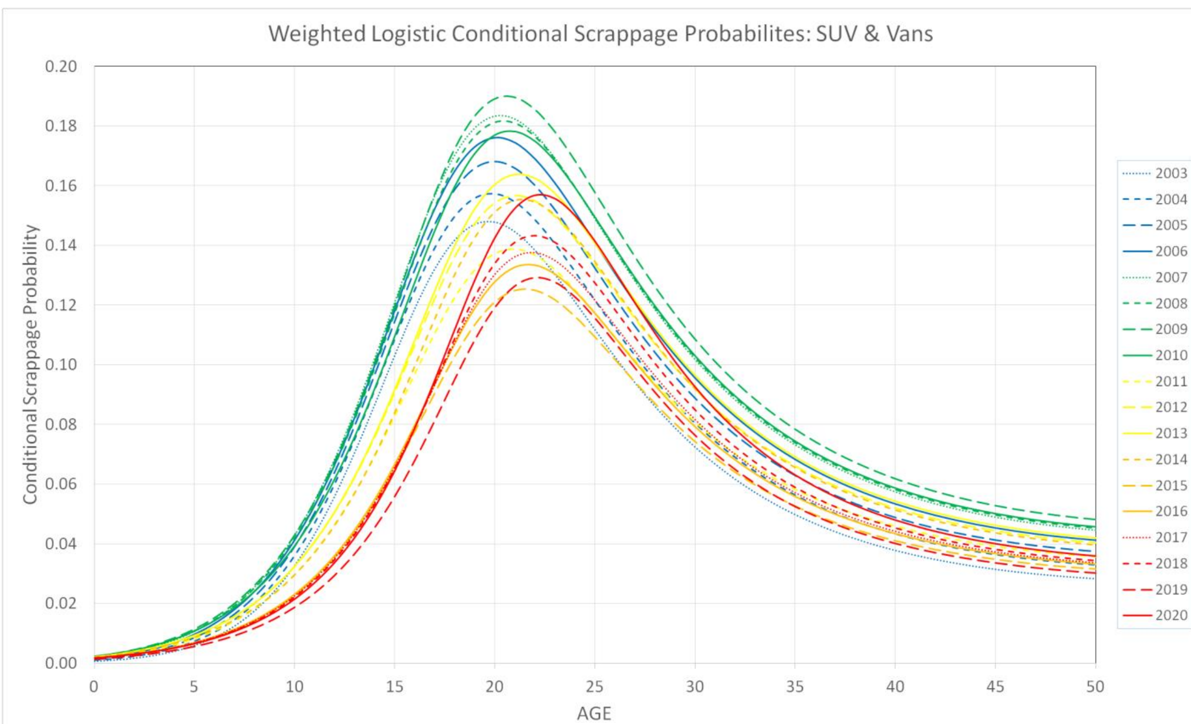


Figure C2b. SUV and Van Scrappage Rates vs. Age: Data Weighted by Vehicles in Operation.

