Vehicle Scrappage and Gasoline Policy

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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 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 changes used vehicle prices and alters the number of fuel-efficient versus fuel-inefficient vehicles scrapped by 16%. 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 central elasticities we estimate suggest that 13-16% 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.

Keywords: fuel economy; scrap rate; gasoline policy; emissions leakage; incomplete regulation.
JEL codes: H23, Q58, L51.

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1 Introduction

The global stock of vehicles has now passed one billion and continues to grow rapidly.[1] In the U.S., passenger vehicles are the source of 19 percent of carbon dioxide emissions and the share is rising rapidly in developing economies (EPA, 2013). While considerable attention has been paid to regulation of fuel consumption of new vehicles, the vast used market – 94% of the vehicle fleet in the U.S. is more than one year old – is much less well understood. The way the used fleet evolves through scrap decisions has important consequences for overall gasoline consumption and the associated environmental and geopolitical externalities.

We examine the relation between used vehicle 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 – influences the entire suite of policies meant to reduce gasoline use.[2] Despite this, there has been surprisingly little empirical guidance on the relevant elasticity of used vehicle scrappage.

We address three specific 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 policy?

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 include all vehicle registrations in the U.S. over the period 1993-2009 and 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. Also, the resale value of fuel-efficient cars rises relative to fuel-inefficient cars.

We then estimate the used vehicle scrap elasticity with respect to vehicle price, using the relationship between gasoline prices and used vehicle values as the first stage in an instrumental variables approach. We estimate this elasticity to average approximately -0.7 with important heterogeneity over ages and vehicle types.[3] Identification in our approach comes from a combination of cross-sectional and time series variation, caused by differential impacts of gasoline price changes on models of different fuel economies as well as the impact of gasoline price changes on a particular vintage through time.

The elasticity we measure captures a combination of individual decisions to repair or discard vehicles of a particular model and is the underlying parameter needed to consider a wide range of policy impacts. A gasoline tax, for example, will lower the value of the least efficient vehicles in

[1]See Ward's World Motor Vehicle Data (Ward's, 2011) and Oak Ridge National Laboratory's Transportation Energy Data Book (Davis, Diegel and Boundy, 2012).

[2]These consequences are especially important for fuel-economy standards as discussed below. Such standards are the dominant gasoline policy instruments in the U.S. and many other countries where gasoline taxes are politically unpalatable, despite several inefficiencies that have been documented in the literature (Goldberg, 1998; Anderson, Parry, Sallee and Fischer, 2011; Jacobsen, 2013).

[3]The scrap elasticity we estimate is implicitly the price elasticity of aggregate supply of used vehicles by model. See Section 3 for details.

the fleet and make them more likely to be scrapped.[4] The higher the scrap elasticity, the greater this effect. More directly, the effectiveness of scrap bonuses used to get clunkers off the road comes immediately from the scrap elasticity. Finally, fuel-economy rules favored in current gasoline policy create a whole pattern of price shifts in the used fleet that translate through the scrap elasticity to fleet composition.

We consider the application to fuel-economy standards in the final portion of our paper. Early work by Gruenspecht (1982) highlights the mechanism we are interested in measuring: 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 used vehicle fleet that also has a lower average fuel efficiency than if scrap rates had remained unchanged. The reduction in scrap is particularly strong for heavy vehicles with large engines. Since manufacturers can comply with fuel-economy standards by selling fewer gas guzzlers and more gas sippers ("mix shifting"), the demand for used gas guzzlers increases, which in turn decreases their scrap rates. This "used car leakage" is a manifestation of incomplete regulation, because the fuel-economy policy applies to the new vehicle market only.[5] Used car leakage is important to the effectiveness of a wide range of existing and proposed fuel-economy standards, including the European Union's 2020 fuel-economy targets, targets in Japan for 2015, and the U.S. Corporate Average Fuel Economy standards.[6,7]

We estimate the magnitude of the effect in a stylized model of the U.S. vehicle fleet, directly tying the results to our estimates of the scrap elasticity. We find that 13-16% of the expected fuel savings from fuel-economy standards will leak away through the used vehicle market. This effect has often been overlooked by economists and policy makers, yet we find that it rivals or exceeds the importance of the often-cited mileage "rebound" effect.

Our work builds on a series of recent papers examining the effects of gasoline prices on the used car market, a relation we take advantage of in our instrumental variables approach. Busse, Knittel and Zettelmeyer (2013), Sallee, West and Fan (2010), and Allcott and Wozny (2013) 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) and Knittel and Sandler (2013) 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 prices.

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. To our knowledge

[4] Our reduced form estimates in Section 3.3 show the size of this effect.

[5] Bushnell, Peterman and Wolfram (2008) and Fowlie (2009) analyze the consequences of geographically incomplete environmental regulation in the electricity sector: California's emissions regulations do not apply to out-of-state emitters, which can lead to substantial emissions leakage.

[6] Many emerging economies, including Brazil, China, India, Indonesia, Mexico and Thailand have also proposed regulation of this type (ICCT, 2013).

[7] European Union: Regulation No. 443/2009 plus amendments (http://ec.europa.eu/clima/policies/transport/vehicles/index_en.htm); Japan: 10-15 Cycle (http://www.transportpolicy.net/index.php?title=Japan:_Light-duty:_Fuel_Economy); United States: Corporate Average Fuel Economy standards (http://www.nhtsa.gov/fuel-economy).

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 (Hahn, 1995; Alberini, Harrington and McConnell, 1998). 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.[8] Bento, Roth and Zhuo (2013) examine scrappage patterns in the United States using aggregate vehicle counts over the period 1969-1999. They find that failing to account for increases in vehicle lifetimes over this history affects the estimates of how much consumers value fuel economy. Their results are suggestive of undervaluation: consumers recognize between \$0.53 and \$0.73 of a \$1 increase in operating cost.

Finally, programs like "cash for clunkers", where new car purchasers receive a subsidy to have their previous vehicle destroyed, are also related to our question.[9] 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 vehicles personally, and may operate them on a salvage title[10] 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, and uses these effects to provide instrumented estimates of the vehicle scrap elasticity. Section 4 applies our elasticity estimates, simulating the influence of the scrap elasticity on 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 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).

[8]The limitations of these estimates notwithstanding, Goulder, Jacobsen and van Benthem (2012) use them to briefly explore the magnitude of "used car leakage". They find that, depending on the scrap elasticity, the effectiveness of fuel-economy standards can be substantially reduced.

[9]Other authors have investigated the effectiveness of the Car Allowance Rebate System ("cash for clunkers") program along several dimensions: Busse, Knittel and Zettelmeyer (2012) find that it increased consumer welfare and did not significantly affect prices in the used market. Mian and Sufi (2012) provide evidence that cash for clunkers changed the timing of new vehicle purchases without leading to additional purchases or significant fiscal stimulus.

[10]A salvage title includes a qualification stating that the vehicle was once considered a total loss by an insurance company or has otherwise been repaired from major damage.

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.[11] 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 to 2009 and we focus our analysis on this period.[12] In each year we consider vehicles between 1 and 19 years old, measuring the fraction scrapped as the percentage change in registrations from the previous year. Specifically, we define the scrap rate as:

$$y_{amt} = \frac{n_{vm(t-1)} - n_{vmt}}{n_{vm(t-1)}} \,|\, (t-v) = a \tag{1}$$

where y_{amt} is the fraction of vehicles of age a and model m that are scrapped between year $t-1$ and t. Age is measured as the difference between observation year t and vintage year v. 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.

Our measure of the 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, though these components appear to be a small part of annual changes in the fleet: U.S. Census Bureau statistics show that exports of used vehicles averaged 390 thousand per year during our sample period, comprising about 5% of our total scrappage measure.[13] Section 3.4 provides a discussion of the individual scrap decisions that combine to produce the overall scrap rate.

Table 1 displays a summary of vehicle scrap rates and prices through age 19. Vehicles that are 20 years 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. Prices are in constant 2009 dollars.

There is also considerable heterogeneity among manufacturers: panel (a) in 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. Panel (b) in Figure 1 displays scrap rates after dividing all vehicles into quartiles by fuel economy. The heterogeneity in this dimension is particularly interesting for

[11] If there are several VIN prefixes that comprise a certain make-model, for example different trims, we observe the price and registrations for each. When we aggregate to the make-model level we weight prices by the number of registrations.

[12] 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.

[13] Davis and Kahn (2010) find a spike of exports to Mexico as regulations changed between 2005 and 2008, though again this is a small fraction of the total changes we observe in the used fleet.

Table 1: Scrap Rate and Used Vehicle Values by Age.

