Statistical Estimation of Trends in Scrappage and Survival of U.S. Light-duty Vehicles

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ABSTRACT

We estimate models of scrappage rates and survival probabilities as a function of vehicle age for U.S. light-duty vehicles. We use counts of vehicles in operation by vehicle type and model year for calendar years 2002-2020, which allows us to estimate scrappage functions for years 2003-2020. We estimate models for three vehicle types: passenger cars, SUVs and vans, and pickup trucks. We found that modified logistic functions fit the data well 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. A review of historical trends in the life expectancies of U.S. light-duty vehicles indicates they have been increasing by 0.5% to 1% per year for over 50 years. We develop a method for projecting future survival functions by extrapolating from our estimated survival functions. Our findings have significant implications for policies geared toward reducing fuel use and greenhouse gas emissions.

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I. 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 scrappage rates and survival probabilities of automobiles 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*.[3] The probability of failure by age *a* is the integral of $f_X(a)$ from 0 to *a*:

$$F_X(a;\lambda,k) = p(X \leq a) = \int_0^a f_X(x;\lambda,k)dx. \tag{1}$$

The survival function, the probability of surviving to at least *a*-years old is $S_X(a) = 1\text{-}F_X(a)$. Note that $f_X(a)$ is not the probability of failure (scrappage) given that the equipment has survived to aga *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).

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

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 the range of 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:

$$p_t(x) \tag{3}$$

The conditional survival probability function (cspf) 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.

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

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[3] 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.

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

$$p(x) = p(x|x-1)p(x-1|x-2) \dots p(1|0)1 \quad (5)$$

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.

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

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: 1) passenger cars, 2) SUVs and vans, and 3) pickup trucks. Functions are estimated for calendar years 2003 to 2020, over which time the number of age groups in the available data 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 of trends in vehicle longevity. Section VI reviews published studies that have estimated historical trends in vehicle longevity using data going back to 1958. Section VII presents a method for extrapolating survival models to predict future survival rates. Section VIII discusses the potential implications of the statistical analysis for public policy and possible directions for future research.

II. 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_t, were estimated by a separate log-linear function of the price of used vehicles, P_t, the ratio of new vehicle sales to total stock (the turnover rate, R_t), and the aggregated mechanistic scrappage rate predicted using equation 7, r_t^*, multiplied by the total stock of vehicles, n_t:

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

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.

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

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*):

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

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. The decline is likely due to the changing nature of light trucks over that period, as discussed further below.

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 11, 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.

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

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[4], 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.

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

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

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

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:

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

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 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

[4] 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.

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[5] 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 the years of data available 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.

$$ln\left(\frac{r_t(a,x)}{1-r_t(a,x)}\right) = \sum_j \beta_j x_{tj} \qquad (15)$$

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 conventional internal combustion engine vehicles. Nakamoto et al. (2019) were also unable to estimate cumulative scrappage functions for different vehicle types

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[5] 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.

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)

III. THE LOGISTIC SCRAPPAGE MODEL

The 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 in 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 $e^{(x-\mu)/\sigma}$.

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

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 calendar year fixed effects, $K_t = \exp(a_t d_t)$, where a_t is a year-specific constant to be estimated and d_t is 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 replaced by $\sigma_0 + \sigma_1 t$ to allow the dispersion of the scrappage functions to change over time. 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.

IV. 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.[6] 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.

V. ESTIMATION OF MODELS WITH TIME TRENDS

The full time-trend 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 mis-specification. Models were estimated for three vehicle types: passenger cars, SUVs and vans, and pickup trucks, without weighted observations and with weighting of scrappage rates 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 and all coefficient estimates of all models were statistically significant at the 0.0001 level, using the robust standard error

[6] 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.

estimates.[7] The detailed results for models including time trended parameters and calendar year fixed effects 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.

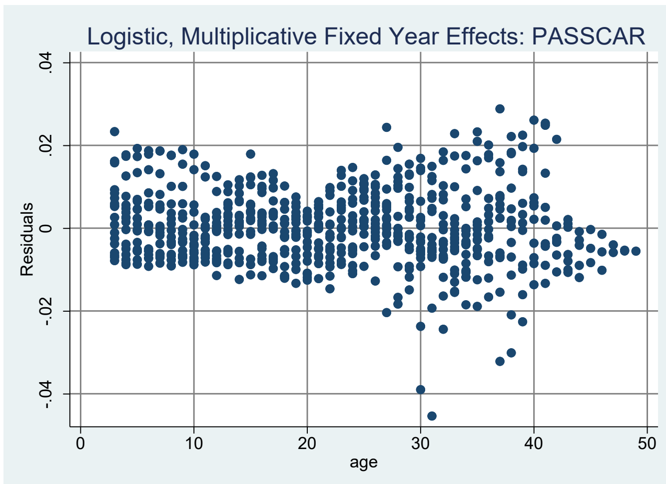
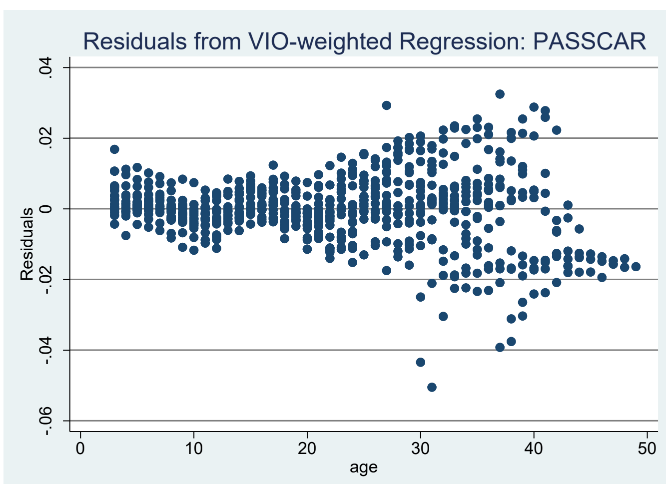


Figure 1a. Residuals from the Full Logistic Scrappage Model for Passenger Cars



[7] 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.

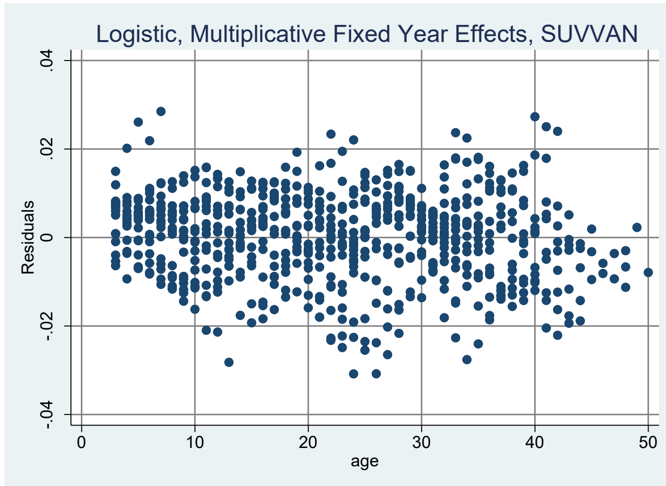


Figure 2a. Residuals from the Full Logistic Scrappage Model for SUVs and Vans

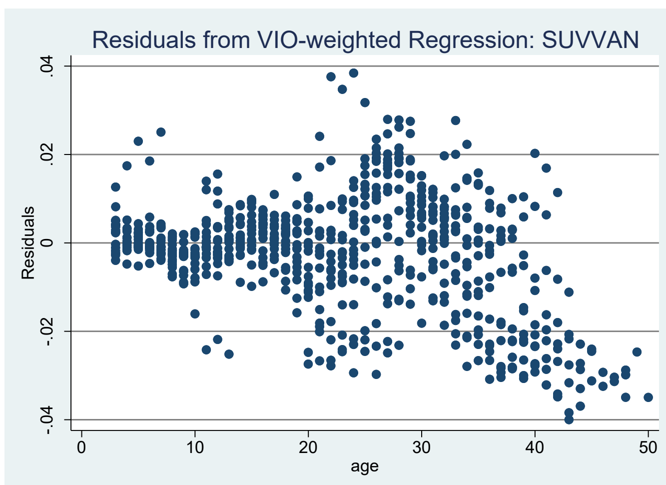


Figure 2b. Residuals from Scrappage Model with VIO-Weighted Observations: SUVs and Vans.

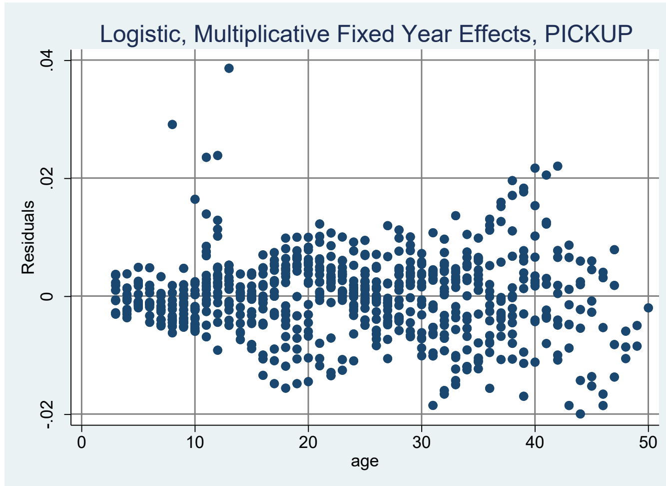


Figure 3a. Residuals from the Full Logistic Scrappage Model for Pickup Trucks

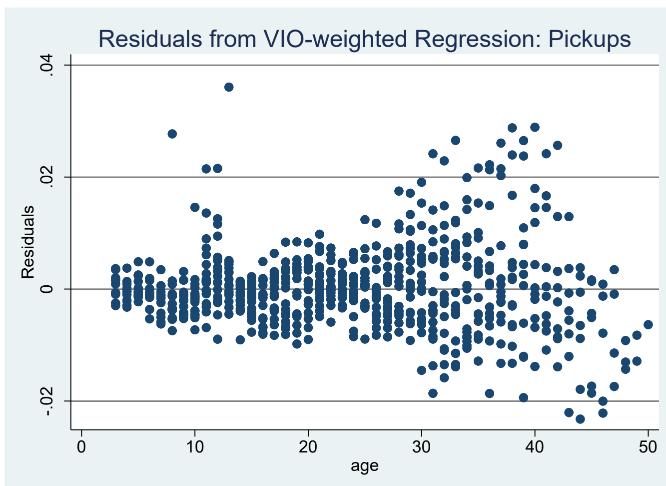


Figure 3b. Residuals from Scrappage Model with VIO-Weighted Observations: Pickups.

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.[8] 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, and 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

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[8] 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.

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.

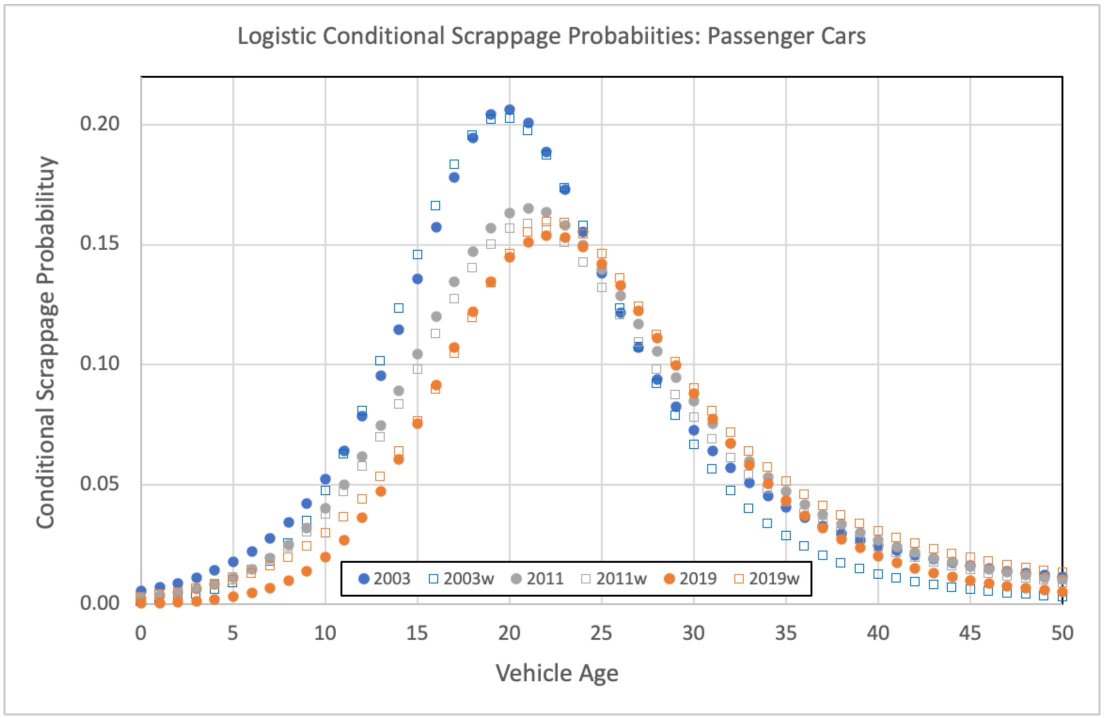

Figure 4. Conditional Scrappage Probability Functions: 2003, 2012, 2020: Passenger Cars.

The SUV and van functions are also broader and peak at lower scrappage rates between 0.13 and 0.17. Unlike passenger cars, the newer SUV and van curves indicate that the peak scrappage rate has increased over the 2003 rate.

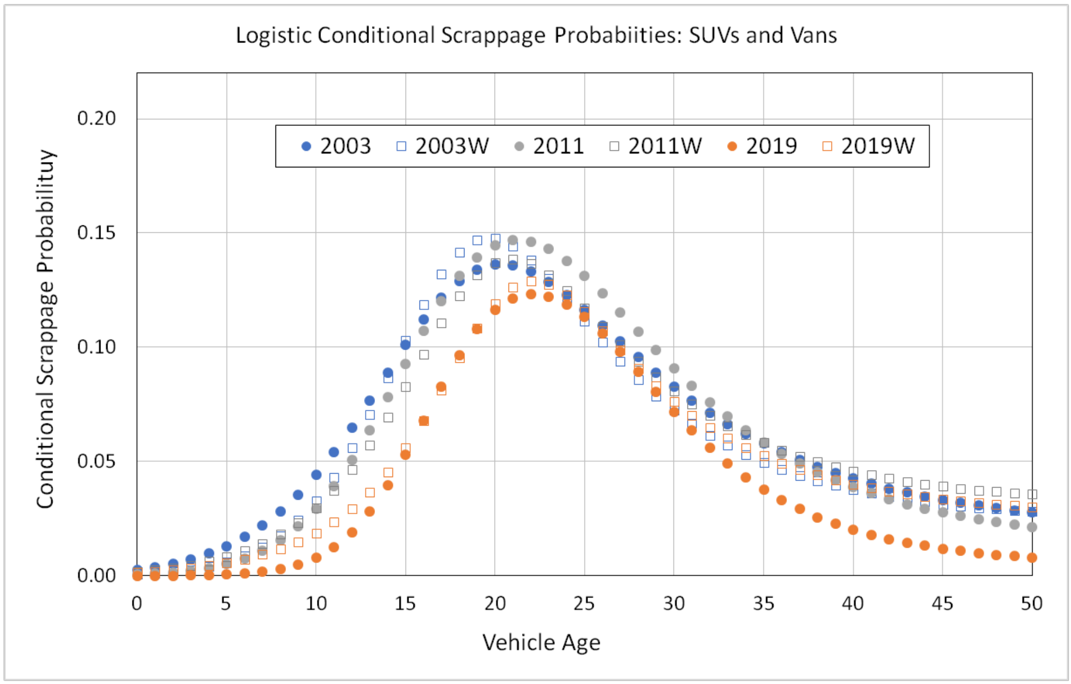

Figure 5. Conditional Scrappage Probability Functions: 2003, 2011, 2019: SUVs and Vans.

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.

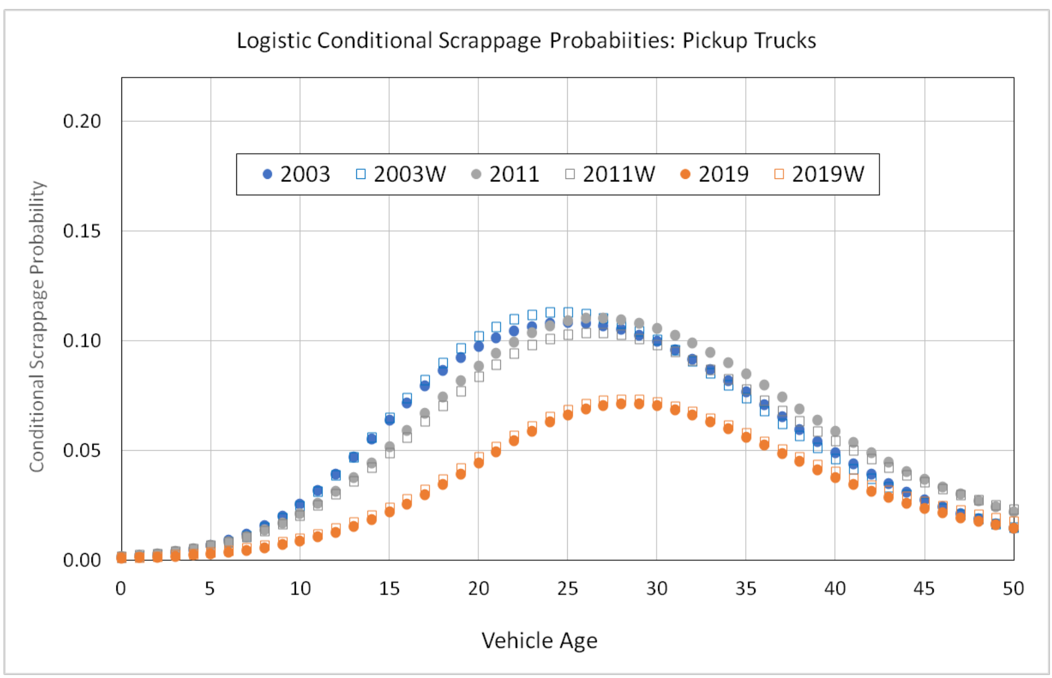

Figure 6. Conditional Scrappage Probability Functions: 2003, 2011, 2019: Pickup Trucks.

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.

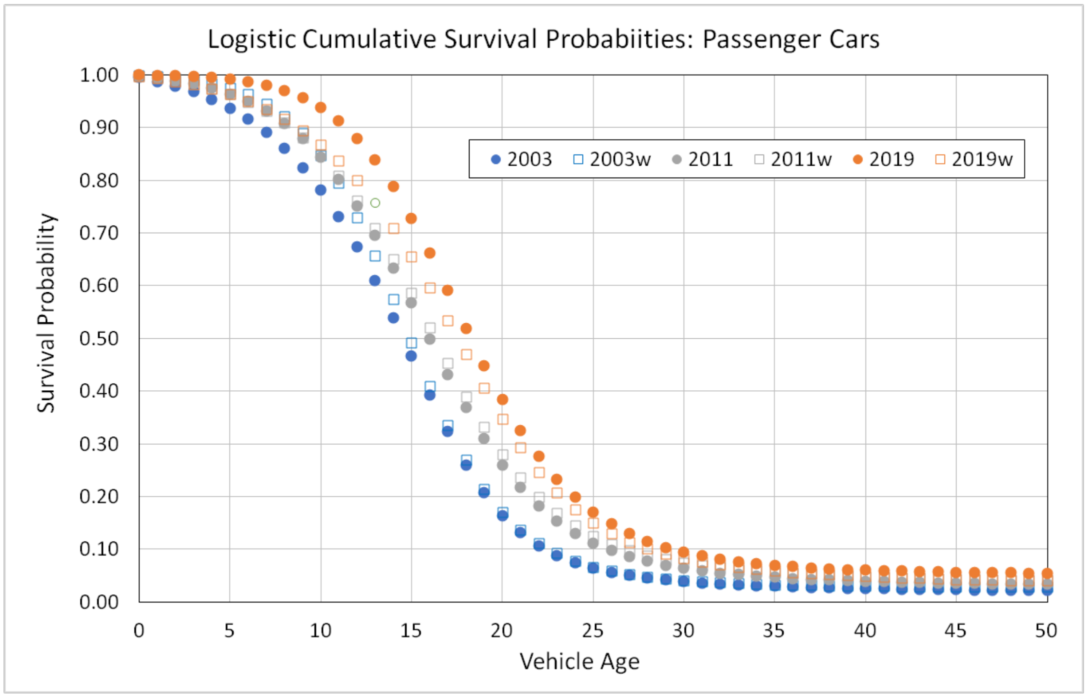

Figure 7. Cumulative Survival Probability Distributions, 2003, 2011 and 2019: Passenger Cars.

