Vehicle Scrappage and Gasoline Policy

Mark R. Jacobsen[a] and Arthur A. van Benthem[b]

January 2013

Abstract

We estimate the sensitivity of scrap decisions to changes in used car values – the "scrap elasticity" – and show how it influences used car fleets under policies aimed at reducing gasoline use. Large scrap elasticities will tend to produce emissions leakage under efficiency standards as the longevity of used vehicles is increased, a process known as the *Gruenspecht Effect*. To explore the magnitude of this leakage we assemble a novel dataset of U.S. used vehicle registrations and prices, which we relate through time via differential effects in gasoline cost: a gasoline price increase or decrease of $1 alters the number of fuel-efficient vs. fuel-inefficient vehicles scrapped by 18%. These relationships allow us to provide what we believe are the first estimates of the scrap elasticity itself, which we find to be about -0.7. When applied in a model of fuel economy standards, the elasticities we estimate suggest that 13-23% of the expected fuel savings will leak away through the used vehicle market. This considerably reduces the cost-effectiveness of the standard, rivaling or exceeding the importance of the often-cited mileage "rebound" effect.

Acknowledgements: We thank Lawrence Goulder, Matt Harding, and seminar participants at Stanford University, UC San Diego, and UC Berkeley for useful comments and suggestions, and the Precourt Energy Efficiency Center for generous financial support.

[a] Department of Economics, University of California, San Diego and NBER. Mailing address: 9500 Gilman Drive, La Jolla, CA 92093-0508. E-mail: m3jacobsen@ucsd.edu.
[b] The Wharton School, University of Pennsylvania. Mailing address: 3010 Steinberg Hall-Dietrich Hall, 3620 Locust Walk, Philadelphia, PA 19104. E-mail: arthurv@wharton.upenn.edu.

1. Introduction

Passenger vehicles currently enjoy long lifetimes and are traded on an extensive used market. We examine the timing of decisions to scrap used cars and the relation between changes in scrap rates, the gasoline price, and used car resale value. The extent to which the fuel economy of used cars is elastic – via differential rates of scrap as used car prices change across the fleet – has important consequences for policies meant to reduce gasoline use. Despite this, there has been surprisingly little empirical guidance on the relevant elasticity of used vehicle scrap rates.

We address three questions: First, what is the effect of gasoline price changes on scrap rates? Second, what is the elasticity of the scrap rate with respect to used vehicle prices? And third, how does this scrap elasticity interact with fuel-economy policies aimed to reduce emissions from new vehicles?

We begin by developing a novel dataset that includes a detailed history of used vehicle prices and registrations at the make, model, and trim level. We use it to estimate the responsiveness of used vehicle prices and scrap rates to changes in the gasoline price, addressing the first question above. Higher retail gasoline prices mean fuel-efficient cars are scrapped less while the largest, thirstiest cars are scrapped more. We provide estimates of the magnitude of this effect using a combination of cross-sectional and time series variation. These changes in the used fleet are part of the mechanism through which changes in gasoline demand are realized when a tax is applied.

We next model the more complex interaction of the scrap elasticity with fuel economy policy. Early work by Gruenspecht (1982) highlights the relevance of the vehicle-scrap margin in this context: when new vehicle prices rise due to tightened fuel-

economy regulation, the prices of used vehicles also increase in equilibrium. This gives used vehicle owners an incentive to postpone the decision to scrap their vehicles, leading to a larger and potentially less fuel-efficient used vehicle fleet. Goulder *et al* (2012) briefly explore the magnitude of this "used car leakage" effect and find that, depending on the scrap elasticity, it can substantially reduce the effectiveness of fuel economy standards.

The magnitude of the effect is tied directly to the scrap elasticity, which we estimate here using variation in gasoline prices and used car demand. We use the influence of gasoline prices on relative demand for different models to instrument for price, recovering an overall elasticity of scrap of -0.7. The detail in our data allows us to further decompose this elasticity according to attributes like age and class of vehicle: preliminary estimates suggest important differences between classes, with pickup trucks tending to have low scrap elasticities and SUVs and convertibles tending to be much more elastic.

Our work follows a series of recent papers examining the effects of gasoline prices on the used car market, a relation we will take advantage of in the first stage of our instrumental variables approach: Busse, Knittel, and Zettelmeyer (2010), Sallee, West, and Fan (2010), and Allcott and Wozny (2012) all consider the nexus between gasoline price changes and changes in used vehicle prices. Precise accounting of the fuel economies and lifespans of used cars allows these authors to recover novel estimates of consumer response to gasoline costs. Li, Timmins, and von Haefen (2009) examine the response of new and used car fuel economies to changes in the gasoline price, including estimates of the relation between scrap rates and gasoline price.

In contrast, we work to isolate the influence of the used vehicle price itself on scrap, allowing us to investigate the *Gruenspecht effect* in the context of fuel economy standards. The elasticities we present here could further be applied to consider the influence of a number of other programs, for example vehicle subsidies that target particular classes, or incentives like scrap bonuses that alter prices and scrap rates in the used market directly.

To our knowledge the only prior empirical work looking at the relation between used vehicle values and the scrap rate consists of two case studies based on policy shocks (Alberini *et al* (1998) and Hahn (1995)). The data from these studies is insufficient to construct price-scrap response curves over a meaningful range and they are confined to small geographic regions. In contrast, our data span the U.S. and cover the 17 years between 1993 and 2009. The detailed cross-sectional variation we have available also allows us to examine differences in scrap responsiveness across vehicle age, class, manufacturer, and fuel economy rating.

Programs like "cash-for-clunkers," where new car purchasers receive a subsidy to have their previous vehicle destroyed, are also related to our question. Such policies by definition influence people considering a new car purchase, who may be very different from the typical final owners of vehicles. These last owners of cars often repair or maintain the vehicle personally, and may operate them on a salvage title long after the typical car consumer would no longer be interested. We are able to capture the decisions of both groups, examining the entire used fleet using data on vehicle registrations.

The rest of the paper is organized as follows: Section 2 describes the dataset we assemble. Section 3 explores the relation between gasoline prices, used vehicle prices,

and scrap rates, with Section 4 offering an alternative specification. Section 5 uses these relationships to provide instrumented estimates of the vehicle scrap elasticity itself. Finally Section 6 provides an application of our elasticity estimates, simulating the influence of the scrap elasticity on fuel savings achieved via U.S. fuel economy standards.