	All vehicles		Pickup/SUV		All vehicles		Pickup/SUV
Age	Scrap rate	Used value ($)	Scrap rate	Age	Scrap rate	Used value ($)	Scrap rate
1	-	22,415	-	11	5.02%	4,284	5.25%
2	1.59%	19,305	2.10%	12	6.28%	3,723	6.36%
3	1.52%	16,416	2.01%	13	7.47%	3,281	7.11%
4	1.77%	13,748	2.43%	14	8.99%	2,944	8.50%
5	1.74%	11,332	2.05%	15	10.30%	2,668	9.15%
6	2.15%	9,365	2.62%	16	11.79%	2,445	10.90%
7	2.35%	7,851	2.52%	17	12.51%	2,263	10.84%
8	2.80%	6,653	3.01%	18	13.53%	2,105	11.57%
9	3.10%	5,742	3.06%	19	14.45%	1,968	11.79%
10	3.99%	4,960	4.21%				

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

3 Estimating the Scrap Elasticity

3.1 Econometric Framework

The scrap elasticity summarizes the key effect we are interested in: changes in the rate at which used vehicles are removed from the fleet when policy influences their price.[14] The scrap elasticity is important not only in evaluating fuel-economy policy (our application below), but also in a wider set of vehicle policies including subsidies for low-emissions vehicles, scrap bounties and registration taxes. Our estimation appears below, together with a discussion of two related results describing the co-evolution of gasoline prices, used vehicle prices and scrappage rates.

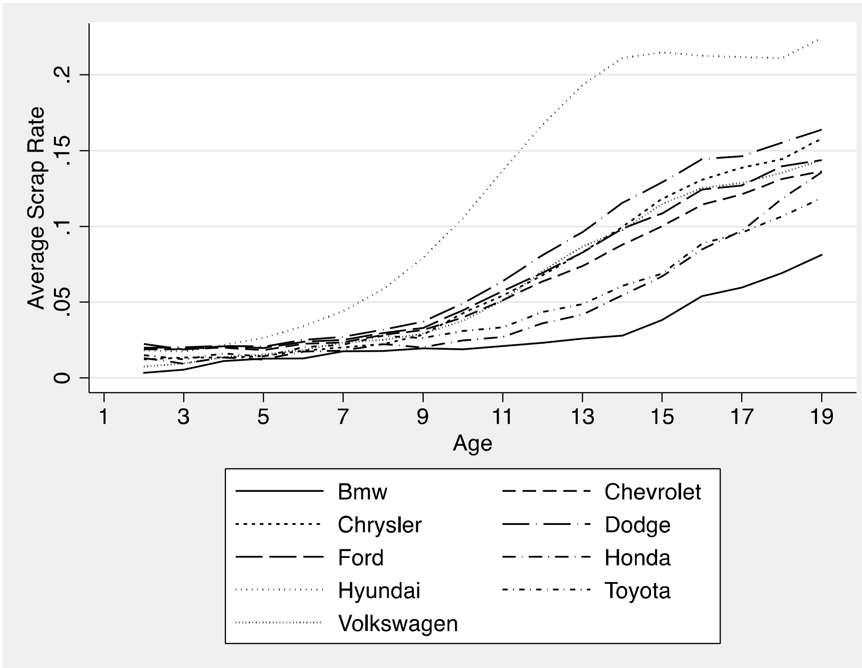
Our elasticity measure employs a panel instrumental variables (IV) estimator, relating the natural logs of the scrap rate y and vehicle price p:

$$ln(y_{amt}) = \gamma ln(\hat{p}_{amt}) + \alpha_{am} + \alpha_{at} + \varepsilon_{amt} \tag{2}$$

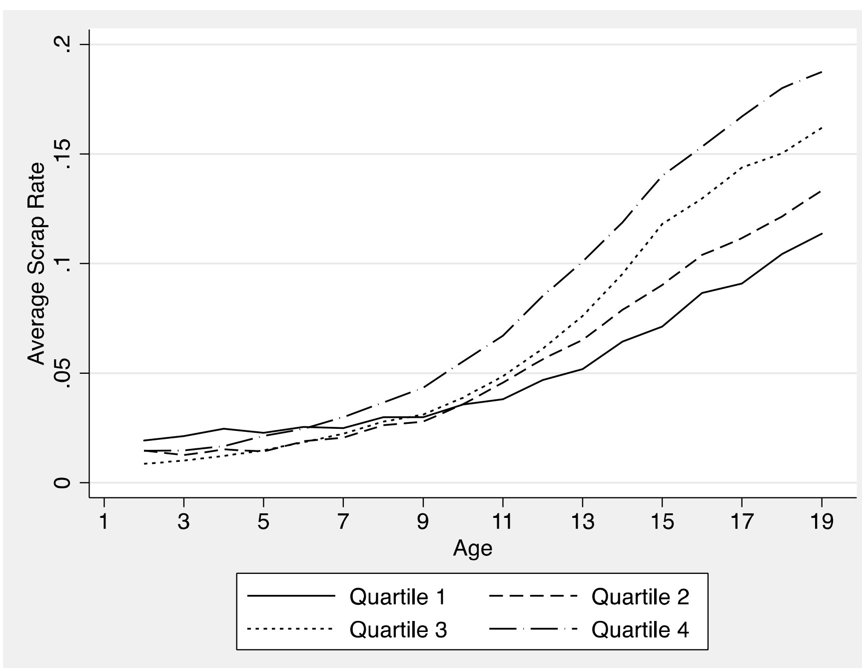
where γ can be interpreted as the scrap elasticity. Subscript a is vehicle age in years, m is make and model (e.g., Toyota Camry) and t is the year of observation. α_{am} are fixed effects for each model-age combination (e.g., a 5-year-old Toyota Camry) and α_{at} are fixed effects for year-age combinations (e.g., all 5-year-old cars in 2009). A particularly appealing aspect of this structure is that it allows us to flexibly account for all changes in scrap rates at the age-year (or even finer) level through fixed effects. Most complications from swings in macroeconomic indicators during our sample period can therefore be absorbed.

[14]We 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.

Figure 1: Scrap Rates by (a) Vehicle Age and Make or (b) MPG Quartile.



(a) Scrap Rates by Vehicle Age and Make.



(b) Scrap Rates by MPG Quartile.

It is important to note that the scrap rates in equation (2) ultimately reflect decisions made on the "supply" side of the used car market. The aggregation of scrap or repair decisions that we model, typically made following collision damage or mechanical problems, combines in equilibrium with movements in demand. Shifts in demand for a particular model will trace out the relationship between prices and scrappage that we want to estimate, but unobserved changes on the scrap side of the market (for example changes in mechanics' wages) would tend to mute the relationship and bias an OLS estimate toward zero. To address this endogeneity we employ instruments that shift demand, using predicted vehicle prices from a first stage, $\hat{p}_{amt}$, in equation (2) above. We present both the OLS and IV results below for comparison.

The instruments we use are the interaction of fuel economy in each vintage and model with contemporaneous gasoline prices.[15] The intuition comes through the differential effects that shocks to gasoline prices have across models. For example, a $1 increase in the gasoline price will increase the resale value of a Toyota Prius relative to a Toyota Camry. Section 3.2 provides details and our empirical estimates of this relationship. Identification of the scrap elasticity requires that these instruments move relative demand across models (influencing equilibrium price) while not directly influencing the scrap decision. We discuss these assumptions and provide a test in Section 3.4.

Sections 3.5 and 3.6 present our overall elasticity estimates and a series of robustness checks. Of particular importance, we experiment with alternative sets of fixed effects that control for changes in scrappage at the age-class-year and age-make-year levels. This allows us to use even finer variation in our instruments (for example, using only fuel economy differences within age-class categories) in identifying the scrap elasticity.

3.2 First Stage: Effect of Gasoline Price on Used Car Prices

The first stage of our estimation measures the relation between gasoline prices and the valuation of used vehicles. We base our instruments on an intuitive effect across vehicles that has been established in the literature: higher gas prices tend to increase the value of used gas sippers and decrease the value of gas guzzlers. We separately interact the fuel economy of each model with gasoline price, so that our instruments are the set of contemporaneous fuel costs for each model. This allows considerable flexibility in that each model can have a separate price response to a change in the gasoline price. We model prices as:

$$ln(p_{amt}) = \alpha_{am} + \alpha_{at} + \beta_m DPM_{mt} + \varepsilon_{amt} \tag{3}$$

where dollars per mile, DPM_{mt}, is calculated as $gasprice_t/MPG_m$ and measures the time-varying cost of a mile driven at the vehicle model level. In an even more flexible specification (which we will use as our preferred model below) we also differentiate by vehicle age:

[15] Other demand shifters, for example changes over time in preference for vehicle size or performance, would be equally valid though are more difficult to collect data on. To the extent these sorts of preference changes have an influence on the price of oil over time (as shown in Kilian (2009)) we implicitly include some of this variation in our existing instruments.

$$ln(p_{amt}) = \alpha_{am} + \alpha_{at} + \beta_{am} DPM_{amt} + \varepsilon_{amt} \tag{4}$$

where DPM_{amt} includes all variation at the age-model-year level.

These approaches exploit a combination of time series and cross-sectional variation, using the differential effect of a change in the gasoline price across vehicles. 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, α_{am}, similarly allow the price of a given model to decay flexibly as it ages. This allows us to control for changes through time (for example, macroeconomic conditions that co-vary with the gasoline price) that increase or decrease the attractiveness of used cars of different ages. The ideal specification would further separate effects by vintage, but since two of the three dimensions (vintage, age, and year) determine the last we can only control for two in a given model. We choose vehicle age and year in our main specification above but explore robustness to alternative combinations of fixed effects in Section 3.6 below and in Appendix C.

The variation that remains in (3) and (4) is the price differential between vehicles of varying fuel economies. Note that there is no restriction that this relation be monotonic: substitution patterns might imply that a small pickup truck (as a substitute for a larger one) could see its price rise in times of high gasoline prices in spite of its poor fuel economy relative to many sedans. These specifications leverage much of the variation in our data and provide strong predictive power in the first stage (F-statistics appear in Table 3 below and the full panel of coefficients is available from the authors).