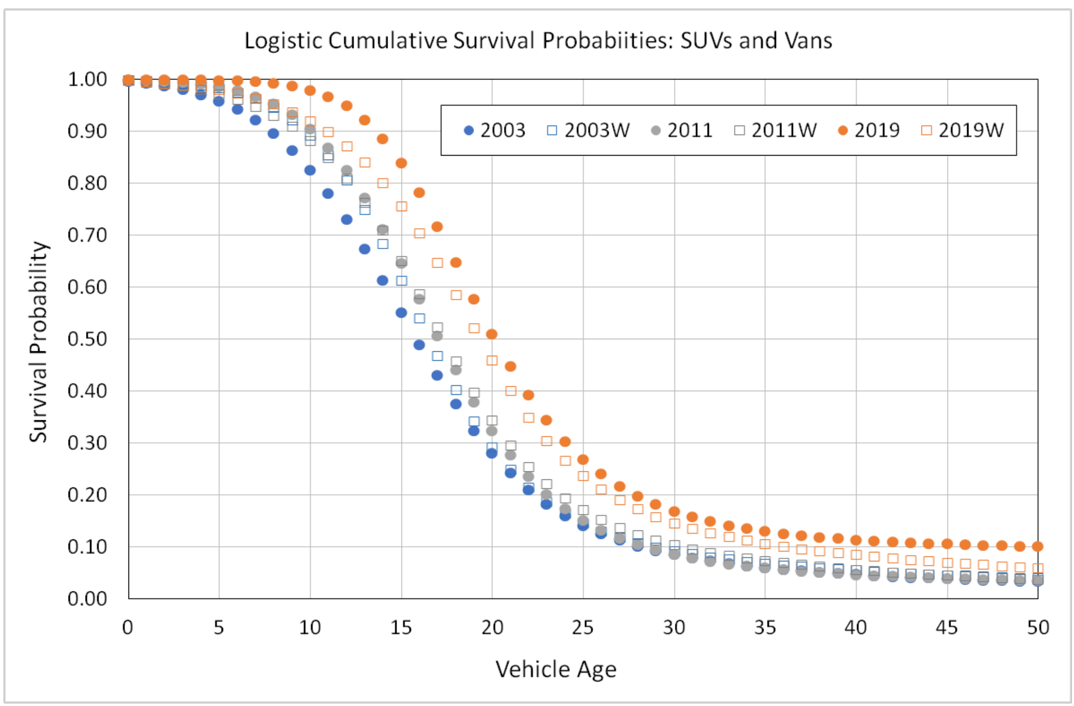

Figure 8. Cumulative Survival Probability Distributions, 2003, 2011 and 2019: SUVs and Vans.

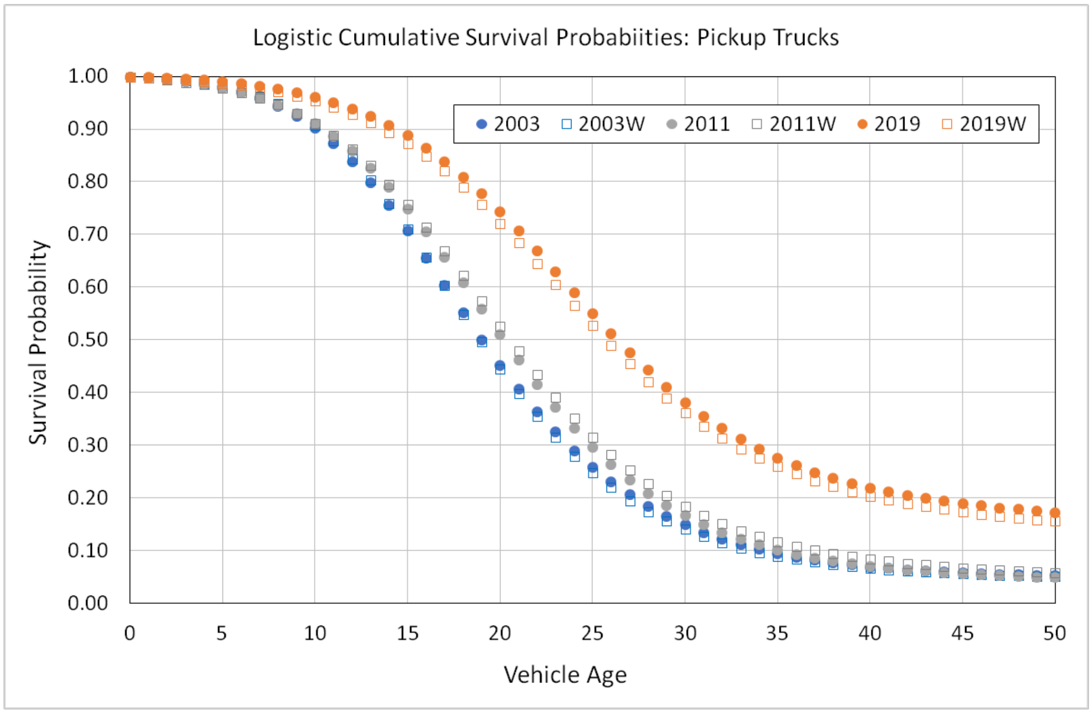

Figure 9. Cumulative Survival Probability Distributions, 2003, 2011 and 2019: Pickup Trucks.

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.

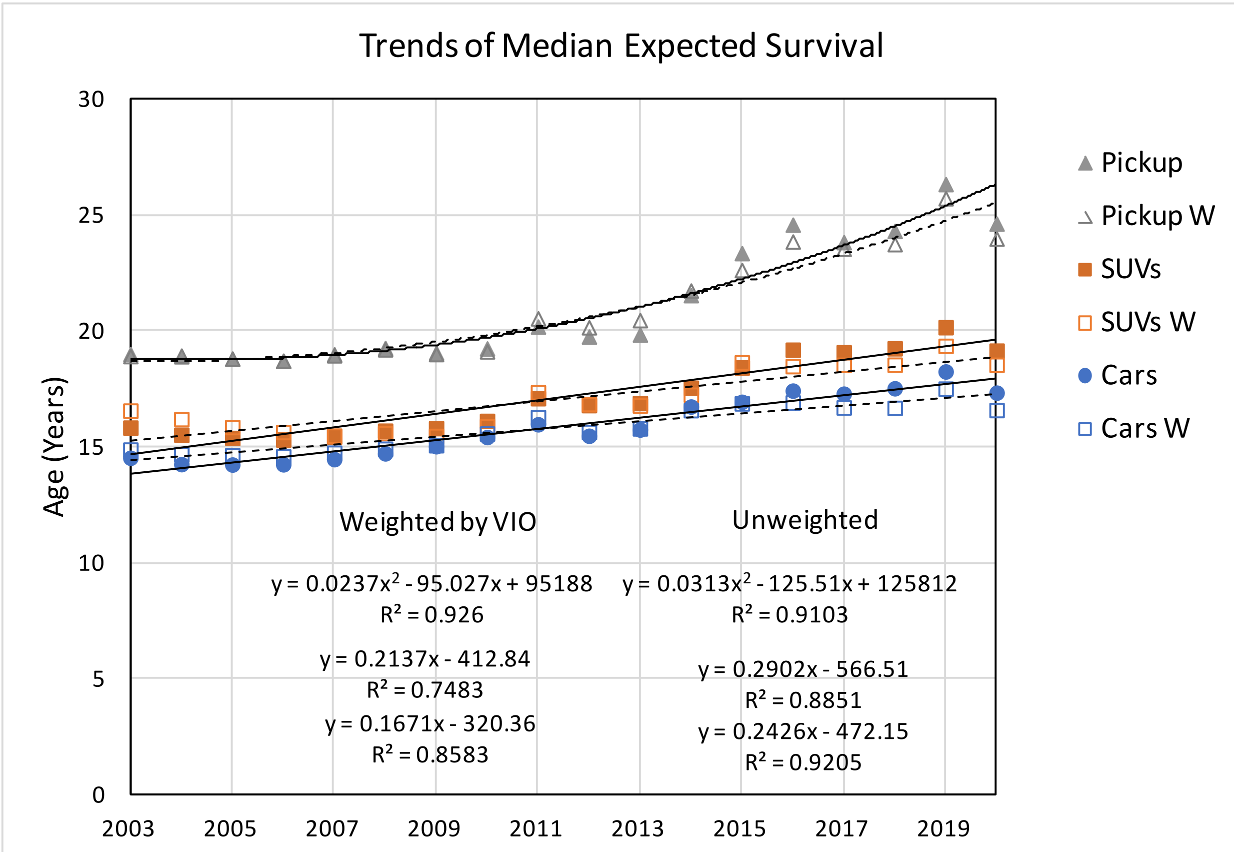

Figure 9. Cumulative Survival Probability Distributions, 2003, 2011 and 2019: Pickup Trucks.

VI. HISTORICAL TRENDS IN VEHICLE LONGEVITY

Increasing longevity of U.S. passenger cars and light trucks has been observed in studies dating back to 1996, using data sets spanning the years from 1958 to 2020. In Table 1, longevity is measured by expected median lifetime, the age at which half of a given vintage of vehicles are expected to be still on the road and half to have been scrapped. Estimates from seven published studies are shown in Table 1, ordered by the starting year of the data used. For each estimate, the table shows the starting and ending years of the data series used in the estimation. For studies that reported estimates based on comparing a series of years rather than year by year, (e.g., Bento et al., 2018 provide expected lifetime estimates for vehicles in use during the years 1969-79 versus 1980-87) the midpoints of the series of years are reported as the starting and ending years. The annual rate of change assumes a constant rate between the starting and ending years, although we observe variations from year-to-year in our analysis of data spanning 2002-2020. Some studies estimate scrappage and survival rates for model years, others for all model years in operation during a calendar year. The two approaches imply similar trends in longevity over time.

All seven studies cited in Table 1 found increasing longevity for U.S. passenger cars at rates close to 1%/year. Estimates for light trucks are mixed, with three of seven estimates indicating decreased longevity for the time period in question. Bento et al. (2018) attributed decreased longevity to changes in the nature and use of light trucks over their study period, during which the introduction and popularity of minivans and passenger sport utility vehicles (SUV) overwhelmed sales of the pickup trucks and cargo vans that made up the great majority of light truck sales prior to 1975. Our and other analyses (Lu, 2006; NHTSA 2022[9]) indicate that the scrappage and survival rates of minivans and SUVs are more like those of shorter-lived passenger cars. As a result, their increasing share of the light truck stock would tend to reduce the expected lifetime of light trucks in comparison to longer-lived pickups and cargo vans. This explanation of the negative changes in light truck longevity seems reasonable because in 1975, light trucks comprised 19.3% of combined car and light truck sales, and two thirds of light trucks sold were pickups (EPA, 2021). By 1995, light trucks accounted for 36.5% of car and light trucks sales, but 60% of light trucks were SUVs, minivans and vans. Separate estimates for the three vehicle types from 2003-2020, show increasing longevity for all three with shorter lifetimes for cars, minivans and SUVs compared to pickups (Greene and Leard, 2022).

The estimated changes in longevity shown in Table 1 indicate that, whether increasing or decreasing, longevity changes slowly, at rates on the order of +/-1% per year. Taken as a whole, the studies indicate generally increasing longevity of U.S. light-duty vehicles over a period of more than half a century. The mean of all estimates is 0.52%/year. Excluding the estimates labeled “Light Trucks” which are likely affected by changing nature of the class since 1975, the mean rate of increase is 0.96%/year, excluding all trucks it is 0.97%, and weighting the light truck and passenger car estimates at 1/3 and 2/3, respectively, the mean annual rate is 0.67% per year. Assuming that longevity will continue to increase at a rate of two-thirds of a percent per year seems reasonable, given the similarity of the magnitude of the various estimates and the consistency of the trend over a very long time period.

Table 1. Estimates of Trends in Light-duty Vehicle Longevity from Seven Studies.

[9] Expected median lifetimes calculated from NHTSA (2022) survival probability tables are 13.85 years for passenger cars, 14.94 for SUVs and vans and 17.61 for pickups.

					Expected Lifetime		Annual %
Source	Vehicle Type	Data Type	Start Year	End Year	Start Year	End Year	Change
Hamilton & McCauley, 1999	Passenger Cars	Model Year	1958	1977	9.0	11.0	1.06%
Greenspan & Cohen, 1999	Cars and Trucks	Model Year	1960	1980	9.8	12.5	1.22%
Davis & McFarlin, 1996	Passenger Cars	Model Year	1970	1985	10.7	12.1	0.83%
Davis & McFarlin, 1996	Trucks	Calendar Year	1969.5	1975.5	14.0	14.6	0.77%
Davis & McFarlin, 1996	Trucks	Calendar Year	1975.5	1983.5	14.6	15.8	0.98%
Davis & Diegel, 2013	Passenger Cars	Model Year	1970	1980	11.6	12.5	0.81%
Davis & Diegel, 2013	Light Trucks	Model Year	1970	1980	16.2	15.2	-0.58%
Bento et al., 2013	Passenger Cars	Calendar Year	1974	1983.5	12.5	14.1	1.29%
Bento et al., 2013	Light Trucks	Calendar Year	1974	1983.5	16.3	15.1	-0.80%
NHTSA, 2006.	Passenger Cars	Calendar Year	1984	1989.5	12.4	13.2	1.10%
NHTSA, 2006.	Light Trucks	Calendar Year	1984	1989.5	15.6	14.1	-1.89%
Greene & Leard, 2022	Passenger Cars	Calendar Year	2003	2020	14.9	16.1	0.46%
Greene & Leard, 2022	SUV & Van	Calendar Year	2003	2020	16.6	18.2	0.54%
Greene & Leard, 2022	Pickup	Calendar Year	2003	2020	18.7	24.0	1.48%
				Mean including light trucks			0.52%
				Mean excluding light trucks			0.96%
				Mean trucks weighted 1/3			0.67%

Note: Davis and McFarlin, 1996 is based on Miaou (1995). Trucks includes light and heavy trucks. However, light trucks predominate by numbers. The survival rate for light trucks was estimated for the 1978-1989 period only but is almost identical to the all trucks numbers. For 1978-89 the expected median lifetime for light trucks was 16, and for all trucks

VII. PROJECTING FUTURE SURVIVAL FUNCTIONS

In this section, we present a methodology for projecting future survival rates. We first estimate calendar year specific scrappage functions to confirm that the trends observed in the Trend Models presented above are also present when separate models are estimated for each calendar year. Survival rates are then calculated for each scrappage function, and the parameters of logistic survival functions are estimated for each vehicle type and calendar year. Future survival functions are projected assuming an annual rate of increasing expected median vehicle lifetime consistent with our models and the historical literature.

Estimating linear trends in scrappage curve parameters even including calendar-year fixed effects may obscure some changes in scrappage rates due to business cycles and other factors. To investigate this possibility, we estimated individual logistic scrappage curves for each year from 2003 to 2020, for each of the three vehicle types. Calendar year scrappage functions require estimating four parameters for each calendar year: μ, σ, K and a, in equation 17. We again weighted the observations by vehicles in operation by age. All the calendar year nonlinear regressions produced coefficient estimates such that the model fit the data well with the exception of three cases in which the nonlinear estimation did not converge. The regressions estimates are provided in Appendix D and graphs of the scrappage and survival curves in Figures 11-16.

Graphs of the calendar year-specific functions for each vehicle type show somewhat greater variability than the trend scrappage functions with calendar year fixed effects, but generally similar changes over time (compare Figures 11-13 to Figures C1b to C3b). In particular, the same trends of increasing longevity for passenger cars, SUVs and vans, and pickup trucks are evident. We see the same shifts in the time of maximum scrappage (μ = mode), and decreasing maximum scrappage rates. In general, the dispersion of scrappage values (σ = scale) increases from passenger cars to SUVs and vans to pickups, although the SUV and van curves show somewhat greater dispersion in the calendar year models than in the trend models (compare Figure 12 to Figure C2b).

The increase in maximum scrappage rates in 2020 is not due to the onset of the COVID 19 pandemic because the underlying data represent the vehicles in operation as of January 1 of 2020 and the first case in the U.S. was recorded on the 18th of January, 2020 (CDC, 2023). In addition, the peak of the curve continued to shift toward increased longevity. Year-to-year changes appear to reflect a combination of content, quality and macroeconomic factors, suggesting interesting avenues for further analysis.

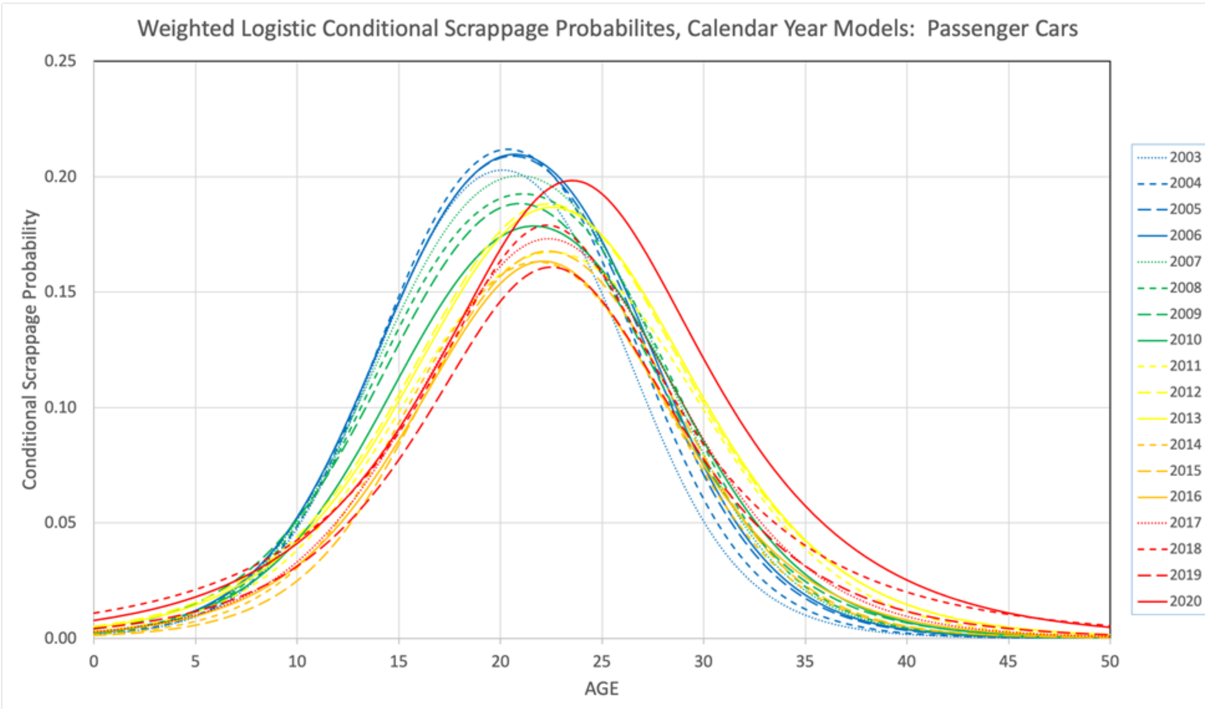

Figure 11. Weighted Logistic Conditional Scrappage Probabilities, Calendar Year Models: Passenger Cars.

