

Vehicle Lifetime and Scrappage Behavior: Trends in the U.S. Used Car Market

Antonio Bento, Kevin Roth,** and Yiou Zuo****

ABSTRACT

Using national data on vehicles in operation, we examine long-run changes in scrappage patterns in passenger cars and light trucks in the United States between 1969 and 2014. We find that the average lifetime for passenger cars has increased from 12.2 to 15.6 years between 1970s and the 2000s. Our central estimate of the elasticity of scrappage with respect to vehicle prices is -0.4 , which is substantially different than values adopted in simulation models. These estimates imply that many policies aimed at reducing gasoline consumption, including Corporate Average Fuel Economy standards and gasoline taxes may produce changes in the used vehicle market that are different than prior studies suggest. We also note that consumer scrappage behavior seems to respond more strongly to changes in vehicle price than changes in gasoline price than standard theory would predict.

Keywords: Automobiles, Scrappage, Technology Innovation, Pollution Controls, Used Vehicles

<https://doi.org/10.5547/01956574.39.1.aben>

1. INTRODUCTION

Many public policies target the efficiency or fuel economy of durable goods. The effectiveness of such a policy will depend in part on the turnover of the existing stock of goods and the expected lifetime of that good. In the case of automobiles, longer vehicle lifetimes may make that task more difficult, and if replacement costs increase, the policy may make individuals hold the older, inefficient goods longer (Gruenspecht, 1982). While this paper deals with the case of cars, this concern also exists for appliances, heating and cooling equipment, and homes. These concerns are particularly important for the recent increase of fuel economy of new vehicles using the Corporate Average Fuel Economy (CAFE) standard in the United States. Vehicle lifetimes are also important for large-scale scrappage programs and may be influenced by energy prices. Without estimates of the average vehicle lifetime, and the elasticity of scrappage with respect to vehicle price, imperfect assumptions must be made to model the effects of these policies on the used car market. It is largely unknown what effect such assumptions have on the outcomes of public policy or the value consumers assign durable goods.

* Corresponding author. Sol Price School of Public Policy and Department of Economics, Ralph and Goldy Lewis Hall 214, University of Southern California, Los Angeles, CA 90089 (213) 821-1762. E-mail: abento@usc.edu.

** Kevin Roth, Department of Economics, University of California, Irvine, 3151 Social Science Plaza, Irvine, CA 92697. E-mail: kroth1@uci.edu.

*** Yiou (Scarlett) Zuo, CelsiusPro AG, Seebahnstrasse 85, CH-8003 Zurich, Switzerland. E-mail: scarlett.zuo@gmail.com.

Our study fills this gap in the literature and has three goals: 1) to examine vehicle lifetime and how it has changed, 2) to estimate the scrappage elasticity with respect to vehicle price, and 3) to explore the implications of these parameters for policies like CAFE standards and gasoline taxes, and for the debate over the value consumers place in fuel efficiency in durable goods known as the energy efficiency paradox.

Our primary findings are that vehicle lifetime has increased, nearly 27% from 1969 to 2014, and that the scrappage elasticity with respect to vehicle price is low, ranging from -0.01 to -0.51 with a value of -0.36 in our preferred specification.¹ Broadly speaking researchers have paid little attention to how vehicle lifetime changes might affect their results and what scrappage elasticity with respect to vehicle price is best suited to the evaluation at hand. Prior research has relied on assumed values that differ substantially from the values estimated here. In cases such as the EPA and NHTSA evaluation of CAFE, this elasticity is assumed to be zero and vehicle lifetimes are assumed to be constant (DOT, 2012). Simulations by economists (e.g. Bento, Goulder, Jacobsen, and Von Haefen, 2009; Jacobsen 2013) have instead adopted the value of -3 from work by Alberini, Harrington, and McConnell (1998). Although not directly estimating this parameter, Alberini et al. (1998) estimate the supply of scrappage using a temporary scrappage incentive. Using an estimate of this parameter from a temporary policy seems likely to incorporate significant inter-temporal substitution and therefore may not be optimal for analysis of permanent policies like gasoline taxes or CAFE.

We demonstrate the importance of these parameters for three key areas of policy analysis: CAFE standards, gasoline taxes, and the energy efficiency paradox. First we show that outdated estimates of vehicle lifetime will be overly optimistic about the pace at which new vehicle regulation like CAFE can affect the used car market. For gasoline taxes we show, using the results of Bento, Goulder, Jacobsen, and von Haefen, (2009), that our elasticity reduces used car scrappage by 565,000 vehicles compared with the elasticity of -3 used in that paper, but using an elasticity of zero, would under-predict this benefit by 70,000 vehicles. Our finding that scrappage is inelastic with respect to operating cost suggests that prior studies may have been slightly more optimistic than warranted about the efficiency of gasoline taxes in the scrappage market. Finally we show that changes in vehicle lifetime may account for up to 7% of the undervaluation in future gasoline costs of vehicles that has concerned policy makers in recent years (Helfand and Wolverton, 2010; Greene 2010). We also compare the scrappage responses due to changes in vehicle prices and gasoline prices and find that our estimates generally suggest they undervalue changes in gasoline price changes. Our estimates suggest consumers may only be recognizing between \$0.22 and \$0.96 of a \$1 increase in future gasoline cost.² These estimates lie within in the range of other studies of that use alternative methodologies.

Our paper complements a large body of literature on scrappage behavior. Several studies have focused on the role technology (Walker, 1968; Greene and Chen, 1981), climate (Hamilton and Macauley, 1999) and gasoline prices (Li, Timmins, and von Haefen, 2009; Jacobsen and van Benthem, 2015) have on scrappage behavior. Other studies using simulation have examined how policies such as CAFE and gasoline taxes can influence vehicle prices and therefore, intentionally or unintentionally, affect the lifetime of used vehicles (Gruenspecht, 1982; Bento, et al. 2009; Jacobsen

1. It is noteworthy that our estimate of this elasticity is remarkably similar to that estimated using an alternate strategy in parallel research by Jacobsen and van Benthem (2015).

2. A scrappage elasticity with respect to vehicle price in the range of -3 suggests a valuation of \$0.15.

2013).³ Another literature has focused on the response to policies directly targeting used vehicles, including inspection and maintenance programs (Ando, McConnell, and Harrington, 2000a), national vehicle retirement programs such as Cash-for-Clunkers (Miravete and Moral, 2011; Li, Linn, and Spiller, 2013; Schiraldi, 2011), and local scrapage subsidies targeted to a specific state or city (Alberini, Harrington, and McConnell, 1995; Hahn, 1995; Alberini et al. 1998; Adda and Cooper, 2000).⁴ We contribute to this literature by estimating the parameters needed to accurately model the used vehicle market and their implications for policy analysis.

The rest of the paper is arranged as the following. Section 2 describes the data and the empirical strategy, section 3 presents results, and section 4 discusses the policy implications and section 5 concludes.

2. BASIC MODEL AND DATA

2.1 Basic Model

The econometric model is based on earlier models of the automobile scrapage ultimately derived from Walker (1968). Vehicles are scrapped when the cost of repairing and operating a vehicle makes its economic value less than zero. The first step of the model fits a logistic curve to mean scrapage rates at each age, which largely captures engineering scrapage arising from mechanical failure.⁵ The second step explains deviations from the mean scrapage function estimated in the first step, generally resulting from cyclical factors such as changes in vehicle price or maintenance and repair costs. Vehicle lifetime can be increased by investing in maintenance and repair, but the owner will not invest in a car whose economic value is less than zero.

The first step uses nonlinear least squares to fit a hazard function of scrapage rates by vehicle age to a logistic curve. The logistic function, which has been shown to fit scrapage data well (Walker, 1968; Park, 1977; Greene and Chen, 1981; Feeney and Cardebring, 1988), is given by:

$$M_{am} = \frac{1}{L + B * e^{(-k*a)}} + \epsilon_{am} \tag{1}$$

where a is age of a vehicle in years and m is the model year. M_{am} is the scrapage rate of vehicles at age a for model year m .⁶ We estimate the parameters $L, B,$ and k to capture the shape of the logistic function. L controls the level of the ‘asymptotic scrapage rate.’ If we take the limit of equation (1) as age approaches infinity, the function asymptotes to $1 / L$.⁷ The error term,

3. Others have examined CAFE but omit scrapage or the used car market (Klier and Linn, 2012; Goldberg, 1998). One implication of our findings is that although important general equilibrium price effects remain in the used vehicle market, they are perhaps less important than would be suggested by alternative parameters.

4. Ando et al. (2000a) find I/M programs are limited in their ability to reduce emissions due to costs. Miravete and Moral (2011) find Cash-for-Clunkers programs can accelerate the adoption of new technology while Li, Linn and Spiller (2013) find it is an expensive method to improve overall fuel economy. Hahn (1995) estimates a scrapage curve from a local policy in California, while Alberini et al. (1998) examine scrapage resulting from a program in Delaware. Sandler (2012) finds adverse selection played a major role in the high initial scrapage rates for a scrapage policy in San Francisco.

5. Parks (1977) describes engineering scrapage as the failure of vehicle components, which gradually become increasingly expensive as the vehicle ages. The rate at which these failures occur depends on the durability of the vehicle, which may be influenced by decisions made by the manufacturer or the environment where the vehicle drives.

6. Precisely M_{at} is the proportion of vehicles surviving a years that are scrapped, on the average, prior to their $(a + 1)$ th birthday. The model year, m , is set to zero for 1969 to aid in comparability across regressions.

7. B and k determine when the scrapage rate starts to increase rapidly and enter the exponential and mature phases. Ceteris Paribus, increasing B (or decreasing k) postpones when the exponential and mature phases occur.

ε_{at} , is assumed to be normally distributed. This function form has several advantages. It controls for the nonlinearity in scrappage rates, but it allows for flexibility in the asymptotic scrappage rate and the location of inflection points. For example using a standard logit would force L to be 1 implying that the asymptotic scrappage rate would be 100%. Conversely a nonparametric or semi-parametric model like Kaplan Meier or Cox Proportional-Hazard model cannot project hazard rates for vehicles older than we observe in our data.⁸ In the appendix B we do, however, examine several alternate functional forms that explicitly control for model year of the vehicle with more flexibility.