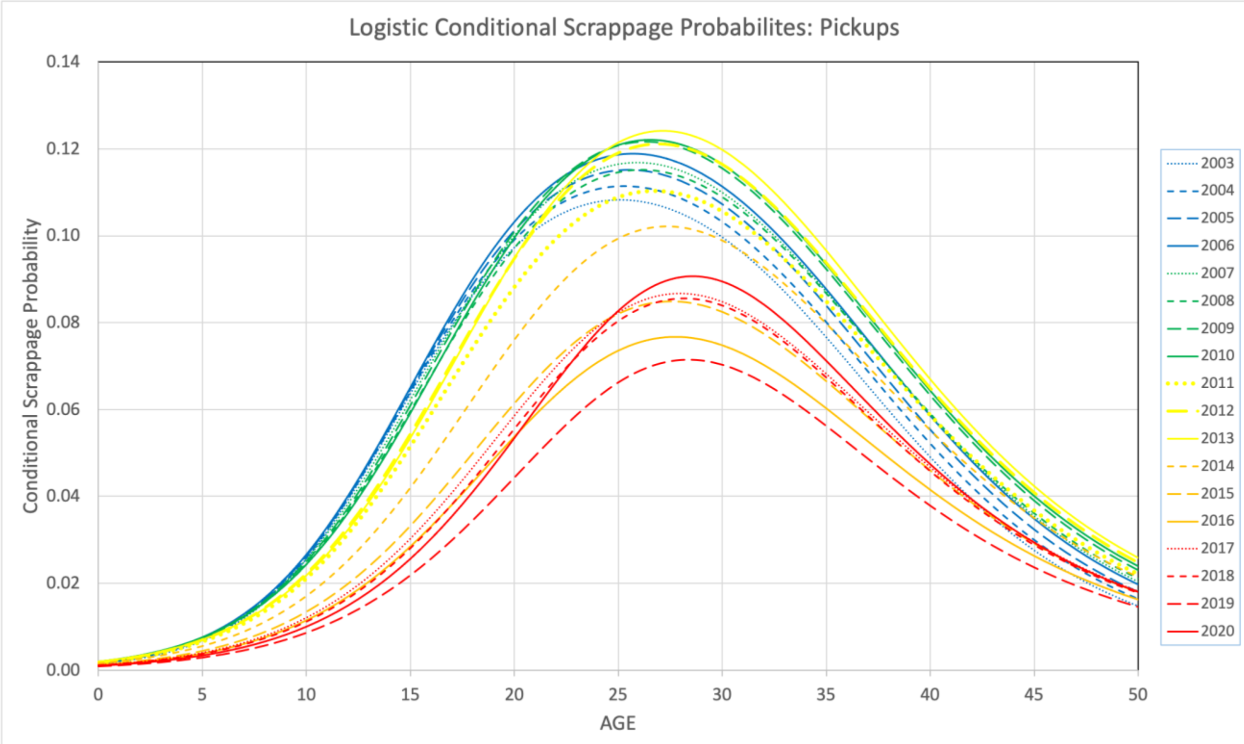


Figure C3a. Pickup Truck Scrappage Rates vs. Age: Unweighted Data

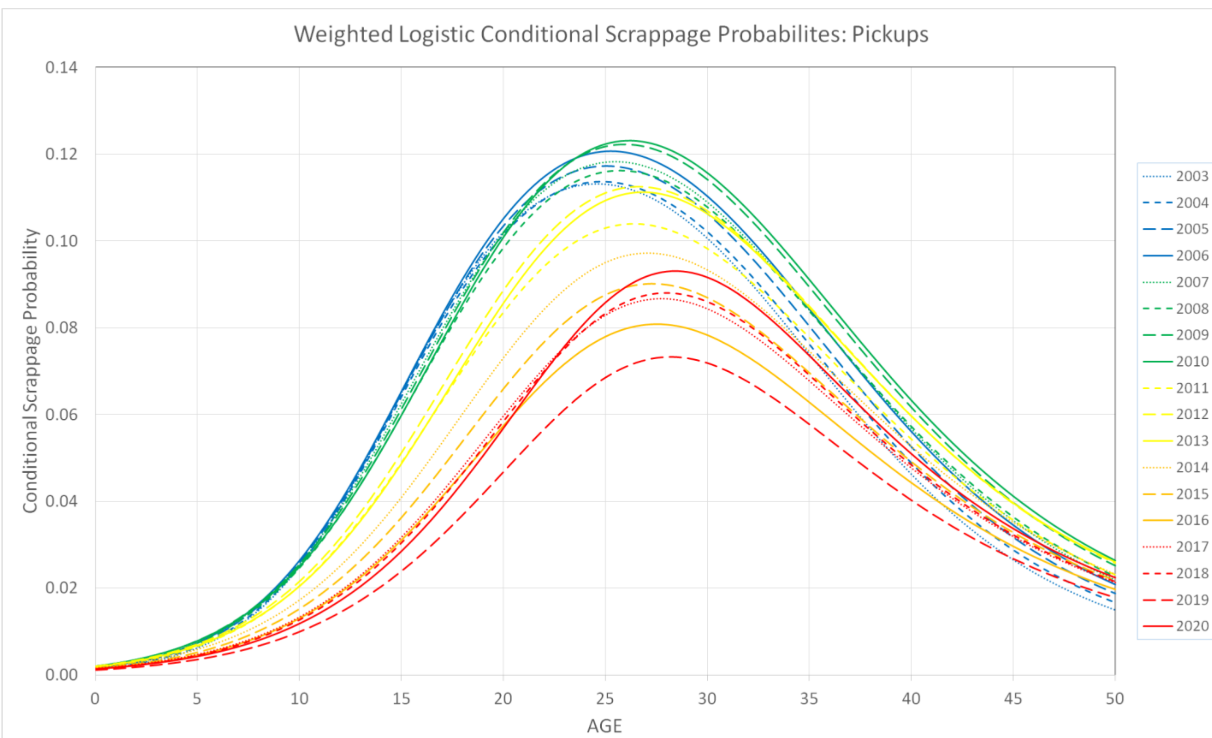