We also estimate a more compact version of our first stage, allowing a summary presentation in Table 2 as well as closer comparison with prior work examining the relation between gasoline and vehicle prices. This specification follows Busse *et al.* (2013) in modeling quartiles of fuel economy: following the logic above, the group of vehicles in the most fuel-efficient quartile should see an increase in demand – and therefore price – when gasoline prices rise, and vice versa. We include the same flexible controls for time and vehicle age as in (3) and (4), allowing us to focus exclusively on compositional effects. The quartile-based specification is:

$$p_{amt} = \alpha_{am} + \alpha_{at} + \boldsymbol{\beta_1}' \left(gasprice_t * MPGquartile_m\right) + \boldsymbol{\beta_2}' \mathbf{z_{amt}} + \varepsilon_{amt} \tag{5}$$

where the vector β_1 contains the coefficients of interest, now by MPG quartile. We omit the lowest MPG quartile (its price changes are absorbed in fixed effects) such that the coefficients below reflect the relative influence of the gasoline price across quartiles. Because we cannot control for vehicle vintage within a given make-model (Busse *et al.* (2013) are able to do this using regional and monthly variation) we instead introduce additional controls in z_{amt} to account for vintage-specific differences in attributes. z_{amt} includes horsepower, weight and the original suggested retail price. We estimate by least squares and cluster standard errors at the make-model-age level.

Table 2 displays our estimates of β_1. A \$1 increase in the gasoline price implies a \$1,401 increase in used car prices in the most efficient quartile relative to the least efficient, where the average fuel economy over the quartiles ranges from 26.7 to 15.4 MPG. The remaining columns divide used vehicles into age groups: the difference in price effects drops off sharply from $2,121 among the newest used cars to less than $800 among vehicles ten years and older (for a constant $1 change in gasoline price).

The younger categories provide the closest comparison with the sample in Busse *et al.* (2013) who draw from the relatively new used cars sold by new car dealers. Using data on individual transactions they estimate an effect of $1,945 between the four quartiles. Our estimates among the newest used vehicles are similar, with remaining differences likely coming from our coarser time series and somewhat different data period. Busse *et al.* go on to show that the price effects across quartiles indicate near-full adjustment on the part of consumers when modeling expected gasoline cost over the vehicle's remaining life. This also corresponds well with our finding of smaller price effects among older, and therefore closer to retirement, used vehicles.

In the reduced form and IV specifications below we return to the full model in equation (4), allowing variation at the vehicle model level. This makes use of additional variation and substitution patterns in demand and improves the precision of our second stage estimates.[16] We have also experimented with using fitted values from the quartile regression as a first stage and obtain very similar point estimates, shown in Appendix Table C.1.

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
	(1)	(2)	(3)	(4)
Gasoline price * MPG quartile 2	101	89	43	264**
	(90)	(227)	(188)	(73)
Gasoline price * MPG quartile 3	710**	873**	1,068**	517**
	(94)	(231)	(206)	(62)
Gasoline price * MPG quartile 4	1,401**	2,121**	1,760**	790**
	(86)	(201)	(196)	(62)
R^2	0.402	0.497	0.374	0.166
Observations	35,107	9,452	9,100	16,555
Number of make-model-age FEs	7,191	1,760	1,663	3,768

Notes: All models include fixed effects for each make-model-age combination and report R^2 for within-group variation. Change in price for the least efficient (first) quartile is omitted in order to allow fixed effects by age-year. Standard errors clustered by make-model-age. *,** indicate significance at the 5% and 1% level, respectively.

3.3 Reduced Form: Effect of Gasoline Price on Scrap Rates

The effect of the gasoline price on vehicle prices leads in turn to changes in scrap rates: higher gasoline prices lead to increased scrappage of gas guzzlers and reduced scrappage of gas sippers.

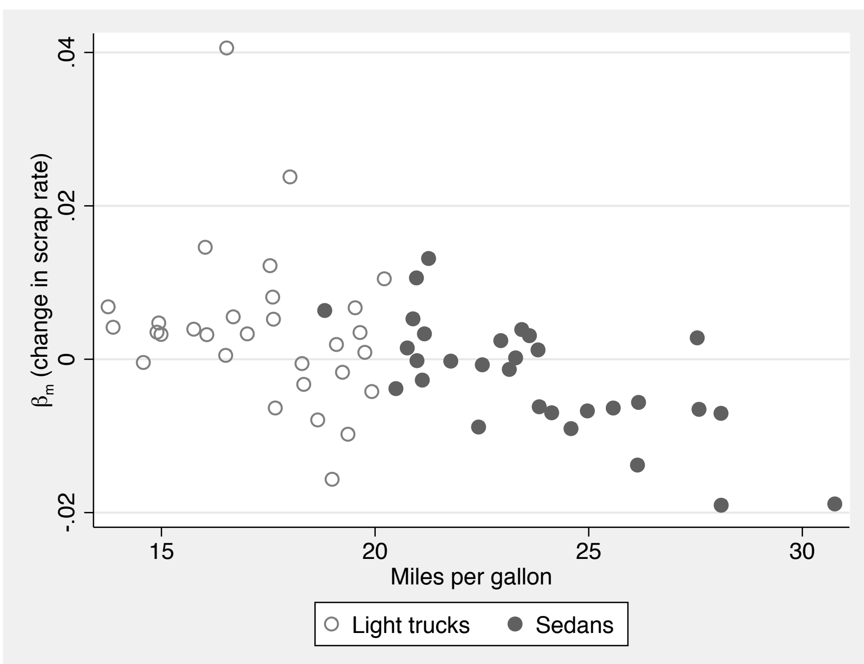
[16] The more flexible model may also avoid potential difficulties coming from uneven distribution of classes and ages across quartiles.

This relation is a reduced form of our scrap elasticity estimate and reflects the set of changes in the used fleet associated with increases in the gasoline price. These changes comprise part of the elasticity of demand for gasoline and (assuming upstream taxes have a similar influence as upstream changes in price) an estimate of the effect of gasoline taxes on the used fleet. For presentation we follow the specification in equation (3), now modeling the scrap rate as a function of changes in model-specific costs per mile:

$$y_{amt} = \alpha_{am} + \alpha_{at} + \beta_m DPM_{mt} + \varepsilon_{amt} \tag{6}$$

where y_{amt} is the fraction of vehicles of age a and model m that are scrapped between year $t-1$ and t. As with the first stage, the coefficients in β_m are relative to fixed effects for vehicle age interacted with year of observation, and so are expressed relative to the mean shift in scrap. Figure 2 displays estimates for vehicles in the light truck and passenger car categories with the highest registration counts. Each point in the figure represents a vehicle model. Positive estimates of β_m reflect a relative increase in the scrap rate for that model when gasoline prices rise. The vertical scale reflects the change in fraction scrapped per year (on a base of 0.055 for the average vehicle) for a $1 increase in the price of gasoline.

Figure 2: Reduced Form Effect of the Gasoline Price on the Scrap Rate by Model.



While the pattern of cross-price elasticities for any particular vehicle model will govern its response to gasoline price changes, more efficient vehicles generally see their scrap rates fall with the gasoline price and vice versa for less efficient models. The average estimates of β_m among models in the most and least efficient quartiles of fuel economy are -0.004 and +0.005 respectively. This corresponds to a 16% difference in the relative number of efficient vs. inefficient vehicles scrapped. The specification above focuses exclusively on relative changes in scrap rates across models as gasoline prices move. In Appendix A we explore an alternative model that imposes more structure but allows for the estimation of "turning points" with respect to fuel economy. We find that, for vehicles 10 years of age or older, an increase in gasoline price decreases scrap rates (and increases resale value) when fuel economy exceeds 23 MPG. The appendix also provides a quartile-based analysis of scrappage parallel to that in equation (5).

3.4 Identifying Assumptions

Moving to our estimation of the scrap elasticity, we require a strong predictive first stage and also that the demand shifters we use as instruments meet an exclusion restriction: unobserved factors determining the scrap rate (for example mechanics' wages, parts prices, and other aspects of used car salvage and dealing) must be uncorrelated with differential fuel cost changes across models. Our age by year effects again enter very importantly: we implicitly allow unobserved factors of this type (even when correlated with gasoline price) that influence the scrap rates of all cars of the same age similarly.

Another way of stating the exclusion restriction is that we need gasoline prices to affect differential scrappage of efficient and inefficient vehicles only through their effect on vehicle prices. The recurring decision problem faced by a used vehicle owner provides a foundation for this argument: 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 price, or scrap it. He will choose scrap if and only if the price in the used market falls below the realized repair cost (net any residual value). If not, he will be better off selling the car to someone else. Importantly, individual decisions to buy, sell or trade cars do not enter our model; we only want to consider the final decision to scrap when no one at all is interested in owning the vehicle. This depends on the used vehicle's market price, repair cost realization, and scrap value, but generally not directly on demand-side parameters such as utility from owning and operating the vehicle and – importantly – not on relative fuel cost versus other models.[17]

The error term in (2) includes the unobservables on supply mentioned above (for example mechanics' wages) as well as any remaining idiosyncratic differences across vintages of a particular model. For example, there may be annual quality differences in production with higher quality vintages having lower scrap rates in each year as they age. We find some evidence of this in Section 3.6[18] but the estimates of the scrap elasticity are unaffected, suggesting that vintage-based effects are not correlated with variation in gasoline prices later in the vehicle's life.