2. Data

We have assembled a panel of data on used vehicles from two industry sources: The R.L. Polk company maintains a database of vehicle registrations in the U.S. by individual vehicle identification number (VIN). The National Automobile Dealer's Association (NADA) combines auction and sale records to produce monthly used vehicle valuations at the sub-model level.

Due to the potential for lag in the registration data (available as often as quarterly) we work only with annual variation. The coarseness of the time series is counterbalanced by very fine cross-sectional variation, where we can measure prices and registrations for each 10-digit VIN prefix separately. This allows us to distinguish not only vehicle models, but also engine, body style (e.g. 4-door or 2-door), and certain optional features (e.g., horsepower, weight, MSRP) in each observation. Data is aggregate at the level of the U.S. (we assume the used car market is liquid across states).

We merge fuel economies, options, and characteristics for each vehicle by VIN prefix. The NADA data provides a crosswalk from the VIN prefix to model, body-style, and "trim" (e.g. "LX", "DX", etc.) as well as data on some car characteristics. From there we match the car description to EPA fuel economy ratings back to 1978.

The most complete and consistently coded data span the period 1999 - 2009 and we currently focus our analysis on this period.[1] In each year we consider vehicles between 1 and 19 years old, measuring the fraction scrapped as the change in registrations from the previous year. Our measure of scrap rate is therefore most precisely described as a change in size of the legally operated U.S. fleet; we do not distinguish exported or unregistered vehicles from those that are scrapped.[2] Equation (3.3) below makes precise our translation from registration counts to scrap rates.

Table 1 displays a summary of vehicle scrap rates and prices through age 19. Vehicles that are 20 and older represent only 1.6% of the registered fleet and we drop them due to difficulty obtaining data for the oldest vintages. Overall, we see that vehicle scrap rates increase gradually with age from 1.6% (for 2-year-old vehicles) to 14.4% (for 19-year-old vehicles). Pickup trucks and SUVs have higher scrap rates when relatively new (corresponding to higher accident frequency) and lower scrap rates at older ages.

There is also considerable heterogeneity among manufacturers: Figure 1 displays scrap profiles by age for a selection of vehicle brands. Scrap rates are relatively similar over the first few years with considerable heterogeneity emerging at older ages. Luxury brands tend to have the lowest scrap rates as they age.

Figure 2 displays scrap rates after dividing all vehicles into quartiles by fuel economy. The heterogeneity in this dimension is particularly interesting for policy: As vehicles age the more fuel-efficient vehicles are scrapped faster. Like differences across brands, heterogeneity in scrap rates appears most strongly in the second decade of the

[1] Note that this period applies to the registration data. Vehicle vintage goes back much further. For example, we have observations up to 19-year-old vehicles in 1999. The limiting factor is used vehicle prices, which are available back to model-year 1980.

[2] To the extent that accounting for used vehicle exports is significant (see Davis and Kahn, 2010) we can integrate explicit data on exports from Ward's Automotive Fact Books.

vehicle's life. For the oldest vehicles, scrap rates are nearly twice as high in the most fuel-efficient cars.

3. Equilibrium Effects of Gasoline Price Changes

We begin with a description of the relation between gasoline prices and valuation of used vehicles, key to the first stage of our scrap elasticity estimates appearing below. Following Busse, Knittel, and Zettelmeyer (2011) we first divide vehicles according to fuel economy quartiles and examine the response to gasoline price changes.

We focus on the relative effect between different quartiles in order to allow flexible controls for time and vehicle age. Macroeconomic indicators that co-vary with gasoline prices, for example, could increase or decrease the attractiveness of used cars in general. This is something we are able to take out by focusing exclusively on composition: higher gas prices increase the value of gas sippers and decrease the value of gas guzzlers. Conversely, this implies that higher gas prices lead to increased scrappage of gas guzzlers and reduced scrappage of gas sippers. The fuel economy of the used fleet is therefore not fixed, but has an elasticity with respect to gasoline price. It is the differential impact of gasoline price changes in our detailed cross-section of vehicles that provide the key source of variation.

In addition to examining used vehicle prices in this section we can also describe the impact of gasoline prices directly on scrap probabilities, suggesting the mechanism described above. We show how in many cases relatively small changes in gasoline price correspond to large deviations from normal scrap rates.

3.1 Effect of Gasoline Price on Used Car Prices

We first report the equilibrium impact of gasoline price on used vehicle prices following the specification in Busse, Knittel, and Zettelmeyer (2011). Our results match theirs closely. We must aggregate vehicle vintages due to our coarser time series and lack of regional variation, but our data has the advantage of measuring the effect on vehicle prices over a much wider range of ages.[3] We employ the following specification for equilibrium price changes:

$$p_{amt} = \alpha_{am} + \alpha_{at} + \beta_1(gasprice_t \cdot MPGquartile_m) + \beta_2 z_{amt} + \varepsilon_{amt} \quad (3.1)$$

where subscript *a* is vehicle age in years, *m* is make and model (e.g. Toyota Camry), and *t* is the year of observation. α_{am} are fixed effects for each model-age combination (e.g. a 5-year-old Toyota Camry) and α_{at} are fixed effects for year-age combinations (e.g. all 5-year-old cars in 2009). The coefficient of interest is β_1, the influence of gasoline price on vehicle price depending on relative fuel efficiency. Because we cannot control for vehicle vintage within a given make-model (Busse *et al* are able to do this using regional and monthly variation) we instead introduce additional controls in z_{amt} to account for model-specific differences in attributes across vintages. z_{amt} includes horsepower, weight, and the original retail price suggested by the manufacturer (MSRP).[4] The estimated coefficients are positive and significant as expected: the prices of used vehicles in more fuel-efficient MPG quartiles rise relative to prices of the least fuel-efficient used

[3] Busse *et al* observe the set of used cars sold at new car dealerships: This is the "high-end" of the used market, where vehicles have an average price of $15,000 and a median age of 3 years.

[4] For example, if 2003 Toyota Camrys had increased horsepower or additional features (captured in the original retail price) we would model an increase in the value of this particular vintage as it aged.

vehicles. We estimate by least squares and cluster all standard errors at the make-model-age level.

The estimation exploits a combination of time series and cross-sectional variation, using the differential effect of a change in gasoline price across vehicles depending on their fuel economies. The fixed effects for age by year allow the average price of vehicles of each age to vary freely over time, and the age-model effects similarly allow the price of each model to vary flexibly as it ages. The variation that remains is the price differential between vehicles of varying fuel economies: we estimate the change in price differential between the least efficient quartile and each of the higher three.