This estimation allows us to calculate vehicle lifetime. To calculate the average lifetime for vehicles, LT , we follow Greene and Chen (1981):

$$LT = \sum_a a * \widehat{M}_a * \prod_{i=1}^{a-1} (1 - \widehat{M}_i) \quad (2)$$

where a is vehicle age and \widehat{M}_a is predicted scrappage rate from equation (1). $(1 - \widehat{M}_i)$ is the predicted survival rate of vehicles aged i , hence $\widehat{M}_a * \prod_{i=1}^{a-1} (1 - \widehat{M}_i)$ gives the probability of a vehicle being scrapped at age a .⁹

The second step captures the deviations from the predicted average scrappage rate in a given calendar year:

$$S_t = \alpha_0 R_t^\alpha P_t^\beta K_t M_t^* \quad (3)$$

where,

$$M_t^* = \sum_{a=1}^{14} \frac{K_{at}}{K_t} \widehat{M}_{at} \quad (4)$$

Equation (3) defines the structural relationship of total scrappage to both engineering and cyclical factors. S_t is the total number of vehicles scrapped in calendar year t across all ages. R_t is the turnover rate of vehicle ownership. This term is traditionally included because the decision to scrap a vehicle is made by used vehicle dealers and will be subject to the volume of trade-in vehicles each year.¹⁰ P_t is the used vehicle price ratio index (the used vehicle price divided by the maintenance and repair costs), capturing the value of holding a vehicle, and K_t is the total number of vehicles in operation in calendar year t . M_t^* is the predicted scrappage rate arising from engineering factors, for the total population, which is weighted using the age distribution of vehicles in year calendar t . It is calculated based on equation (4) and is a weighted average of the age-specific scrappage rates, M_{am} , estimated using equation (1). The weights used are the number of vehicles of age a in calendar year t , K_{at} , over the total number of vehicles in calendar year t . We note that the gasoline price is absent from this regression. If gasoline prices affect scrappage rates it will be because they reduce the economic value of a vehicle and reduce its price, a topic that has been studied extensively

8. The Cox Proportional-Hazard model also does not calculate a baseline hazard rate which does not allow for calculation of vehicle lifetime. Kaplan Meier fits a survival function rather than a hazard but, like the Cox Proportional-Hazard Model, it does not allow for the projection of survival rates after 14 years of age.

9. Note that this value is not identical to the average age of a vehicle on the road. Assuming identical starting quantities of vehicles in year 0 this would be $\sum_a a * \prod_{i=1}^{a-1} (1 - \widehat{M}_i)$. This value will typically be younger than the average vehicle lifetime vehicle.

10. Using the number of new vehicles entering the system is the traditional proxy for turnover rate, which has the useful interpretation that if a new vehicle entering the system pushes an old vehicle to be scrapped α will be 1. We also examine GDP as an alternate proxy for turnover rate in some robustness checks.

in the energy efficiency paradox literature (Helfand and Wolverton, 2010; Greene 2010). Therefore any effect this has on scrapage should be captured by used vehicle prices. We do however include gasoline prices in robustness checks and examine the interaction these might have with fuel economy in the appendix.¹¹

To empirically estimate equation (3) we transform the equation using logarithms. This allows us to estimate this second step using ordinary least squares (OLS). In our central specification, this equation becomes:

$$\ln \frac{S_t}{K_t} - \ln(M_t^*) = const + \alpha * \ln(R_t) + \beta * \ln(gp_t) + \epsilon_t \quad (5)$$

The coefficient of interest is β , which measures the elasticity of scrapage with respect to vehicle price. This elasticity is important for simulation models of the used vehicle market where scrapage adjusts to changes in vehicle price. The first term on the left hand side, $\ln \frac{S_t}{K_t}$, is the log of the observed scrapage rate in calendar year t , the second term, $\ln(M_t^*)$, is the predicted scrapage rate from engineering factors related to aging.¹² The residual scrapage rate is the difference of these terms. It is explained by a constant, a proxy for turnover rate, and the vehicle price ratio index. Finally we assume the error term, ϵ_t , is normally distributed and Newey-West standard errors are estimated in all regressions.¹³ To address the possibility that vehicle price is endogenous we examine the ramp up of the CAFE standard as an instrument in section 3.3. We use the number of new vehicles as a proxy for turnover rate following prior literature but it may be endogenous with the scrapage rate and therefore we test an alternate proxy, GDP, which is less likely to suffer from endogeneity in section 3.1.

We also estimate the scrapage elasticity with respect to gasoline price by modifying the second equation as follows:

$$\ln \frac{S_t}{K_t} - \ln(M_t^*) = const + \alpha * \ln(R_t) + \beta * \ln(gp_t) + \epsilon_t \quad (6)$$

This equation is identical to equation (5) except $\ln(gp_t)$, gasoline price in calendar year t , is substituted for the vehicle price ratio index.¹⁴

2.2 Data

The data used for our regressions primarily comes from public data on counts of automobiles collected by Ward's Automotive Yearbooks in calendar years 1981–2002 and private data collected by R.L. Polk from 2002–2014. These two data sources, covering model years 1969–2014, provide annual counts of U.S. passenger cars and light trucks by model year. While covering a long

11. Changes in gasoline price will also change the composition of vehicle fuel economy in the cars on the road, a question analyzed in Jacobsen and van Benthem (2015). Our focus is on the change in aggregate scrapage rather than these changes in composition.

12. Because the estimates from the first step only enter as dependent rather than independent variables, the uncertainty of those estimates will not affect the standard errors of the second step parameters.

13. See Appendix B for further discussion of the advantages of the two-step approach adopted here relative to other potential models.

14. We use the gasoline price index to be consistent across the estimation of the two nonlinear specifications, although using real gasoline price does not significantly alter the estimates.

time period, these data only distinguish between passenger cars and light trucks and do not provide model or class counts.

These sources report the number of vehicles in operation as of July 1st for 14 model years, allowing us to calculate scrappage rates for a model year at each age. For example in 1990 Ward's provides the count of passenger cars and light trucks in operation for model years 1976 through 1990.¹⁵ Population counts from the 1991 Ward's Yearbook allow for calculation of the number of vehicles that were scrapped in the interim. The benefit of data from this source are that they available at earlier years allowing for an examination of change, they are only for aggregate categories of car and truck and not for sub-classes (for example SUV, pickup truck etc). The scrappage rate is calculated as the number of vehicles removed from operation at age a divided by the number of vehicles of that model year in operation at the previous age, $a-1$. The long time span enables us to compare with previous studies (Walker, 1968; Greene and Chen, 1981) and establish how vehicle lifetimes and scrappage elasticity with respect to vehicle price have changed over time.¹⁶

The censorship of population counts beyond 14 years of age limits our ability to observe the tail of the scrappage curve, and we infer scrappage rates beyond 14 years from the pattern established before this cut-off based on the functional forms of scrappage established in this literature. Scrappage rates of very young vehicles are also removed from analysis. Occasionally, vehicle counts increase in the first year of vehicle lifetime implying a negative scrappage rate. New vehicle models tend to enter the market ahead of the calendar year, and are often sold through the next calendar year; therefore, vehicles populations for the first year are removed from our analysis allowing us to calculate scrappage rates for ages 1 through 14.¹⁷ This results in 944 scrappage rate observations for cars and light trucks.¹⁸ Initially to examine the changes in vehicle lifetime we divide our data into three groups of model years 1969–1979, 1980–1987 and 1987–2014. The first two groups are estimated separately around introduction of the CAFE standard and the final group is estimated with the privately held Polk data. A fourth vehicle lifetime estimation combines all data sources and years. Robustness checks with flexible parametric assumptions are estimated in Appendix B. Vehicle price elasticity regressions also use data from all sources and years.

Table 1 shows average scrappage rates of cars and trucks at various ages. These are calculated for three sets of model years: 1969–1979, 1980–1987, and 1987–2014 to examine changes in vehicle lifetime. Previous studies (Walker, 1968; Park, 1977; Greene and Chen, 1981; Feeney and Cardebring, 1988) have used the logistic curve to fit these scrappage rates because they grow slowly for the first several years, increase rapidly around six years of age and finally after ten years begin to asymptote towards a high, but stable level. The fact that the yearly scrappage rate asymptotes at levels from 7% to 20%, rather than 100%, explains the presence of some extremely old vehicles in

15. As noted by Davis and Kahn (2010) used cars could not be sold to Mexico, a potentially confounding factor, until NAFTA removed these trade restrictions in 2005.

16. Another source occasionally used in this literature, the National Household Transportation Survey is not usable in this analysis for two reasons. First the survey is not annual implying that scrappage rates for a given model year would require significantly more structure to estimate. Second the survey contains only household vehicle holdings. Rental or corporate vehicles may distort those vehicle counts as the vehicle ages.

17. For example, a 2000 model year vehicle may appear in calendar year 1999 and may still be sold as new in 2001. Scrappage for extremely new vehicles are usually very low, due only to serious accidents. Therefore, the data we observe for 0 and 1-year-old vehicles often change mostly due to the sales of these inventories. Including these first two years does not significantly change the point estimates of our regressions but does increase the standard errors in some specifications.

18. Some calendar years are missing vehicles 14 years of age. Total car observations are 481 and trucks have 463 observations.

Table 1: Percent Scrapage Rate by Age for Passenger Cars and Light Trucks

Model Year	Passenger Cars			Light Trucks		
	1969–1979	1980–1987 ^a	1987–2014 ^b	1969–1979	1980–1987 ^a	1987–2014 ^b
Vehicle Age						
2	1.51%	0.61%	0.87%	0.78%	0.99%	0.64%
3	1.84%	1.45%	0.92%	1.32%	0.65%	0.69%
4	2.03%	1.15%	1.30%	1.27%	1.10%	0.96%
5	2.56%	1.74%	1.62%	1.61%	1.27%	1.13%
6	3.79%	3.28%	2.11%	2.20%	1.99%	1.37%
7	5.30%	3.94%	2.56%	2.99%	2.23%	1.56%
8	7.17%	5.32%	3.38%	3.75%	2.73%	2.06%
9	9.40%	6.86%	4.24%	4.40%	3.71%	2.74%
10	11.75%	8.57%	5.59%	5.85%	4.99%	4.08%
11	13.84%	10.13%	6.97%	5.33%	4.79%	5.09%
12	15.65%	11.77%	8.84%	6.57%	6.86%	5.99%
13	17.18%	13.13%	10.64%	7.08%	6.54%	6.94%
14	18.29%	14.56%	12.78%	7.53%	9.16%	8.07%

Notes: The table presents average scrapage rates from passenger cars and light trucks in several time periods at ages 2 to 14 years old. Because inventories are not entirely sold until the second year the true base of cars is established at age 1 rather than age 0.