The estimates are robust to heterogeneity in consumer preferences across vehicles and also to

[17] Determinants of demand, including things like the price of other vehicles and relative fuel cost, can enter our model freely through the vehicle's price; our assumption is that they do not enter scrap directly through factors such as repair costs or accident rates.

[18] This would create positive autocorrelation in the error. Harvesting effects, where removal of many cars in the previous period suggests the remaining ones are higher quality, act similarly and would lead instead to negative autocorrelation.

heterogeneous 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. Because most owners of old vehicles will expect to buy a new vehicle within the next few years, a large repair cost shock triggering a scrap decision shifts forward the transaction cost in time, but does not represent an entire extra transaction. The effective cost that needs to be overcome is therefore the cost of moving the transaction forward, rather than the complete cost of the process.

In addition, there are a variety of reasons why even complete transaction costs are likely to be small for vehicles on the margin. First, the final person to face the scrap-or-repair decision for a given vehicle is likely to be a mechanic, dealer, towing company 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. Vehicle owners who want to get rid of a car usually contact a towing company which takes the vehicle and, if available, the title. Subsequently, the company decides whether or not to sell or repair the vehicle or scrap it for parts and metal.[19] This sequence of events ensures that most vehicles that are worth repairing will be repaired at some point in the process.

Second, a separate used vehicle transaction data set obtained from R.L. Polk shows that ownership tenure for old vehicles is relatively short. The average period of ownership is 2.2 years for all used vehicles, and 1.6 years for vehicles 16 years and older. This suggests that transaction costs are low among a fairly broad group of owners. Further, the frequent trades act as an additional force to ensure that vehicles are scrapped when they should be. See Appendix B for details.

While we argue that the network of towing companies, dealers and salvage yards typically ensures that repairs are made when worthwhile, it is possible that transaction costs induce private owners to pay for repairs that exceed the value of a replacement.[20] This creates an asymmetry in the price-scrap relationship that becomes stronger the more important are transactions costs: vehicle price changes in either direction encourage owners to re-optimize their vehicle choice, and scrap or sell their old vehicle. This mutes (exaggerates) the scrap elasticity for vehicles whose value increases (decreases). We provide details and an empirical test in Appendix B. We find very little asymmetry, providing additional reassurance that transactions costs play a minor role in our setting.

[19] Industry participants and a policy maker provided us with details of this process. A towing company and a scrap yard owner stated that consumers incur very little time cost when they give up their vehicle. Whenever possible, a title transfer occurs and a scrap vs. repair decision is made by the company. Even without a title, vehicles can be repaired and legally sold and re-registered after obtaining a "bonded title." This process was further confirmed by a government official in California. Related information can be found at http://www.dmv.org/ca-california/salvaged-vehicles.php.

[20] Note that the repair cost to a mechanic is often much less than the repair cost to an individual, meaning few of these decisions constitute problematic scrappage choices in the context of our model: if the individual's repair cost exceeds the used value but the mechanic's cost does not, then a towing company would have repaired the vehicle anyway.

3.5 Results

The first panel of Table 3 presents the elasticity estimates, γ, estimated from Equation (2) by OLS. The elasticity over all vehicles averages -0.58. The remaining two panels detail our IV approach, accounting for potential bias by isolating shifts in the demand side of the market using fuel economy interacted with the gasoline price. The panels correspond to increasing flexibility in the first stage of the IV estimator between specifications (3) and (4).[21]

Table 3: The Used Vehicle Price Elasticity of Scrappage.

	OLS				
		By age category			
	All ages	Age 2-5	Age 6-9	Age 2-9	Age 10-19
	(1)	(2)	(3)	(4)	(5)
Scrap elasticity (γ)	-0.579**	-1.084**	-0.492**	-0.737**	-0.477**
	(0.032)	(0.104)	(0.069)	(0.059)	(0.037)
R^2	0.237	0.190	0.198	0.191	0.313
Observations	36,665	7,804	8,213	16,017	20,648
Number of make-model-age FEs	5,657	1,226	1,234	2,460	3,197
	IV - First stage: DPM by make-model				
		By age category			
	All ages	Age 2-5	Age 6-9	Age 2-9	Age 10-19
	(1)	(2)	(3)	(4)	(5)
Scrap elasticity (γ)	-0.694**	-1.154**	-0.687**	-0.842**	-0.646**
	(0.043)	(0.140)	(0.078)	(0.080)	(0.040)
R^2	0.236	0.190	0.197	0.190	0.311
Observations	36,665	7,804	8,213	16,017	20,648
Number of make-model-age FEs	5,657	1,226	1,234	2,460	3,197
First stage F-statistic	66.67	21.37	25.53	34.82	31.73
	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
	(1)	(2)	(3)	(4)	(5)
Scrap elasticity (γ)	-0.711**	-1.210**	-0.710**	-0.909**	-0.589**
	(0.035)	(0.128)	(0.072)	(0.069)	(0.035)
R^2	0.233	0.182	0.199	0.187	0.310
Observations	36,665	7,804	8,213	16,017	20,648
Number of make-model-age FEs	5,657	1,226	1,234	2,460	3,197
First stage F-statistic	18.15	16.70	20.68	19.82	14.44

Notes: Fixed effects are for each make-model-age and each age-year combination. Standard errors are clustered by make-model-age and R^2 is reported for within-group variation. *,** indicate significance at the 5% and 1% level, respectively.

The second and third panels show the IV results using (3) and (4) as the first stage, respectively. The strength of the instruments in influencing demand is reflected in the high first stage F-statistics

[21] Since the basic intuition for our instrumenting strategy comes out of the quartile model in Equation (5), Appendix Table C.1 presents results that import these estimates (appearing in Table 2) directly as the first stage. The overall elasticity estimate is -0.83.

shown alongside the instrumented elasticity estimates. Using model-specific fuel cost responses as instruments in the first stage, the average elasticity is -0.70. The more flexible model-age specific responses yields quite similar elasticities to the somewhat more aggregate instruments used in the second panel.

Table 3 also explores differences in the elasticity across age categories. Generally we find fairly similar elasticities across ages, declining somewhat for the very oldest cars. We estimate the price elasticity of used vehicle scrappage to be about -0.7 for all vehicle ages grouped together. Our preferred specifications indicate that scrappage of 2-9 year-old vehicles is slightly more price elastic (-0.9) than scrappage of 10-19 year-old vehicles (-0.6). This likely reflects high baseline scrap rates among the oldest vehicles.

While we expect the OLS estimates to be biased toward zero, the IV estimates suggest that the size of the bias is relatively small. This would be the case if the variation in our setting is coming mainly through shocks to demand. This accords well with anecdotal evidence about the car market: changes in gasoline prices and vehicle preferences seem to be rapid and large relative to movements in the physical repair and salvage costs governing the scrappage side of the market.

3.6 Heterogeneity and Robustness Checks

Table 4 decomposes our elasticity estimates by vehicle class, again employing the most detailed set of instruments. Heterogeneity across classes is fairly limited with the exception of pickup trucks: our point estimate is a scrap elasticity of -0.4 as compared with -0.7 in the full sample. We find somewhat more heterogeneity in the scrap elasticity for older used vehicles, which are also the most relevant group from a policy perspective given their high absolute scrap rates. Older pickups exhibit much more inelastic scrap behavior, while scrappage of small and large sedans is also somewhat less elastic (-0.5). In contrast, the scrap elasticity for older SUVs and vans is larger than average (-0.9). Since SUVs and vans are the majority of the light truck fleet, this suggests that the scrappage of old, large vehicles on average tends to respond the most strongly to changes in used vehicle prices.

Table 4: The Used Vehicle Price Elasticity of Scrappage by Vehicle Class.

		By vehicle class				
	All classes	Small sedan	Large sedan	Pickup	SUV	Van
	(1)	(2)	(3)	(4)	(5)	(6)
Scrap elasticity (γ)	-0.711**	-0.578**	-0.668**	-0.363**	-0.710**	-0.772**
(All ages)	(0.035)	(0.040)	(0.049)	(0.163)	(0.116)	(0.174)
Scrap elasticity (γ)	-0.598**	-0.514**	-0.499**	-0.186	-0.862**	-0.918**
(Age 10-19)	(0.036)	(0.038)	(0.051)	(0.198)	(0.160)	(0.176)
R^2 (all ages)	0.233	0.476	0.316	0.506	0.507	0.458
Observations (all ages)	36,665	11,035	12,458	4,463	4,559	4,150
Number of make-model-age FEs (all ages)	5,657	1,730	1,956	685	732	554

Notes: 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 and report R^2 for within-group variation. Standard errors clustered by make-model-age appear in parentheses.

We next consider robustness to changes in miles driven across vehicles. If gas price movements cause strong substitution in miles driven between vehicles this has the potential to make our elasticity estimates conservative. For example, if small cars are driven relatively more when gas prices rise they will have more accidents and breakdowns, shifting the distribution of repair cost shocks that underlies the scrap decision. We expect this effect to be small: the price changes identifying the elasticity reflect fuel costs over the life of the vehicle while any effects from mileage adjustment would enter only in the year of observation. Nevertheless, we conduct an experiment with the data to bound this effect by adjusting all scrap rates in our data based on aggressive assumptions about differences in miles driven as driving costs change across models.[22] This adjustment increases the magnitude of our elasticity estimates by only about 0.01, leading us to abstract from mileage in the main specification.