Table 2 displays the estimates of β_1 in specification (3.1). Full regression output is available from the authors. Average fuel-efficiency in the least efficient quartile is 15.4 MPG as compared with 26.7 MPG in the most efficient quartile. A $1 increase in the gasoline price would imply a $1,762 increase in used car prices in the most efficient quartile relative to the least efficient quartile.

There is enough power to divide these estimates into age categories, which allows us to draw a more direct comparison with the Busse *et al* estimates. When we restrict the sample to vehicles less than 6 years old (making the median age 3 as in Busse *et al*) we find that a $1 increase in the gasoline price increases the relative price of the most efficient quartile by $2,943. Busse *et al* find a very similar price change ($2,800 between the highest and lowest quartiles), and argue that this large effect indicates near-full adjustment on the part of consumers. They show that gasoline cost changes over the remaining expected life of the vehicles are similar in magnitude.

Table 2 also shows the price changes for older vintages; the absolute changes are smaller as would be predicted given the shorter remaining life of older vehicles, but the overall patterns remain the same.

3.2 Effect of Gasoline Price on Scrap Rates: Composition

We now depart from the analysis in Busse *et al* and begin our examination of scrap rates. As shown in Figures 1 and 2, the scrap rate for relatively new vehicles is low and rises slowly through the first five years of age. This is not surprising considering that these vehicles still retain much of their original value; scrappage for such vehicles is mostly the result of severe accidents yielding damage to the structure of the vehicle. We will show that gasoline prices do not affect the scrap rate of this newer set of used cars very much (in absolute terms) as they imply relatively small percentage changes in vehicle value. Instead, absolute changes in scrap rates concentrate in much older vehicles where maintenance and minor accidents yield a more flexible margin for the scrap decision.

We repeat the specification in (3.1), now considering scrap rates in place of prices:

$$y_{amt} = \alpha_{am} + \alpha_{at} + \beta_1(gasprice_t \cdot MPGquartile_m) + \beta_2 z_{amt} + \varepsilon_{amt} \qquad (3.2)$$

where y_{amt} is the fraction of vehicles of age *a* and model *m* that are scrapped between year *t*-1 and *t*. We construct scrap rates by tracking individual vehicle models of each vintage and mapping the scrap rates as they pass different ages. Age is measured as the

difference between observation year *t* and vintage year *v*. Specifically, we define the scrap rate as:

$$y_{amt} = \frac{n_{ym(t-1)} - n_{ymt}}{n_{ym(t-1)}} \mid (t - y) = a \tag{3.3}$$

The numerator is the count of vehicles scrapped (we observe each registration) and the denominator is the count in the previous year. The overall measure is then the fraction scrapped from one year to the next.

The results from specification (3.2) are presented in Table 3. Overall, we find that when gasoline price increases by $1, vehicles with the best fuel economy experience a change in their scrap rate that is about 1 percentage point less than vehicles with the worst fuel economy. In terms of scrap counts, this corresponds to an 11% reduction in the number of efficient vehicles that are scrapped relative to the least efficient quartile.

The effects of gasoline price changes on scrap rates are largest for the older subset of vehicles in the sample: Among cars more than 9 years old scrap rates in the highest MPG quartile fall by more than 2 percentage points for a $1 increase in the price of gasoline (relative to cars in the lowest MPG quartile). On a base scrap rate of 12.8%, this effect amounts to an 18% decline in the count of fuel-efficient vehicles scrapped.

4. Alternative Specifications

In this section we consider alternative versions of specifications (3.1) and (3.2), now estimating the impact of gasoline price changes on used vehicles and scrap rates as a continuous function of each vehicle's fuel-economy. We adopt a specification similar to

Li *et al* (2009) that allows a precise measure of the "turning points" for our effects. Our data on prices allows us to adopt their approach not only for scrap rates, but also for used vehicle prices. Section 5 will relax this structure and return to a more general approach.

We estimate the following models:

$$p_{amt} = \alpha_{am} + \alpha_a \cdot t + \beta_1 DPM_{mt} + \beta_2 gasprice_t + \beta_3 z_{amt} + \varepsilon_{amt} \quad (4.1)$$

$$y_{amt} = \alpha_{am} + \alpha_a \cdot t + \beta_1 DPM_{mt} + \beta_2 gasprice_t + \beta_3 z_{amt} + \varepsilon_{amt} \quad (4.2)$$

where dollars per mile, DPM_{mt}, is calculated as $gasprice_t/MPG_m$ and $\alpha_a \cdot t$ is a linear time trend that varies by age. Equations (4.1) and (4.2) impose the restriction that vehicles at the extremes (highest and lowest DPM) will see the largest changes in price and scrap. Specifically, if $\beta_1 > 0$ and $\beta_2 < 0$, there exists a critical MPG-value above which used vehicle prices increase (or above which scrap rates decrease) when the gasoline price goes up.

Table 4 reports the results of specifications (4.1) and (4.2), including estimates for all vehicles (columns 1 and 3) and a restricted sample of vehicles ten years and older (columns 2 and 4). The signs of the coefficients on $gasprice_t$ and DPM_t are opposite in all four cases, allowing calculation of the desired "turning point" in MPG where the sign of the response changes. When gasoline price increases vehicles with fuel economies above the turning point see their prices increase and scrap rates decrease.

For older vehicles turning points in the price and scrap regressions are similar, between 22 and 23 MPG. To interpret the estimates in the table consider for example a vehicle with average MPG (20.0 in our sample): a $1 increase in the gasoline price will decrease its price by $227 and increase its scrap rate 0.34 percentage points. Vehicles

with a fuel economy of 15 MPG are predicted to respond much more dramatically: a $1 gasoline price increase decreases their value by $786 on average, and increases scrap rates by 1.56 percentage points. Conversely, high-MPG cars benefit from higher gas prices: the value of a 40 MPG vehicle increases by $611 following a $1 gasoline price increase, while the scrap rate decreases by 1.49 percentage points.

These results are consistent with Tables 2 and 3. The average fuel-economy in quartile 1 is 15.2 MPG, while the average MPG in quartile 4 is 27.2. The estimates in Table 4 predict a price differential of $974 and a scrap rate differential of 2.12 percentage points. This corresponds closely to the price differential of $952 in Table 2 and the scrap rate differential of 2.27 percentage points.

The turning point specification here has the nice feature of using continuous variation in fuel economy, but suffers from the requirement that linear trends be imposed on prices and scrap rates over time.[5] This restriction leads to much less plausible results for newer vehicles in our sample: sharp effects of the recession, for example, cannot be modeled and could explain the asymmetric turning points in price and scrap.