Figure C3b. Pickup Truck Scrappage Rate vs. Age: Weighted by Vehicles in Operation.

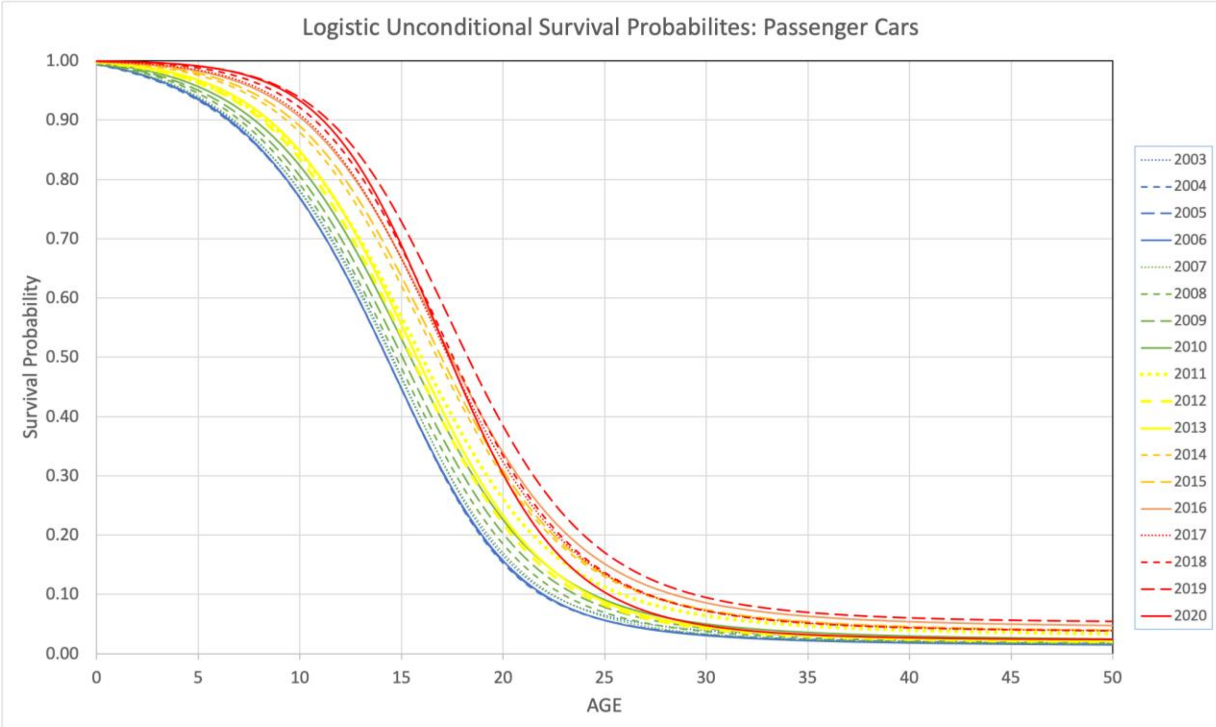


Figure C4a. Passenger Car Survival Probability Function: Unweighted Data.