Finally, Table 5 explores a variety of subsets of the data and additional alternative assumptions. We find that the elasticity estimates are generally robust:

Excluding luxury models: Excluding luxury models (about 25% of our make-model combinations when classified on brand and price) has only a small effect on the estimates. Average prices are of course much lower in this subset, suggesting similar elasticities across prices within an age category.

Using only increases/decreases in the gasoline price: Our point estimate is somewhat smaller when using only years where gas prices have fallen, though it remains similar and the difference is not statistically significant. This suggests that macroeconomic indicators correlated with gasoline price movements have limited influence after our controls for time.

Excluding 2009: We exclude 2009 (covering scrappage during the period July 2008 - July 2009) as this corresponds to the start of the financial crisis, which had major impacts on the car market. The effects of the crisis on the demand side could influence the strength of our instruments, and influences on the scrap side of the market (differentially by fuel economy) could violate the exclusion restriction. Reassuringly, omitting this period has almost no effect on our elasticity estimates.

Class/make by age by year fixed effects: We experiment with more detailed fixed effects, allowing flexible patterns in scrappage by class-age-year and make-age-year. This reduces the variation we use for identification to only relative fuel economies within class or make, absorbing other changes. Additional alternative specifications along this dimension, including make-model-year (instead of make-model-age) fixed effects appear in Appendix C. The elasticity results remain robust to utilizing these smaller slices of variation in the data.

Log-log instead of semi-log first stage: The results from prediction using the log of dollars-per-mile in the first stage produce very similar elasticity estimates. The semi-log form in the main model

[22] This calculation consists of the following steps. First, in line with the literature, we assume that the component of driving cost that is not fuel related is constant across models and equal to the average fuel cost across all models. In reality, such non-fuel costs will be somewhat larger for larger, more expensive models, but assuming that the non-fuel costs are constant conservatively leads to the largest scrap rate adjustments. Second, using the gasoline price time series and the fuel-economy data, we calculate annual changes in total driving costs (fuel plus non-fuel) for all models. Third, we apply a high price elasticity of driving of 1.0 (near the top of the range of estimates in the literature). Finally, we adjust all scrap rates fully proportionally with miles driven. The fixed non-fuel component in driving cost provides an asymmetric response in miles driven across vehicle models of different fuel economies. The results are robust to variations in the fraction of non-fuel operating cost.

Table 5: Elasticity Estimates from Alternative Models.

	Excluding luxury models (1)	Using only gas price increases (2)	Using only gas price decreases (3)	Excluding 2009 (4)
Scrap elasticity (γ)	-0.637**	-0.711**	-0.625**	-0.698**
(All ages)	(0.052)	(0.048)	(0.091)	(0.041)
Scrap elasticity (γ)	-0.768**	-0.670**	-0.484**	-0.646**
(Age 10-19)	(0.047)	(0.046)	(0.081)	(0.037)
R^2 (all ages)	0.268	0.232	0.282	0.218
Observations (all ages)	28,121	25,987	10,678	33,716
Number of make-model-age FEs (all ages)	4,224	5,657	5,462	5,657
	Class by age by year effects (5)	**Make by age by year effects (6)**	**First stage DPM in logs (7)**	**Control for vintage fraction remaining (8)**
Scrap elasticity (γ)	-0.693**	-0.687**	-0.680**	-0.701**
(All ages)	(0.041)	(0.045)	(0.042)	(0.043)
Scrap elasticity (γ)	-0.592**	-0.653**	-0.637**	-0.655**
(Age 10-19)	(0.040)	(0.042)	(0.039)	(0.040)
R^2 (all ages)	0.434	0.304	0.236	0.237
Observations (all ages)	36,665	36,665	36,665	36,665
Number of make-model-age FEs (all ages)	5,657	5,657	5,657	5,657

Notes: All estimates here are variations on the make-model-age level instruments reported in the third panel of Table 3. All include fixed effects for each make-model-age and each age-year combination and report R^2 for within-group variation. Standard errors clustered by make-model-age appear in parentheses.

visually fits the shape of the price data better.

Fraction of each vintage remaining: Here we include the remaining fraction of the original production for each vintage as a regressor on the right hand side of equation (2). The coefficient on this new variable is negative, suggesting that quality differences in vintages are persistent over time. Including this term does not influence our elasticity estimates, however, suggesting that this sort of variation is orthogonal to cross-sectional changes in vehicle prices.

Appendix Table C.2 provides estimates from several additional alternative models, including small vs. large changes in the gasoline price, alternative fixed effects, weighting, and a specification including accident rates. The point estimates remain similar.

4 Application to Fuel-Economy Standards: The *Gruenspecht Effect*

We now apply our scrap elasticity estimates in a simulation model to measure the magnitude of the *Gruenspecht effect*. We define leakage to the used market as the extent to which tighter fuel-economy standards lead to increased gasoline consumption in the used fleet. We choose the example of the Corporate Average Fuel Economy (CAFE) standards in the United States, although used vehicle leakage applies to many similar existing or proposed fuel-economy standards across the world (ICCT, 2013). The simulation is similar in structure to the model developed in Goulder *et al.* (2012). We refer to that paper for details, but outline the model below.

4.1 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 fleet (car or truck). Large and small here refer to attributes such as engine size or weight that are effectively favored or discouraged by the fuel-economy regulation.

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 in the following order: vehicles vs. other goods, fleet, size, age and manufacturer. At the highest nest, the consumer chooses the mix between vehicles (v) and other goods (x):

$$\max_{v,x} U(v,x) = (\alpha_v v^{\rho_u} + \alpha_x x^{\rho_u})^{\frac{1}{\rho_u}} \tag{7}$$

subject to a budget constraint:

$$p_v v + p_x x \leq I \tag{8}$$

where I is total income[23], 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 scale parameters. This relatively simple structure for demand focuses explicitly on car choice and scrappage, leaving miles driven and corresponding estimates of the "rebound effect" as exogenous. In our discussion below we will then compare the leakage we identify from scrappage and vehicle choice with estimates of mileage rebound from the existing literature.

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 fleet f and size s) subject to fuel-economy standards.[24] The profit maximization problem for manufacturer k is given by:

$$\max_{p_{f,s}, e_{f,s}} \sum_{f,s=1,2} [(p_{f,s} - c_{f,s}(e_{f,s})) * q_{f,s}(\mathbf{p}, \mathbf{e})] \tag{9}$$

[23]Total income I is exogenous and grows at a fixed rate over time.

[24]Manufacturers may improve the fuel economy of individual models in two ways: via technological substitution (by changing the mix of components that are already available under today's technology, such as installing different transmissions or tires) or via technological change (discovering new technology, such as improved aerodynamic design). For details, see Goulder *et al.* (2012).

subject to the CAFE standards for cars and trucks:

$$\frac{\sum_{s=1,2} q_{1,s}}{\sum_{s=1,2}\left(\frac{q_{1,s}}{e_{1,s}}\right)} \geq \bar{e}_C \tag{10}$$

$$\frac{\sum_{s=1,2} q_{2,s}}{\sum_{s=1,2}\left(\frac{q_{2,s}}{e_{2,s}}\right)} \geq \bar{e}_T \tag{11}$$

where the decision variables $p_{f,s}$ and $e_{f,s}$ denote vehicle prices and fuel economies, respectively. $c_{f,s}$ 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:

$$q_{f,s,a+1,k}(t+1) = (1 - y_{f,s,a+1,k}(t+1))\, q_{f,s,a,k}(t) \qquad a = 0, 1, \ldots, 18 \tag{12}$$

where t indexes time, a indicates age ($a = 0$ refers to new cars) and $y_{f,s,a,k}$ is the end-of-period scrappage probability. At the end of the period, all 18-year-old cars are scrapped. The scrap probability for each vehicle and vintage is endogenous and depends on the vehicle's resale value, following our empirical specification of the scrap elasticity above:

$$y_{f,s,a,k} = b_{f,s,a,k}(p_{f,s,a,k})^{\gamma} \tag{13}$$

where $b_{f,s,a,k}$ is a scale parameter that calibrates baseline scrap rates and γ is the scrap elasticity estimated above.

The used car purchase price $p_{f,s,a,k}$ is the sum of scrap-adjusted, discounted future rental prices $r_{f,s,a,k}$. We assume consumer expectations for these future used prices update with current policy but are myopic with respect to future policy: consumers 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.[25,26] This allows us to recursively solve for used vehicle purchase prices:

[25] This form for expectations is similar in nature to the empirical finding that consumers expect gasoline prices to remain constant (Anderson, Curtis, Kellogg and Sallee, 2011; Anderson, Kellogg and Sallee, 2013).