We therefore move to a more flexible specification in Section 5 that combines the best features of the models in Sections 3 and 4: we will use a continuous measure of fuel economy (as in Section 4) while maintaining the flexibility of the quartile model in Section 3 that exploits changes in relative, rather than absolute, prices and fuel economies.

[5] Flexible controls for year are incompatible with the turning point structure since they permit arbitrary increases or decreases in all prices and scrap rates together, leaving the turning point undefined.

5. Estimating the Scrap Elasticity

In this section, we estimate the used vehicle price elasticity of the scrap rate[6] using an instrumental variables approach. While the estimates above demonstrate the reduced form influence of rising gasoline prices on scrap rates (and therefore could suggest the effect of an increase in the gasoline tax), our goal here is to instead model the effect of *vehicle* price changes in the used market. For example, a policy to subsidize new vehicles of a particular type will reduce demand for used versions of those vehicles, reducing their value. This in turn creates a change in the scrap rate that we will be able to measure.

More generally, fuel economy rules will generate a whole pattern of price shifts through the used fleet. Our elasticity estimates in this section can be used to model the effect of these (or any other) price changes on the used fleet. We will show in the next section that such effects can have important implications for the performance of fuel-economy standards.

Estimating the scrap elasticity by directly regressing the scrap rate on the used vehicle price suffers from the usual endogeneity of prices in equilibrium: we are trying to uncover parameters that control the scrap (i.e. supply) side of the used market, meaning we require an instrument that shifts demand.

We will use the differential impact of gasoline prices across used vehicle models as one such instrument. The evidence presented in Sections 3 and 4 above show how gasoline prices can predict used vehicle prices, operating through differential changes in demand for vehicles with better or worse fuel economies. Our instrument therefore

[6] We will define this elasticity as the percent change in the scrap rate associated with a 1% increase in the value of a vehicle on the used market.

predicts prices quite strongly, reflected in the high first-stage F-statistics shown alongside the instrumented elasticity estimates below.

Validity of our instrument also depends on an exclusion restriction applying to the supply (scrappage) side of the model: we require that unobserved factors determining the scrap rate (for example, mechanics' wages) be uncorrelated with the differential fuel cost changes across vehicle models as gasoline prices move. In other words, we need to assume that gasoline prices affect scrappage only through their effect on used vehicle prices.

To see why this is a reasonable assumption consider the recurring decision problem faced by a used vehicle owner: in any given year, he faces a random repair cost shock and must decide whether to repair and keep the vehicle, repair and sell it at the current market price, or scrap the vehicle. He will choose scrap if and only if the price in the used market falls below the realized repair cost plus any residual value. If not, he will be better off selling the car to someone else. Thus, the decision to scrap a car depends on the used vehicle price, repair cost realization, and scrap value, but generally not on demand-side parameters such as utility from owning and operating the vehicle and – importantly – not on relative fuel cost versus other models.[7]

A particularly appealing aspect of using gasoline prices as our instrument is that it uses the differential variation that gas price movements produce across models with

[7] This conclusion does not change if there is heterogeneity in consumer preferences across vehicles, or if consumers are heterogeneous in their valuation of fuel economy. A potentially complicating factor is transaction cost, which can make keeping a vehicle more attractive relative to either scrapping or selling. Under some conditions, the scrap decision could then depend on prices of other vehicles, which in turn depend on gasoline cost. We argue that the relevant transaction cost in our setting is likely to be limited: the final person to face the scrap-or-repair decision for a given vehicle is likely to be a mechanic or someone operating the vehicle on a salvage title. This group generally faces lower search and information costs than a typical owner, making the scrap-or-repair margin we have in mind the relevant choice. This simple model can be formalized and the derivation is available upon request.

different fuel economies, allowing aggregate changes in scrap rates over all vehicles to be removed. Complications from the dramatic swings in macroeconomic variables during our sample period can therefore be absorbed.

We estimate the following model using a panel IV estimator, relating the natural logs of the scrap rate *y* and the vehicle price *p* such that γ can be interpreted as the elasticity:

$$\ln(y_{amt}) = \gamma \ln(\hat{p}_{amt}) + \alpha_{am} + \alpha_{at} + \varepsilon_{amt} \quad (5.1)$$

As before, the model includes a full set of fixed effects for each model-age of vehicle (e.g. a 5-year-old Toyota Camry receives its own fixed effect for the scrap rate). We also include flexible age-year effects that allow patterns like improved reliability in newer vintages or macroeconomic shocks that shift scrap rates for vehicles of certain ages.

The first panel of Table 5 presents the elasticity estimates, γ, estimated from Equation (5.1) by OLS. The elasticity over all vehicles averages -0.58. We expect these results to be biased toward zero, as they reflect equilibrium outcomes coming from shifts in both supply (i.e. determinants of scrap) and vehicle demand. The remaining three panels detail our instrumental variables approach that instead takes advantage of demand shifts based on relative gasoline cost.

The basic intuition for our instrumenting strategy comes out of the quartile model in Equation (3.1). Relative gasoline cost changes (across fuel efficiency quartiles) differentially shift used vehicle demand. Following this logic, we first present results that import the quartile model appearing in Equation (3.1) directly as the first stage.

Instrumented prices are the predicted values reported in Table 2. The elasticity results from this basic specification appear in the second panel of Table 5, with an overall elasticity estimate of -0.83.

We next move to a pair of specifications that take advantage of considerably more variation across vehicles. Rather than lumping all vehicles of the same quartile together to predict prices, we can add detail at the make-model level. The first stage becomes:

$$\ln(p_{amt}) = \alpha_{am} + \alpha_{at} + \beta_m \cdot DPM_{mt} + \varepsilon_{amt} \tag{5.2}$$

where as above DPM_{mt} measures the time-varying cost of a mile driven at the vehicle model level. We prefer this approach since it leverages much more of the variation in our data, creating more precise first stage estimates and also removing bias that could result from uneven distribution of cars of different age categories across quartiles. These results appear in the third panel where the average elasticity is -0.70.

Finally, we move to our most flexible (and preferred) specification. Now we instrument not only with relative fuel cost changes at the make-model level, but also differentiate by vehicle age. Specifically, our preferred first stage is:

$$\ln(p_{amt}) = \alpha_{am} + \alpha_{at} + \beta_{am} \cdot DPM_{amt} + \varepsilon_{amt} \tag{5.3}$$

We continue to include the full set of fixed effects and now predict price changes for each make-model and age separately; DPM_{amt} includes all variation at the age-model-time level. The fourth panel reveals quite similar elasticities to the somewhat more aggregate instruments used in the third panel.