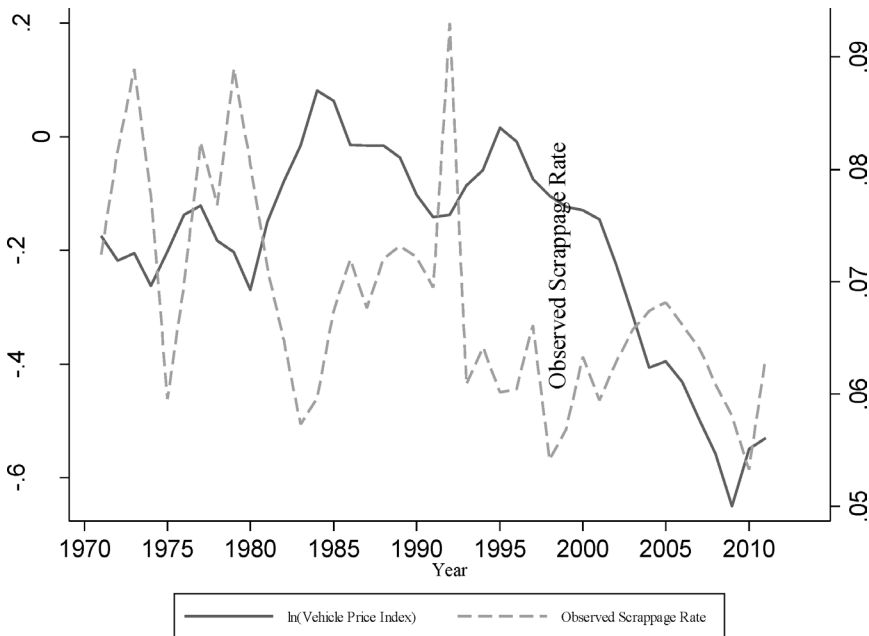
^a Uses data exclusively from Wards Automotive Yearbooks.

^b Uses data exclusively from Polk/HIS, after 1987.

the current fleet.¹⁹ Table 1 also demonstrates that scrapage rates for trucks are consistently lower at any given age than they are for cars. These raw scrap rates also show that more recent model years are more durable, possibly due to technology improvements, and have lower scrapage rates.

We use a variety of data from other sources to construct key variables that affect scrapage rates. To examine the scrapage elasticity with respect to vehicle price, we require data not only on used vehicle prices, but also on maintenance and repair costs. These variables will affect the reservation value for scrapping a vehicle. Studies that look to Walker (1968) create a vehicle price ratio index by dividing a used vehicle price index by a maintenance and repair cost index. This assumes that these variables will have equal but opposite effects on scrapage: as used vehicle prices increase or maintenance and repair costs decrease, consumers will scrap vehicles at a lower rate. Our main specification also imposes this restriction but we examine this assumption in our robustness checks by including each of the indexes individually. The used vehicle price index and the motor vehicle maintenance and repair cost index, gathered by the Bureau of Labor Statistics (BLS), are subcategories used in the calculation of the Consumer Price Index. Both indexes are seasonally adjusted with the base period of 1982 to 1984. In the construction of the used vehicle price index the BLS

19. The small but increasing number of extremely old vehicles on the road can also be noted from subsequent NHTS surveys. In the 1995 NHTS, for example, 1.6% vehicles are over 25 years old. This number grows to 3.1% in 2001 NHTS and 3.7% in the 2009 NHTS.

Figure 1: $\ln(\text{Vehicle Price Index})$ and $\ln(\text{Residual Scrappage Rates})$ 

Notes: The figure plots the log of the vehicle price index, which is the ratio of the used vehicle price index and the motor vehicle maintenance and repair cost index, gathered by the Bureau of Labor Statistics. The ‘Observed Scrappage Rate’ is the percentage of all vehicles in operation in a given calendar year that are removed from operation.

averages vehicle auction prices from National Automobile Dealers Association (NADA) and prices published by Kelly Blue Book.²⁰

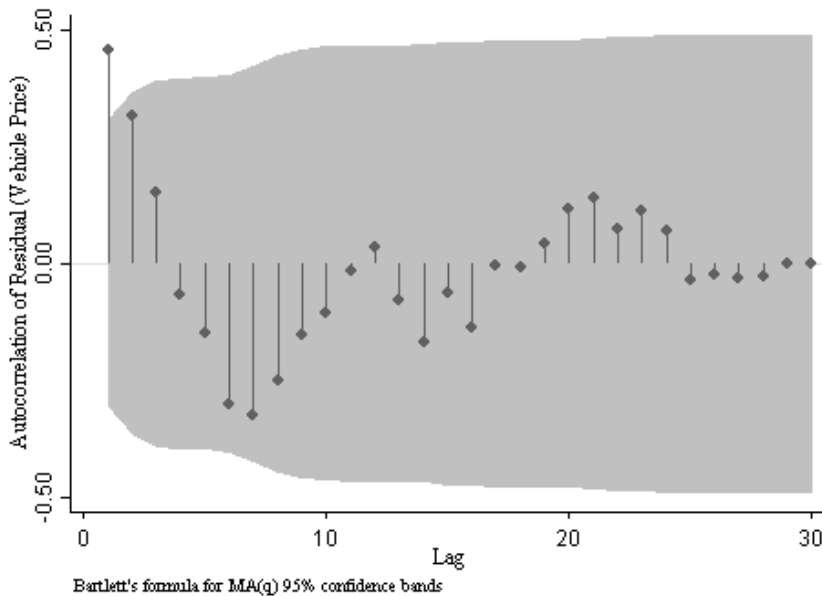
Figure 1 plots the logged vehicle price ratio index and the aggregate observed scrappage rate from 1970 to 2012. There is a pronounced decrease in vehicle scrap rates after the 1980s. Consistent with Gruenspecht (1982), CAFE standards would have raised the price of new vehicles causing substitution towards used vehicles, in turn increasing the price of used vehicles. We explore the use of this demand shift as an instrument for used vehicle prices in section 3.3.

As noted by Walker (1968) vehicle turnover rate may affect scrappage rates and will depend on many factors including credit availability, income, and assets. Following this literature we proxy for the rate of turnover with the ratio of new vehicle registrations to total vehicle ownership. The total number of new vehicles is taken as the number of age-zero vehicles from Ward’s Automotive Yearbooks. The total number of vehicles in operation for each calendar year is provided by Ward’s Motor Vehicle Facts and Figures. It is possible that this proxy for turnover rate is endogenous. We therefore examine another proxy for turnover rate: annual GDP, taken from International Financial Statistics.

Annual real gasoline price data are collected from the Department of Energy. For robustness tests, we use the annual average U.S. steel scrap price per metric ton from the U.S. Geological Survey,²¹ the new vehicle price index collected by the BLS, and U.S. imports vehicle sales data from

20. For more detail see Pashigian (2001).

21. 1969–1998 data are from: http://minerals.usgs.gov/minerals/pubs/metal_prices/, http://minerals.usgs.gov/minerals/pubs/commodity/iron_&_steel_scrap/360798.pdf. And 1999–2001 data are from http://minerals.usgs.gov/minerals/pubs/commodity/iron_&_steel_scrap/index.html#myb, http://minerals.usgs.gov/minerals/pubs/commodity/iron_&_steel_scrap/360303.pdf.

Figure 2: Autocorrelation Plot of Vehicle Price Regression Residuals

Ward's yearbooks. The percentage of vehicles imported is constructed by dividing these values by the number of new vehicles sales. Further details, including descriptive statistics, can be found in Appendix Table A.1.

2.3 Time Series Properties of the Data

In the second step of the regression, standard tests fail to reject the presence of a unit-root for scrappage rates as well as vehicle prices. With 45 data points, unit-root tests of the residuals are often marginal and sensitive to specification. A Dickey-Fuller test strongly suggests the residuals are stationary above the 1% level, while the Elliot-Rothenberg-Stock test cannot reject a unit-root.²² Autocorrelation plots are displayed in Figures 2 and 3. While the evidence is not decisive for stationary or nonstationary residuals, the cyclicity of the residuals in these figures can be the result of an AR(2) process (Harvey, 1981).

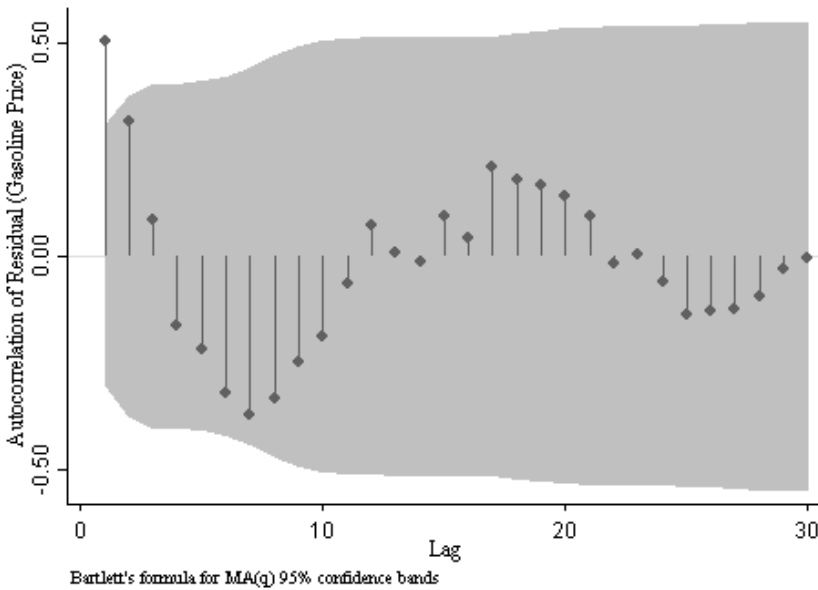
In our basic specifications, we view the model as a cointegrated model, as is implicitly assumed by prior work in this area. Although not traditionally modeled as an autoregressive process, we address the possibility that the residuals are non-stationary with an AR(2) model.