[26] Myopic consumers revise their expectations about future vehicle prices more slowly than forward-looking consumers, but update in the right direction. Importantly, myopia does not affect the steady state that will be reached after fuel-economy standards remain constant for a long time. Hence, myopia does not affect our leakage results in the long run. In settings where a more stringent fuel-economy standard is phasing in rapidly the implicit myopia will be more restrictive than in cases where the policy represents a small, flat increment. It is reassuring that we find relatively little difference in our overall leakage results across these settings.

$$p_{f,s,18,k} = r_{f,s,18,k}$$

$$p_{f,s,a,k} = r_{f,s,a,k} + \frac{(1 - y_{f,s,a,k})p_{f,s,a+1,k}}{1+\delta} \tag{14}$$

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. Because the set of constraints that bind for the various producers also enters, we solve for equilibrium using a nested iterative procedure: going from the "lowest" to "highest" nest, the model solves for a set of used vehicle prices that clear the used market, given new car prices and a guess of which fuel-economy standards bind for each firm. One level up, the model solves for new vehicle prices given the set of fuel-economy constraints that bind. At the highest level, it iterates over the set of binding fuel-economy constraints such that all other markets also clear. The resulting equilibria are calculated for every year in sequence over the simulation period from 2009 to 2025.

4.2 Data and Parameters

We calibrate the model to prices and composition (obtained from *Automotive News*), and fuel economies (obtained from EPA) of the 2009 U.S. vehicle fleet, as well as 2009 GDP ($14.2 trillion) and gasoline price ($1.83/gallon). We assume an income growth rate of 2.0 percent per year (average GDP growth rate for the United States, 2001-2008), and an autonomous rate of improvement in fuel-economy technology of 1.8 percent per year (Knittel, 2011). For all other parameters (e.g., demand elasticities, parameters of the fuel-economy cost functions), we follow Goulder *et al.* (2012).

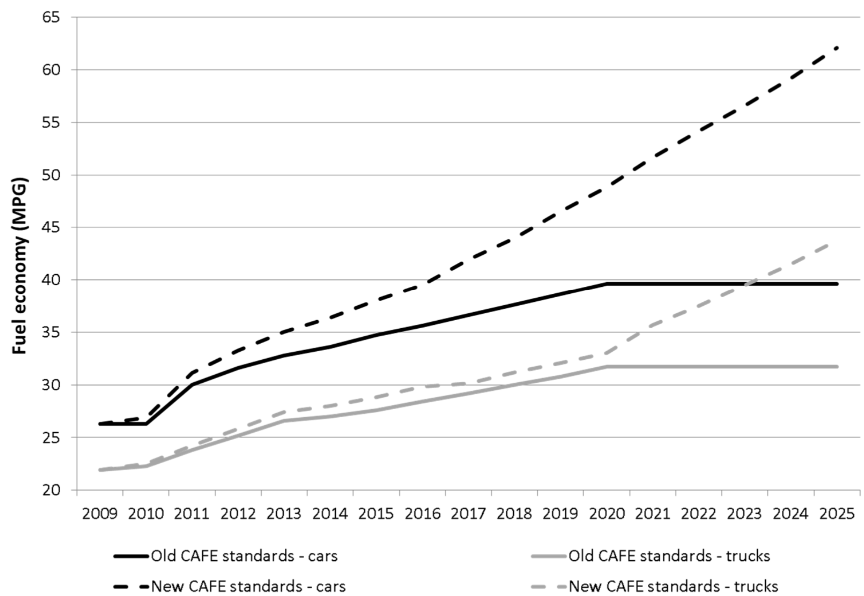
The model incorporates age, type (car/truck), and size (small/large) specific averages for vehicle miles traveled (VMT) obtained from the 2009 National Household Transportation Survey (see Appendix Table D.1). Average VMT is 12,951 for new vehicles and 6,297 for 18-year-old vehicles. These combine with scrap rates and fuel economies to determine gasoline consumption in the fleet.

4.3 Policy Experiments

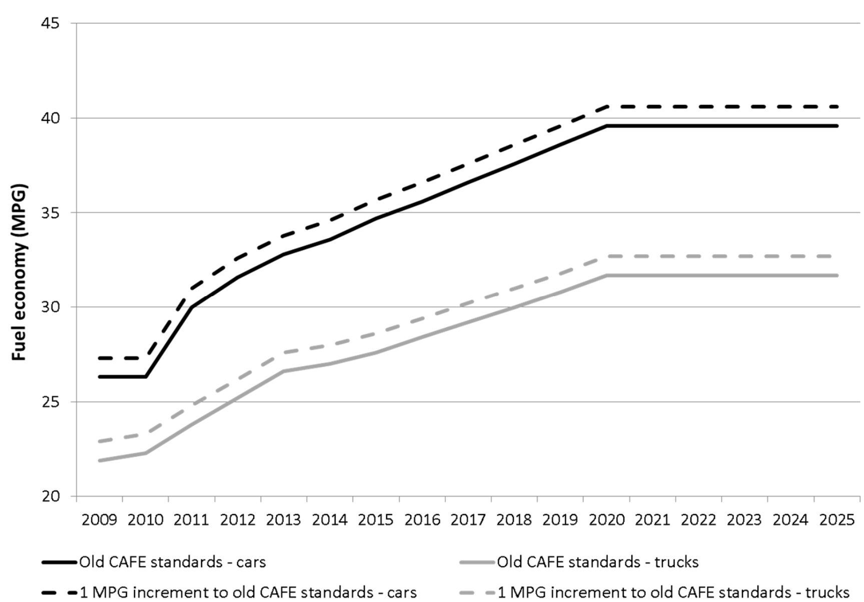
We consider the recent tightening of federal CAFE standards to a target of 41.7 MPG in 2020 and 54.5 MPG in 2025 (EPA and NHTSA, 2012). The reference case to which this is compared corresponds to a previously announced goal of 35 MPG in 2020. We will refer to these as the "new" and "old" CAFE standards and report leakage from the change as our central policy experiment. The timing of this policy change matches well with our 2009 base year, also consistent with the 1999-2009 used vehicle registration data.

We also consider a second central policy experiment: a constant 1 MPG increase in the stringency of the CAFE standards (we consider the 1 MPG increment to the old and new standards

Figure 3: Policy Experiments: Old CAFE Standards vs. (a) New CAFE Standards or vs. (b) a 1 MPG Increment.



(a) Old CAFE Standards vs. New CAFE Standards.



(b) A 1 MPG Increment to the Old CAFE Standards.

separately). This presents a much more symmetric increase in car and light trucks standards than the actual new CAFE standards, which are heavily back-loaded to the period 2020-2025. It also balances the policy change more evenly across simulation periods. Figure 3 shows the time paths in fuel-economy standards under both policy experiments.

It is important to emphasize that our policy setting also has implications for a wide variety of other fuel-economy standards. We keep the model here relatively simple, considering aggregate vehicles that simply represent those favored and discouraged by standards placed on new cars (then tracking how those same types of vehicles do in the used market). This allows us to demonstrate how our estimated scrap elasticities control the *Gruenspecht effect* in a general setting. More richly detailed simulations could identify favored and discouraged vehicles at the level of model names and configurations, producing analysis of specific rules in Europe, Japan or the recently adopted "footprints" in the U.S.[27]

4.4 Used Vehicle Leakage Results

We calculate the magnitude of emissions leakage to used vehicles under the fuel-economy policies described above. In both the central policy experiment and the 1 MPG increment experiment, we consider scrap elasticity estimates differentiated by vehicle type and age, similar to those in Table 4.[28] This weights the effect of the elasticities by the quantity of vehicles in each category. The table also explores sensitivity of the results to alternative, uniform scrap elasticities of -0.5, -0.8 and -1.0. These values span a range that includes some of the most and least elastic subgroups in our data.

We express leakage as the fraction of expected gasoline savings (when fuel-efficient new vehicles make their way through the fleet over time) that are never realized due to changes in used vehicle scrap rates. Panel A of Table 6 presents accumulated gasoline savings and leakage by 2025 for the two central policy experiments (old vs. new CAFE and a 1 MPG increment). By 2025, leakage is 12.5% for the central policy experiment and 14.0-15.8% for the 1 MPG increment policies. That is, 13 to 16% of the gross emissions reductions in the new vehicle market are offset.

These overall leakage effects come via a set of equilibrium price changes that combine with our elasticity estimates. The largest of the price changes occur for new cars, reflecting that the much stricter CAFE standards trigger costly technology improvements: new vehicle prices under the new standards rise by $505 per year relative to the old standards.[29] Used vehicle prices are

[27]Relabeling the four vehicles in our aggregate model to match categories favored or discouraged by a particular rule allows the wider range of interpretation. Leakage of the type we examine will be present for all major fuel-economy policies. The E.U. standards, for example, bear many similarities to U.S. CAFE standards. In turn, the footprint rules create used car leakage that follows fuel economy conditioned on footprint rather than only the car vs. truck distinction. In either case the cost of new vehicles, and particularly the less efficient ones (consider versions of a pickup truck with 8-cylinder engines), rises and substitution into the used market influences prices and scrap.

[28]To match the simulation model we redefined vehicle classes in our estimation into "small" vs. "large" cars and light trucks. The resulting scrap elasticities are -0.758 and -0.514 (small cars; $\leq$9 years old and $\geq$10 years old), -0.979 and -0.500 (large cars), -0.816 and -0.811 (small trucks), and -0.617 and -1.018 (large trucks).