Table 5 also explores differences in the elasticity across age categories. Generally we find fairly similar elasticities across ages, declining somewhat for the very oldest cars. This likely reflects the larger repair cost shocks and high existing scrap rates among the oldest vehicles.

Table 6 further decomposes our elasticity estimates by vehicle class, using instruments at the make-model-age level. While still preliminary these results suggest that some of the least efficient vehicles (pickups and cargo vans) have lower scrap elasticities, whereas high scrap elasticities are observed for vehicles across the fuel-efficiency spectrum (SUVs, minivans and convertibles). Future drafts will incorporate this heterogeneity into the simulations below and further investigate the importance of differences across age and class groups.

6. Application to Fuel Economy Standards: The *Gruenspecht Effect*

We now consider the price elasticity of the scrap rate in a simulation model of the U.S. vehicle fleet. The idea is to estimate the magnitude of the *Gruenspecht Effect*; the simulations reveal to what extent tighter CAFE standards lead to increased gasoline consumption from used vehicles. The simulation model is similar in nature to the model used in Goulder *et al* (2012). We refer to that paper for details, but outline the model structure below.

6.1 Model Structure

We model the following economic agents: new vehicle producers, used vehicle suppliers, and households. Vehicles differ by manufacturer, age (new to 18 years old), size (large or small) and type (car or truck).

Vehicle demand is derived from the utility function of a representative consumer, who derives utility from the various vehicles and a composite consumption good. The representative consumer has a nested CES utility function, with nesting the following nesting order: vehicles vs. other goods, type, size, age, and manufacturer. At the highest nest, the consumer chooses the mix between vehicles (v) and other goods (x) while satisfying its budget constraint:

$$\max_{v,x} U(v,x) = \left(\alpha_v v^{\rho_u} + \alpha_x x^{\rho_u}\right)^{\frac{1}{\rho_u}} \tag{6.1}$$

subject to

$$p_v v + p_x x \leq M \tag{6.2}$$

and non-negativity constraints. M is total income, p_v is the implicit rental price of the composite vehicle (which includes expected depreciation and fuel cost), p_x is the price of other goods, ρ_u is the elasticity of substitution between vehicles and other goods, and α_v and α_x are distribution parameters.

We also model the supply of both new and used vehicles. New vehicle manufacturers k (7 in total: Ford, GM, Chrysler, Toyota, Honda, Other Asian, European) engage in Bertrand competition and maximize profits by choosing the prices and fuel-economies of four vehicle classes (combinations of type t and size s) subject to CAFE

fuel-economy standards. The profit maximization problem for manufacturer k is given by:

$$\max_{\{p_{t,s},\, e_{t,s}\}} \sum_{t,s=1,2} \left[\left(p_{t,s} - c_{t,s}(e_{t,s}) \right) \cdot q_{t,s}(\boldsymbol{p}, \boldsymbol{e}) \right] \tag{6.3}$$

subject to the CAFE standards for cars and trucks:

$$\frac{\sum_{s=1,2} q_{1,s}}{\sum_{s=1,2} \left(\frac{q_{1,s}}{e_{1,s}} \right)} \geq \bar{e}_C \tag{6.4}$$

$$\frac{\sum_{s=1,2} q_{2,s}}{\sum_{s=1,2} \left(\frac{q_{2,s}}{e_{2,s}} \right)} \geq \bar{e}_T \tag{6.5}$$

where the decision variables $p_{t,s}$ and $e_{t,s}$ denote the vehicle prices and fuel economies, respectively. $c_{t,s}$ refers to the marginal production cost; $\bar{e}_C$ and $\bar{e}_T$ refer to the CAFE requirements for cars and trucks.

Used vehicle supply is determined by last period's supply net of scrapping:

$$q_{t,s,a+1,k}(\tau+1) = \left(1 - y_{t,s,a+1,k}(\tau+1)\right) q_{t,s,a,k}(\tau) \qquad a = 0,1,\ldots,18 \tag{6.6}$$

where τ indexes time, a indicates age (a = 0 refers to new cars) and $y_{t,s,a,k}$ is the end-of-period scrappage probability. All 18-year-old cars are scrapped at the end of the period. The scrap probability for each vehicle type and vintage is endogenous and depends on the vehicle's resale value. A car will be scrapped when its resale value falls below the repair costs to keep the vehicle running. Since vehicles of model t,s,a,k actually represent an aggregate category of similar cars with different quality, condition, and value, we assume

that a fraction of these vehicles will face repair costs that are high enough to scrap the car (rather than repairing the vehicle). This fraction is inversely related to the vehicle type's resale value in working condition and modeled as:

$$y_{t,s,a,k,r} = b_{t,s,a,k,r}(p_{t,s,a,k,r})^{\gamma} \tag{6.7}$$

where $b_{t,s,a,k,r}$ is a scale parameter (determined in a calibration procedure) to actual scrap rates and γ is the price elasticity of the scrap rate, estimated above in Section 5.

The used car purchase price $p_{t,s,a,k,r}$ is the sum of scrap-adjusted, discounted future rental prices $r_{t,s,a,k,r}$. Used car owners are assumed to exhibit myopia in that they expect the rental price of their used car next year to be the same as that of a one-year-older used car this year. Under this assumption, we can recursively solve for used vehicle purchase prices:

$$p_{t,s,18,k,r} = r_{t,s,18,k,r} \tag{6.8}$$

$$p_{t,s,a,k,r} = r_{t,s,a,k,r} + \frac{(1 - y_{t,s,a,k,r})p_{t,s,a+1,k,r}}{1+\delta}$$

where δ is the annual discount rate.

The model solves for prices and fuel economies of new vehicles and used car purchase prices that clear both new and used vehicle markets and are consistent with firms' profit-maximizing behavior. These equilibria are calculated for every year in a sequence of equilibria over the simulation period (2009-2020).

6.2 Data and Parameters

We calibrate the model to prices and composition (obtained from *Automotive News*), and fuel economies (obtained from the EPA) of the 2009 U.S. vehicle fleet, as well as the 2009 GDP and gasoline price. We assume an income growth rate of two percent per year, and an autonomous rate of improvement in fuel economy technology of 1.8 percent per year (Knittel, 2011). For all other parameters, we follow Goulder *et al* (2012).

6.3 Used Vehicle Leakage Results

We now estimate the magnitude of emissions leakage to used vehicles as a result of tightened fuel-economy regulation for new vehicles. We consider scrap elasticity estimates of -0.5 and -0.8, spanning the range of estimates in Table 5.