3. RESULTS

3.1 Scrappage by Vehicle Age

Table 2 reports the results of estimation of equation (1), which fits a logistic curve to scrappage rates by age. The first panel of Table 2 shows the results for passenger cars across three

22. The estimated value of rho in AR-1 and AR-2 regressions is less than 0.48, which cannot be judged as statistically distinct from 1 with a sample size of 45 years' worth of data.

Figure 3: Autocorrelation Plot for Gasoline Price Regression Residuals

periods as well as the comparison with model years 1966 through 1977 estimated by Greene and Chen (1981) and post-World War II models estimated by Walker (1968). Figure 4 displays these estimated scrappage rate curves for passenger cars for various model years. Figure 4 and Table 2 show that the asymptotic scrappage rate has been declining over the last century and that scrappage rates at a given age have generally decreased for more recent vehicle model years, particularly after age 6 when larger number vehicles begin to be scrapped. The lifetime for passenger cars has increased from ten years for post-war cohort, to 12.25 for the 70s cohort, 13.92 years for the 80s cohort and 15.59 for the most recent cohort. The 95% confidence intervals, given in brackets, show that these values are statistically different from one another.²³

The second panel of Table 2 shows the results for light trucks. We first confirm that light trucks display longer lifetimes than passenger cars.²⁴ While light truck lifetime does increase, from 16.29 in the 70s, to 16.48 in the 80s, and 18.22 for more recent model years, the increase seems to slow considerably during the 80s compared with cars. We suspect that much of this may be due a trend encouraged by the CAFE standard to make light trucks more like cars over time with the introduction of vans, SUVs, and, recently, CUVs, which are all categorized as light trucks. This has also resulted in a change in the type of driver who owns a light truck. Light trucks, which were once largely comprised of pickup trucks driven in rural locations, are now operated by individuals who one would have owned a car resulting in different usage patterns.

Previous literature (Walker, 1968; Greene and Chen, 1981; Hamilton and Macauley, 1999; Lu, 2006) has noted the increased lifetime for passenger cars or the fleet as a whole, but it has generally been attributed to events that are unlikely to explain its persistent increase, or why it should

23. In Appendix B we combine all data and control for model year parametrically. These regressions show model year is statistically significant and will lower the scrappage rate as the model year increases.

24. Davis et al. (2013) is an exception to this general pattern, finding the average car lifetime to be longer than truck lifetimes. For 1970s cars they estimate a median lifetime of 11.5 years and 12.5 years for 1980s cars matching our estimates but differ from our 1990 estimates finding this lifetime to be 16.9.

Table 2: Estimates of Logistic Parameters of Engineering Scrapage

Panel A: Passenger Cars

	1969-1979	1980-1987 ^a	1987-2014 ^b	1969-2014 ^c	Post-War ^d
	I	II	III	IV	V
L_0	4.723*** (0.221)	5.504*** (0.600)	2.724*** (0.965)	5.141*** (0.474)	3.8*** (0.011)
B	256.049*** (62.063)	265.637** (80.301)	314.030*** (63.314)	279.257*** (67.885)	890.48*** (33.83)
k	-0.419*** (0.031)	-0.367*** (0.041)	-0.275*** (0.275)	-0.354*** (0.031)	0.76*** (0.006)
Obs	149	104	156	481	
R-Squared	0.972	0.963	0.973	0.884	

Year	1969-1979	1980-1987 ^a	1987-2014 ^b	1969-2014 ^c	Post-War ^d
Average Lifetime ^e	12.3	13.9	15.6	14.3	10.0
95% C.I.	[11.9, 12.4]	[13.5, 14.1]	[14.9, 15.6]	[13.7, 14.5]	[9.9, 10.1]

Panel B: Light Trucks

	1969-1979	1980-1987 ^a	1987-2014 ^b	1969-2014 ^c	Post-War ^d
	I	II	III	IV	V
L_0	9.838*** (1.110)	6.388** (2.008)	7.235*** (1.031)	6.542*** (1.302)	
B	200.325*** (53.909)	261.917** (86.127)	646.336*** (141.367)	174.724*** (25.535)	
k	-0.303*** (0.040)	-0.287*** (0.048)	-0.323*** (0.025)	-0.236*** (0.023)	
Obs	136	122	153	463	
R-Squared	0.948	0.927	0.975	0.915	

Year	1969-1979	1980-1987 ^a	1987-2014 ^b	1969-2014 ^c	Post-War ^d
Average Lifetime ^e	16.3	16.5	18.2	16.9	
95% C.I.	[15.9, 16.6]	[15.1, 16.8]	[17.8, 18.3]	[16.6, 17.0]	

Notes: L, B, k values are results from logistic regression of mean scrapage rate on age, following Eq. 1. The first three columns are results from scrap rate at corresponding age of model-year 1969-1979, 1980-1989, and 1990-1999, respectively. Specifications controlling for model year with parametric functional forms are included in Appendix B. Wards and Polk report vehicle counts by age up to age 15. In some years, back inventories are sold resulting in negative scrapage rates, which are deleted. Robust standard errors are in parenthesis. * significant at 10%, ** significant at 5%, *** significant at 1%.

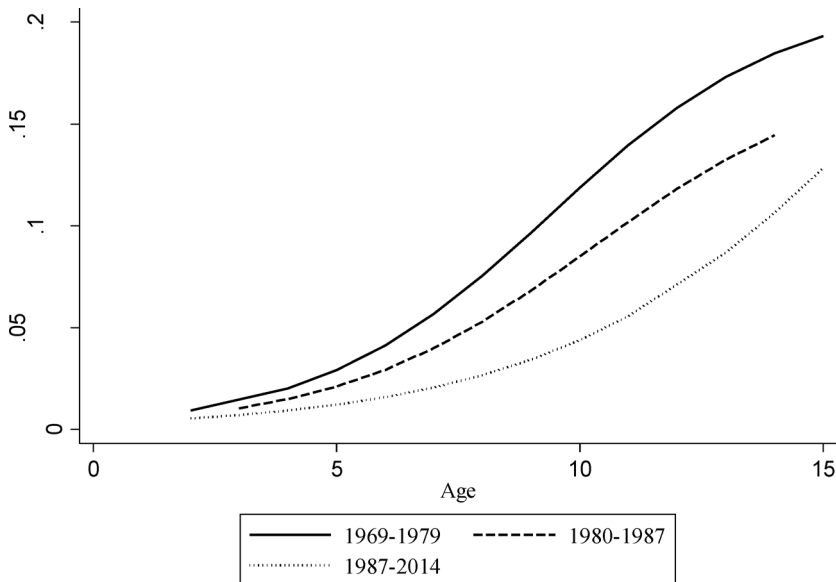
^a Uses data exclusively from Wards Automotive Yearbooks.

^b Uses data exclusively from Polk/HIS, after 1987

^c Combines data from both sources

^d Columns V is from Walker (1968), Table 1.

^e Average Lifetime is measured in years.

Figure 4: Scrappage Rate Curves

Notes: The figure plots the fitted scrappage rate curves estimated in Table 2 for passenger cars as a function of age. The 1969–1979 and 1980–1988 curves are estimated using annual vehicle counts by model year published by Ward’s Automotive Yearbooks. The 1987–2014 curve is estimated using data from Polk.

be observed even within passenger cars. Reasons that have been suggested in the past include a change in post-war technology (Walker, 1968), or an increase in the share of light trucks (Greene and Chen, 1981). There is also evidence that, while gasoline vehicles drive fewer miles, they may last more years than diesel (Kolli, 2011), but, as diesel is a very small share of the U.S. market, this likely plays a small role. Hamilton and Macauley (1999), who only examine passenger cars, suggest shifts in population to the Sunbelt are the source of this increased lifetime. Another explanation is technology change. For example rustproofing, improved lubricants, the removal of lead and sulfur from fuel, and onboard diagnostic systems to prevent large mechanical failures may also extend vehicle lifetime (EPA, 2002). This reasoning would also explain why similar trends are noted in the vehicle fleets of other countries like Sweden (Feeney and Cardebring, 1988) that have not had similar population shifts.

3.2 Elasticity of Scrappage with Respect to Used Vehicle Price

Table 3 column I reports the OLS estimates of equation (5) for passenger cars. For each regression the table reports the coefficients and standard errors. Using our basic specification in Column I, our estimate of the scrappage elasticity with respect to vehicle price is -0.36 .²⁵

Table 3 columns II through VIII examine the robustness of the scrappage elasticity with respect to vehicle price estimated in Column I and all find this parameter to be inelastic. Following Walker (1968), the vehicle price ratio index regressor is the log of the ratio of the used vehicle price index and the maintenance and repair cost index, which assumes that coefficients of these two variables are equal in magnitude but opposite sign. We separately estimate these coefficients in Column

25. Turnover rate is higher although statistically indistinguishable from earlier estimates.

Table 3

	I	II	III	IV	V	VI	VII	VIII
	Various Regressors							
Ln(Price Index)	-0.360** (0.136)		-0.212 (0.144)	-0.439*** (0.095)	-0.521*** (0.186)	-0.349*** (0.124)	-0.441*** (0.127)	-0.059 (0.256)
Ln(Turnover Rate)	1.108*** (0.081)	0.817*** (0.207)		1.125*** (0.066)	1.105*** (0.123)	0.343*** (0.070)	1.116*** (0.097)	0.767*** (0.169)
Ln(Used Vehicle Price Index)		-0.287* (0.156)						
Ln(Maintenance and Repair Index)		0.152 (0.215)						
Ln(GDP)			-0.883*** (0.051)					
Ln(Gasoline Price)				-0.092 (0.104)				
Ln(New Car Price)								
Ln(Steel Price)								
Ln(Percent Imported)								
Constant	3.427*** (0.170)	3.333*** (0.174)	8.702*** (0.468)	3.525*** (0.107)	3.392*** (0.311)	2.106*** (0.156)	3.435*** (0.231)	2.610*** (0.386)
L.ar					0.410** (0.197)		0.473** (0.192)	
L2.ar					0.195 (0.150)			
N	41	41	41	41	41	41	41	41

Notes: This regression estimates the second step of Walker, (1968), specification (4), using 31 calendar years of observations. Values shown are coefficients from a regression of ln(scrapage) on the covariates listed. Turnover rate are calculated as new car registration over total car in use, for each year. Price Index is the ratio of the Used Vehicle Price Index and Used Vehicle Maintenance and Repair Cost Index constructed by the BLS with a base of 1982–1984. Robust standard errors are in parenthesis. * significant at 10%, ** significant at 5%, *** significant at 1%.