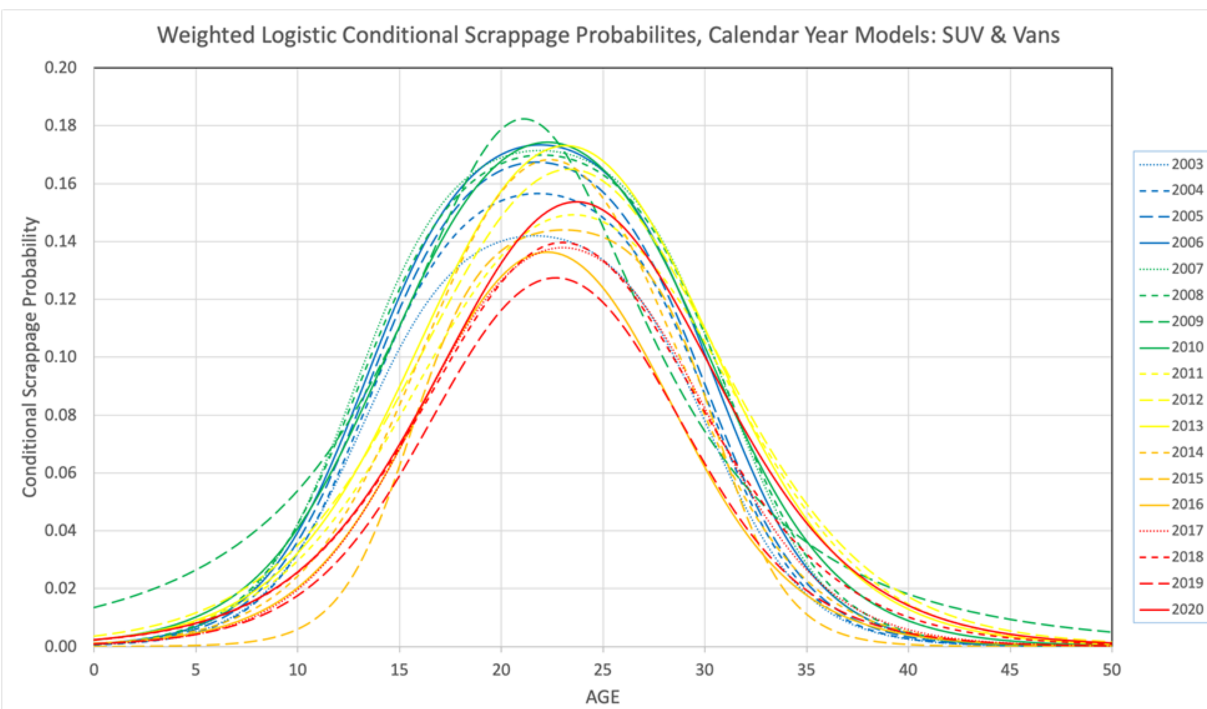

Figure 12. Weighted Logistic Conditional Scrappage Probabilities, Calendar Year Models: SUVs and Vans.

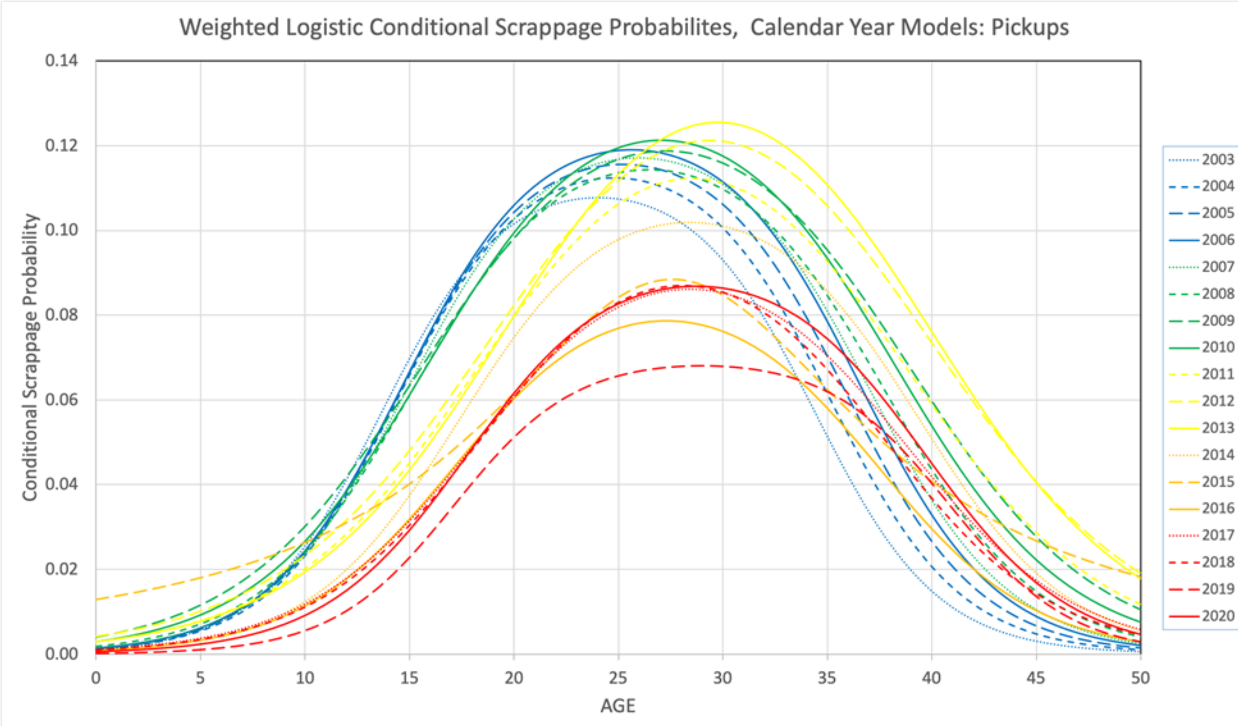

Figure 13. Weighted Logistic Conditional Scrappage Probabilities, Calendar Year Models: Pickups.

Not surprisingly, the patterns and trends in the survival curves are also generally similar to those seen in the trend models (Figures C4b to C6b). As might be expected from the greater flexibility in the Calendar Year models, there is more variability from year to year, especially for the younger ages.

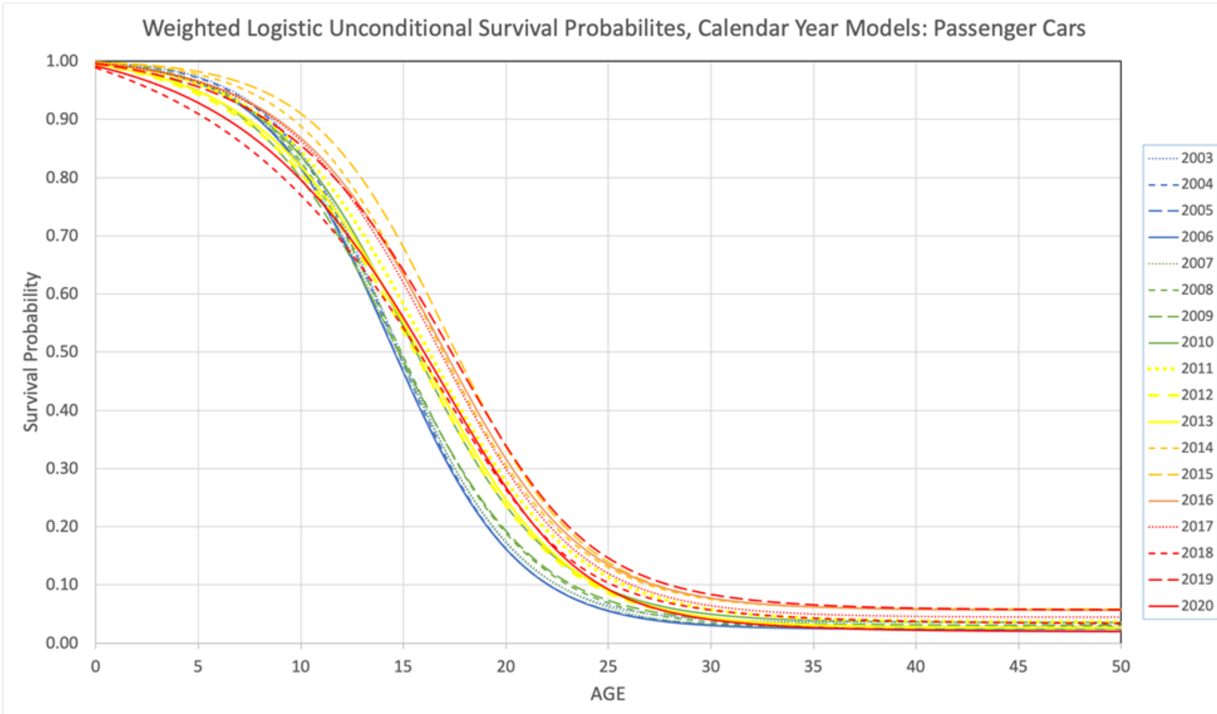

Figure 14. Weighted Logistic Unconditional Survival Probabilities, Calendar Year Models: Passenger Cars.

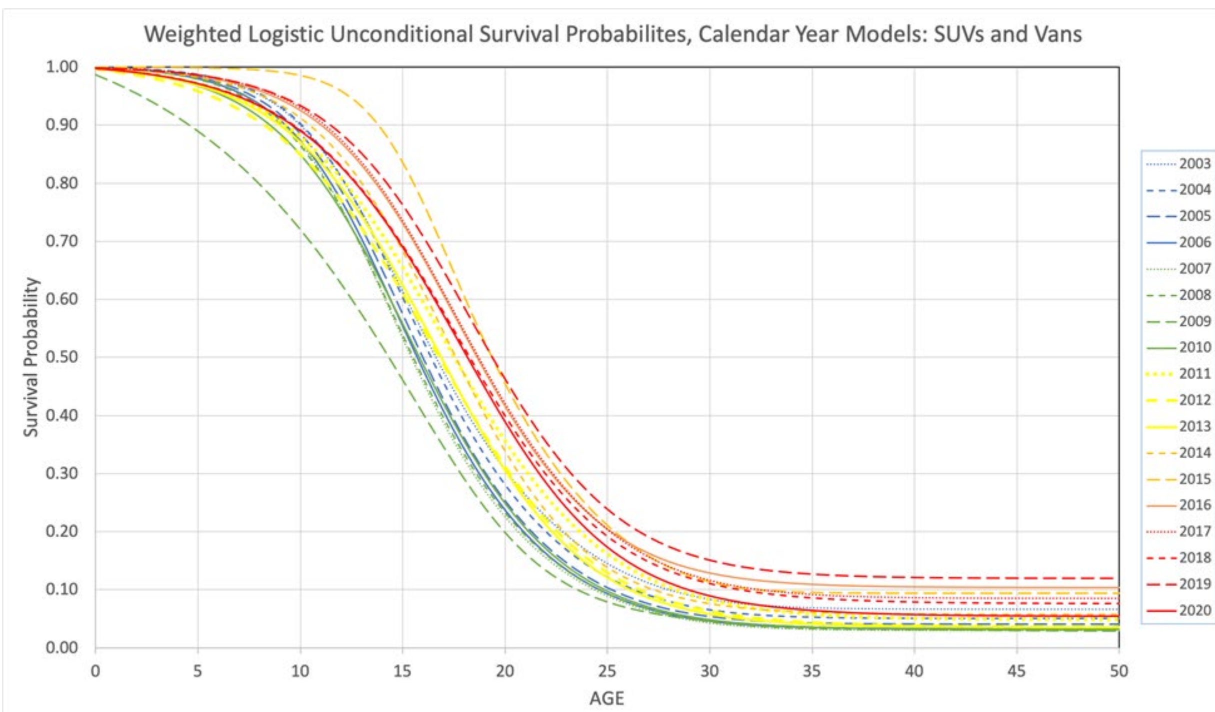

Figure 15. Weighted Logistic Unconditional Survival Probabilities, Calendar Year Models: SUVs and Vans.

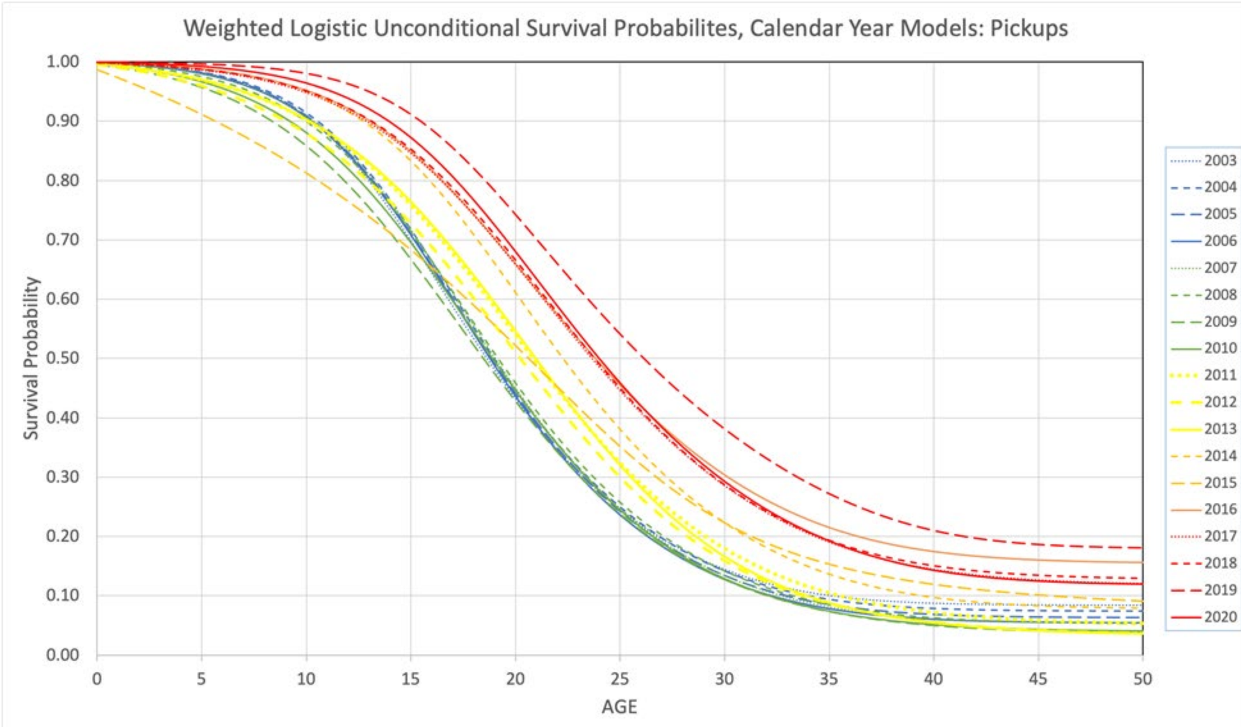

Figure 16. Weighted Logistic Unconditional Survival Probabilities, Calendar Year Models: Pickups.

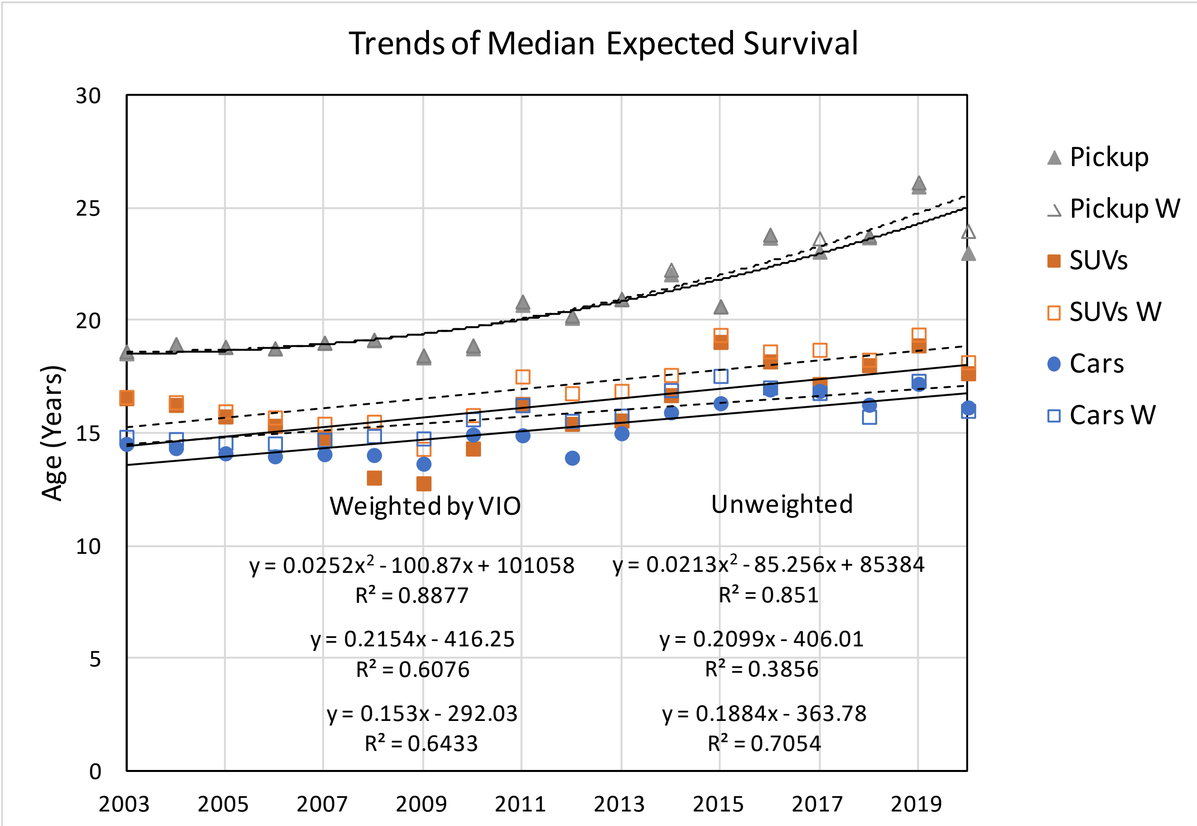

Figure 17. Trends in Median Expected Survival: Calendar Year Models.

Trends in median survival rates based on the Calendar Year models (Figure 17) are also similar to those based on the Time Trends models (Figure 10) except for the greater year-to-year variability allowed by the Calendar Year models. Once again, while linear models fit the passenger car and SUV and van models well, a quadratic curve provides a much better fit to the pickup truck values. The predicted increases in longevity are almost identical to those estimated by the Trend models.

Extrapolating Calendar Year Survival Curves to 2075

Current trends toward increasing vehicle automation, connectivity and electrification suggest that the content and durability of light-duty vehicles may continue to increase for decades. Assuming that the half-century trend of increasing longevity continues at the same rate for another half century into the future, the logistic survival functions can be extrapolated by including trends in parameter values. Beginning with the calendar year-specific scrappage curve, the extrapolation process consists of three steps:

1. Calculate unconditional survival curves for 2003-2020 using the calendar year conditional survival probability (scrappage) curves;
2. Fit simplified, 3-parameter unconditional logistic survival curves to the numerically calculated unconditional survival curves and verify the goodness of fit;
3. Using the 2020 simplified survival curves extrapolate future year-by-year survival curves by adjusting the parameters to insure that the expected median lifetime increases by 0.67%/year.

The unconditional probability of a vehicle surviving to age a is calculated using equation (5), where the conditional probability of surviving to age a given survival to a-1 is $p(a|a-1)$, and the unconditional probability of surviving to age a is $P(a)$.

$$P(a) = \prod_{i=0}^{a} p(a-i|a-i-1) \tag{18}$$

The fitted unconditional survival function is a cdf and requires only three parameters: μ, σ and k, as shown in equation (19). In the logistic probability distribution, the mean, median and mode are equal to the location parameter, μ. In the modified logistic survival function the median of the cumulative survival function is the point, x, at which the cumulative function equals 0.5.

$$0.5 = \frac{1}{1+e^{-(x-\mu)/\sigma+k}} \tag{19}$$

Solving for the median expected lifetime, x:

$$x = \mu - \sigma \ln(1-k) \tag{20}$$

The historical studies cited above indicate that the median expected lifetime has increased at an average annual rate of approximately 0.67% per year. Because the median expected lifetime depends on all three parameters (μ, σ, k), there are many combinations of the three that could produce the desired increase in median expected lifetime. Assuming that this trend is equally driven by the two right-hand-side terms in equation (20), μ should increase by 0.67%/year and σln(1-k) should also.

$$x_t = 1.0067x_{t-1} = 1.0067(\mu - \sigma \ln(1-k) = 1.0067\mu - 1.0067\sigma ln(1-k) \tag{21}$$

Since there is no obvious reason to change one parameter more than the other, it again seems reasonable to assign an equal rate of increase to the two components, σ and $ln(1-k)$. This requires multiplying σ by sqrt(1.0067) and solving for a value for k_t that makes:

$$\frac{ln(1-k_t)}{ln(1-k_{t-1})} = (1.0067)^{0.5} \tag{22}$$

No unique ratio of k_t to k_{t-1} solves equation (22) for all time period. Instead, because the values of k in the fitted survival curves range only from 0.02 to 0.06, we set the ratio $k_t/k_{t-1} = k_{t-1}(1.0067)^{0.5}$ as an approximation. Although solving for a constant ratio of k_t/k_{t-1} does not give an exact solution for all forecast years, it changes the ratio of logarithms by only 0.001% for cars up to 0.005% for pickups over the period from 2020 to 2075. In terms of the percent change of the annual rate of change (approximately 0.33%/year) the error ranges from about 0.5% to 1.5% of 0.33%. Thus, $k_t = k_{t-1}(1.0067)^{0.5}$ for all t, is used to approximate equation 22.