Leakage will be expressed as the fraction of expected gasoline savings that are never realized due to changes in used vehicle scrap rates. We calibrate the model to consider the recent tightening of federal CAFE standards to a target of 41.7 MPG in 2020 (the policy reaches 54.5 MPG in 2025).[8] The reference case to which this is compared corresponds to a previously announced goal of 35 MPG in 2020. We model the separate requirements CAFE imposes on passenger cars and light-duty trucks.

Figure 3 (a) considers the scrap elasticity of -0.5 and shows the difference in total gasoline consumption over the period 2009-2020 between the reference and policy cases. The blue line ignores the impacts of the tightened CAFE standards in the used vehicle market. The red line accounts for these effects, and reveals smaller reductions in gasoline consumption. Both lines are downward sloping, indicating that gasoline reductions

[8] EPA (2012).

accumulate as additional generations of fuel-efficient new vehicles enter the fleet. The difference between the two lines is the leakage to used vehicle markets, and by 2020 amounts to about 13%: that is, 13% of the gross emissions reductions in the new vehicle market are offset by increased emissions from used vehicles.

Figure 3 (b) displays a parallel set of results in a setting where the scrap elasticity is increased to -0.8, close to the most elastic of our estimates in Table 5. This larger elasticity increases leakage to used vehicle markets to 23%.

While we believe ours is the first empirical estimate of the *Gruenspecht Effect*, it may be instructive to draw a comparison with the "rebound effect" estimated in a number of earlier papers. The rebound effect refers to the increased driving as a result of lower per-mile driving costs under a fuel economy rule and has been placed between 5% and 10%, for example in Gillingham (2011). The 13-23% *Gruenspecht Effect* that we estimate here adds to the rebound effect as a source of leakage, rivaling or exceeding it in magnitude.[9]

7. Conclusions

We estimate the sensitivity of the decision to scrap used vehicles to changes in the value of those vehicles on the used market, the scrap elasticity. Our estimates imply that changes in used vehicle prices lead to significant changes in composition and scrappage in the used fleet. This has important implications for fuel-economy policy: tightened standards for new vehicles lead to reduced scrappage for used vehicles. We estimate that this effect offsets 13-23% of expected gasoline savings.

[9] We find that leakage to used vehicles becomes even greater when the stringency of policy is further increased. We are currently incorporating these results, as well as simulations exploiting more detail in the range of elasticity estimates by vehicle type and age.

Our empirical strategy combines variation in gasoline prices through time with finely detailed information on used vehicle values and scrap rates. We include fixed effects on the price and scrap rate for each vehicle model at each age of its life, using variation from the differential effect of gasoline price on used vehicle values depending on their fuel economies.

We find that a $1 increase in gasoline price corresponds to a more than $2,500 increase in the price differential between the most and least efficient fuel economy quartiles for newer used vehicles (less than 10 years old). This is comparable to the findings in Busse *et al* (2011). We can also investigate the composition of vehicles scrapped: A $1 increase in gasoline price corresponds to an 18% decline in the number of old, but efficient, vehicles scrapped relative to scrap of the least efficient vehicles.

We incorporate these effects on vehicle prices as the first stage of an instrumental variables approach to estimate the elasticity of scrap rates with respect to the used vehicle's value. Our central case estimate is -0.7 with significant heterogeneity across vehicle ages and classes. Finally, we incorporate a simulation model of the U.S. vehicle fleet to estimate the effect of a range of scrap elasticities between -0.5 and -0.8. Throughout this range used car price changes represent an important source of leakage, rivaling or exceeding the rebound effect in magnitude.

Our ongoing work looks particularly at the heterogeneity in elasticities across class and age categories. Greater elasticity in the extremes of the fuel economy distribution, for example, tends to magnify the leakage effect even further. We believe our findings also suggest an interesting overlap with the literature on local air pollution: many of the gross polluters in terms of smog and ozone precursors tend to be the very

oldest vehicles on the road. Our model and estimates of the scrap elasticity could therefore be extended to draw direct comparisons on local air pollution between CAFE standards and gasoline taxes.

References

Alberini, A., W. Harrington, and V. McConnell (1998). "Fleet Turnover and Old Car Scrap Policies." RFF Discussion Paper 98-23.

Allcott, H., and N. Wozny (2012). " Gasoline Prices, Fuel Economy, and the Energy Paradox." NBER Working Paper 18583.

Busse, M.R., C.R. Knittel, and F. Zettelmeyer (2010). "Pain at the Pump: How Gasoline Prices Affect Automobile Purchasing." Working paper, University of California at Davis.

Davis, L.W. and M.E. Kahn (2010). "International Trade in Used Vehicles: The Environmental Consequences of NAFTA." American Economic Journal: Economic Policy 2(4): 58-82.

Environmental Protection Agency and Department of Transportation (2012). *2017 and Later Model Year Light-Duty Vehicle Greenhouse Gas Emissions and Corporate Average Fuel Economy Standards*. Federal Register 77 (199), October 2012.

Gillingham, K. (2011). "Sorting on Anticipated Driving and the Consumer Response to Changing Gasoline Prices. Working paper.

Goulder, L.H., M.R. Jacobsen and A.A. van Benthem (2012). "Unintended Consequences from Nested State & Federal Regulations: the Case of the Pavley Greenhouse-Gas-per-Mile Limits." *Journal of Environmental Economics and Management* 63(2): 187-207.

Gruenspecht, H. (1982). "Differentiated Regulation: The Case of Auto Emissions Standards." American Economic Review 72(2): 328-331.

Hahn, R.W. (1995). "An Economic Analysis of Scrappage." *The RAND Journal of Economics* 26(2): 22-242.

Knittel, C. (2011). "Automobiles on Steroids: Product Attribute Trade-offs and Technological Progress in the Automobile Sector." *The American Economic Review* 101(7): 3368-3399.

Li, S., C. Timmins and R.H. von Haefen (2009). "How Do Gasoline Prices Affect Fleet Fuel Economy?" *American Economic Journal: Economic Policy* 1(2): 113-137.

Sallee, J.M., S.E. West and W. Fan (2010). " Do Consumers Recognize the Value of Fuel Economy? Evidence from Used Car Prices and Gasoline Price Fluctuations." Working paper.