II and find that the estimate of 0.156 on ‘Maintenance and Repair Cost Index’ is indistinguishable from negative of that on the ‘Used Vehicle Price Index’ at -0.287 , supporting this assumption.

Because new vehicle sales and scrappage rates may be endogenous, we examine GDP as another proxy for turnover rate in column III finding this measure only further reduce the scrappage elasticity with respect to vehicle price to -0.21 .

Column V examines several other potentially important covariates, including steel price, GDP, gasoline price, new vehicle price, and percentage imported vehicles. Steel price is included to capture changes in value of scrap metal. Because it is also possible that the entrance of foreign competitors may affect vehicle lifetime (Hamilton and Macauley, 1999), we also control for the percentage of the fleet that is imported. These additional covariates are limited in their coverage and reduce the number of usable observations but result in our lowest point estimate of -0.01 .

Column VI examines the possibility that younger vehicles may be subject to a different scrappage process and so we limit this regression to vehicles younger than ten years of age. The estimate of -0.349 is slightly smaller, but not statistically different from, our main specification.

Columns VII examines the robustness of our estimates to an AR(2) model. The point estimate of -0.85 is statistically indistinguishable from the point estimate in column I.

Column VIII of Table 3 presents the result for the light truck regression. We find this elasticity is also quite low with a point estimate of -0.06 , which is not statistically different from zero but is statistically different from -1 . Because of the dramatic changes in the definition of light trucks over this time period, we leave the truck regressions for Appendix D. Broadly speaking these results are similar in that they suggest a very inelastic response of scrappage to changes in vehicle price, but they are estimated with considerably less precision than the car regressions.

The key finding of Table 3 is that the scrappage elasticity with respect to vehicle price is inelastic and far lower than values that are derived from temporary and local scrappage programs (Hahn, 1995; Alberini et al. 1995; Alberini et al. 1996; Alberini et al., 1998). These studies imply elasticities between -1.7 and -3 .²⁶ The geographic and temporal limits of these policies likely results in a substantially larger scrappage elasticity with respect to vehicle price than would be expected by a permanent, national policy like CAFE standards or a gasoline tax because vehicle owners may change their scrappage decisions to take advantage of the program. Further, as documented in Sandler (2012), these programs suffer from adverse selection, which may further overstate the scrappage elasticity with respect to vehicle price.

3.3 Instrumenting for Simultaneous Equations

A potential concern in recovering the supply curve of scrappage is that shifts in both the demand and supply of used vehicles may result in biased estimates of the scrappage elasticity with respect to vehicle price. It is possible that shifts in supply could occur due to increased accident rates or changes in the behavior of used car dealers who make the decision to scrap or attempt to resell a vehicle.

We address this concern by attempting to instrument for vehicle price using the introduction of the CAFE standard. Because CAFE regulates the fuel economy of new vehicles, it will in-

26. Table 6 in Alberini et al. (1995) suggests the average scrappage elasticity with respect to vehicle price is -1.7 for waived vehicles and -2.56 for non-waived vehicles. Table 4 in Alberini et al. (1996) implies that the scrappage elasticity with respect to vehicle price is -1.8 at the mean vehicle value. Alberini et al (1998) Figure 3b suggests scrappage rises from approximately 70 to 210 vehicles for a \$1000 bounty, which is 65% of the average vehicle value of \$1535.58 given in Appendix A 2.1, implying a scrappage elasticity of -3 . Table 2 in Hahn (1995) implies an average scrappage elasticity of -1.75 .

Table 4: Elasticity of Scrapage with Respect to Vehicle Price Instrument using CAFE Level

	Instrumental Variables		
	I	II	III
Ln(Price Index)	-0.400*** (0.150)	-0.482** (0.190)	-0.421** (0.190)
Ln(Turnover Rate)	1.124*** (0.087)	1.140*** (0.091)	
Ln(Gasoline Price)		-0.108 (0.096)	-0.221** (0.109)
Ln(GDP)			-0.939*** (0.085)
Constant	3.461*** (0.208)	3.566*** (0.245)	9.333*** (0.789)
R-squared	0.837	0.840	0.810
N	41	41	41
	First Stage		
F-Stat	42.12	31.466	57.812
R-Squared	0.672	0.741	0.813

Robust standard errors are in parenthesis. * significant at 10%, ** significant at 5%, *** significant at 1%.

crease the price of new vehicles encouraging substitution towards relatively cheaper used vehicles. Such behavior will raise the price of used vehicles and increase their lifetime as noted by Gruenspecht (1982). As can be noted in Figure 1, the gradual increase in the CAFE standard from 1978 to 1985 resulted in a substantial increase in the value of used vehicles. While it is difficult to exclude other possible explanations for this rise in vehicle prices, partly because the increase in CAFE standards was linear, we control for gasoline price as this is the most likely other cause of this increase in the price index.²⁷

We estimate equation (5) using the level of CAFE as an instrument for vehicle price. Table 4 presents estimates from the second step using two-stage least squares. Column I presents coefficients from our basic specification with a point estimate of -0.40 , which is statistically significant at the 10% level. With an F-statistic of 42, the instrument appears to be highly relevant. Because the introduction of CAFE corresponded with large fluctuations in gasoline price, column II adds this regressor, however, the point estimate on Ln(Price Index) changes only slightly to -0.48 , which is statistically significant at the 5% level. Column III replaces the turnover rate proxy, with GDP resulting in a small change in the point estimate to -0.421 . These results suggest that shifts in supply curve produce a relatively minor bias in our estimates as the instrumental variable estimates are statistically indistinguishable from our results using our basic specification.²⁸

27. There is also some variation in the CAFE standard for cars at the start of end of our dataset starting in 2011. We present similar regressions for light trucks in Appendix D but the instrument is weak for truck prices and does not provide valid estimates.

28. We also note that our results are similar to those of Jacobsen and van Benthem (2015) who use another possible identification strategy that relies on disaggregate data, which is available in more recent years, to examine how gasoline prices capitalize into vehicle prices based on fuel economy ratings. Using this strategy they estimate this elasticity at -0.7 to -0.8 .

Table 5

	I	II	III	IV	V	VI
	Various Regressors			<10 Years	<10 Years	AR2
Ln(Gasoline Price)	0.064 (0.097)	0.028 (0.107)	0.211 (0.301)	0.043 (0.101)	0.310 (0.324)	0.049 (0.109)
Ln(Turnover Rate)	0.975*** (0.098)	0.661*** (0.221)	0.209 (0.309)	0.212*** (0.064)	-0.014 (0.385)	0.944*** (0.134)
Ln(GDP)		-0.294* (0.172)	-0.903** (0.409)		0.003 (0.410)	
Ln(New Car Price)			0.237 (0.295)		-0.212 (0.456)	
Ln(Percent Imported)			-0.028 (0.112)		-0.073 (0.131)	
Ln(Steel Price)			-0.025 (0.157)		-0.180 (0.176)	
Constant	3.107*** (0.225)	5.019*** (1.098)	8.304*** (2.565)	1.802*** (0.140)	2.818 (2.949)	3.043*** (0.294)
L.ar						0.466** (0.208)
L2.ar						0.097 (0.099)
N	41	35	27	27	27	41

Notes: This regression estimates the second step of Walker (1968), specification equation (4), using 31 calendar years of observations. Values shown are coefficients from a regression of $\ln(\text{scrapage})$ on the covariates listed. Turnover rate are calculated as new car registration over total car in use, for each year. Vehicle price index is the ratio of the Used Vehicle Price and Used Vehicle Maintenance and Repair Cost indices constructed by the BLS with a base of 1982-1984=100. Robust standard errors are in parenthesis. * significant at 10%, ** significant at 5%, *** significant at 1%.

3.4 Results from Gasoline Price Specifications

In Table 5 column I we estimate this elasticity using equation (6). These regressions, which replace vehicle price with gasoline price, suggest that aggregate scrapage does not respond very much to gasoline prices with a point estimates ranging from 0.03 to 0.31. The point estimate from our simplest specification is 0.064 and is not statistically different from zero. Columns II through VII examine the robustness of this estimate and generally suggest an inelastic response to changes in gasoline price. The change in the point estimate when including GDP is particularly large suggesting that omitting income effects may bias this coefficient towards elastic values. Without these controls, gasoline prices will capture the substitution towards used vehicles that occurs during recessions. Column VI shows the results from an AR(2) model, which, although still imprecise and not statistically different from zero, is statistically different from 1 and very inelastic with a point estimate of 0.05. Ideally we would be able to instrument for gasoline prices but finding an instrument is difficult for several reasons. First, very few valid instruments for gasoline price have been found in the literature and those that do use recent supply shocks that are temporary (e.g. Hughes, Knittel, and

Sperling, 2008).²⁹ While consumers may make short-run adjustments to VMT in response to these fluctuations, they seem less likely to make major capital investments based on transitory shocks, and there is evidence that consumers anticipate the return of gasoline prices to earlier levels during particularly salient shocks (Anderson, Kellogg, Sallee, and Curtin, 2011). Generally, we conclude from Table 5 that the estimated elasticities are quite small as they are always statistically different from 1 but are sensitive to the model used. However, the values estimated here, and in other papers, seem too inelastic to agree with any estimate of the scrapage elasticity with respect to vehicle price, which we examine in depth in the next section.