Because vehicles are sold incrementally in the initial model year, and because a significant number of vehicles of any given model year are sold in the year following their model year, the first two years of data were not used in the statistical estimation of scrappage functions. In calculating scrappage and survival rates using the estimated scrappage functions, we assumed no vehicles were scrapped during the transition from age 0 to age 1. In fact, a small number of vehicles are scrapped in their initial year due to severe crashes and other causes. To reflect this, we adjusted the survival curves to include a 0.5% scrappage rate in their first year. The resulting projected unadjusted and adjusted survival curves are shown in Figures 18-20.

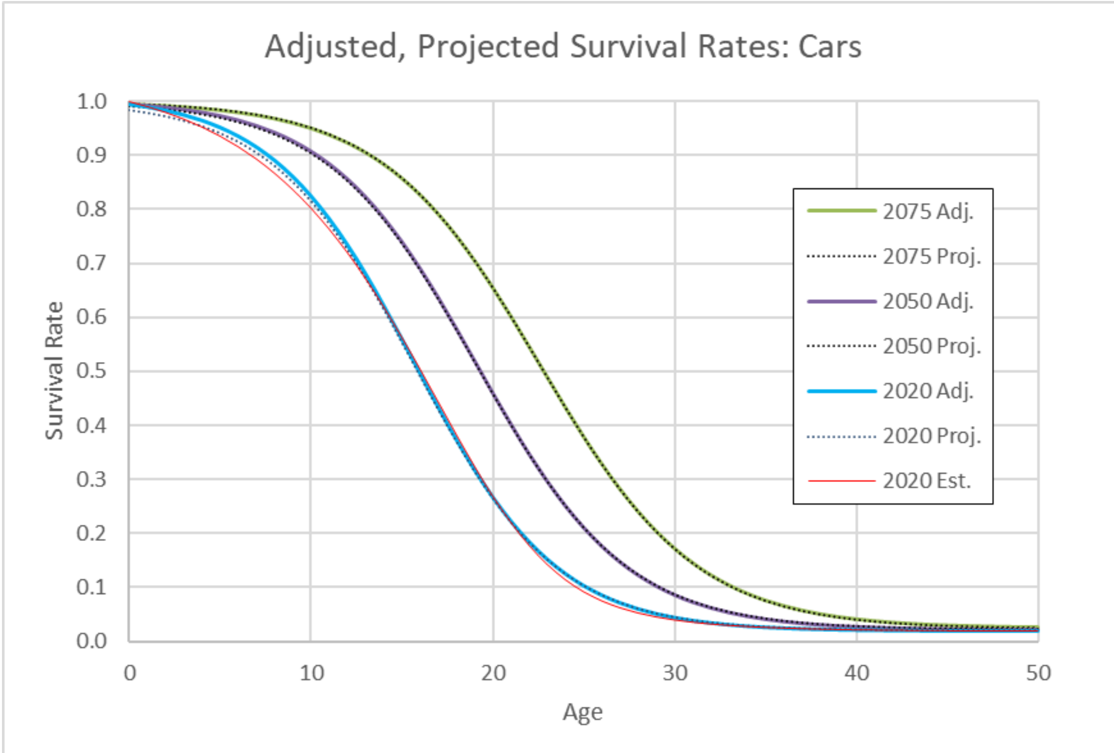

Figure 18. Adjusted, Projected Survival Rates, Calendar Year Models: Passenger Cars.

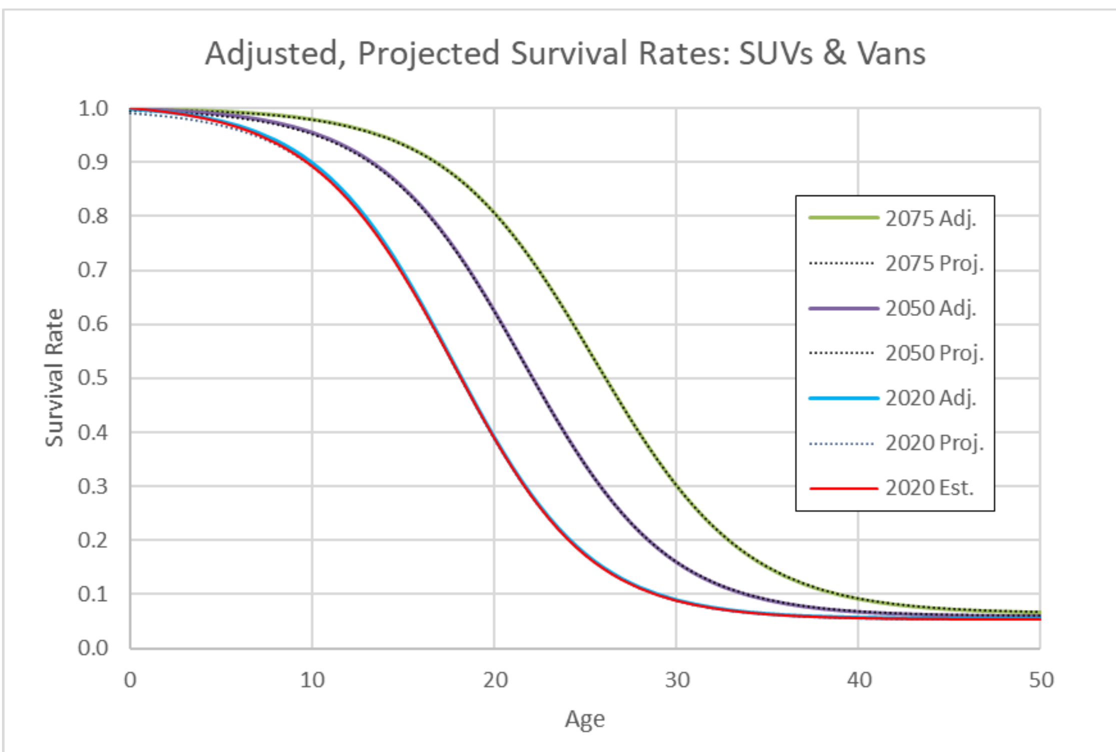

Figure 19. Adjusted, Projected Survival Rates, Calendar Year Models: SUVs and Vans.

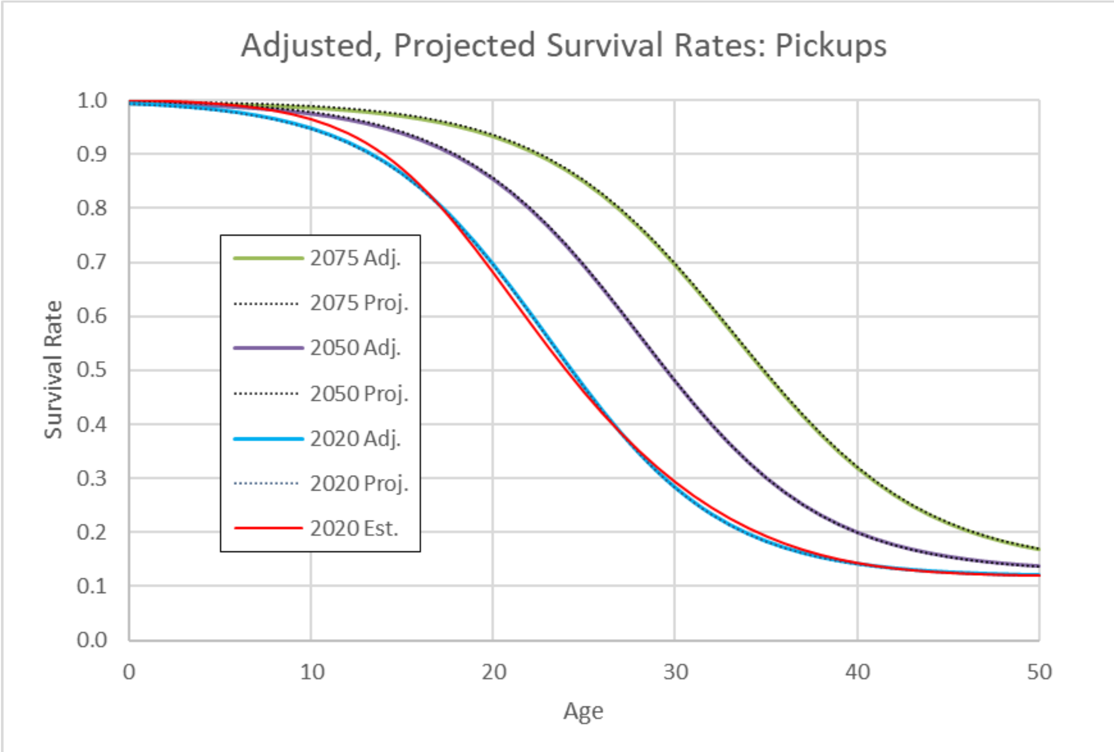

Figure 20. Adjusted, Projected Survival Rates, Calendar Year Models: Pickups.

VIII. 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 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. The persistence and relatively consistent rates of increasing vehicle longevity over the past 70 years suggest that vehicles may continue to have longer lifetimes well into the future. Further increases in vehicle content through automation, improved crash avoidance, and the transition to electric drive could be driving forces for greater life expectancy in the future. Whether past trends will continue 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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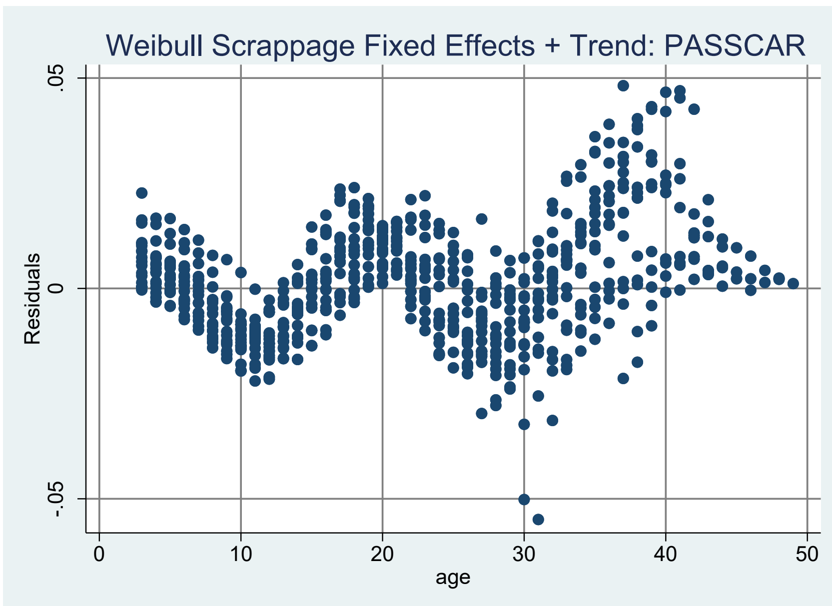
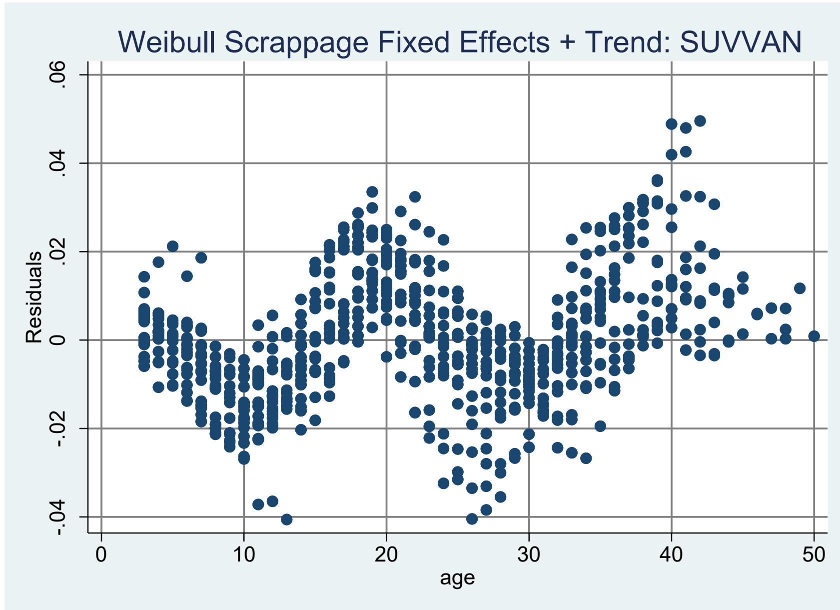
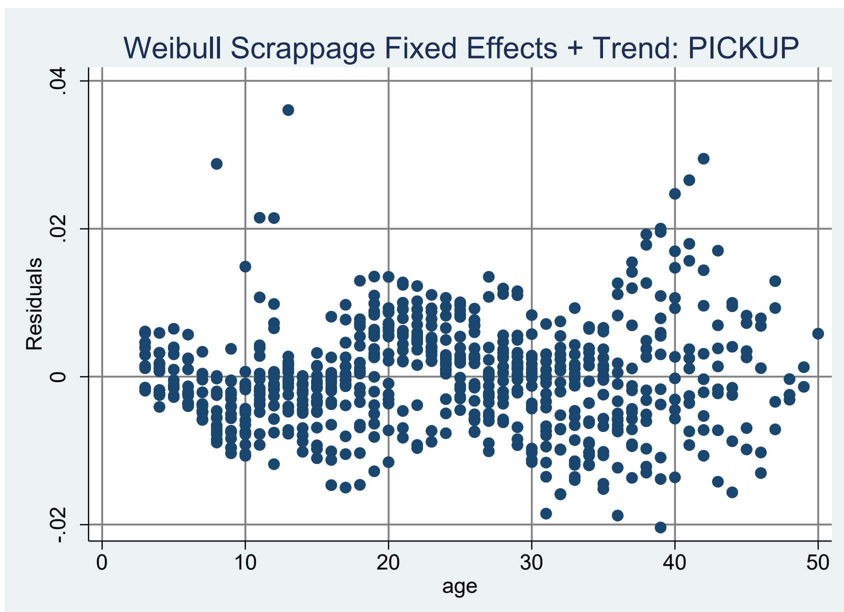
APPENDIX A. RESIDUALS FROM WEIBULL MODELS

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 WITH TIME TRENDS

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

Unweighted

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

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

Weighted

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

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 OF TIME TREND MODLES BY CALENDAR YEAR

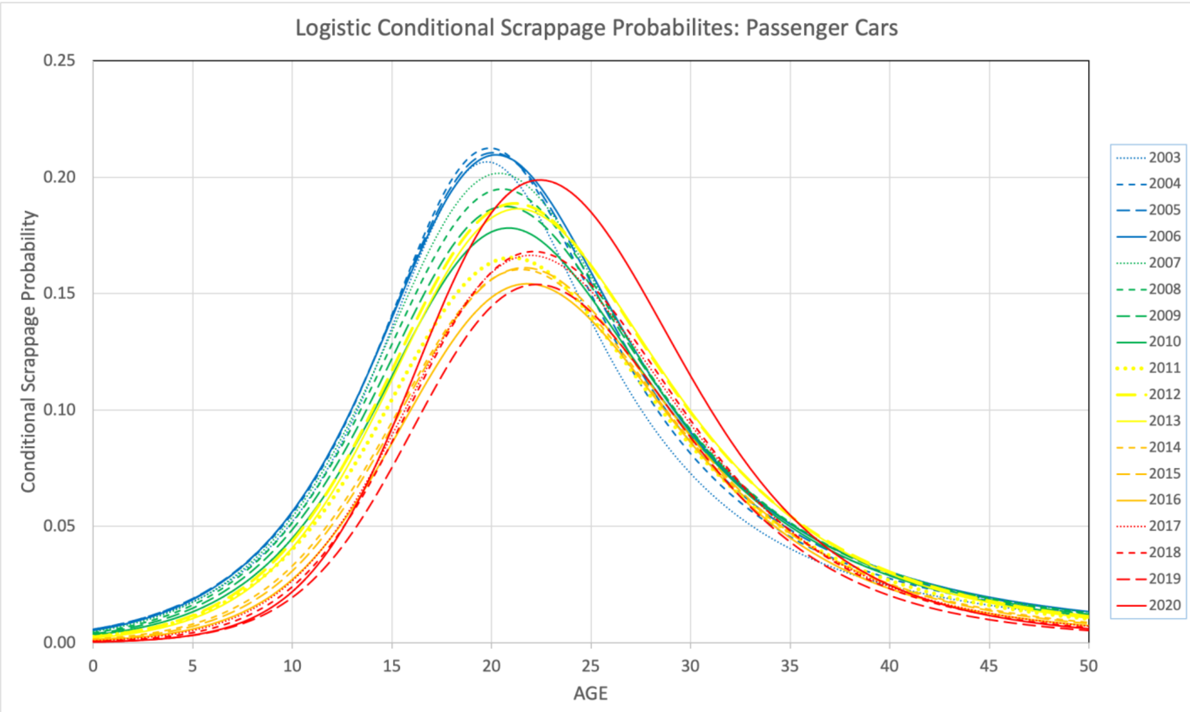


Figure C1a. Passenger Car Scrappage Rates vs. Age: Unweighted Data

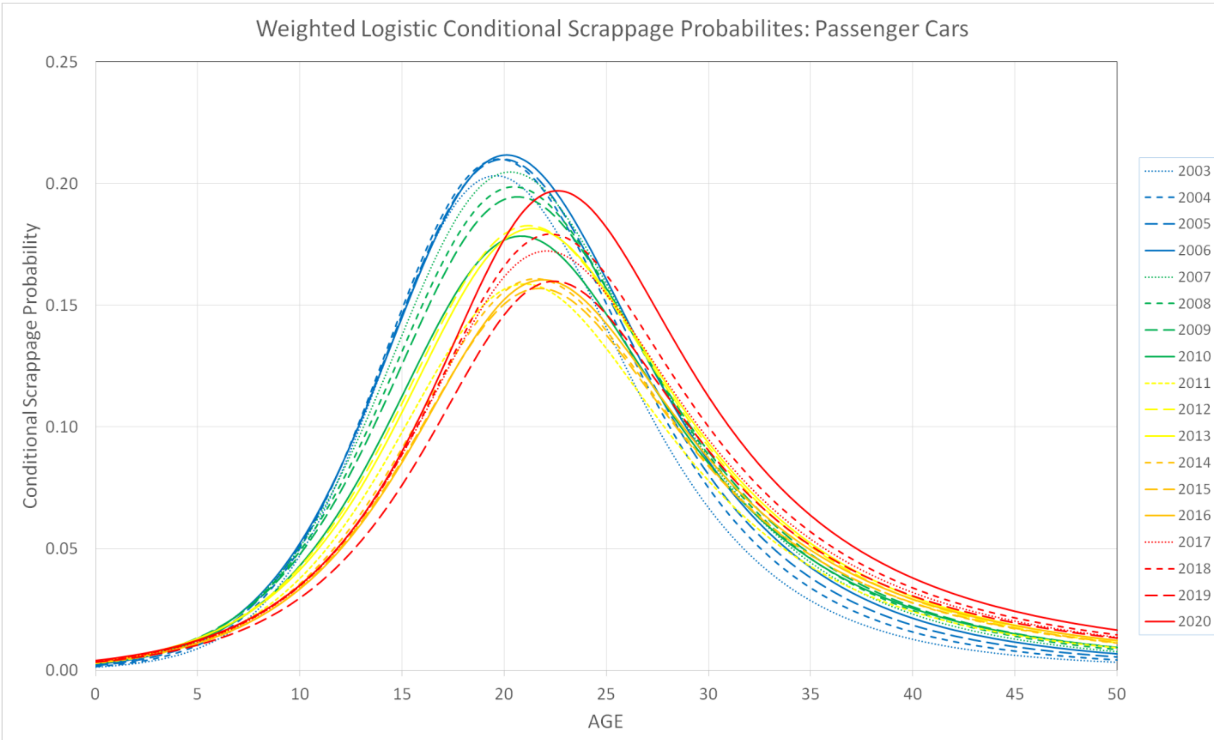


Figure C1b. Passenger Car Scrappage Rates vs. Age: Data Weighted by Vehicles in Operation.