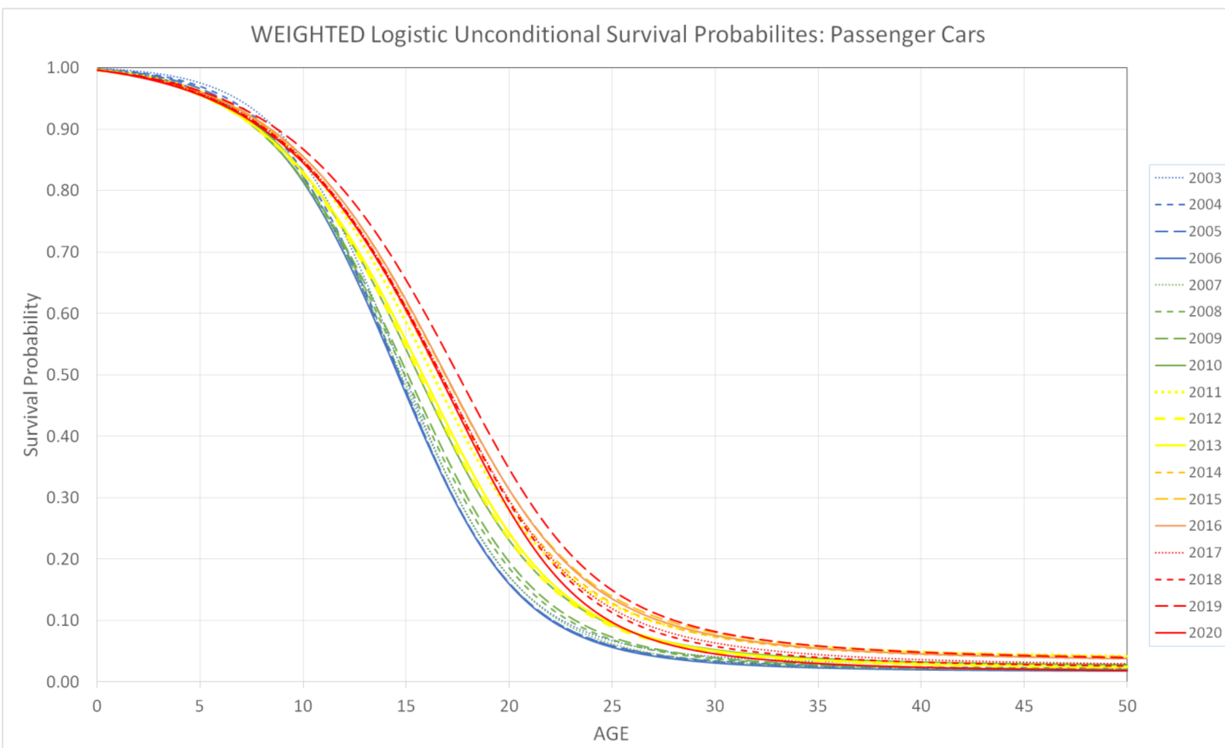


Figure C4b. Passenger Car Survival Probability Function: Data Weighted by Vehicles in Operation.