3.5 Comparison of the Elasticities of Scrapage with Respect to Vehicle and Gasoline Prices

According to economic theory, there should be a direct relationship between the scrapage elasticities with respect to vehicle and gasoline price. A change in gasoline price will change the operating cost of the vehicle. If consumers are rational, gasoline price changes will be capitalized into the used vehicle price. This allows us to compare our estimated elasticities. To the extent that these two elasticities do not provide consistent results may be evidence of undervaluation in the discounted future fuel costs of operating a vehicle, also known as the ‘energy efficiency paradox.’ We then equate the change in scrapage that would occur through this gasoline price change with the change in scrapage that would occur if this gasoline price change were fully capitalized into the price of the vehicle.

$$\varepsilon_{GP} \cdot \frac{\Delta_{GP}}{GP} = \theta \cdot \varepsilon_{VP} \cdot \left[\sum_a \frac{(1-\delta)^a \prod_{i=1}^{a-1} (1-M_i) VMT_a (\Delta_{GP})}{mpg} \right] / VP \quad (7)$$

The goal of this exercise is to solve for the undervaluation parameter, θ . The term on the left calculates the scrapage that should occur for a given gasoline price change, Δ_{GP} . The term on the right calculates the change in expected discounted future fuel cost of the vehicle with that gasoline price change and, using the vehicle price elasticity, the scrapage that should occur. If more scrapage occurs when the gasoline price is properly capitalized into the vehicle price than when the change was evaluated through the gasoline price elasticity, this would be evidence of undervaluation. The expression in brackets is the change in discounted lifetime operating cost.

For the discount rate, δ , we use 5%. Values estimated by Polk and the Bureau of Transportation Statistics put the mean fuel economy, mpg , of used vehicles at 23.8 mpg, and vehicle price, VP , at \$8,786.³⁰ Annual mileage, VMT_a , is taken from Lu (2006). We find that consumers seem to underreact to changes in gasoline price although but we do not have sufficient precision to reject full valuation. The estimated scrapage elasticity with respect to vehicle price, ε_{VP} , of our instrumental variables method in Table 4 column I, -0.40 , paired with the estimate of the scrapage elasticity with respect to gasoline price, ε_{GP} , from Table 5 column I of 0.06 gives a value of θ equal to 0.22 . This suggests that consumers recognize only \$0.22 of a \$1 increase in operating cost. Using the

29. These authors use supply disruptions from Hurricane Katrina as an instrument for gasoline price. While such temporary price shocks may encourage drivers to temporarily decrease the miles they drive, they seem less likely to have the scrapage effect that a permanent increase of the same magnitude would. Occasionally state level gasoline taxes are used but the scrapage market for used vehicles is national preventing us from using state level variation.

30. This calculation is done for a representative used vehicle which is, according to Polk, 11 years of age. The base gasoline price is \$3. Vehicle scrapage rates are from our estimates from 1980–1987, section 4.3 discusses the sensitivity of this statistic to using other years for estimation of the vehicle lifetime. We are not able to capture any effects that compositional changes in fuel economy may happen when gasoline prices change because our data is aggregate, but to the extent that increasing gasoline prices make the fleet more efficient, the vehicle appreciation will be smaller resulting in larger values of θ .

higher value of the gasoline price elasticity from Table 5 column III brings this value closer to full valuation at \$0.96. While pairings of other robustness checks can give values higher or lower, most point to undervaluation in this range. These calculations are, of course, sensitive to assumptions. While the error may not be isolated to undervaluation and could arise from the choice of VMT, discount rate, etc., these estimates are similar to others of this undervaluation studied through alternative methods (Helfand and Wolverton, 2010; Greene, 2010).

4. DISCUSSION

Estimates presented above have implications for nearly all studies of the used vehicle market. Here we focus on the implications for several particularly active areas of research including CAFE standards, gasoline taxes, and the energy efficiency paradox. Here we provide several back-of-the-envelope calculations attempting to show the importance of our estimates for these studies.

4.1 Implications for CAFE Standards

To predict the potential gasoline savings of CAFE, it is important to understand the rate at which aging removes old vehicles from the road. Problematically, these vehicle lifetimes may be based off of scrappage curves that are several decades old. In order to estimate vehicle lifetimes, one must observe the full scrappage curve of a specific model year until most of the vehicles have been scrapped, which may take several decades. The estimates of vehicle lifetime presented in section 3.1 suggest that vehicles made in the past had considerably shorter lifetimes than vehicles of similar age but made more recently. Longer vehicle lifetime could substantially impede the diffusion of new vehicles influenced by CAFE into the used vehicle fleet, which may make accelerated scrappage programs more important (Alberini, 1996).

To illustrate how longer vehicle lifetimes may impede this diffusion we predict the fuel economy profile of the used vehicle market using two scrappage curves estimated 30 years apart.³¹ This gives some indication of how much discrepancy may occur between the predicted levels of fuel economy based on an outdated scrappage curve and the true scrappage curve that recognize the technology change during the intervening years. To simplify this calculation we focus on the passenger car segment, which has a separate, higher standard than the light truck segment under CAFE. Historically CAFE has mandated that manufacturers achieve 27.5 mpg on average for passenger cars or pay fines based on the shortfall.³² For our simulation, we generate an initial fleet that uniformly meets the 27.5-mpg standard and predict how quickly a new fleet produced at a uniform 40 mpg affects the used vehicle market.³³ Using a shorter vehicle lifetime will imply these changes in the new vehicle fleet will change the used vehicle fleet faster than when using a longer vehicle lifetime. The fuel economy of the average used vehicle over time is presented in Table 6 and plotted in Figure 5. The dashed blue line in Figure 5 projects the average fuel economy using the older

31. Specifically we use Walker's Postwar (1952–1957) estimates for the old scrappage curve and our estimates from the midpoint of our data, 1980–1987, as the new scrappage curve. Using the estimated lifetime from the beginning and end of our data produces similar results.

32. For passenger cars the old CAFE standard required a minimum average fuel economy of 27.5 mpg. This standard has been changed and started to increase in 2011. Additional changes to the standard allowed for a flexible target based on the footprint of the vehicle. These changes may affect magnitudes but not the qualitative conclusions of this calculation.

33. We generate this population by projecting a fleet back in time assuming each year 10,000 vehicles are produced and are reduced by the estimated scrappage curve at each age. We omit the possibility of any Gruenspecht effect although this will compound these results.

Table 6: Average MPG of Fleet after CAFE Increase

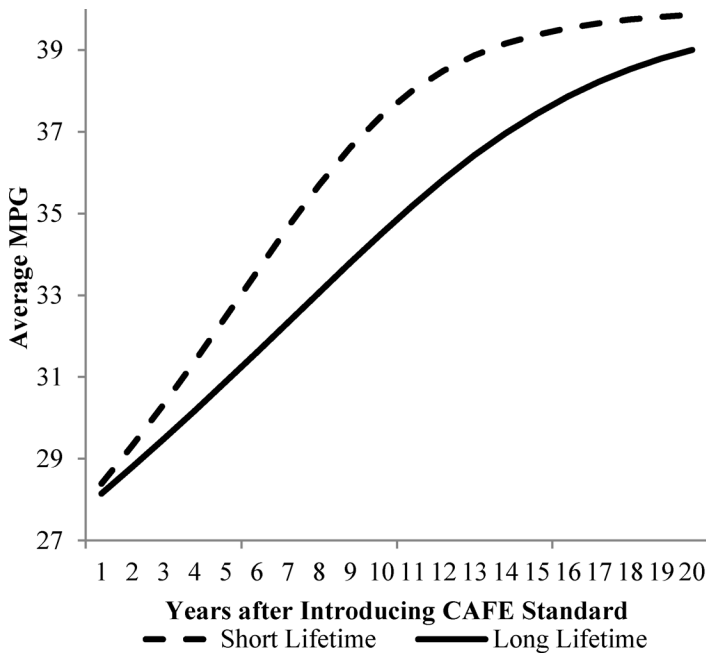
Year	Short Lifetime	Long Lifetime
1	28.39	28.15
2	29.33	28.80
3	30.33	29.48
4	31.38	30.17
5	32.47	30.88
6	33.58	31.61
7	34.67	32.34
8	35.7	33.07
9	36.61	33.80
10	37.38	34.51
11	38.00	35.19
12	38.49	35.83
13	38.87	36.42
14	39.16	36.96
15	39.37	37.44
16	39.54	37.86
17	39.66	38.22
18	39.75	38.53
19	39.81	38.79
20	39.86	39.00

Notes: Suppose there are 40 years of vehicle production, with 10,000 cars each year. For the first 20 years, average MPG is 27.5. In year 21, introduce CAFE standard as 40. The two columns show the expected average MPG trends in 20 years after the introduction of CAFE, based on short and long lifetime, respectively.

scrapage curves, which imply shorter vehicle lifetimes, while the red solid line shows the outcomes under the newer scrapage curve, which imply longer vehicle lifetimes. The old curve suggests that the higher CAFE standard will affect the used vehicle market much faster than the new curve and is over optimistic about the speed at which CAFE can affect the fuel economy of the used vehicle fleet. Table 6 shows that some intermediate targets, like 35 mpg, can take a full four years longer to achieve using our new scrapage rates. During the transition the difference can be substantial. At ten years the difference in efficiency is roughly 8% indicating that there would be roughly 90 million more tons of carbon than anticipated.³⁴

A second back-of-the-envelope calculation shows this delay from another perspective. Policy makers may want to know what CAFE standard is needed to increase the fuel economy of the whole fleet above a particular target within a set time frame. In Table 7 we calculate the CAFE standard required to achieve a variety of fleet targets within ten or 15 years assuming that the fleet starts at an average of 27.5 mpg. For example using the old scrapage curves it will take a CAFE standard of 42.7 to achieve a fleet average of 40 within ten years. But the new scrapage rates suggest that the correct CAFE standard to achieve this goal is 50.7. Increasing the standard by eight miles per gallon

34. This calculation is done assuming this efficiency applies to all 1134.5 million tons of carbon emitted by light-duty vehicles in the U.S. (EPA, 2012).