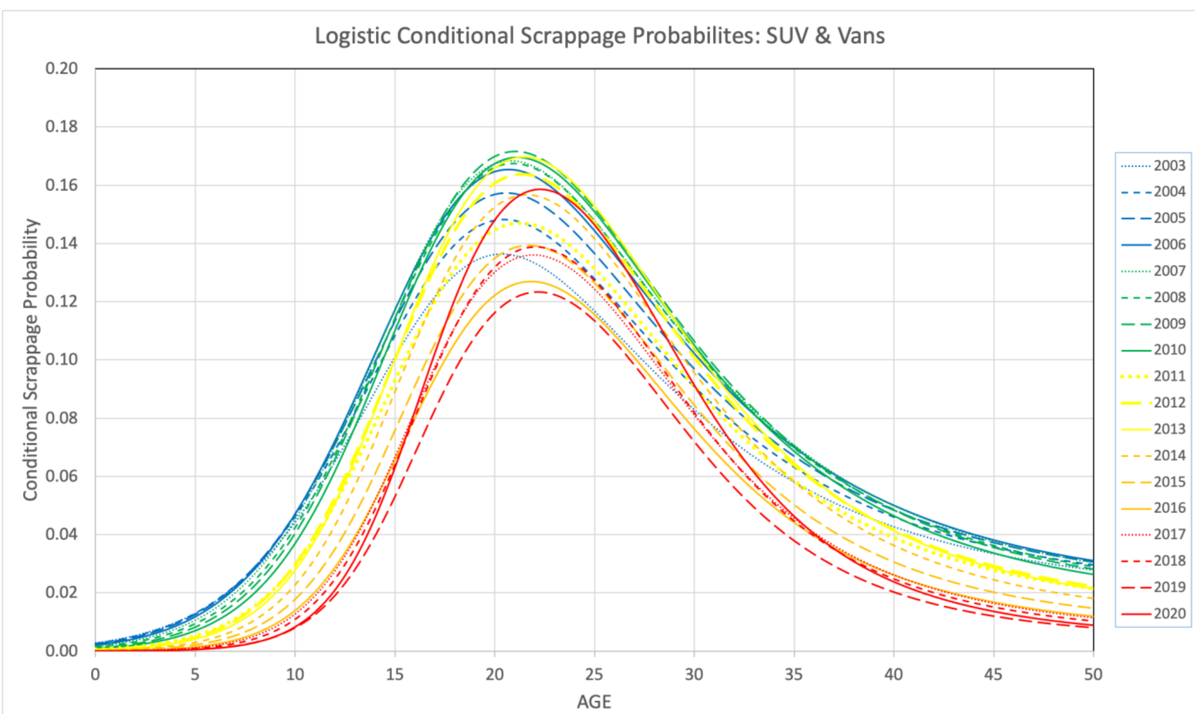


Figure C2a. SUV and Van Scrappage Rates vs. Age: Unweighted Data

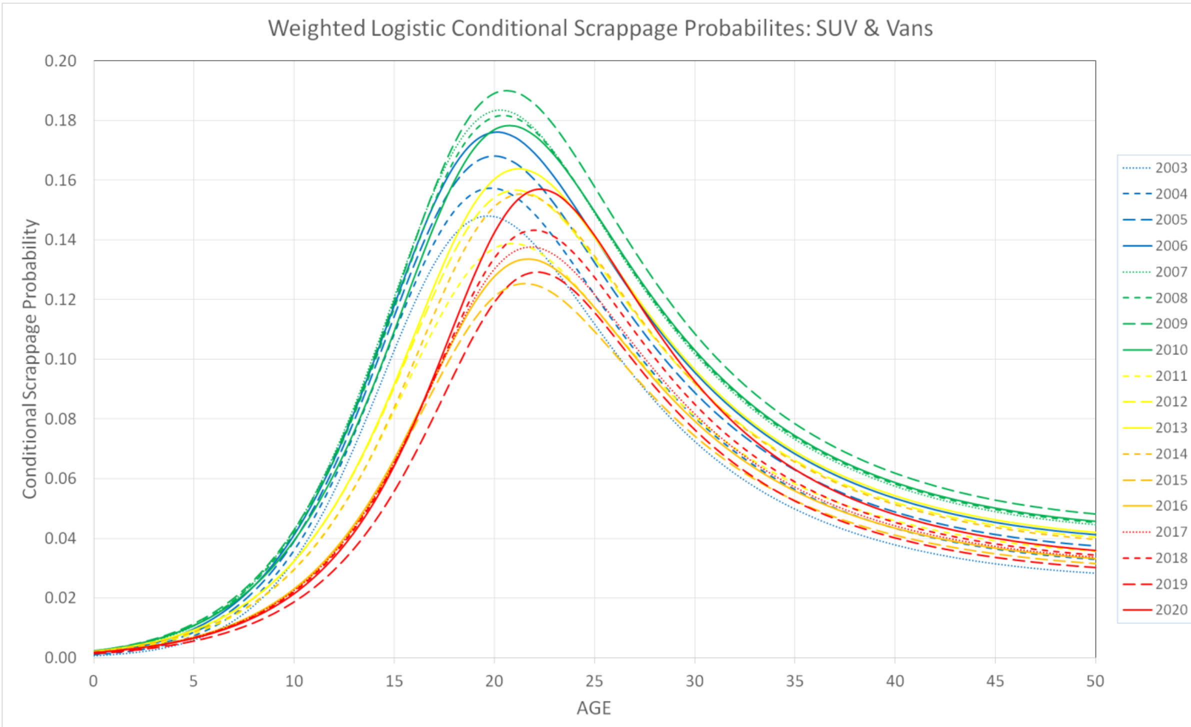


Figure C2b. SUV and Van Scrappage Rates vs. Age: Data Weighted by Vehicles in Operation.

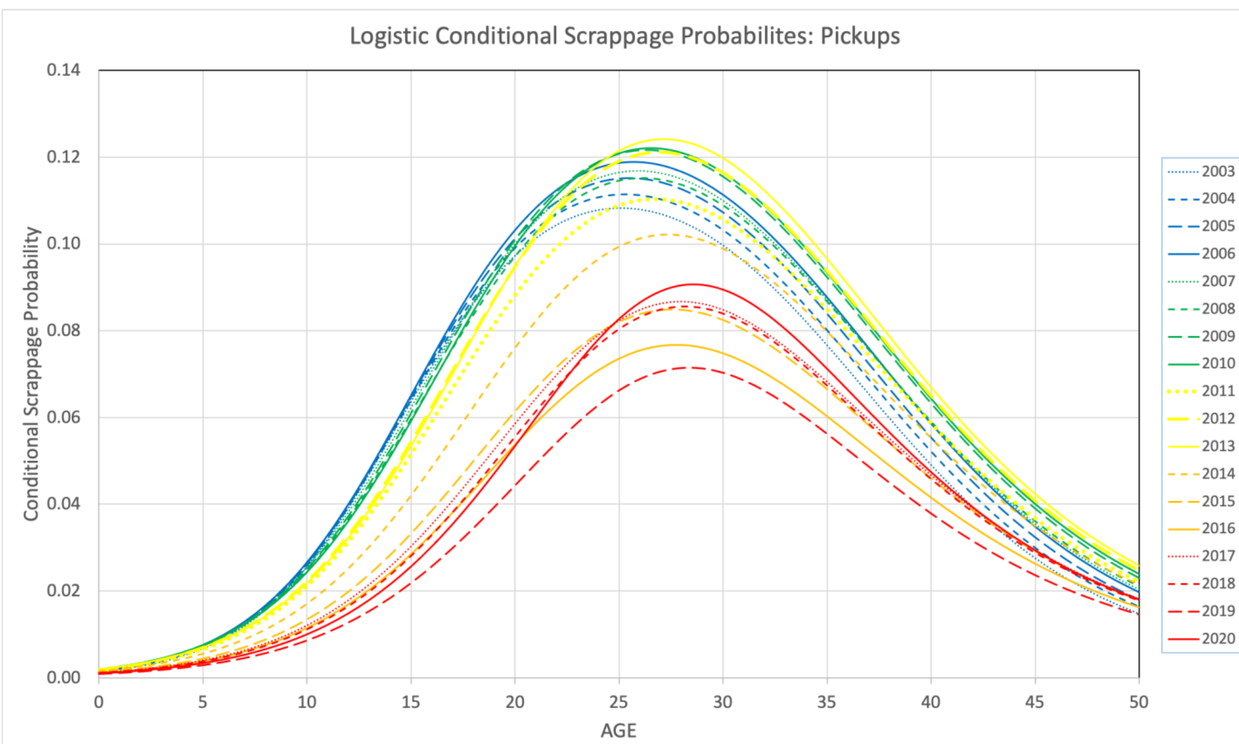


Figure C3a. Pickup Truck Scrappage Rates vs. Age: Unweighted Data

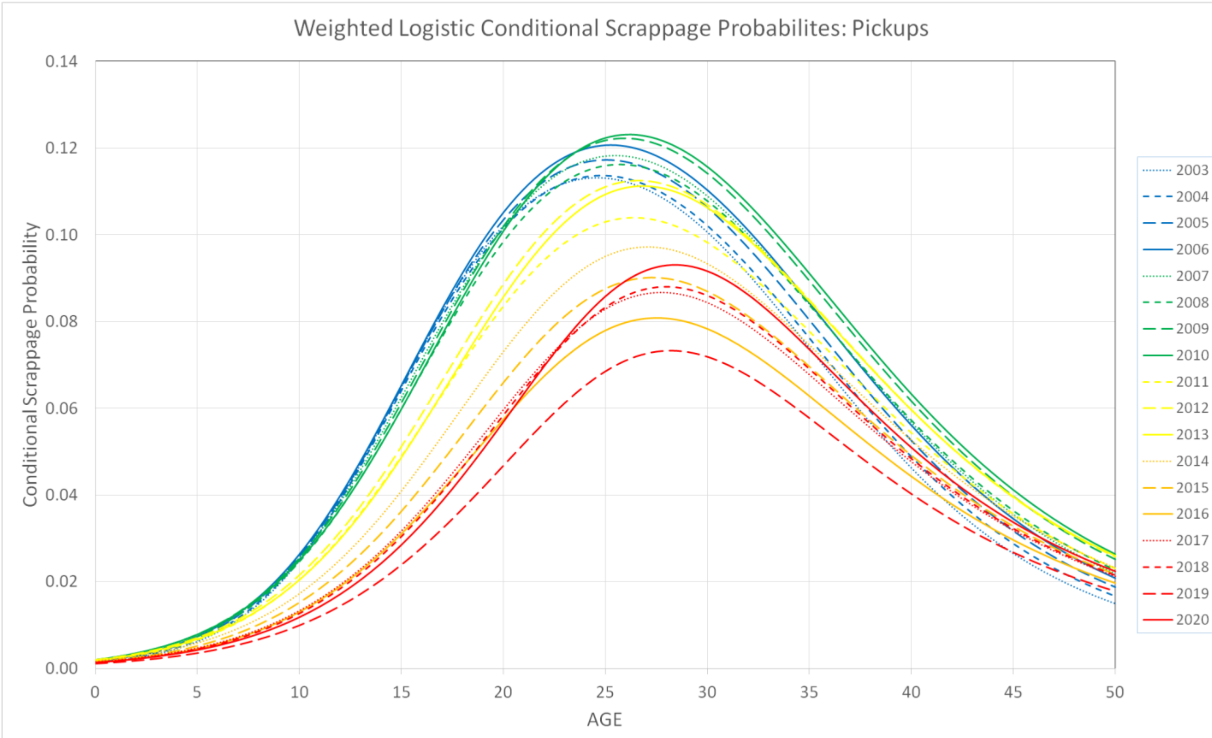


Figure C3b. Pickup Truck Scrappage Rate vs. Age: Weighted by Vehicles in Operation.

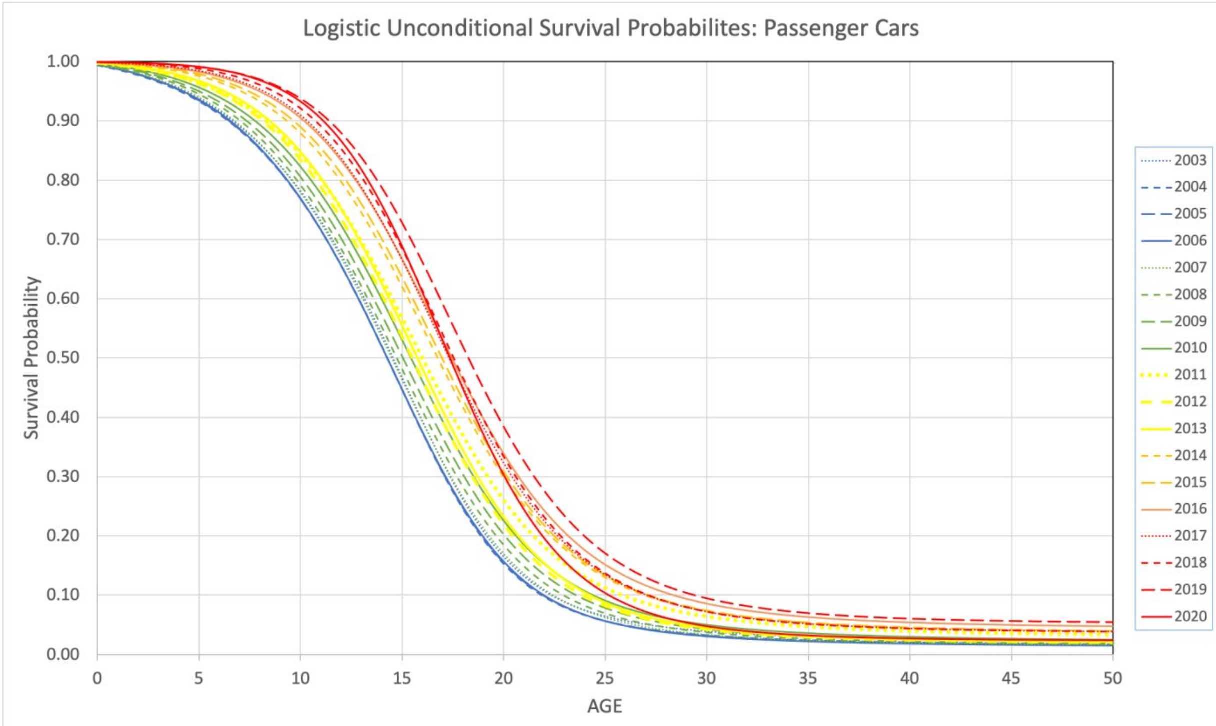


Figure C4a. Passenger Car Survival Probability Function: Unweighted Data.

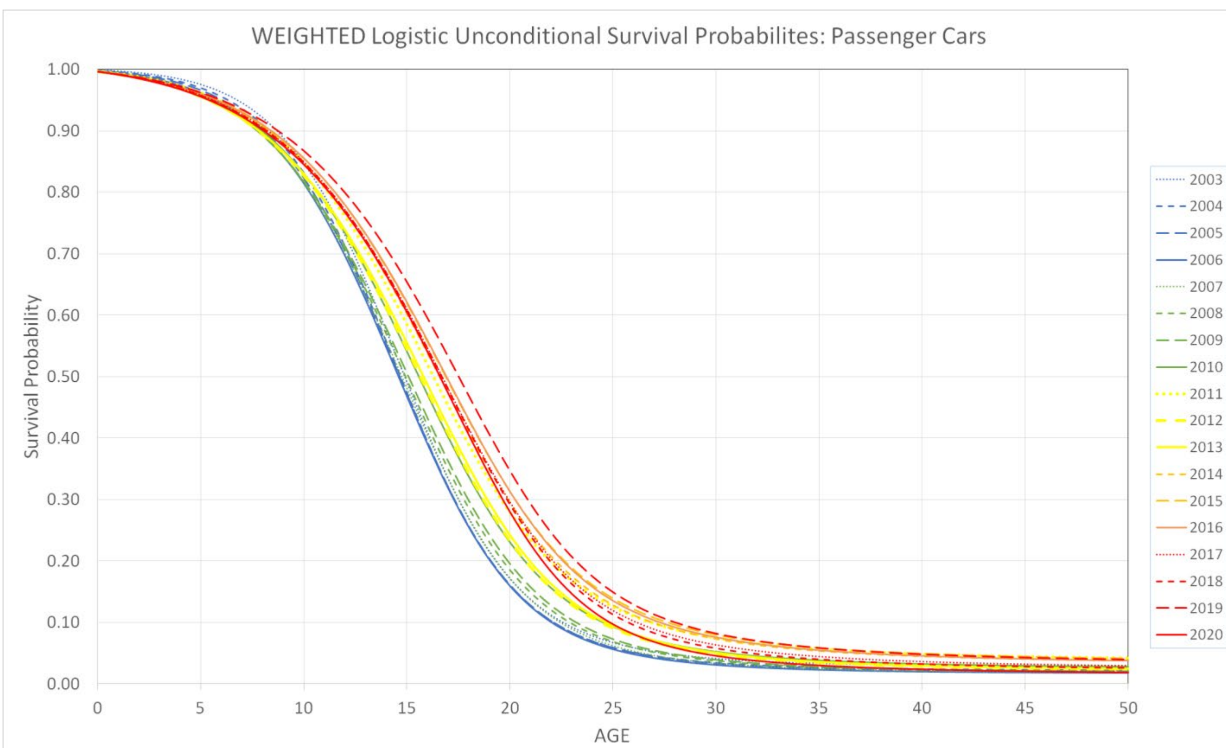


Figure C4b. Passenger Car Survival Probability Function: Data Weighted by Vehicles in Operation.

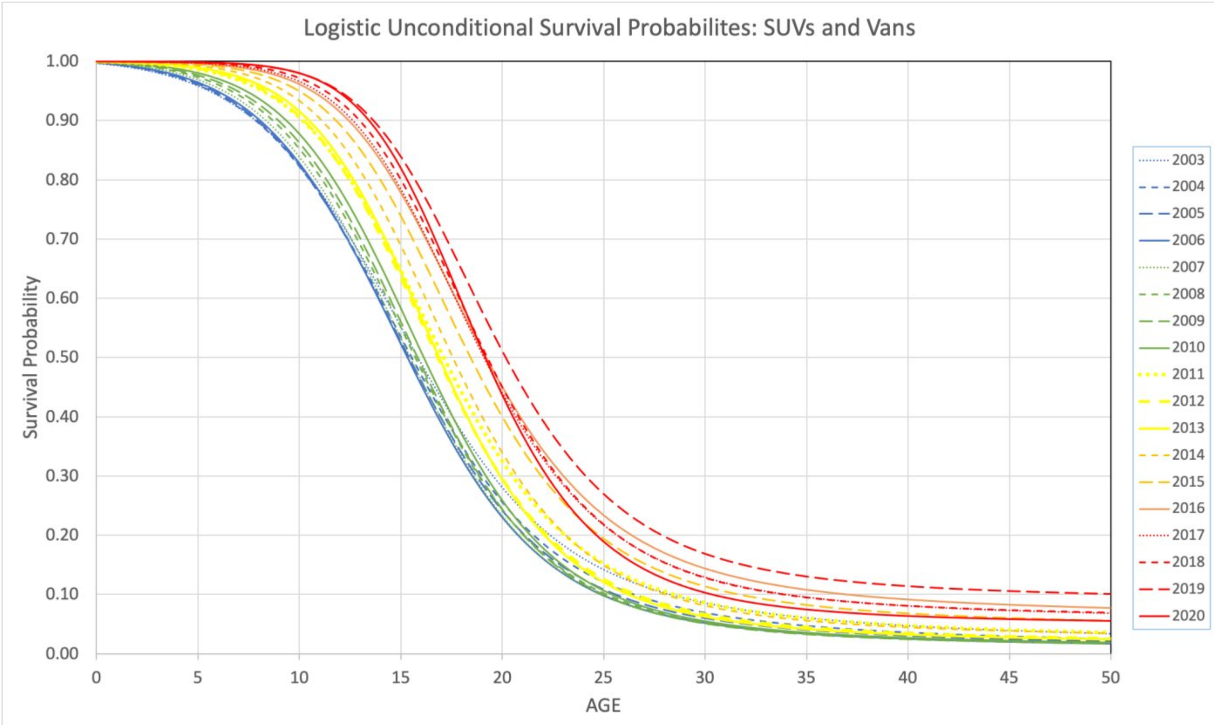


Figure C5a. SUV and Van Survival Probability Function: Unweighted Data.