Table 1: Scrap Rate and Used Vehicle Values by Age

	All Vehicles		Pickups/SUV's
Age	Scrap Rate	Used Value ($)	Scrap Rate
1	-	22415	-
2	1.59%	19305	2.10%
3	1.52%	16416	2.01%
4	1.77%	13748	2.43%
5	1.74%	11332	2.05%
6	2.15%	9365	2.62%
7	2.35%	7851	2.52%
8	2.80%	6653	3.01%
9	3.10%	5742	3.06%
10	3.99%	4960	4.21%
11	5.02%	4284	5.25%
12	6.28%	3723	6.36%
13	7.47%	3281	7.11%
14	8.99%	2944	8.50%
15	10.30%	2668	9.15%
16	11.79%	2445	10.90%
17	12.51%	2263	10.84%
18	13.53%	2105	11.57%
19	14.45%	1968	11.79%

Table 2: The Effect of Gasoline Prices on Used Vehicle Prices by MPG Quartile

		By age category		
	All ages	Age 2-5	Age 6-9	Age 10-19
Gasoline price * MPG quartile 2	106	-183	362	264*
	(138)	(321)	(294)	(116)
Gasoline price * MPG quartile 3	1113**	1596**	1431**	664**
	(121)	(270)	(270)	(76)
Gasoline price * MPG quartile 4	1762**	2943**	2255**	952**
	(115)	(244)	(276)	(79)
R-squared	0.982	0.9757	0.9612	0.9652
N	35107	9452	9100	16555
Number of make-model-age FE's	7191	1760	1663	3768

Note: All models include fixed effects for each make-model-age combination. Change in price for the least efficient (first) quartile is omitted in order to further allow fixed effects by age-year. Standard errors clustered by make-model-age. *,** indicate significance at the 5% and 1% level, respectively.

Table 3: The Effect of Gasoline Prices on Scrap Rates by MPG Quartile

		By age category		
	All Ages	Age 2-5	Age 6-9	Age 10-19
Gasoline price * MPG quartile 2	-0.305** (0.094)	-0.269 (0.153)	0.197 (0.153)	-0.758** (0.159)
Gasoline price * MPG quartile 3	-0.568** (0.075)	-0.213 (0.114)	0.412** (0.103)	-1.591** (0.141)
Gasoline price * MPG quartile 4	-0.945** (0.093)	-0.125 (0.121)	0.33** (0.115)	-2.266** (0.167)
R-squared	0.8604	0.509	0.6185	0.8318
N	35603	9641	9240	16722
Number of make-model-age FE's	7305	1798	1688	3819

Note: All models include fixed effects for each make-model-age combination. Change in price for the least efficient (first) quartile is omitted in order to further allow fixed effects by age-year. Standard errors clustered by make-model-age. *,** indicate significance at the 5% and 1% level, respectively.

Table 4: Price and Scrap Rates Effect as a Continuous Function of Fuel-Economy

	Vehicle price		Scrap rate	
	All ages	Age 10-19	All ages	Age 10-19
Gas price	3409** (-188)	1450** (-144)	-0.0091** (-0.0015)	-0.0331** (-0.0028)
Dollars-per-mile	-61020** (-3787)	-33541** (-2988)	0.3173** (-0.0275)	0.7301** (-0.0502)
R-squared	0.9804	0.9635	0.8469	0.8135
N	35107	16555	35603	16722
Number of make-model-age FE's	7191	3768	7305	3819
Critical MPG	17.9	23.1	34.9	22.1

Note: Estimation follows equations (4.1) and (4.2). All models include fixed effects for each make-model-age combination, and a linear time trend for each age. Standard errors clustered by make-model-age. *,** indicate significance at the 5% and 1% level, respectively.

Table 5: The Used Car Price Elasticity of Scrappage

	OLS				
		By age category			
	All ages	Age 2-5	Age 6-9	Age 2-9	Age 10-19
Scrap elasticity (γ)	-0.5790**	-1.0836**	-0.4922**	-0.7373**	-0.4774**
	(0.0322)	(0.1036)	(0.0685)	(0.0590)	(0.0371)
R-squared	0.589	0.164	0.330	0.281	0.550
N	36665	7804	8213	16017	20648
Number of make-model-age FE's	5657	1226	1234	2460	3197
	IV - First stage: quartile regressions				
		By age category			
	All ages	Age 2-5	Age 6-9	Age 2-9	Age 10-19
Scrap elasticity (γ)	-0.8346**	-0.9118**	-0.6083**	-0.8024**	-1.2663**
	(0.0926)	(0.1922)	(0.1548)	(0.1271)	(0.1187)
R-squared	0.6115	0.164	0.334	0.286	0.584
N	31082	7792	8189	15981	15101
Number of make-model-age FE's	5466	1226	1234	2460	3006
F-statistic first stage	30.98	53.74	35.79	45.00	16.27
	IV - First stage: DPM by make-model				
		By age category			
	All ages	Age 2-5	Age 6-9	Age 2-9	Age 10-19
Scrap elasticity (γ)	-0.6977**	-1.1509**	-0.6862**	-0.8415**	-0.6426**
	(0.0427)	(0.1395)	(0.0776)	(0.0801)	(0.0400)
R-squared	0.639	0.163	0.288	0.331	0.016
N	36665	7804	8213	16017	20648
Number of make-model-age FE's	5657	1226	1234	2460	3197
F-statistic first stage	49.89	36.71	35.77	49.79	32.43
	IV - First stage: DPM by make-model-age				
		By age category			
	All ages	Age 2-5	Age 6-9	Age 2-9	Age 10-19
Scrap elasticity (γ)	-0.7192**	-1.2202**	-0.7091**	-0.9155**	-0.5976**
	(0.0358)	(0.1303)	(0.0746)	(0.0710)	(0.0356)
R-squared	0.233	0.182	0.199	0.187	0.309
N	36665	7804	8213	16017	20648
Number of make-model-age FE's	5657	1226	1234	2460	3197
F-statistic first stage	9.34	13.44	12.42	12.82	7.08

Note: All models include fixed effects for each make-model-age and each age-year combination. Standard errors clustered by make-model-age. *,** indicate significance at the 5% and 1% level, respectively.

Table 6: The Used Car Price Elasticity of Scrappage by Vehicle Class

		By vehicle class					
	All classes	Convertible	Minivan	Pickup	Sedan	Utility	Van
Scrap elasticity (γ)	-0.7192**	-0.8374**	-0.7008**	-0.4447**	-0.6639**	-0.7435**	-0.3620
	(0.0358)	(0.1891)	(0.1683)	(0.1697)	(0.0337)	(0.1319)	(0.4259)
R-squared	0.233	0.419	0.601	0.503	0.341	0.508	0.467
N	36665	1884	2217	4122	22090	4419	1933
Number of make-model-age FE's	5657	522	317	685	3636	765	237

Note: The first stage of the IV includes DPM by make-model-age variables. All models include fixed effects for each make-model-age and each age-year combination. Standard errors clustered by make-model-age. *,** indicate significance at the 5% and 1% level, respectively.