Figure 5: Fleet Average MPG Predictions from CAFE Increase

Notes: Simulation assumes an initial fleet achieves an average mpg of 27.5 mpg. 10,000 cars each year and older vehicles are scrapped according to the engineer scrappage rates of the older, shorter vehicle lifetime or the new, longer vehicle lifetime. In year 1 a new CAFE standard of 40 mpg is introduced. The two curves show the expected average mpg levels achieved over a 20 years period.

is likely to be expensive. Extrapolating the engineering cost curves for the subcompact category of car, a car that can achieve that target at lower cost than other vehicles (NRC 2002), suggest this eight-mpg improvement would cost at least \$1,000 more per vehicle.³⁵ As the target becomes more aggressive, the discrepancy becomes larger. To achieve a fleet average of 50 mpg within ten years, the older scrappage curves would only require a CAFE standard of 56.3 while the newer curve would require a standard in excess of 80 mpg. The final pair of columns shows that as the time frame is extended to 15 years, an age where most vehicles have been scrapped, this discrepancy decreases but is still surprisingly large. For example to achieve 40 mpg in 15 years the old curve would require the CAFE standard to be 40.5 while the new curve suggests the standard would need to be 42.9.

There are additional effects that may further undermine higher CAFE standards. Because CAFE raises the price of new vehicles, consumers will substitute towards used vehicles increasing their price (Gruenspecht, 1982). This will reduce their scrappage rate, an implication examined in depth by Jacobsen and van Benthem (2015). The inelasticity of this parameter suggests that accurately modeling vehicle lifetime is of first order importance, as most scrappage will occur due to age-related, exogenous scrappage rather than policy induced, endogenous scrappage.

35. Alternatively the cost of this higher target can be calculated using the coefficients from the hedonic cost study by Berry, Kortum, and Pakes (1996) and converting to 2012 dollars. The higher target would cost \$1,400 more per vehicle using these estimates rather than \$1000 estimated from the engineering cost curves in the NRC (2002) study.

Table 7: The Required CAFE Standard to Achieve Various Fleet MPG Targets

Average MPG Target	10 years		15 years	
	Short Lifetime	Long Lifetime	Short Lifetime	Long Lifetime
30	30.4	31.4	30.1	30.5
31	31.6	33	31.2	31.6
32	32.8	34.7	32.2	32.8
33	34	36.4	33.2	34
34	35.2	38.2	34.3	35.3
35	36.4	40.1	35.3	36.5
36	37.6	42	36.4	37.7
37	38.9	44.1	37.4	39
38	40.1	46.2	38.4	40.3
39	41.4	48.4	39.5	41.6
40	42.7	50.7	40.5	42.9
41	44	53.1	41.6	44.2
42	45.3	55.5	42.7	45.5
43	46.6	58.2	43.7	46.9
44	47.9	60.9	44.8	48.3
45	49.3	63.7	45.8	49.7
46	50.7	66.7	46.9	51.1
47	52	69.9	48	52.5
48	53.4	73.2	49	53.9
49	54.8	76.7	50.1	55.4
50	56.3	80.4	51.2	56.8

Notes: Simulation assumes an initial fleet achieves an average mpg of 27.5 mpg. 10,000 cars each year and older vehicles are scrapped according to the technical scrapage rates of the older, shorter vehicle lifetime or the new, longer vehicle lifetime. In year 1 a new CAFE standard of 40 mpg is introduced. The two curves show the expected average mpg levels achieved over a 20 years period.

4.2 Implications for Gasoline Taxes

Our estimates of the scrapage elasticity with respect to vehicle price also have implications for the ability of gasoline taxes to improve fuel economy. Equilibrium models of the automobile market have generally used scrapage elasticities with respect to vehicle price that range from -3 to -6, or assumed this value to be zero. This elasticity is particularly important for gasoline taxes because a major effect of gasoline taxes is to increase the operating cost of inefficient used vehicles and decrease their price. By preferentially scrapping inefficient used vehicles, the average fuel economy of this market rises faster than would occur with aging alone.

To illustrate this we show how this parameter choice can affect predicted policy outcomes in Table 8. Bento et al. (2009) calculates the increased scrapage from a 25-cent gasoline tax using a price elasticity of -3 under three revenue-recycling methods. This value is based on a local scrapage policy studied in Alberini et al. (1998). Table 8 presents results for each revenue-recycling method using our vehicle price elasticity of -0.4. We find the scrapage rate would have increased by only 0.04%, rather than the 0.35% simulated in the original study. The 95% confidence intervals show this new scrapage rates are statistically different than 0.35% and from 0%, the value implied

Table 8: Impact on Used Car Retention Simulating a Gasoline Tax

	Bento et al. 2009 Change in Used Car Ownership	Implied Percent Change in Price with Elasticity of -3	Change in Used Car Ownership with Elasticity of -0.83
Flat Recycling of \$0.25 gas tax	-0.35%	0.12%	-0.04% [-0.08, -0.01]
Income-based recycling of \$0.25 gas tax	-0.37%	0.12%	-0.05% [-0.08, -0.01]
VMT-based recycling of \$0.25 gas tax	-0.39%	0.13%	-0.05% [-0.09, -0.01]

Notes: Values taken from Table 7 of Bento et al. (2009). Excludes general equilibrium effects on price of higher retention rates. Values in brackets below represent 95% confidence intervals that incorporate the standard errors on $\log(\text{Vehicle Price Index})$ from column I of Table 3.

if the elasticity were assumed to be 0. While this value implies nearly 565,000 vehicles fewer would be removed than using the elasticity of -3, it is nearly 70,000 more than if this elasticity is assumed to be 0.³⁶

This calculation illustrates that a low scrappage elasticity with respect to vehicle price reduces the ability of gasoline taxes to influence the used vehicle market and increases the role of scrappage due to aging. This implies that the CAFE standards and gasoline taxes are somewhat closer in terms of efficiency than previous literature suggests.³⁷

4.3 Further Implications for Studies of the Energy Efficiency Paradox

As discussed in section 3.5 above, economic theory suggests a rational consumer will pay \$1.00 more for a vehicle that reduces discounted future fuel costs by \$1.00, but consumers seem to undervalue these reductions in future fuel cost. Empirically there has been considerable disagreement of the magnitude of this undervaluation (Helfand and Wolverton, 2010; Greene, 2010) ranging from \$0.25 (Kilian and Sims, 2006) to \$0.76 (Allcott and Wozny, 2014) to full valuation of \$1.00 (Sallee, West, and Fan, 2016). We also found evidence of undervaluation using our estimated scrappage elasticities, but our estimate of the increase in vehicle lifetime also has implications for this debate.

To properly evaluate the benefit of efficiency improving technology, both consumers and the researcher must specify how long a vehicle is likely to last. Longer vehicle lifetimes will increase the likelihood that consumers will realize the returns of a technology that improves fuel efficiency. Generally, researchers have applied one schedule of scrappage rates (Lu, 2006) to all vehicles regardless of model year. If consumers update their beliefs slower than researchers, this will result in undervaluation. To give some insight into the magnitude of error this may generate in these calculations we examine the value to the consumer of a technology that increases fuel econo-

36. This calculation only captures savings due to scale effects that reduce the total number of cars on the road and does not capture any compositional effects of scrappage. It also omits any equilibrium price effects that may occur.

37. It is important to note that this does not imply that the two policies are identical in terms of gasoline savings. The CAFE standard increases the use of vehicles because improving the fuel economy of the fleet without increasing the price for driving results in more vehicle miles traveled, a phenomenon commonly referred to as the rebound effect (Small and Van Dender, 2007). The two policies also produce different results in the new vehicle market as CAFE implicitly taxes inefficient vehicles and subsidizes efficient ones (Kwoka, 1983).

my from 20 to 30 mpg under two scrapage curves estimated 30 years apart.³⁸ When using the older scrapage curve with shorter vehicle lifetime, we find that the value of the technology is \$5663.50 while using the newer curve with a longer vehicle lifetime provides a benefit of \$6075.10. If the consumer uses a shorter vehicle lifetime to assess the value of this technology while researcher use longer vehicle lifetimes, the researcher will bias the results 7% towards undervaluation. Conversely if the researcher updates more slowly than the consumer, this would result in 7% overvaluation.

5. CONCLUSION

Despite the large size of the used vehicle market and its importance to policies such as CAFE and gasoline taxes, relatively little attention has been paid to the parameters used to model it. Our paper shows that the lifetime of passenger cars has continued to increase for much of the past century. Using a nonlinear specification we estimate that the average lifetime of passenger cars has increased from about ten years in the 1950s to about 15.6 in the 2000s. While the two most commonly used values of scrapage elasticity with respect to vehicle price are 0 and -3 , we estimate this parameter as -0.36 , with a range from -0.01 and -0.52 .

Our findings have several important policy implications. The increased vehicle lifetimes we estimate imply that the updated CAFE standards may take several years longer to affect the used vehicle fleet than otherwise predicted. We also show that our estimate of the scrapage elasticity with respect to vehicle price reduces the ability of gasoline taxes to remove used vehicle by 90%. These estimates are also useful for examining the value consumers place on technology that reduces the future fuel cost of vehicles. The scrapage elasticities with respect to vehicle and gasoline prices we estimate suggest that consumers may only recognize \$0.22 to \$0.96 for every \$1 change in future gasoline costs. We also show that failing to account for the increase in vehicle lifetime when calculating the discounted future fuel costs for vehicles may result in over or underestimates of the energy efficiency paradox of 7%.

There are also important implications for a variety of other programs. Longer vehicle lifetime suggests standards for local pollutants, which are placed on new vehicles only and therefore have relatively high costs (Small and Kazimi, 1995), will take longer to affect the entire fleet of vehicles. Inspections and maintenance programs, which focus on pollution reductions for the oldest vehicles (Ando, McConnell, and Harrington, 2000b), may become more important for achieving emission reductions. Alternatively policy makers may seek to incentivize manufacturers to build vehicles with emissions reducing technology that lasts the life of the vehicle, which other authors have found to be particularly effective (Harrington, McConnell, and Ando, 2000). Our evidence of increasing vehicle lifetime and low scrapage elasticity with respect to vehicle price also suggest that it may be difficult to use policy to remove the large quantity of fuel inefficient vehicles that built up over the low gasoline prices of the past decades. If the past is any indicator many policies will be implement to reduce emissions from used vehicles and the parameters estimated here may help policy makers to accurately evaluate these programs in the coming years.