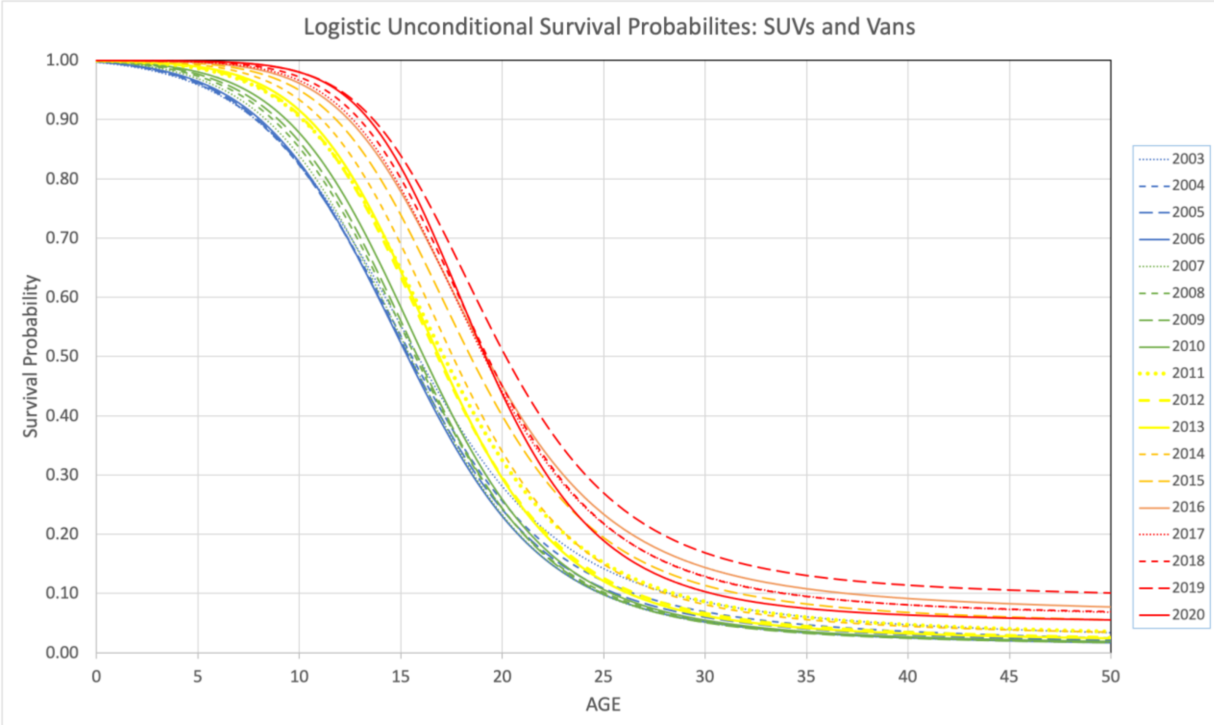


Figure C5a. SUV and Van Survival Probability Function: Unweighted Data.