[29]Under the old CAFE standards, the average price of new cars increases by $244 per year while under the new, much stricter, standards this rises to $749. Note that the leakage percentage is similar for the 1 MPG increment to

affected as a result of increased demand when new vehicle prices go up, but to a smaller degree: they rise an average of $103. The difference in price changes across used vehicles with different fuel economies (prices rise more for less fuel-efficient vehicles) drive our key compositional effects: prices for smaller, more fuel-efficient vehicles that are favored under the fuel-economy standards increase less quickly than prices for larger, fuel-inefficient vehicles. When CAFE standards are tightened, prices for small used cars and small used trucks do not rise as fast ($96 and $62 per year for the average vehicle, respectively) as prices for large used cars and trucks ($164 and $92 per year).[30] These price changes translate through the scrap elasticity into the used fleet, and then on to overall leakage relative to a world without changes in scrap.[31]

Table 6: Leakage Estimates for Policy Experiments.

	Accumulated gasoline savings by 2025		Cumulative leakage by 2025
	With leakage	Without leakage	
Panel A: policy experiments			
Central policy experiment	6,212	7,097	12.5%
1 MPG increment to old CAFE	310	360	14.0%
1 MPG increment to new CAFE	279	331	15.8%
Panel B: changing the scrap elasticity in the central policy experiment			
Scrap elasticity: -0.5	6,345	7,063	10.2%
Scrap elasticity: -0.8	6,129	7,181	14.7%
Scrap elasticity: -1.0	6,010	7,252	17.1%
Panel C: additional sensitivity analysis			
More stringent new CAFE standard	8,210	9,716	15.5%
Less stringent new CAFE standard	3,517	3,882	9.4%
Higher gasoline price: $3/gallon	5,031	6,403	21.4%
Slower autonomous fuel economy improvements	6,250	7,361	15.1%
Alternative cost of fuel economy improvements	6,619	7,710	14.2%
50% higher elasticity of substitution between vintages	6,129	7,290	15.9%
50% lower elasticity of substitution between vintages	6,323	6,772	6.6%

Notes: The central policy experiment refers to a comparison between the old and the new CAFE standards. Gasoline savings are expressed in millions of gallons.

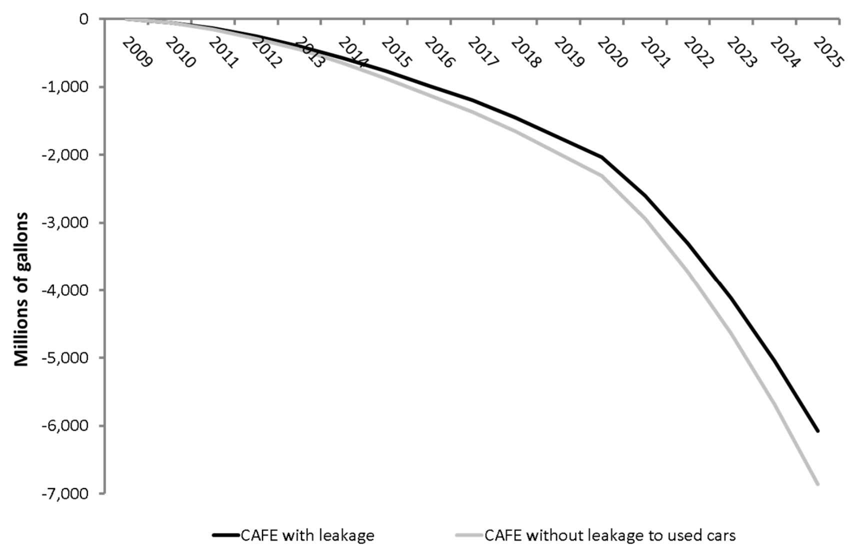
fuel-economy policy even though this reflects much smaller average price increases.

[30] Prices for used cars increase faster than prices for trucks, as the new CAFE standards are more lenient for trucks than for cars.

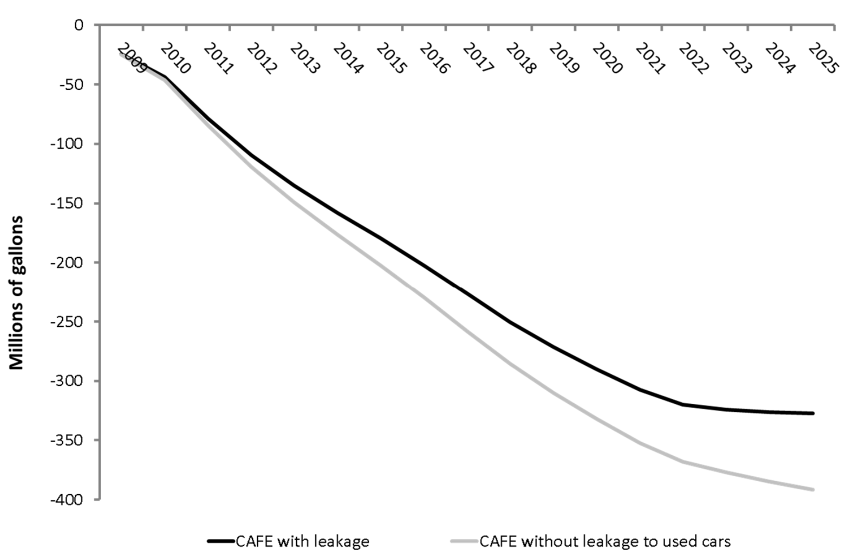
[31] Along these lines, Appendix D contains a calculation using a highly simplified version of our simulation model in which vehicles are pooled across ages (leaving only the four types by class and size) and a single scrap elasticity is applied to all vehicles. The above-mentioned price changes for these four vehicle classes result in changes in gasoline consumption and leakage that are close to the results from the full simulation model.

Figure 4 shows the difference in total gasoline consumption over the period 2009-2025 between the reference and policy cases for our central policy experiments. The gray line ignores the impacts of the tightened CAFE standards in the used vehicle market. The black line accounts for these effects and reveals smaller reductions in gasoline consumption. Both lines are downward sloping, indicating that gasoline reductions accumulate as additional generations of fuel-efficient new vehicles enter the fleet. The difference between the two lines is the leakage reported in Table 6.

Figure 4: Gasoline Savings from Tightened CAFE Standards on Gasoline Consumption over Time: Old CAFE Standards vs. (a) New CAFE Standards or vs. (b) a 1 MPG Increment.



(a) Old CAFE Standards vs. New CAFE Standards.



(b) A 1 MPG Increment to the Old CAFE Standards.

Panel B in Table 6 shows the magnitude of leakage to used vehicle markets as the scrappage elasticity varies between -0.5 and -1.0. Leakage by 2025 grows from 10 to 17 percent as the elasticity changes, underscoring the importance of carefully estimating the magnitude of this parameter.

While we believe ours is the first empirical estimate of the *Gruenspecht effect*, it may be useful to draw comparisons 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. Small and Van Dender (2007) place this effect between 2.2 and 10.7 percent for the period 1997-2001. EPA and NHTSA use a value of 10 percent in their analyses[32] while Gillingham (2011) leverages a recent and rich data set to arrive at a value of about 15 percent. The 13-16 percent range we estimate here for the *Gruenspecht effect* adds to mileage rebound as a source of leakage, rivaling or exceeding it in magnitude.

4.5 Additional Sensitivity Analysis

We now consider sensitivity to a number of other key simulation parameters. Panel C of Table 6 reports the results when repeating the policy case shown in the first line of the table.

First, we consider a more stringent new CAFE standard: the difference between the new and old CAFE standards is increased by 50% each year. Under this much stricter standard, used vehicle leakage increases only modestly to 15.5% by 2025. The change is due to an increase in the number of binding CAFE constraints across firms and fleets, pushing more of the substitution into the used market. Symmetrically, a 50% weaker standard somewhat reduces leakage.

Next we consider a much higher gasoline price, raising it from $1.83 per gallon in the central policy experiment (the average in 2009) to $3.00 per gallon (closer to current levels). This increases leakage fairly substantially to 21.4%, again due to changes in the set of binding constraints and competition across firms.[33]

The fourth row of Panel C assumes a lower rate of autonomous fuel-economy improvements (1.0 instead of 1.8 percent growth in the exogenous component of fuel economy) and this increases leakage slightly: more manufacturers are now bound by CAFE in one or both fleets.

Next, we re-parameterize the fuel-economy cost function using recent estimates from the National Highway Traffic Safety Administration's *CAFE Compliance and Effects Modeling System* ("*The Volpe Model*") (NHTSA, 2012). The curvature of these cost functions are about half, one third and two thirds that of our central policy experiment for small cars, large cars and small trucks respectively, and somewhat larger for large trucks. While marginal technology costs change fairly substantially, we find that leakage is affected only slightly: the Volpe Model parameters cause more of new car gasoline savings to come from technology changes and less from mix shifting in the fleet, which increases leakage on the MPG technology margin but decreases it on the vehicle mix margin. The two largely offset, leaving leakage slightly higher on net.

[32] Greene (2010) also arrives at a point estimate of about 10% for the rebound effect.

[33] Specifically, manufacturers like Honda and Toyota experience growth in demand for their larger (relatively fuel-efficient) cars and trucks when gasoline prices rise. This causes their CAFE constraints to bind, again pushing more demand into the used market, raising used prices and reducing scrap rates.