REFERENCES

Adda, J., R. Cooper (2000). "Baladurette and Jupette: A Discrete Analysis of Scrapping Subsidies." *Journal of Political Economy* 108(4): 778–806. <https://doi.org/10.1086/316096>.

38. For this calculation we assume a gasoline price of \$3 and annual VMT according to Lu (2006).

- Alberini, A., W. Harrington, and V. McConnell (1995). "Determinants of Participation in Accelerated Vehicle-retirement Programs." *Rand Journal of Economics* 26(1): 93–112. <https://doi.org/10.2307/2556037>.
- Alberini, A., W. Harrington, and V. McConnell (1996). "Estimating an Emissions Supply Function From Accelerated Vehicle Retirement Programs." *Review of Economics and Statistics* 78(2): 251–265. <https://doi.org/10.2307/2109927>.
- Alberini, A., W. Harrington, and V. McConnell (1998). "Fleet Turnover and Old Car Scrap Policies." *Resources for the Future Discussion Paper*, 98–23.
- Allcott, H., and N. Wozny (2014). "Gasoline Prices, Fuel Economy, and the Energy Paradox." *The Review of Economics and Statistics* 96(5): 779–795. https://doi.org/10.1162/REST_a_00419.
- Anderson, S., R. Kellogg, J. Sallee, and R. Curtin (2011). "Forecasting Gasoline Prices using Consumer Surveys." *American Economic Review Papers & Proceedings* 101(3): 110–114. <https://doi.org/10.1257/aer.101.3.110>.
- Ando, A., V. McConnell, and W. Harrington (2000a). "Are Vehicle Emissions Inspection Programs Living up to Expectations?" *Transportation Research Part D* 5(3): 153–172. [https://doi.org/10.1016/S1361-9209\(99\)00029-2](https://doi.org/10.1016/S1361-9209(99)00029-2).
- Ando, A., V. McConnell, and W. Harrington (2000b). "Cost, Emissions Reductions, and Vehicle Repair: Evidence from Arizona." *Journal of the Air and Waste Management Association* 49(10): 1153–1167. <https://doi.org/10.1080/10473289.1999.10463910>.
- Bento, A., L. Goulder, M. Jacobsen, and R. Von Haefen (2009). "Distributional and Efficiency Impacts of Increased U.S. Gasoline Taxes." *American Economic Review* 99(3): 667–699. <https://doi.org/10.1257/aer.99.3.667>.
- Berry, S., S. Kortum, and A. Pakes (1996). "Environmental Change and Hedonic Cost Function for Automobiles" *Proceedings of the National Academy of Sciences of the United States of America* 93(23): 12731–12738. <https://doi.org/10.1073/pnas.93.23.12731>.
- Davis, S., S. Diegel, and R. Boundy (2013). *Transportation Energy Data Book: Edition 32*. Washington, DC: Office of Transportation Technologies, U.S. Department of Energy.
- Environmental Protection Agency (2002). OBD: Frequently Asked Questions, EPA420-F-02-014.
- Environmental Protection Agency (2012). "U.S. Greenhouse Gas Emissions and Sinks." 1990–2010, EPA-420-F-12-063.
- Feeney, B., and P. Cardebring (1988). "Car Longevity in Sweden: A Revised Estimate." *Transportation Research Part A, General* 22(6): 455–465. [https://doi.org/10.1016/0191-2607\(88\)90049-0](https://doi.org/10.1016/0191-2607(88)90049-0).
- Goldberg, P.K. (1998). "The effects of the corporate average fuel efficiency standards in the US." *The Journal of Industrial Economics* 46(1): 1–33. <https://doi.org/10.1111/1467-6451.00059>.
- Greene, D. (2010). "How Consumers Value Fuel Economy: A Literature Review." Office of Transportation and Air Quality, EPA-420-R-10-008. Washington, DC: U.S. Environmental Protection Agency.
- Greene, D., and C. Chen (1981). "Scrapage and Survival Rates of Passenger Cars and Light Trucks." *Transportation Research Part A* 15(5): 383–389. [https://doi.org/10.1016/0191-2607\(81\)90144-8](https://doi.org/10.1016/0191-2607(81)90144-8).
- Gruenspecht, H. (1982). "Differentiated Regulation: The Case of Auto Emissions Standards." *American Economic Review* 72(2): 328–331.
- Hahn, R. (1995). "An Economic Analysis of Scrapage." *The Rand Journal of Economics* 26(2), 222–242. <https://doi.org/10.2307/2555914>.
- Hamilton, B., and M. Macauley (1999). "Heredity or Environment: Why is Automobile Longevity Increasing?" *The Journal of Industrial Economics* 49(3): 251–261. <https://doi.org/10.1111/1467-6451.00100>.
- Hamilton, J. (2009). "Understanding Crude Oil Prices." *The Energy Journal* 30(2): 179–206. <https://doi.org/10.5547/ISSN0195-6574-EJ-Vol30-No2-9>.
- Harrington, W., V. McConnell, and A. Ando (2000). "Are Vehicle Emission Inspection Programs Living up to Expectations?" *Transportation Research Part D* 5(3): 153–172. [https://doi.org/10.1016/S1361-9209\(99\)00029-2](https://doi.org/10.1016/S1361-9209(99)00029-2).
- Harvey, A.C. (1981). *The Econometric Analysis of Time Series*, second ed. Pearson Education, pp.34.
- Helfand, G., and A. Wolverton (2010). "Evaluating the Consumer Response to Fuel Economy: A Review of the Literature." Working paper No. 09-04, National Center for Environmental Economics.
- Hughes, J., C. Knittel, and D. Sperling (2008). "Evidence of a Shift in the Short-run Price Elasticity of Gasoline Demand." *The Energy Journal* 29(1): 113–134. <https://doi.org/10.5547/ISSN0195-6574-EJ-Vol29-No1-9>.
- Jacobsen, M., and A. van Benthem (2015). "Vehicle Scrapage and Gasoline Policy." *American Economic Review* 105(3): 1312–1338. <https://doi.org/10.1257/aer.20130935>.
- Jacobsen, M. (2013). "Evaluating U.S. Fuel Economy Standards in a Model with Producer and Household Heterogeneity." *American Economic Journal: Applied Economics* 5(2): 148–187.
- Kilian, L., and E. Sims (2006). "The Effects of Real Gasoline Prices on Automobile Demand: A Structural Analysis using Micro Data." Working Paper, University of Michigan.
- Klier, T., and J. Linn (2012). "New Vehicle Characteristics and the Cost of the Corporate Average Fuel Economy Standard." *The RAND Journal of Economics* 43(1): 186–213. <https://doi.org/10.1111/j.1756-2171.2012.00162.x>.

- Kolli, Z (2011). "Car Longevity: A Biometric Approach." Working Paper. Accessed March 29, 2014: <http://indico.conferences.dtu.dk/getFile.py/access?contribId=117&sessionId=54&resId=1&materialId=paper&confId=72>
- Kwoka, J. (1983). "The Limits of Market Oriented Regulatory Techniques: The Case of Automotive Fuel Economy." *The Quarterly Journal of Economics* 98(4): 695–704. <https://doi.org/10.2307/1881784>.
- Li, S., J. Linn, and E. Spiller (2013). "Evaluating 'Cash for Clunkers': Program Effects on Auto Sales and the Environment." *Journal of Environmental Economics and Management* 65(2): 175–193. <https://doi.org/10.1016/j.jeem.2012.07.004>.
- Li, S., C. Timmins, and R. von Haefen (2009). "How do Gasoline Prices Affect Fleet Fuel Economy?" *American Economic Journal: Economic Policy* 1(2): 113–137. <https://doi.org/10.1257/pol.1.2.113>.
- Lu, S. (2006). "Vehicle Survivability and Travel Mileage Schedules" NHTSA's National Center for Statistics and Analysis, DOT HS 809 952.
- Miravete, E., and M. Moral (2011). "Qualitative Effects of 'Cash for Clunkers' Programs." Working Paper, University of Texas at Austin.
- National Automobile Dealers Association (2012). NADA state of the industry report, Accessed Dec. 24, 2012. <http://www.nada.org/NR/rdonlyres/C1C58F5A-BE0E-4E1A-9B56-1C3025B5B452/0/NADADATA2012Final.pdf>
- National Research Council (2002). *Effectiveness and impact of Corporate Average Fuel Economy (CAFE) standards*, National Academy Press.
- Park, R. (1977). "Determinants of Scrapping Rates for Postwar Vintage Automobiles." *Econometrica*, 45(5): 1099–1115. <https://doi.org/10.2307/1914061>.
- Parry, I., C. Fischer, and W. Harrington (2007). "Do Market Failures Justify Tightening Corporate Average Fuel Economy (CAFE) Standards?" *The Energy Journal* 28(4): 1–30.
- Pashigian, P. (2001). "The Used Car Price Index: A Checkup and Suggested Repairs." BLS Working Paper 338.
- Sallee, J. M., S. West, and W. Fan (2016). "Do Consumers Recognize the Value of Fuel Economy? Evidence from Used Car Prices and Gasoline Price Fluctuations." *Journal of Public Economics* 135: 61–73. <https://doi.org/10.1016/j.jpubeco.2016.01.003>.
- Sandler, R. (2012). "Clunkers or Junkers? Adverse Selection in a Vehicle Retirement Program." *American Economic Journal: Economic Policy* 4(4): 253–258. <https://doi.org/10.1257/pol.4.4.253>.
- Schiraldi, P. (2011). "Automobile Replacement: A Dynamic Structural Approach." *RAND Journal of Economics* 42(2), 266–291. <https://doi.org/10.1111/j.1756-2171.2011.00133.x>.
- Small, K., and K. Van Dander (2007). "Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect." *The Energy Journal* 28(1): 25–51. <https://doi.org/10.5547/ISSN0195-6574-EJ-Vol28-No1-2>.
- Small, K., and C. Kazimi (1995). "On Costs of Air Pollution from Motor Vehicles." *Journal of Transport Economics and Policy* 29(1): 7–32.
- Walker, F., (1968). "Determinants of Auto Scrapage." *Review of Economics and Statistics* 50(4): 503–506. <https://doi.org/10.2307/1926820>.



Connect with
IAEE
on facebook