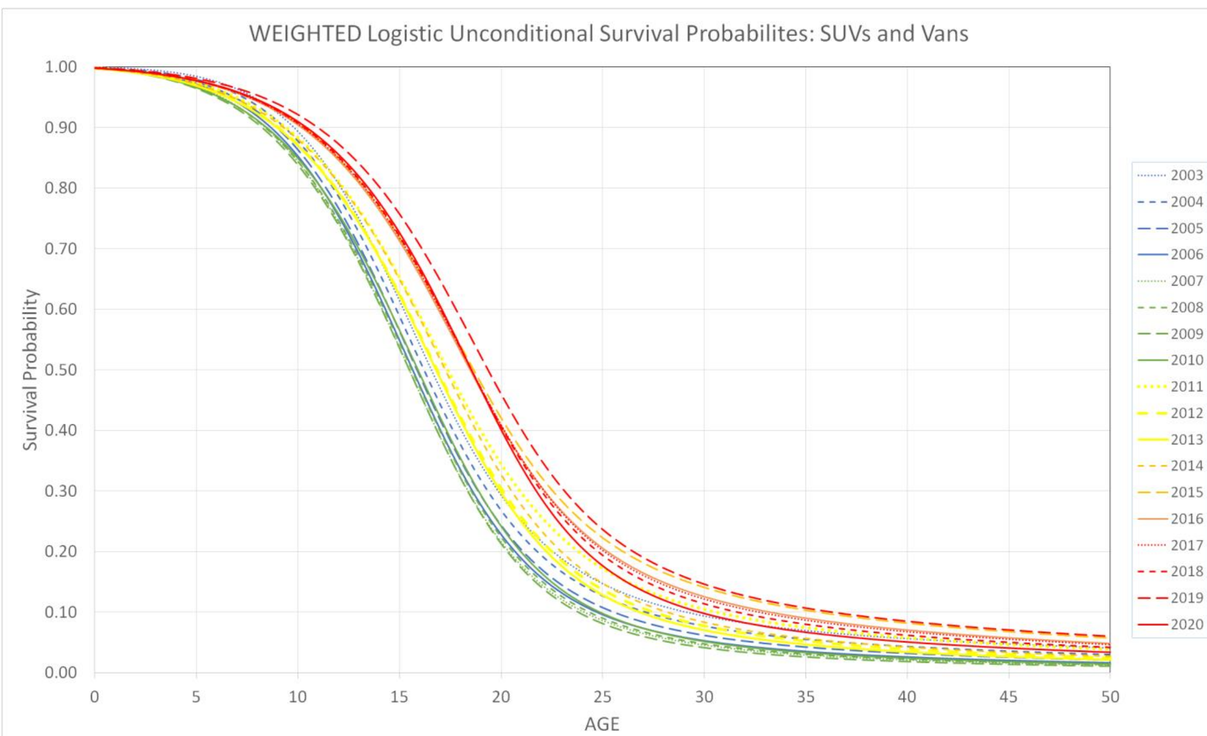


Figure C5b. SUV and Van Survival Probability Function: Data Weighted by Vehicles in Operation.