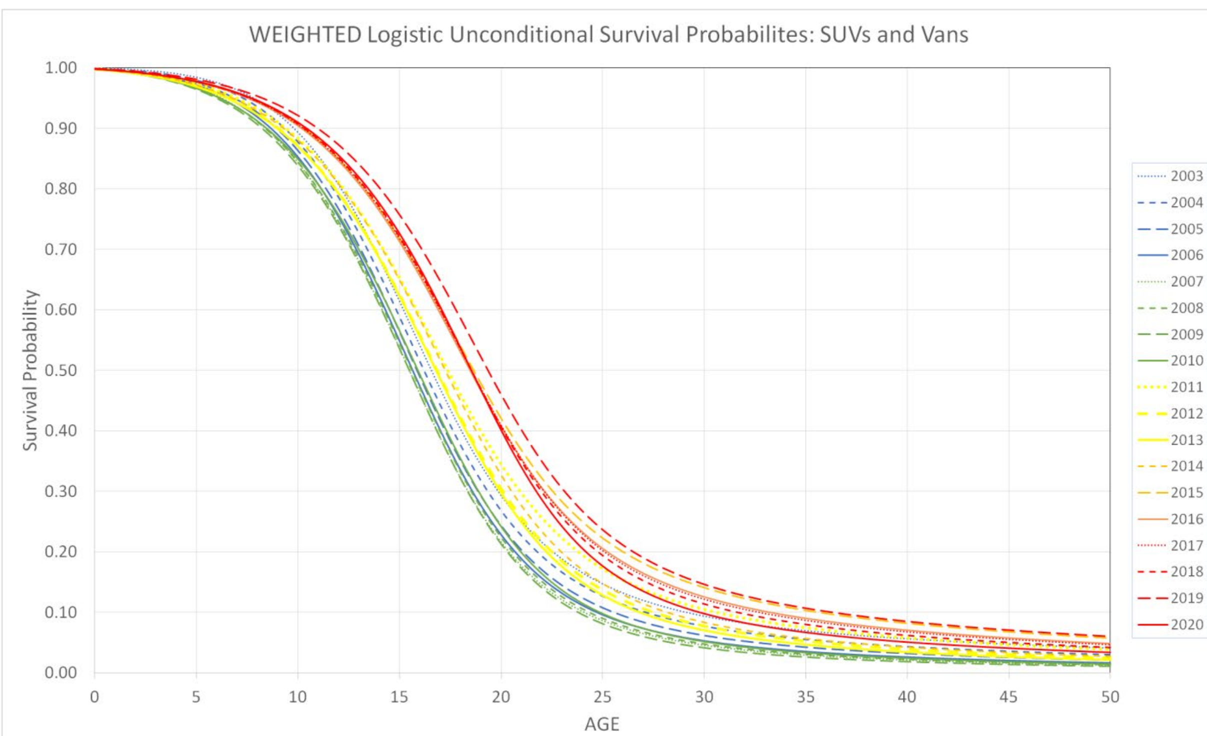


Figure C5b. SUV and Van Survival Probability Function: Data Weighted by Vehicles in Operation.

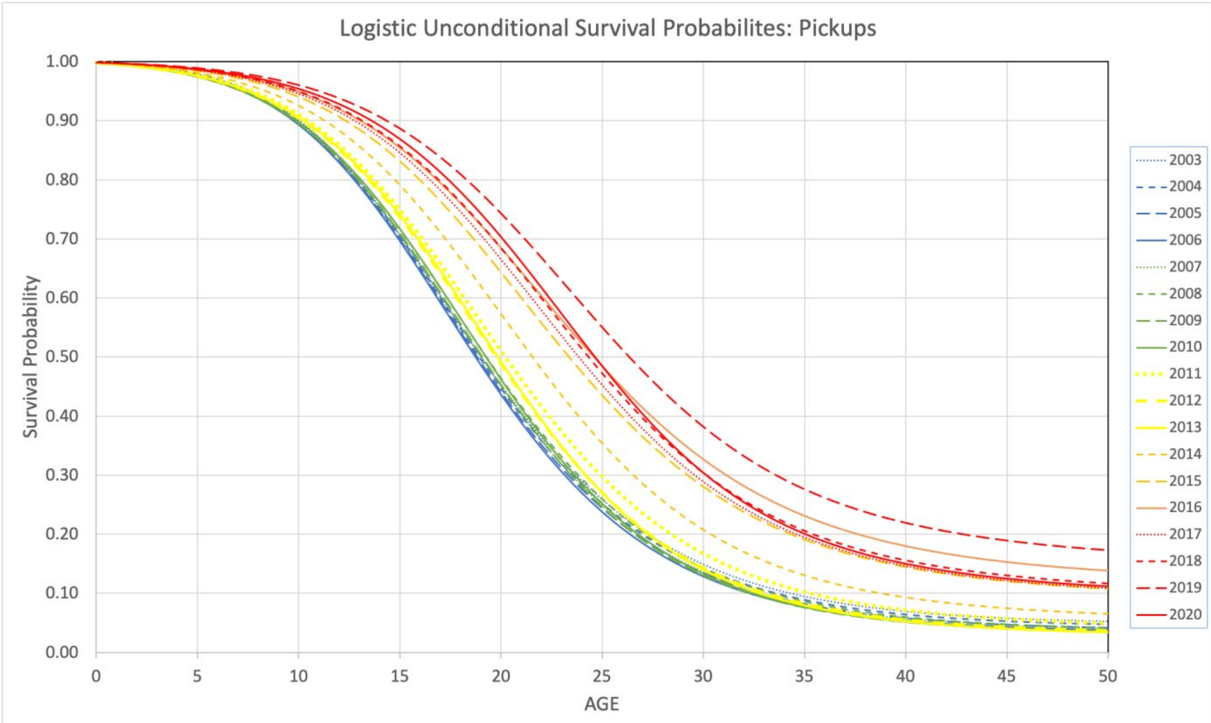


Figure C6a. Pickup Truck Survival Probability Function: Unweighted Data.

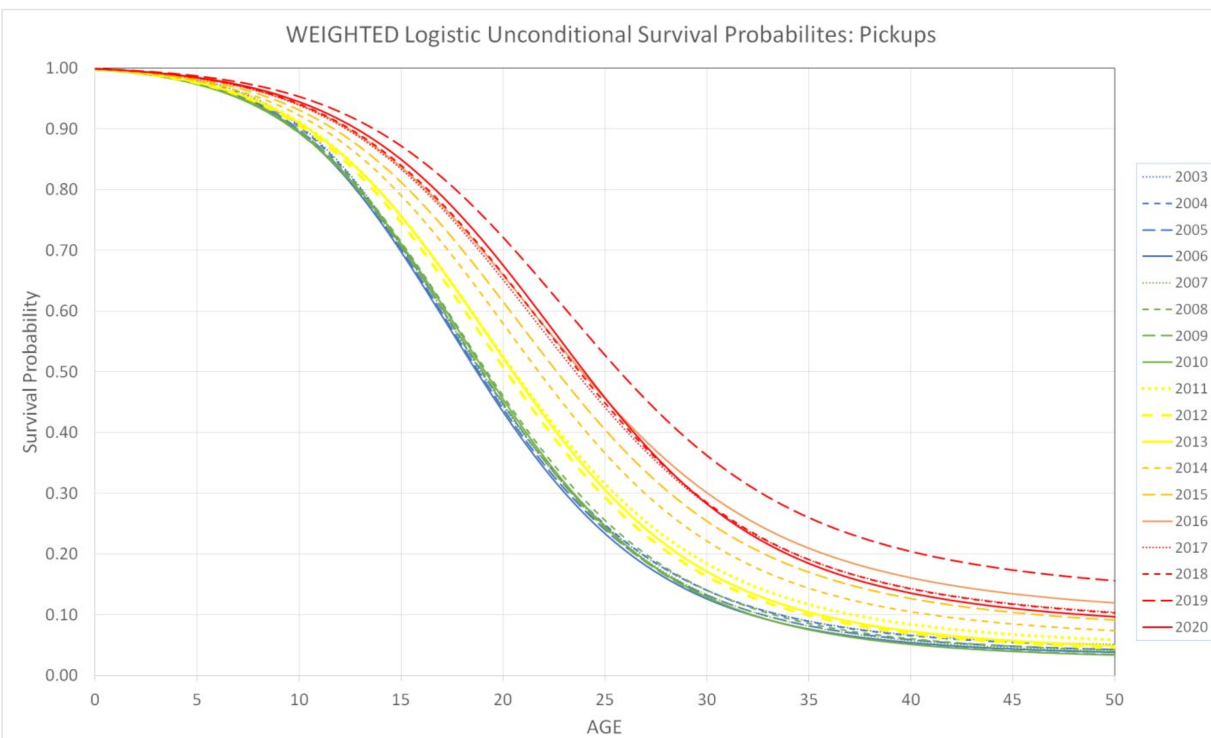


Figure C6b. Pickup Truck Survival Probability Function: Data Weighted by Vehicles in Operation.

APPENDIX D. CALENDAR YEAR SCRAPPAGE MODEL PARAMETER ESTIMATES

Weighted Nonlinear Regression Results

Passenger Cars

2020

Nonlinear regression

Number of obs	=	103416219
R-squared	=	0.9963
Adj R-squared	=	0.9963
Root MSE	=	.0052495
Res. dev.	=	-6.93e+08

Logistic Scrappage Functions by Year: PASSCAR Thursday June 16 09:45:02 2022

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.06978	.0290479	2.40	0.016	.0128472	.1267129
/s	.1693117	.0196327	8.62	0.000	.1308324	.2077911
/mu	23.51246	.1123496	209.28	0.000	23.29226	23.73266
/a	-.3252457	.072258	-4.50	0.000	-.4668689	-.1836226

2019

Nonlinear regression

Number of obs	=	104705503
R-squared	=	0.9925
Adj R-squared	=	0.9925
Root MSE	=	.0061619
Res. dev.	=	-6.70e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.0874602	.0445682	1.96	0.050	.0001082	.1748122
/s	.2048469	.028611	7.16	0.000	.1487705	.2609234
/mu	22.49463	.1267341	177.49	0.000	22.24624	22.74302
/a	-.2752942	.170987	-1.61	0.107	-.6104225	.0598341

2018

Nonlinear regression		
Number of obs	=	104457115
R-squared	=	0.9971
Adj R-squared	=	0.9971
Root MSE	=	.0042939
Res. dev.	=	-7.45e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.0164183	.0074392	2.21	0.027	.0018378	.0309987
/s	.1177578	.0150929	7.80	0.000	.0881762	.1473395
/mu	22.28887	.1935544	115.16	0.000	21.90951	22.66823
/a	-.3792775	.0189814	-19.98	0.000	-.4164803	-.3420747

2017

Nonlinear regression		
Number of obs	=	103645387
R-squared	=	0.9985
Adj R-squared	=	0.9985
Root MSE	=	.0029891
Res. dev.	=	-8.32e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.2271633	.048109	4.72	0.000	.1328714	.3214551
/s	.2558804	.0136249	18.78	0.000	.229176	.2825848
/mu	22.35462	.0408863	546.75	0.000	22.27449	22.43476
/a	.288616	.2316887	1.25	0.213	-.1654856	.7427175

2016

Nonlinear regression		
Number of obs	=	104106410
R-squared	=	0.9980
Adj R-squared	=	0.9980
Root MSE	=	.0032913
Res. dev.	=	-7.98e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.1917423	.0468915	4.09	0.000	.0998366	.283648
/s	.2526265	.0156691	16.12	0.000	.2219157	.2833373
/mu	22.10014	.088211	250.54	0.000	21.92725	22.27303
/a	.1621993	.2302429	0.70	0.481	-.2890685	.613467

2015

Nonlinear regression

Number of obs	=	102862147
R-squared	=	0.9956
Adj R-squared	=	0.9956
Root MSE	=	.0047488
Res. dev.	=	-7.12e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.4429226	.0706795	6.27	0.000	.3043933	.5814518
/s	.3166654	.0108831	29.10	0.000	.295335	.3379958
/mu	22.33773	.1385588	161.21	0.000	22.06616	22.6093
/a	1.37491	.3880898	3.54	0.000	.6142684	2.135553

2014

Nonlinear regression

Number of obs	=	101968168
R-squared	=	0.9924
Adj R-squared	=	0.9924
Root MSE	=	.0064417
Res. dev.	=	-6.43e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.434433	.114618	-3.79	0.000	-.6590801	-.2097858
/s	-.3108343	.0166178	-18.70	0.000	-.3434046	-.2782641
/mu	21.80346	.2567151	84.93	0.000	21.3003	22.30661
/a	-1.421698	.6627805	-2.15	0.032	-2.720724	-.1226723

2013

Nonlinear regression

Number of obs	=	102827462
R-squared	=	0.9981
Adj R-squared	=	0.9981
Root MSE	=	.0035789
Res. dev.	=	-7.70e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.2187892	.0292424	-7.48	0.000	-.2761033	-.1614751
/s	-.2354928	.0075626	-31.14	0.000	-.2503154	-.2206703
/mu	22.52029	.1276153	176.47	0.000	22.27017	22.77041
/a	-.2286538	.1313743	-1.74	0.082	-.4861427	.0288351

2012

Nonlinear regression

Number of obs =	104541497
R-squared =	0.9960
Adj R-squared =	0.9960
Root MSE =	.0052538
Res. dev. =	-7.03e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.1960163	.0364459	-5.38	0.000	-.267449	-.1245836
/s	-.2282398	.0103502	-22.05	0.000	-.2485259	-.2079538
/mu	22.36648	.1563114	143.09	0.000	22.06012	22.67285
/a	-.1278217	.1570691	-0.81	0.416	-.4356714	.180028

2011

Nonlinear regression

Number of obs =	106806980
R-squared =	0.9943
Adj R-squared =	0.9943
Root MSE =	.0053993
Res. dev. =	-7.14e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.3688313	.0806711	-4.57	0.000	-.5269436	-.2107189
/s	-.2700656	.0122888	-21.98	0.000	-.2941512	-.2459799
/mu	22.52402	.2338926	96.30	0.000	22.0656	22.98244
/a	-1.214601	.4734246	-2.57	0.010	-2.142496	-.2867056

2010

Nonlinear regression

Number of obs =	106445824
R-squared =	0.9979
Adj R-squared =	0.9979
Root MSE =	.0036711
Res. dev. =	-7.96e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.4544739	.0674923	-6.73	0.000	-.5867565	-.3221914
/s	-.2917831	.0096007	-30.39	0.000	-.3106001	-.272966
/mu	21.63079	.1226291	176.39	0.000	21.39044	21.87114
/a	-1.377734	.3492425	-3.94	0.000	-2.062237	-.6932315

2009

Nonlinear regression

Number of obs =	105977382
R-squared =	0.9965
Adj R-squared =	0.9965
Root MSE =	.0051556
Res. dev. =	-7.22e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.3773006	.0781627	-4.83	0.000	-.5304966	-.2241046
/s	-.2784151	.0132718	-20.98	0.000	-.3044273	-.2524028
/mu	20.94271	.1636121	128.00	0.000	20.62203	21.26338
/a	-.889272	.3709072	-2.40	0.017	-1.616237	-.1623072

2008

Nonlinear regression

Number of obs =	106672726
R-squared =	0.9969
Adj R-squared =	0.9969
Root MSE =	.0049455
Res. dev. =	-7.38e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.8802295	.1566588	-5.62	0.000	-1.187275	-.5731838
/s	-.3353762	.0122651	-27.34	0.000	-.3594153	-.3113371
/mu	21.10137	.1594589	132.33	0.000	20.78883	21.4139
/a	-3.228065	.7982073	-4.04	0.000	-4.792523	-1.663607

2007

Nonlinear regression

Number of obs =	107205676
R-squared =	0.9977
Adj R-squared =	0.9977
Root MSE =	.0044023
Res. dev. =	-7.69e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.8358752	.1212575	-6.89	0.000	-1.073536	-.5982148
/s	-.3343087	.0099742	-33.52	0.000	-.3538578	-.3147596
/mu	20.91541	.130511	160.26	0.000	20.65962	21.17121
/a	-2.831104	.6131384	-4.62	0.000	-4.032833	-1.629375

2006

Nonlinear regression

Number of obs =	108323347
R-squared =	0.9977
Adj R-squared =	0.9977
Root MSE =	.0044806
Res. dev. =	-7.75e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.7432878	.1050855	-7.07	0.000	-.9492515	-.5373241
/s	-.3295666	.0094834	-34.75	0.000	-.3481536	-.3109795
/mu	20.70065	.1275647	162.28	0.000	20.45063	20.95067
/a	-2.225102	.5041504	-4.41	0.000	-3.213218	-1.236985

2005

Nonlinear regression

Number of obs =	109288715
R-squared =	0.9977
Adj R-squared =	0.9977
Root MSE =	.0044907
Res. dev. =	-7.84e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.7355038	.1097206	-6.70	0.000	-.9505523	-.5204554
/s	-.3320866	.0099733	-33.30	0.000	-.3516338	-.3125393
/mu	20.60071	.1321018	155.95	0.000	20.3418	20.85963
/a	-2.189858	.5250928	-4.17	0.000	-3.219021	-1.160696

2004

Nonlinear regression

Number of obs =	109925273
R-squared =	0.9977
Adj R-squared =	0.9977
Root MSE =	.0044135
Res. dev. =	-7.96e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.8606134	.1455649	-5.91	0.000	-1.145915	-.5753114
/s	-.355843	.0121353	-29.32	0.000	-.3796277	-.3320583
/mu	20.36526	.1263953	161.12	0.000	20.11753	20.61299
/a	-2.638728	.6702596	-3.94	0.000	-3.952413	-1.325043

2003

Nonlinear regression

Number of obs =	110252292
R-squared =	0.9980
Adj R-squared =	0.9980
Root MSE =	.0039981
Res. dev. =	-8.23e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.8281319	.1551695	-5.34	0.000	-1.132258	-.5240053
/s	-.3619242	.0145938	-24.80	0.000	-.3905276	-.3333208
/mu	20.09417	.115551	173.90	0.000	19.86769	20.32065
/a	-2.63331	.7259036	-3.63	0.000	-4.056055	-1.210566

SUVs and Vans

2020

Nonlinear regression

Number of obs =	85,427,590
R-squared =	0.9959
Adj R-squared =	0.9959
Root MSE =	.003946
Res. dev. =	-5.62e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.2137639	.0626698	-3.41	0.001	-.3365946	-.0909333
/s	-.2479397	.0173343	-14.30	0.000	-.2819144	-.2139651
/mu	23.67686	.1260549	187.83	0.000	23.4298	23.92392
/a	-.3992918	.3574117	-1.12	0.264	-1.099806	.3012222

2019

Nonlinear regression

Number of obs =	81,362,354
R-squared =	0.9970
Adj R-squared =	0.9970
Root MSE =	.0027955
Res. dev. =	-6.01e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.2813431	.068232	-4.12	0.000	-.4150753	-.1476109
/s	-.3041296	.0172395	-17.64	0.000	-.3379184	-.2703408
/mu	22.66503	.089753	252.53	0.000	22.48912	22.84095
/a	-.9919975	.4851464	-2.04	0.041	-1.942867	-.041128

2018

Nonlinear regression

Number of obs	= 76,991,371
R-squared	= 0.9970
Adj R-squared	= 0.9970
Root MSE	= .0031303
Res. dev.	= -5.55e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.1926617	.0508469	-3.79	0.000	-.2923198	-.0930036
/s	-.2515318	.0152634	-16.48	0.000	-.2814475	-.2216161
/mu	23.00354	.1571992	146.33	0.000	22.69543	23.31164
/a	-.3728361	.324369	-1.15	0.250	-1.008588	.2629155

2017

Nonlinear regression

Number of obs	= 73,365,177
R-squared	= 0.9971
Adj R-squared	= 0.9971
Root MSE	= .0029428
Res. dev.	= -5.34e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.5524669	.1148147	-4.81	0.000	-.7774995	-.3274343
/s	-.3312868	.0132347	-25.03	0.000	-.3572263	-.3053472
/mu	23.01577	.1645812	139.84	0.000	22.6932	23.33835
/a	-2.683018	.8246519	-3.25	0.001	-4.299306	-1.06673

2016

Nonlinear regression

Number of obs	= 70,390,879
R-squared	= 0.9968
Adj R-squared	= 0.9968
Root MSE	= .0029779
Res. dev.	= -5.18e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.3400207	.0738912	-4.60	0.000	-.4848448	-.1951965
/s	-.3146086	.0140106	-22.46	0.000	-.3420689	-.2871483
/mu	22.24629	.1740348	127.83	0.000	21.90519	22.5874
/a	-1.233838	.5082165	-2.43	0.015	-2.229924	-.237752