Figure 1: Scrap Rates by Vehicle Age and Make

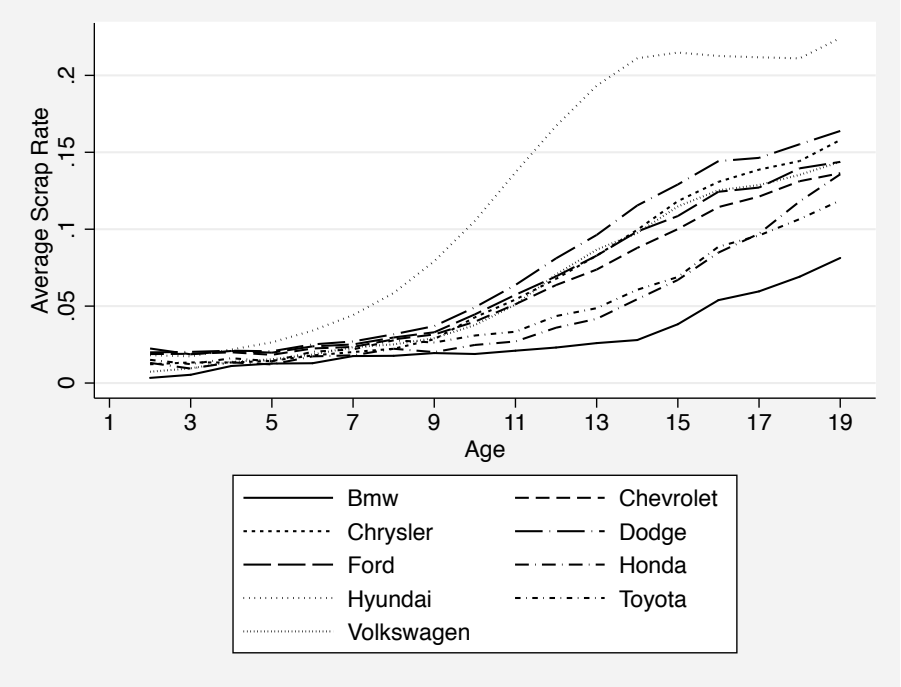


Figure 2: Scrap Rates by Vehicle Age and MPG Quartile

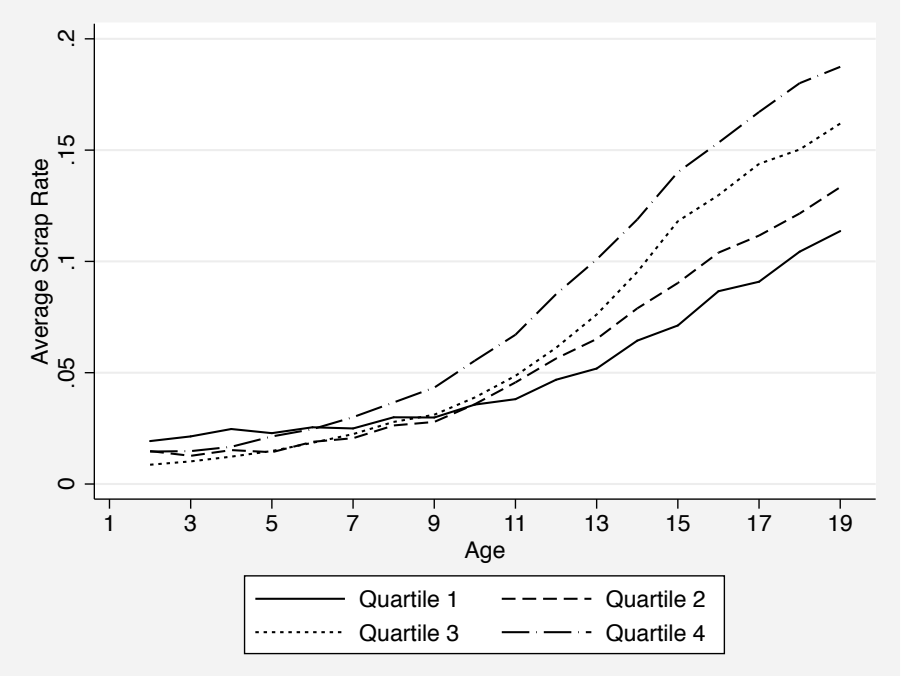
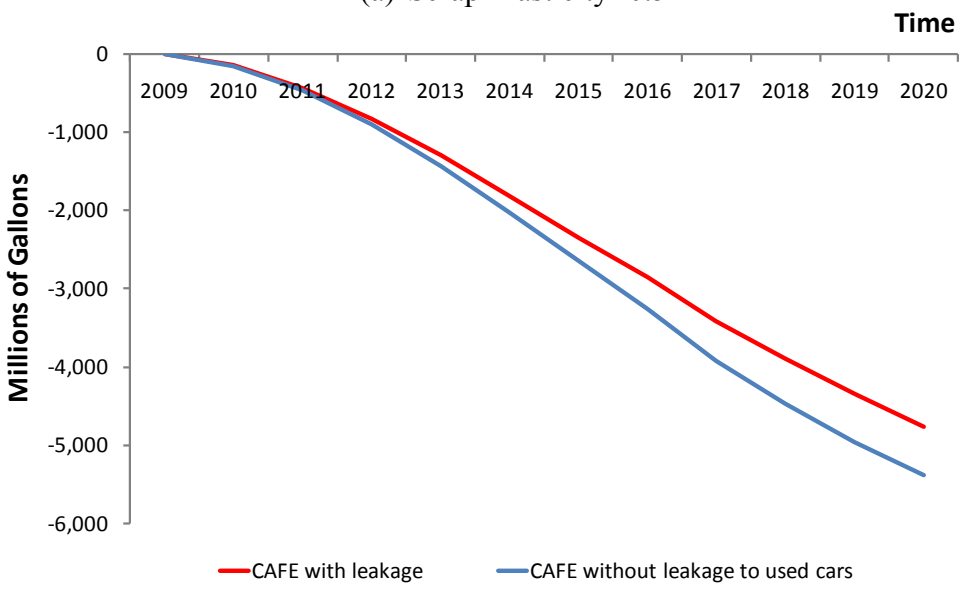


Figure 3: Impacts of Tightened CAFE Standards on Gasoline Consumption over Time

(a) Scrap Elasticity -0.5



(b) Scrap Elasticity -0.8