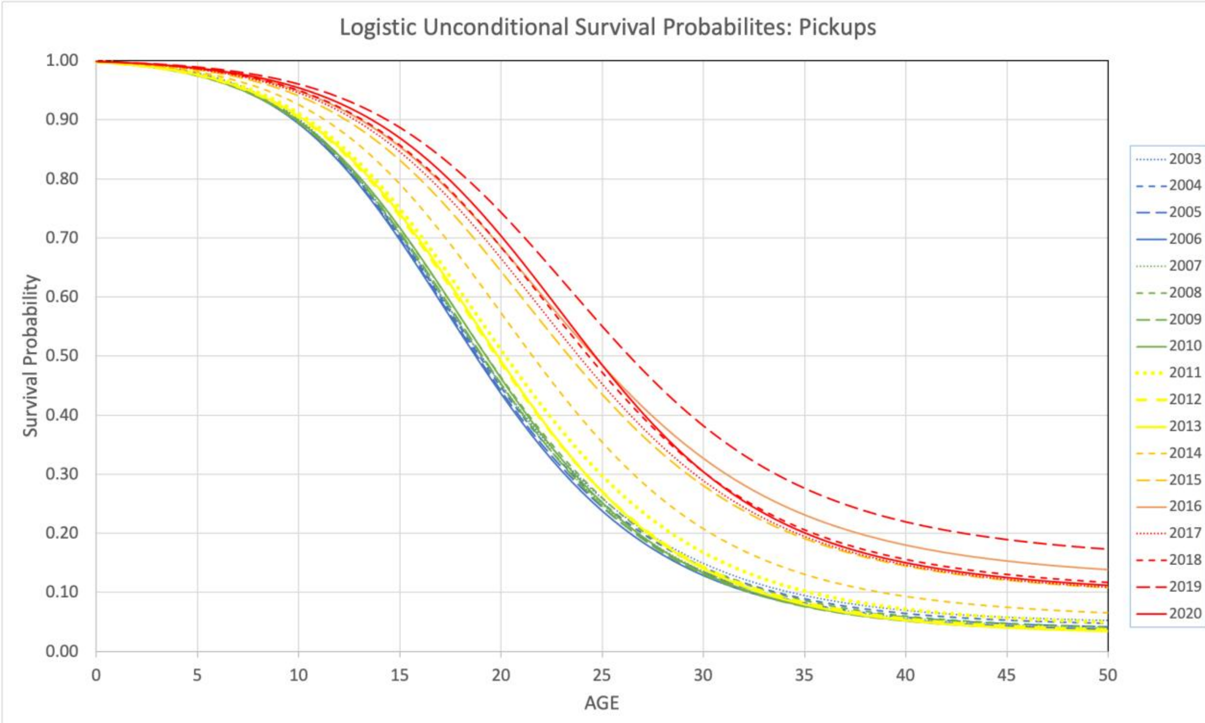


Figure C6a. Pickup Truck Survival Probability Function: Unweighted Data.

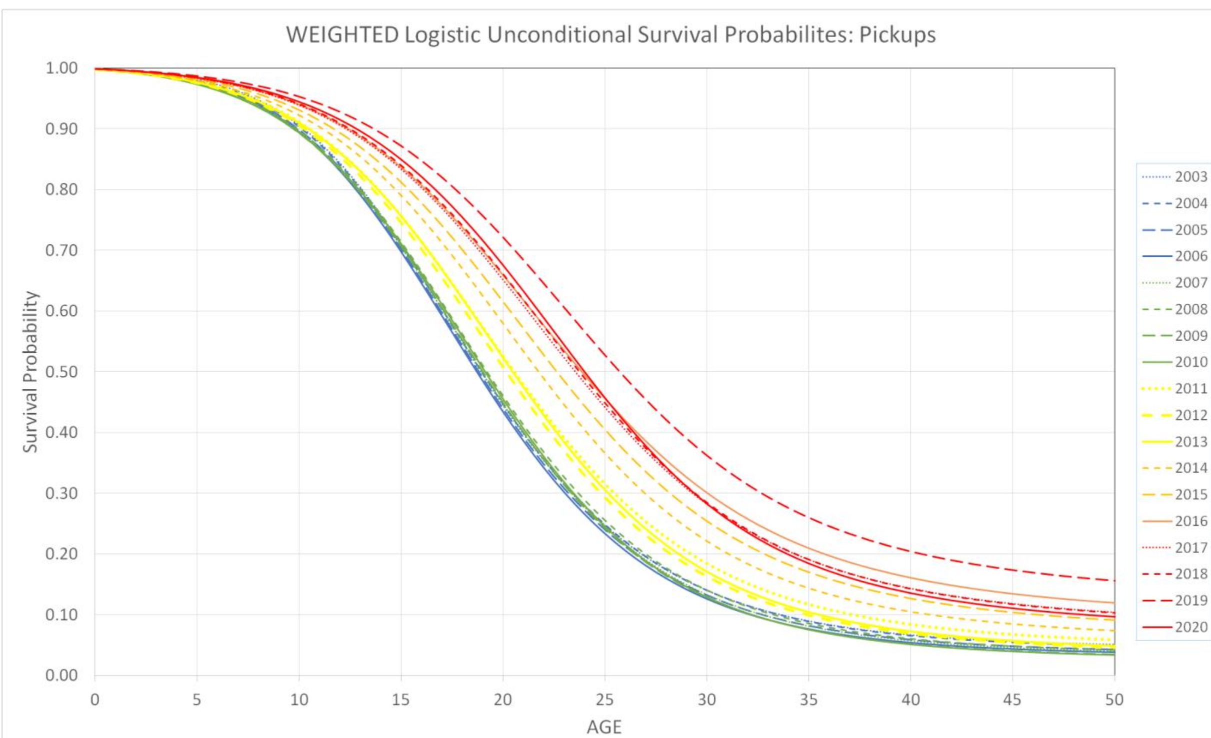


Figure C6b. Pickup Truck Survival Probability Function: Data Weighted by Vehicles in Operation.