2015

Nonlinear regression

Number of obs	=	58,018,189
R-squared	=	0.9865
Adj R-squared	=	0.9865
Root MSE	=	.0062732
Res. dev.	=	-3.37e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-6.195514	3.713987	-1.67	0.095	-13.47479	1.083766
/s	-.5708405	.0599143	-9.53	0.000	-.6882703	-.4534107
/mu	23.06636	.1225281	188.25	0.000	22.82621	23.30652
/a	-40.72751	26.4158	-1.54	0.123	-92.50152	11.0465

2014

Nonlinear regression

Number of obs	=	65,243,984
R-squared	=	0.9953
Adj R-squared	=	0.9953
Root MSE	=	.0040565
Res. dev.	=	-4.35e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.463961	.106095	-4.37	0.000	-.6719033	-.2560187
/s	-.3203013	.0158216	-20.24	0.000	-.351311	-.2892916
/mu	22.37769	.1907194	117.33	0.000	22.00388	22.75149
/a	-1.475667	.596982	-2.47	0.013	-2.64573	-.3056035

2013

Nonlinear regression

Number of obs	=	63,419,357
R-squared	=	0.9952
Adj R-squared	=	0.9952
Root MSE	=	.0042076
Res. dev.	=	-4.15e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.392643	.0936883	-4.19	0.000	-.5762688	-.2090173
/s	-.2757845	.0131428	-20.98	0.000	-.301544	-.250025
/mu	23.15936	.250893	92.31	0.000	22.66762	23.6511
/a	-1.163363	.5309503	-2.19	0.028	-2.204006	-.1227196

2012

Nonlinear regression

Number of obs	=	62,660,368
R-squared	=	0.9935
Adj R-squared	=	0.9935
Root MSE	=	.0046057
Res. dev.	=	-4.00e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.2514569	.071368	3.52	0.000	.1115781	.3913357
/s	.2419526	.0144834	16.71	0.000	.2135657	.2703396
/mu	23.34447	.3080543	75.78	0.000	22.7407	23.94825
/a	.555833	.4045423	1.37	0.169	-.2370552	1.348721

2011

Nonlinear regression

Number of obs	=	62,677,207
R-squared	=	0.9921
Adj R-squared	=	0.9921
Root MSE	=	.0043385
Res. dev.	=	-4.08e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.3907378	.1161606	-3.36	0.001	-.6184084	-.1630672
/s	-.2733752	.0164068	-16.66	0.000	-.3055318	-.2412185
/mu	23.53865	.3099146	75.95	0.000	22.93123	24.14607
/a	-1.524333	.7504367	-2.03	0.042	-2.995162	-.053504

2010

Nonlinear regression

Number of obs	=	59,960,569
R-squared	=	0.9935
Adj R-squared	=	0.9935
Root MSE	=	.0049387
Res. dev.	=	-3.77e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.7379826	.1978002	3.73	0.000	.3503013	1.125664
/s	.3124052	.0150689	20.73	0.000	.2828706	.3419398
/mu	22.26298	.2574436	86.48	0.000	21.7584	22.76756
/a	2.985033	1.129618	2.64	0.008	.7710223	5.199043

2009

Nonlinear regression

Number of obs	= 57,467,696
R-squared	= 0.9797
Adj R-squared	= 0.9797
Root MSE	= .0094851
Res. dev.	= -2.89e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.0200011	.0195243	1.02	0.306	-.0182658	.0582681
/s	.1221964	.0354771	3.44	0.001	.0526625	.1917304
/mu	21.09101	.2742681	76.90	0.000	20.55345	21.62856
/a	-.3791474	.0377274	-10.05	0.000	-.4530918	-.3052029

2008

Nonlinear regression

Number of obs	= 55,479,582
R-squared	= 0.9923
Adj R-squared	= 0.9923
Root MSE	= .0054256
Res. dev.	= -3.43e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	2.48136	.8007915	3.10	0.002	.9118378	4.050883
/s	.3940765	.0236347	16.67	0.000	.3477534	.4403996
/mu	22.00247	.2247097	97.92	0.000	21.56205	22.44289
/a	13.03208	4.75352	2.74	0.006	3.715353	22.34881

2007

Nonlinear regression

Number of obs	= 52,010,255
R-squared	= 0.9927
Adj R-squared	= 0.9927
Root MSE	= .0053749
Res. dev.	= -3.25e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	3.320234	.8787261	3.78	0.000	1.597963	5.042506
/s	.4168026	.0203519	20.48	0.000	.3769136	.4566917
/mu	21.89951	.2041517	107.27	0.000	21.49938	22.29964
/a	17.68993	5.213885	3.39	0.001	7.4709	27.90895

2006

Nonlinear regression

Number of obs	=	48,439,270
R-squared	=	0.9947
Adj R-squared	=	0.9947
Root MSE	=	.004426
Res. dev.	=	-3.25e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.975264	.4237045	4.66	0.000	1.144819	2.80571
/s	.387606	.0153501	25.25	0.000	.3575203	.4176917
/mu	21.91029	.2032391	107.81	0.000	21.51194	22.30863
/a	9.83916	2.511656	3.92	0.000	4.916405	14.76192

2005

Nonlinear regression

Number of obs	=	44,914,900
R-squared	=	0.9935
Adj R-squared	=	0.9935
Root MSE	=	.0047154
Res. dev.	=	-2.99e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.944391	.4920051	3.95	0.000	.9800788	2.908703
/s	.397885	.0182067	21.85	0.000	.3622004	.4335695
/mu	21.73648	.1981207	109.71	0.000	21.34817	22.12479
/a	10.01419	3.064466	3.27	0.001	4.007946	16.02043

2004

Nonlinear regression

Number of obs	=	41,073,642
R-squared	=	0.9939
Adj R-squared	=	0.9939
Root MSE	=	.0042899
Res. dev.	=	-2.84e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	2.457624	.7400059	3.32	0.001	1.007239	3.908009
/s	.4216241	.0203661	20.70	0.000	.3817072	.461541
/mu	21.79385	.1833678	118.85	0.000	21.43446	22.15325
/a	14.01393	5.109857	2.74	0.006	3.998791	24.02906

2003

Nonlinear regression

Number of obs	= 28,426,210
R-squared	= 0.9952
Adj R-squared	= 0.9952
Root MSE	= .0041116
Res. dev.	= -2.02e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	2.130445	.6208909	3.43	0.001	.9135214	3.347369
/s	.4139546	.0181947	22.75	0.000	.3782936	.4496156
/mu	21.63294	.1603605	134.90	0.000	21.31864	21.94724
/a	13.354	4.816551	2.77	0.006	3.913729	22.79426

Pickups

2020

Nonlinear regression

Number of obs	= 38,253,648
R-squared	= 0.9964
Adj R-squared	= 0.9964
Root MSE	= .0029465
Res. dev.	= -3.10e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.6294634	.1590454	3.96	0.000	.3177402	.9411866
/s	.2872818	.0141785	20.26	0.000	.2594926	.3150711
/mu	28.72229	.2136118	134.46	0.000	28.30362	29.14096
/a	6.100428	1.813667	3.36	0.001	2.545706	9.655151

2019

Nonlinear regression

Number of obs	= 32,997,022
R-squared	= 0.9940
Adj R-squared	= 0.9940
Root MSE	= .0032139
Res. dev.	= -2.60e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.42862	.4611015	3.10	0.002	.5248779	2.332363
/s	.3438781	.0191024	18.00	0.000	.3064382	.3813181
/mu	28.98619	.2275166	127.40	0.000	28.54027	29.43212
/a	19.60166	6.909434	2.84	0.005	6.05942	33.1439

2018

Nonlinear regression

Number of obs	= 39,229,459
R-squared	= 0.9959
Adj R-squared	= 0.9959
Root MSE	= .0028966
Res. dev.	= -3.19e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.2756777	.0942203	2.93	0.003	.0910094	.460346
/s	.2483929	.0189239	13.13	0.000	.2113027	.2854831
/mu	28.05839	.1718711	163.25	0.000	27.72153	28.39525
/a	2.177039	1.042608	2.09	0.037	.1335655	4.220512

2017

Nonlinear regression

Number of obs	= 34,643,777
R-squared	= 0.9972
Adj R-squared	= 0.9972
Root MSE	= .0024852
Res. dev.	= -2.91e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.3145267	.0729874	4.31	0.000	.171474	.4575794
/s	.2473635	.0118635	20.85	0.000	.2241114	.2706156
/mu	28.40978	.1920933	147.90	0.000	28.03328	28.78627
/a	2.659323	.848421	3.13	0.002	.9964485	4.322198

2016

Nonlinear regression

Number of obs	= 36,116,198
R-squared	= 0.9979
Adj R-squared	= 0.9979
Root MSE	= .0019757
Res. dev.	= -3.20e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.3544481	.0726698	-4.88	0.000	-.4968782	-.212018
/s	-.2673113	.0110633	-24.16	0.000	-.288995	-.2456275
/mu	27.27296	.1473816	185.05	0.000	26.9841	27.56182
/a	-3.438316	.9378251	-3.67	0.000	-5.276419	-1.600213

2015

Not estimated due to anomalies in data.

2014

Nonlinear regression

Number of obs	= 43,493,261
R-squared	= 0.9958
Adj R-squared	= 0.9958
Root MSE	= .002982
Res. dev.	= -3.53e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.6779479	.1618438	-4.19	0.000	-.9951559	-.3607398
/s	-.2803241	.0117661	-23.82	0.000	-.3033852	-.257263
/mu	28.3913	.2877928	98.65	0.000	27.82723	28.95536
/a	-5.527701	1.600379	-3.45	0.001	-8.664386	-2.391016

2013

Nonlinear regression

Number of obs	= 43,230,627
R-squared	= 0.9984
Adj R-squared	= 0.9984
Root MSE	= .002093
Res. dev.	= -3.82e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.2202721	.0316009	-6.97	0.000	-.2822087	-.1583356
/s	-.1982306	.0054221	-36.56	0.000	-.2088578	-.1876034
/mu	29.7471	.1799958	165.27	0.000	29.39431	30.09988
/a	-.9611648	.2512221	-3.83	0.000	-1.453551	-.4687786

2012

Nonlinear regression

Number of obs	= 43,692,959
R-squared	= 0.9982
Adj R-squared	= 0.9982
Root MSE	= .0022491
Res. dev.	= -3.81e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.1832294	.0298977	-6.13	0.000	-.2418278	-.124631
/s	-.1853388	.0067426	-27.49	0.000	-.1985541	-.1721235
/mu	29.36086	.2094301	140.19	0.000	28.95039	29.77134
/a	-.7704847	.2304173	-3.34	0.001	-1.222094	-.3188751

2011

Nonlinear regression

Number of obs	44,497,350
R-squared	0.9976
Adj R-squared	0.9976
Root MSE	.0023223
Res. dev.	-3.86e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.233296	.0382122	-6.11	0.000	-.3081905	-.1584015
/s	-.2084969	.0066602	-31.30	0.000	-.2215507	-.195443
/mu	28.51954	.2718604	104.91	0.000	27.9867	29.05238
/a	-1.242963	.3260609	-3.81	0.000	-1.88203	-.6038952

2010

Nonlinear regression

Number of obs	44,008,913
R-squared	0.9966
Adj R-squared	0.9966
Root MSE	.0033249
Res. dev.	-3.51e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.4875775	.0936885	-5.20	0.000	-.6712036	-.3039513
/s	-.2414945	.0096179	-25.11	0.000	-.2603453	-.2226437
/mu	27.03545	.2140209	126.32	0.000	26.61597	27.45492
/a	-3.056254	.7688709	-3.97	0.000	-4.563213	-1.549294

2009

Nonlinear regression

Number of obs	32,090,996
R-squared	0.9950
Adj R-squared	0.9950
Root MSE	.0046296
Res. dev.	-2.36e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.4213184	.1547153	-2.72	0.006	-.7245548	-.118082
/s	-.2248931	.0195776	-11.49	0.000	-.2632646	-.1865217
/mu	27.24937	.2080246	130.99	0.000	26.84165	27.65709
/a	-2.648834	1.25629	-2.11	0.035	-5.111117	-.1865507

2008

Nonlinear regression

Number of obs	= 42,497,613
R-squared	= 0.9960
Adj R-squared	= 0.9960
Root MSE	= .0034586
Res. dev.	= -3.38e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.7846714	.1795552	-4.37	0.000	-1.136593	-.4327497
/s	-.2762821	.0140115	-19.72	0.000	-.3037442	-.2488201
/mu	26.43259	.2088595	126.56	0.000	26.02323	26.84194
/a	-5.755329	1.547262	-3.72	0.000	-8.787906	-2.722751

2007

Nonlinear regression

Number of obs	= 41,578,725
R-squared	= 0.9972
Adj R-squared	= 0.9972
Root MSE	= .0029454
Res. dev.	= -3.45e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-1.016758	.2289668	-4.44	0.000	-1.465524	-.567991
/s	-.2988273	.0133011	-22.47	0.000	-.324897	-.2727577
/mu	25.94086	.1968159	131.80	0.000	25.55511	26.32661
/a	-7.488329	1.943949	-3.85	0.000	-11.2984	-3.67826

2006

Nonlinear regression

Number of obs	= 40,290,065
R-squared	= 0.9970
Adj R-squared	= 0.9970
Root MSE	= .0031472
Res. dev.	= -3.31e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.120587	.2857875	3.92	0.000	.560454	1.68072
/s	.3069955	.014946	20.54	0.000	.2777018	.3362892
/mu	25.61391	.1877998	136.39	0.000	25.24582	25.98199
/a	8.182281	2.392878	3.42	0.001	3.492325	12.87224

2005

Nonlinear regression

Number of obs	= 36,595,747
R-squared	= 0.9965
Adj R-squared	= 0.9965
Root MSE	= .003467
Res. dev.	= -2.95e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.114997	.3289391	3.39	0.001	.4702881	1.759706
/s	.3143529	.0176724	17.79	0.000	.2797157	.34899
/mu	25.19497	.210497	119.69	0.000	24.78241	25.60754
/a	8.386398	2.856588	2.94	0.003	2.787587	13.98521

2004

Nonlinear regression

Number of obs	= 38,350,696
R-squared	= 0.9962
Adj R-squared	= 0.9962
Root MSE	= .0034023
Res. dev.	= -3.11e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.121588	.316411	3.54	0.000	.5014334	1.741742
/s	.324225	.0169751	19.10	0.000	.2909544	.3574955
/mu	24.76565	.2060598	120.19	0.000	24.36178	25.16952
/a	8.686668	2.842707	3.06	0.002	3.115065	14.25827

2003

Nonlinear regression

Number of obs	= 34,098,093
R-squared	= 0.9962
Adj R-squared	= 0.9962
Root MSE	= .0035994
Res. dev.	= -2.74e+08

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.32776	.3609149	3.68	0.000	.62038	2.03514
/s	.3404077	.0167898	20.27	0.000	.3075002	.3733152
/mu	24.02753	.2272234	105.74	0.000	23.58218	24.47288
/a	10.96174	3.391257	3.23	0.001	4.315001	17.60849

Unweighted

Passenger Cars

2020

Nonlinear regression

Number of obs =	47
R-squared =	0.9977
Adj R-squared =	0.9975
Root MSE =	.004994
Res. dev. =	-368.9554

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.1370106	.0281254	4.87	0.000	.0802902	.1937309
/s	.201502	.0109153	18.46	0.000	.1794891	.2235149
/mu	23.62679	.0748694	315.57	0.000	23.4758	23.77778
/a	-.1025762	.1059436	-0.97	0.338	-.3162319	.1110795

2019

Nonlinear regression

Number of obs =	45
R-squared =	0.9958
Adj R-squared =	0.9954
Root MSE =	.0054234
Res. dev. =	-346.0167

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.1117686	.0330209	3.38	0.002	.0450815	.1784557
/s	.2124859	.0162695	13.06	0.000	.1796289	.2453428
/mu	22.68256	.111025	204.30	0.000	22.45834	22.90678
/a	-.1383345	.1527213	-0.91	0.370	-.4467614	.1700925

2018

Nonlinear regression

Number of obs =	44
R-squared =	0.9900
Adj R-squared =	0.9890
Root MSE =	.0094572
Res. dev. =	-289.4937

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.0534768	.0312079	1.71	0.094	-.0095967	.1165504
/s	.1723624	.0266708	6.46	0.000	.1184587	.2262661
/mu	22.21676	.1973826	112.56	0.000	21.81784	22.61569
/a	-.3926383	.0709592	-5.53	0.000	-.5360522	-.2492243

2017

Nonlinear regression

Number of obs =	37
R-squared =	0.9981
Adj R-squared =	0.9978
Root MSE =	.0045003
Res. dev. =	-299.0989

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.3378764	.0850478	3.97	0.000	.1648453	.5109075
/s	.2822427	.0183216	15.40	0.000	.2449672	.3195181
/mu	22.36533	.0473258	472.58	0.000	22.26905	22.46162
/a	.841742	.4323765	1.95	0.060	-.0379347	1.721419

2016

Nonlinear regression

Number of obs =	42
R-squared =	0.9978
Adj R-squared =	0.9976
Root MSE =	.0041463
Res. dev. =	-345.7972

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.1114491	.0257256	4.33	0.000	.0593702	.1635279
/s	.2191235	.0128784	17.01	0.000	.1930527	.2451944
/mu	22.11758	.0849211	260.45	0.000	21.94566	22.28949
/a	-.2037511	.107496	-1.90	0.066	-.4213653	.0138631

2015

Nonlinear regression

Number of obs =	42
R-squared =	0.9795
Adj R-squared =	0.9774
Root MSE =	.0133477
Res. dev. =	-247.5911

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.0181929	.0236363	0.77	0.446	-.0296564	.0660421
/s	.122787	.0499868	2.46	0.019	.021594	.22398
/mu	22.64574	.1841996	122.94	0.000	22.27285	23.01863
/a	-.3839805	.0609821	-6.30	0.000	-.5074324	-.2605287

2014

Nonlinear regression

Number of obs	=	42
R-squared	=	0.9787
Adj R-squared	=	0.9764
Root MSE	=	.01356
Res. dev.	=	-246.2658

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.162975	.1004642	1.62	0.113	-.0404042	.3663542
/s	.2118752	.0334012	6.34	0.000	.1442581	.2794923
/mu	22.69889	.2979888	76.17	0.000	22.09564	23.30213
/a	.2202508	.536041	0.41	0.683	-.8649073	1.305409

2013

Nonlinear regression

Number of obs	=	41
R-squared	=	0.9952
Adj R-squared	=	0.9947
Root MSE	=	.0075714
Res. dev.	=	-288.2926

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.0788426	.0312176	2.53	0.016	.0155897	.1420955
/s	.1695075	.019423	8.73	0.000	.1301527	.2088623
/mu	22.80004	.1248853	182.57	0.000	22.547	23.05308
/a	-.2488859	.094208	-2.64	0.012	-.4397694	-.0580024

2012

Nonlinear regression

Number of obs	=	40
R-squared	=	0.9877
Adj R-squared	=	0.9863
Root MSE	=	.0124868
Res. dev.	=	-241.346

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.0079644	.0183942	-0.43	0.668	-.0452695	.0293408
/s	-.0823421	.0610089	-1.35	0.186	-.206074	.0413897
/mu	22.70363	.1873157	121.21	0.000	22.32374	23.08352
/a	.2864061	.1446153	1.98	0.055	-.0068874	.5796996

2011

Nonlinear regression

Number of obs	=	39
R-squared	=	0.9817
Adj R-squared	=	0.9796
Root MSE	=	.0135222
Res. dev.	=	-229.2104

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.0386741	.0507732	-0.76	0.451	-.1417492	.0644011
/s	-.1345394	.0530582	-2.54	0.016	-.2422533	-.0268256
/mu	22.93339	.256498	89.41	0.000	22.41267	23.4541
/a	.2891808	.1187834	2.43	0.020	.0480376	.5303241

2010

Nonlinear regression

Number of obs	=	38
R-squared	=	0.9940
Adj R-squared	=	0.9933
Root MSE	=	.0083428
Res. dev.	=	-260.15

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.1269962	.0646186	1.97	0.058	-.0043247	.2583171
/s	.2016579	.0285122	7.07	0.000	.1437142	.2596016
/mu	21.83853	.1208458	180.71	0.000	21.59294	22.08412
/a	-.0900228	.2561947	-0.35	0.727	-.6106731	.4306274

2009

Nonlinear regression

Number of obs	=	37
R-squared	=	0.9905
Adj R-squared	=	0.9894
Root MSE	=	.0111907
Res. dev.	=	-231.6894

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.0463837	.0425459	-1.09	0.284	-.132944	.0401766
/s	-.1483973	.0408063	-3.64	0.001	-.2314184	-.0653763
/mu	21.18471	.1647162	128.61	0.000	20.84959	21.51983
/a	.3448667	.0680149	5.07	0.000	.2064893	.4832441

2008

```
Nonlinear regression                              Number of obs =         36
                                                  R-squared     =     0.9910
                                                  Adj R-squared =     0.9898
                                                  Root MSE      =   .0114416
                                                  Res. dev.     =  -223.9524
```

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.1657996	.1017228	-1.63	0.113	-.3730021	.041403
/s	-.2125228	.0359186	-5.92	0.000	-.2856866	-.139359
/mu	21.26323	.1568578	135.56	0.000	20.94372	21.58274
/a	-.0186214	.3990319	-0.05	0.963	-.8314227	.7941799

2007

```
Nonlinear regression                              Number of obs =         35
                                                  R-squared     =     0.9937
                                                  Adj R-squared =     0.9929
                                                  Root MSE      =   .0099645
                                                  Res. dev.     =   -227.533
```

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.2635142	.1246073	-2.11	0.043	-.5176524	-.009376
/s	-.2426576	.0304218	-7.98	0.000	-.3047033	-.1806119
/mu	21.07019	.1244037	169.37	0.000	20.81647	21.32392
/a	-.363612	.5250297	-0.69	0.494	-1.434417	.7071931

2006

```
Nonlinear regression                              Number of obs =         34
                                                  R-squared     =     0.9942
                                                  Adj R-squared =     0.9934
                                                  Root MSE      =   .0099591
                                                  Res. dev.     =  -221.1983
```

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.3227953	.1410781	-2.29	0.029	-.6109152	-.0346755
/s	-.2575012	.0295686	-8.71	0.000	-.3178883	-.1971142
/mu	20.87417	.1254064	166.45	0.000	20.61806	21.13028
/a	-.5484011	.5841683	-0.94	0.355	-1.741432	.6446298

2005

Nonlinear regression

Number of obs =	33
R-squared =	0.9949
Adj R-squared =	0.9942
Root MSE =	.0093997
Res. dev. =	-218.6411

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.4265939	.1776082	-2.40	0.023	-.7898436	-.0633443
/s	-.278259	.0294275	-9.46	0.000	-.3384449	-.218073
/mu	20.7981	.1273366	163.33	0.000	20.53767	21.05853
/a	-.9969259	.7725796	-1.29	0.207	-2.577029	.5831768

2004

Nonlinear regression

Number of obs =	32
R-squared =	0.9954
Adj R-squared =	0.9947
Root MSE =	.0090158
Res. dev. =	-214.8227

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.5101245	.202319	-2.52	0.018	-.9245563	-.0956927
/s	-.3013889	.0296738	-10.16	0.000	-.3621729	-.240605
/mu	20.53948	.1250167	164.29	0.000	20.28339	20.79556
/a	-1.276745	.8771212	-1.46	0.157	-3.073446	.5199565

2003

Nonlinear regression

Number of obs =	31
R-squared =	0.9965
Adj R-squared =	0.9960
Root MSE =	.0075589
Res. dev. =	-219.1805

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.5045976	.1754198	-2.88	0.008	-.8645293	-.1446659
/s	-.3106189	.0271468	-11.44	0.000	-.3663194	-.2549183
/mu	20.24799	.1086898	186.29	0.000	20.02497	20.471
/a	-1.301178	.7838118	-1.66	0.108	-2.909427	.3070715

SUVs and Vans

2020

Nonlinear regression

Number of obs =	48
R-squared =	0.9946
Adj R-squared =	0.9941
Root MSE =	.0060478
Res. dev. =	-358.3324

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.0993842	.0362155	2.74	0.009	.0263966	.1723718
/s	.1942485	.0181205	10.72	0.000	.157729	.230768
/mu	23.98196	.1332093	180.03	0.000	23.7135	24.25043
/a	-.1240496	.1739238	-0.71	0.479	-.47457	.2264708

2019

Nonlinear regression

Number of obs =	45
R-squared =	0.9925
Adj R-squared =	0.9918
Root MSE =	.0057867
Res. dev. =	-340.182

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.065609	.0308708	2.13	0.040	.0032641	.1279538
/s	.1993855	.0262727	7.59	0.000	.1463268	.2524442
/mu	22.90446	.1135869	201.65	0.000	22.67507	23.13385
/a	-.2847731	.1415356	-2.01	0.051	-.5706101	.0010639

2018

Nonlinear regression

Number of obs =	43
R-squared =	0.9953
Adj R-squared =	0.9949
Root MSE =	.0053573
Res. dev. =	-331.8895

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.2050062	.0596277	3.44	0.001	.0843978	.3256146
/s	.2443799	.0166175	14.71	0.000	.2107677	.277992
/mu	23.30077	.1313398	177.41	0.000	23.03512	23.56643
/a	.5311698	.3873374	1.37	0.178	-.2522941	1.314634

2017

Nonlinear regression

Number of obs	=	44
R-squared	=	0.9933
Adj R-squared	=	0.9926
Root MSE	=	.0062796
Res. dev.	=	-325.5265

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.2473155	.0830051	2.98	0.005	.0795559	.4150752
/s	.2604414	.0212144	12.28	0.000	.2175654	.3033173
/mu	23.29876	.1447033	161.01	0.000	23.0063	23.59121
/a	.7848979	.5358558	1.46	0.151	-.2981071	1.867903

2016

Nonlinear regression

Number of obs	=	41
R-squared	=	0.9931
Adj R-squared	=	0.9924
Root MSE	=	.006267
Res. dev.	=	-303.7976

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.1240437	.0457949	2.71	0.010	.0312543	.2168331
/s	.2318256	.0221446	10.47	0.000	.1869563	.2766949
/mu	22.51149	.1618631	139.08	0.000	22.18353	22.83946
/a	-.0093497	.2520916	-0.04	0.971	-.5201359	.5014365

2015

Nonlinear regression

Number of obs	=	39
R-squared	=	0.9893
Adj R-squared	=	0.9881
Root MSE	=	.0089623
Res. dev.	=	-261.2918

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.4777228	.2453211	1.95	0.060	-.0203054	.9757511
/s	.3352294	.0427924	7.83	0.000	.2483562	.4221026
/mu	23.19223	.1326572	174.83	0.000	22.92293	23.46154
/a	1.755561	1.45318	1.21	0.235	-1.194551	4.705673

2014

Nonlinear regression

Number of obs =	41
R-squared =	0.9864
Adj R-squared =	0.9849
Root MSE =	.0110303
Res. dev. =	-257.4387

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.119012	.0714715	1.67	0.104	-.0258029	.263827
/s	.2061964	.0335509	6.15	0.000	.1382158	.2741769
/mu	22.89491	.1688258	135.61	0.000	22.55284	23.23699
/a	-.0940397	.3213535	-0.29	0.771	-.7451638	.5570843

2013

Nonlinear regression

Number of obs =	41
R-squared =	0.9822
Adj R-squared =	0.9803
Root MSE =	.0137938
Res. dev. =	-239.1058

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.0828507	.0699013	1.19	0.243	-.0587828	.2244842
/s	.1662751	.0389278	4.27	0.000	.0874	.2451502
/mu	23.71347	.2685032	88.32	0.000	23.16943	24.25751
/a	-.1636465	.2753579	-0.59	0.556	-.7215746	.3942815

2012

Nonlinear regression

Number of obs =	40
R-squared =	0.9804
Adj R-squared =	0.9782
Root MSE =	.0143355
Res. dev. =	-230.3008

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.1065239	.1019132	1.05	0.303	-.1001655	.3132134
/s	.1684361	.0448068	3.76	0.001	.0775637	.2593085
/mu	24.27264	.3308481	73.36	0.000	23.60165	24.94363
/a	.026359	.495089	0.05	0.958	-.977728	1.030446

2011

Nonlinear regression

Number of obs =	39
R-squared =	0.9748
Adj R-squared =	0.9719
Root MSE =	.0148947
Res. dev. =	-221.6694

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.1494768	.1491421	1.00	0.323	-.1532978	.4522514
/s	.1892133	.0513107	3.69	0.001	.0850472	.2933795
/mu	24.3092	.3854789	63.06	0.000	23.52664	25.09177
/a	.3404898	.8952559	0.38	0.706	-1.476976	2.157956

2010

Nonlinear regression

Number of obs =	38
R-squared =	0.9789
Adj R-squared =	0.9764
Root MSE =	.0159398
Res. dev. =	-210.9462

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.0851961	.0954523	-0.89	0.378	-.2791785	.1087862
/s	-.1660904	.0534385	-3.11	0.004	-.2746904	-.0574904
/mu	22.58521	.3084991	73.21	0.000	21.95826	23.21216
/a	.1546432	.3607502	0.43	0.671	-.5784894	.8877759

2009

Nonlinear regression

Number of obs =	37
R-squared =	0.9812
Adj R-squared =	0.9789
Root MSE =	.0155945
Res. dev. =	-207.1339

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.0167623	.0320844	-0.52	0.605	-.0820386	.048514
/s	-.097442	.0584933	-1.67	0.105	-.2164476	.0215635
/mu	22.22169	.342874	64.81	0.000	21.52411	22.91928
/a	.2895924	.0433338	6.68	0.000	.2014291	.3777558

2008

Not estimated due to data anomalies.

2007

Nonlinear regression

Number of obs =	35
R-squared =	0.9761
Adj R-squared =	0.9730
Root MSE =	.0178203
Res. dev. =	-186.841

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.533028	1.261984	1.21	0.234	-1.040804	4.106861
/s	.3254073	.0567862	5.73	0.000	.2095911	.4412236
/mu	22.49111	.2869065	78.39	0.000	21.90596	23.07626
/a	8.545664	8.15954	1.05	0.303	-8.095827	25.18715

2006

Nonlinear regression

Number of obs =	34
R-squared =	0.9817
Adj R-squared =	0.9793
Root MSE =	.0155449
Res. dev. =	-190.9214

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	2.733868	2.15049	1.27	0.213	-1.658018	7.125754
/s	.370439	.0552153	6.71	0.000	.2576742	.4832038
/mu	22.63239	.2523509	89.69	0.000	22.11702	23.14776
/a	16.3904	14.42688	1.14	0.265	-13.07322	45.85402

2005

Nonlinear regression

Number of obs =	33
R-squared =	0.9817
Adj R-squared =	0.9792
Root MSE =	.0150087
Res. dev. =	-187.7565

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	3.898165	3.347167	1.16	0.254	-2.947561	10.74389
/s	.4064602	.0624316	6.51	0.000	.2787731	.5341472
/mu	22.49023	.2685159	83.76	0.000	21.94105	23.0394
/a	25.05295	23.5523	1.06	0.296	-23.11692	73.22282

2004

Nonlinear regression

Number of obs =	32
R-squared =	0.9862
Adj R-squared =	0.9843
Root MSE =	.0124497
Res. dev. =	-194.1688

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	4.909004	3.667852	1.34	0.192	-2.604249	12.42226
/s	.4382331	.0568922	7.70	0.000	.3216948	.5547714
/mu	22.38906	.241193	92.83	0.000	21.895	22.88313
/a	33.49258	27.02451	1.24	0.226	-21.86463	88.84979

2003

Nonlinear regression

Number of obs =	29
R-squared =	0.9911
Adj R-squared =	0.9897
Root MSE =	.0096883
Res. dev. =	-190.942

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	4.31248	2.528892	1.71	0.101	-.8958696	9.52083
/s	.4427467	.0461578	9.59	0.000	.3476829	.5378105
/mu	22.0405	.1940494	113.58	0.000	21.64085	22.44015
/a	31.53653	20.0203	1.58	0.128	-9.696051	72.7691

Pickups

2020

Nonlinear regression

Number of obs =	44
R-squared =	0.9898
Adj R-squared =	0.9887
Root MSE =	.0058895
Res. dev. =	-331.1701

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.1723063	.0943201	1.83	0.075	-.0183217	.3629342
/s	.2072199	.0282986	7.32	0.000	.1500262	.2644135
/mu	29.02705	.21582	134.50	0.000	28.59086	29.46324
/a	1.162243	.9878937	1.18	0.246	-.8343642	3.158851

2019

Nonlinear regression

Number of obs	=	40
R-squared	=	0.9870
Adj R-squared	=	0.9855
Root MSE	=	.0055997
Res. dev.	=	-305.5022

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.6176012	.3511015	1.76	0.087	-.0944656	1.329668
/s	.2777124	.0318247	8.73	0.000	.213169	.3422558
/mu	29.34375	.2309905	127.03	0.000	28.87528	29.81222
/a	8.376502	5.398538	1.55	0.130	-2.572241	19.32524

2018

Nonlinear regression

Number of obs	=	43
R-squared	=	0.9938
Adj R-squared	=	0.9932
Root MSE	=	.0044778
Res. dev.	=	-347.312

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.1707535	.0726611	2.35	0.024	.0237825	.3177244
/s	.2212053	.0225825	9.80	0.000	.175528	.2668826
/mu	28.17628	.1592773	176.90	0.000	27.85411	28.49845
/a	1.051402	.7545357	1.39	0.171	-.4747903	2.577595

2017

Nonlinear regression

Number of obs	=	39
R-squared	=	0.9931
Adj R-squared	=	0.9923
Root MSE	=	.005074
Res. dev.	=	-305.6666

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.069923	.0466847	1.50	0.143	-.0248521	.164698
/s	.1658175	.029837	5.56	0.000	.1052451	.2263898
/mu	28.64269	.1903434	150.48	0.000	28.25628	29.02911
/a	.1386153	.4291921	0.32	0.749	-.7326909	1.009922

2016

Nonlinear regression

Number of obs =	39
R-squared =	0.9945
Adj R-squared =	0.9938
Root MSE =	.0040815
Res. dev. =	-322.6441

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.2583476	.1007258	2.56	0.015	.0538632	.4628319
/s	.2437667	.0219116	11.12	0.000	.1992837	.2882497
/mu	27.46822	.1616322	169.94	0.000	27.14009	27.79635
/a	2.324941	1.245974	1.87	0.070	-.2045199	4.854403

2015 (The data for 2015 was checked and appears to contain anomalies.)

Nonlinear regression

Number of obs =	39
R-squared =	0.9715
Adj R-squared =	0.9692
Root MSE =	.0103089
Res. dev. =	-249.275

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	-.0000966	.0000125	-7.74	0.000	-.0001219	-.0000713
/s	-.0207004	.0000402	-514.34	0.000	-.020782	-.0206188
/mu	27.24647	.3715951	73.32	0.000	26.49284	28.0001
/a	.0817211	.	.	.	.	.

2014

Nonlinear regression

Number of obs =	42
R-squared =	0.9920
Adj R-squared =	0.9912
Root MSE =	.0063102
Res. dev. =	-310.5223

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.489078	.1880211	2.60	0.013	.1084492	.8697069
/s	.25214	.020491	12.30	0.000	.2106583	.2936218
/mu	28.77746	.259906	110.72	0.000	28.2513	29.30361
/a	3.845631	1.803215	2.13	0.039	.1952133	7.496049

2013

Nonlinear regression

Number of obs =	41
R-squared =	0.9978
Adj R-squared =	0.9976
Root MSE =	.0040542
Res. dev. =	-339.5116

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.2600273	.0405661	6.41	0.000	.1778327	.342222
/s	.203669	.0063686	31.98	0.000	.1907651	.216573
/mu	29.89107	.1722634	173.52	0.000	29.54204	30.24011
/a	1.268124	.3126969	4.06	0.000	.6345401	1.901709

2012

Nonlinear regression

Number of obs =	40
R-squared =	0.9979
Adj R-squared =	0.9977
Root MSE =	.0039673
Res. dev. =	-333.0739

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.2461272	.0414503	5.94	0.000	.162062	.3301923
/s	.1941805	.007491	25.92	0.000	.178988	.2093729
/mu	29.60037	.2086093	141.89	0.000	29.17729	30.02345
/a	1.290452	.3343239	3.86	0.000	.6124121	1.968493

2011

Nonlinear regression

Number of obs =	39
R-squared =	0.9958
Adj R-squared =	0.9953
Root MSE =	.0051608
Res. dev. =	-304.3429

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.3133556	.0597436	5.25	0.000	.1920696	.4346416
/s	.215844	.0092414	23.36	0.000	.197083	.234605
/mu	28.83097	.2970968	97.04	0.000	28.22784	29.43411
/a	2.001025	.5286852	3.78	0.001	.9277369	3.074313

2010

Nonlinear regression

Number of obs =	38
R-squared =	0.9966
Adj R-squared =	0.9962
Root MSE =	.0051713
Res. dev. =	-296.499

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.4715493	.117443	4.02	0.000	.2328764	.7102222
/s	.2345474	.013218	17.74	0.000	.2076852	.2614096
/mu	27.28224	.1795064	151.98	0.000	26.91744	27.64704
/a	2.982657	.9688832	3.08	0.004	1.01365	4.951665

2009

Nonlinear regression

Number of obs =	33
R-squared =	0.9973
Adj R-squared =	0.9969
Root MSE =	.0049844
Res. dev. =	-260.5093

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.3712787	.148407	2.50	0.018	.0677523	.6748051
/s	.2164955	.0212465	10.19	0.000	.1730415	.2599496
/mu	27.4057	.1807166	151.65	0.000	27.03609	27.77531
/a	2.248836	1.184636	1.90	0.068	-.1740164	4.671689

2008

Nonlinear regression

Number of obs =	36
R-squared =	0.9972
Adj R-squared =	0.9969
Root MSE =	.0045169
Res. dev. =	-290.8713

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	.859072	.2599572	3.30	0.002	.3295565	1.388588
/s	.2774262	.0178516	15.54	0.000	.2410637	.3137888
/mu	26.61169	.1835473	144.99	0.000	26.23782	26.98556
/a	6.448917	2.264939	2.85	0.008	1.835388	11.06245

2007

Nonlinear regression

Number of obs =	35
R-squared =	0.9977
Adj R-squared =	0.9974
Root MSE =	.004222
Res. dev. =	-287.6425

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.111097	.3194494	3.48	0.002	.4595753	1.762618
/s	.3008894	.0170787	17.62	0.000	.2660572	.3357216
/mu	26.07493	.1821526	143.15	0.000	25.70343	26.44643
/a	8.3337	2.722929	3.06	0.005	2.780249	13.88715

2006

Nonlinear regression

Number of obs =	34
R-squared =	0.9979
Adj R-squared =	0.9977
Root MSE =	.0040955
Res. dev. =	-281.622

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.114714	.3262234	3.42	0.002	.4484764	1.780951
/s	.3058258	.0175222	17.45	0.000	.2700406	.341611
/mu	25.68082	.1787994	143.63	0.000	25.31566	26.04597
/a	8.09762	2.71228	2.99	0.006	2.558407	13.63683

2005

Nonlinear regression

Number of obs =	32
R-squared =	0.9973
Adj R-squared =	0.9969
Root MSE =	.0046282
Res. dev. =	-257.4981

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.163149	.4071715	2.86	0.008	.329096	1.997202
/s	.3156541	.0212138	14.88	0.000	.2721997	.3591086
/mu	25.26087	.1957748	129.03	0.000	24.85984	25.66189
/a	8.760985	3.533103	2.48	0.019	1.52375	15.99822

2004

Nonlinear regression

Number of obs	=	32
R-squared	=	0.9972
Adj R-squared	=	0.9968
Root MSE	=	.0045302
Res. dev.	=	-258.8687

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.07827	.3401553	3.17	0.004	.3814935	1.775047
/s	.3209591	.0196095	16.37	0.000	.2807909	.3611273
/mu	24.79162	.1789228	138.56	0.000	24.42512	25.15813
/a	8.230286	3.026792	2.72	0.011	2.030183	14.43039

2003

Nonlinear regression

Number of obs	=	30
R-squared	=	0.9971
Adj R-squared	=	0.9967
Root MSE	=	.0045587
Res. dev.	=	-242.5996

scraprate	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
/k	1.08173	.3290791	3.29	0.003	.4052982	1.758162
/s	.3275136	.0198585	16.49	0.000	.2866938	.3683334
/mu	24.01296	.1853162	129.58	0.000	23.63204	24.39388
/a	8.579924	3.017303	2.84	0.009	2.377769	14.78208