The final two rows in the table alter the elasticity of substitution across vintages, directly influencing the mechanism by which used car leakage occurs. The more elastic is substitution between the new and used market the more leakage occurs: an increase in the elasticity of substitution by 50% increases leakage to 15.9% while a decrease of 50% reduces leakage to 6.6%.

When considering the full variety of cases in the table two key drivers of leakage emerge: the scrap elasticity and the elasticity of substitution between new and used vintages. High scrap elasticities combined with large amounts of substitution into the used market make the *Gruenspecht effect* its strongest.

5 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 current fuel-economy policy in the U.S., Europe, China and Japan: in our simulations, tightened standards for new vehicles lead to a leakage effect that offsets 13 to 16 percent of expected gasoline savings.

The effect of used car leakage on the overall effectiveness of policy is often ignored by policy makers, even though its magnitude rivals or exceeds the often-cited mileage "rebound" effect. In order to highlight the key factors creating this leakage we investigate sensitivity to a broad range of simulation parameters: the scrap elasticity, estimated here, combines with demand elasticities between new and used vehicles as the most important drivers of leakage to the used market.

Our main 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 the gasoline price on used vehicle values depending on their fuel economies. These effects on prices become the first stage of our 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.

Our results on scrappage can also be applied to a range of other gasoline policies that affect the scale and composition of the used vehicle fleet, such as a gasoline tax, vehicle subsidies that target particular classes like low-emissions vehicles, or direct incentives in the form of scrap bonuses. 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 fuel-economy standards and gasoline taxes.

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Appendix A Alternative First Stage and Reduced Form Specifications

Reduced Form Using MPG Quartiles

The reduced form of our scrap elasticity estimates is the relation between gasoline prices and scrap rates. Analagous to the first stage results in Section 3.2, we show the results for a reduced form specification using fuel-economy quartiles. We repeat the specification in equation (5), now considering scrap rates in place of prices:

$$y_{amt} = \alpha_{am} + \alpha_{at} + \boldsymbol{\beta_1}' \left(gasprice_t * MPGquartile_m\right) + \boldsymbol{\beta_2}' \mathbf{z_{amt}} + \varepsilon_{amt} \tag{A.1}$$

where y_{amt} is the fraction of vehicles of age a and model m that are scrapped between year $t-1$ and t.

The results from specification (A.1) are presented in Table A.1. 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. Overall, we find that when the gasoline price increases by $1, vehicles with the best fuel-economy experience a decrease in their scrap rate by about -0.7 percentage point relative to cars in the lowest MPG quartile. The compositional effect grows with age. Among cars 10 years and older scrap rates in the highest MPG quartile fall by about 1.7 percentage points relative to the lowest quartile.

Table A.1: 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
	(1)	(2)	(3)	(4)
Gasoline price * MPG quartile 2	-0.254**	-0.195*	0.104	-0.590**
	(0.059)	(0.095)	(0.093)	(0.105)
Gasoline price * MPG quartile 3	-0.503**	-0.143	0.296**	-1.32**
	(0.057)	(0.091)	(0.077)	(0.107)
Gasoline price * MPG quartile 4	-0.675**	-0.186*	0.298**	-1.69**
	(0.057)	(0.090)	(0.069)	(0.108)
R^2	0.145	0.109	0.156	0.160
Observations	35,603	9,641	9,240	16,722
Number of make-model-age FEs	7,305	1,798	1,688	3,819

Notes: Coefficient values reflect percentage point changes. All models include fixed effects for each make-model-age and report R^2 for within-group variation. Change in scrap rate for the least efficient (first) quartile is omitted in order to allow fixed effects by age-year. Standard errors clustered by make-model-age. *,** indicate significance at the 5% and 1% level, respectively.

First Stage and Reduced Form with MPG Turning Points

The flexible specifications for the first stage and reduced form of the IV (equations (3) and (6) in the main paper) focus exclusively on relative changes in used vehicle values and scrap rates as gasoline prices move. This section describes an alternative specification that imposes more structure to allow for the estimation of "turning points" with respect to fuel economy. We now specify prices and scrap rates as a direct function of each vehicle's fuel economy. The model we adopt is similar to Li *et al.* (2009). Our data allows us to consider their approach not only for scrap rates, but also for used vehicle prices. We estimate the following models:

$$p_{amt} = \alpha_{am} + \alpha_a * t + \beta_1 DPM_{mt} + \beta_2 gasprice_t + \boldsymbol{\beta_3}' \mathbf{z_{amt}} + \varepsilon_{amt} \tag{A.2}$$

$$y_{amt} = \alpha_{am} + \alpha_a * t + \beta_1 DPM_{mt} + \beta_2 gasprice_t + \boldsymbol{\beta_3}' \mathbf{z_{amt}} + \varepsilon_{amt} \tag{A.3}$$

where DPM_{mt} indicates fuel cost and $\alpha_a * t$ is a linear time trend that varies by age. Equations (A.2) and (A.3) 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. The reverse holds for scrap rates in equation (A.3).

Table A.2 reports the estimation results of specifications (A.2) and (A.3), for all vehicles (columns 1 and 3) and for a restricted sample of vehicles ten years and older (columns 2 and 4). The coefficients on $gasprice_t$ and DPM_{mt} have opposite signs in all four cases, allowing calculation of the "turning point" in MPG where the sign of the response changes. Turning points in the price and scrap regressions are similar for older vehicles, between 22 and 23 MPG.

Table A.2: Price and Scrap Rate Effect as a Continuous Function of Fuel Economy.

	Vehicle price		Scrap rate	
	All ages	Age 10-19	All ages	Age 10-19
	(1)	(2)	(3)	(4)
Gasoline price	3,409**	1,450**	-0.0091**	-0.0331**
	(167)	(126)	(0.0013)	(0.0024)
Dollars-per-mile	-61,020**	-33,541**	0.3173**	0.7301**
	(3,376)	(2,625)	(0.0245)	(0.0441)
R^2	0.349	0.127	0.064	0.072
Observations	35,107	16,555	35,603	16,722
Number of make-model-age FEs	7,191	3,768	7,305	3,819
MPG turning point	17.9	23.1	34.9	22.1

Notes: Estimation follows equations (A.2) and (A.3). All models include fixed effects for each make-model-age combination, and a linear time trend for each age. R^2 is reported for within-group variation. Standard errors clustered by make-model-age. *,** indicate significance at the 5% and 1% level, respectively.

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.

The turning point specification 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.[34] We find that this restriction leads to much less plausible results for newer vehicles in our sample: sharp effects of the recession, for example, cannot be absorbed by age-year fixed effects and could explain the asymmetric turning points in price and scrap shown in the tables. We therefore prefer the more flexible specification for our main elasticity estimates presented in Section 3.

Appendix B Evidence on Used Vehicle Transaction Costs

Summary Statistics on the Tenure of Used Vehicle Owners

We employ a data set on used vehicle ownership tenure from R.L. Polk. The data set covers the period 2001-2012. A unit of observation is a used vehicle transaction recorded to the state department of motor vehicles. The data set contains all used vehicles that were transacted during the period 2001-2007 in eight states (Colorado, Idaho, Kentucky, Michigan, New Mexico, North Dakota, Texas and West Virginia) plus all subsequent transactions, including those in the period 2008-2012. Note, importantly, that all subsequent transactions of the same used vehicle are included, including those cars which are exported out-of-state. The total number of transactions in our data set is slightly over 61 million.

We calculate tenure as the time between two subsequent ownership-changing transactions of the same vehicle. Our sample limits the maximum observable tenure to 12 years (January 2001 - December 2012) for cars first transacted in 2001, but this truncation becomes more stringent for cars that first transacted in 2007. We therefore restrict the sample to cars that transacted at least once during the period 2001-2002, although the results are very similar to those using the full sample. The restricted sample contains approximately 28 million observations.[35]

Figure B.1 shows the distribution of vehicle age and owner's tenure. As the sample represents the universe of traded vehicles, the age distribution is smooth and spans a wide range from 0 to 30 years. The average tenure has a mean of 2.19 years with a standard deviation of 2.21 years: used vehicles are traded frequently.[36] Older vehicles are traded even more often. The average tenure for

[34] Flexible age-year controls 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.

[35] We do not observe the tenure of the last owner, as the data does not contain information on whether and when a vehicle was scrapped.

[36] We checked that these results are not driven predominantly by vehicles with *very* short tenures, such as dealer-to-dealer transactions. Removing zero- or one-month tenure observations does not affect the outcomes very much: average tenure conditional on tenure lasting for at least two months is 2.42 years.

cars that were at least 16 years old at the time of transaction is 1.57 years (the standard deviation is 1.71 years). Figure B.2 shows that the tenure distribution shifts to the left as vehicle age increases. Of the vehicles that are 16-20 years old, 71% of the owners that we observe in the data sell their cars within the first two years of ownership. This percentage is even higher for 21-25 year old vehicles (76%) and vehicles over 25 years of age (86%). These statistics suggest that transaction costs for trading used vehicles are limited. Even vehicles with little value are traded every year and a half on average.

Empirical Test for the Influence of Transaction Costs

Transaction costs may cause some car owners to pay for repairs that exceed the price of a replacement vehicle. If the number of these "excess"(but rational given transaction cost) repairs moves significantly with gasoline price this could enter the scrap equation and influence our elasticity estimates. We test for this possibility using an asymmetry in the effect of transactions costs on aggregate scrap.

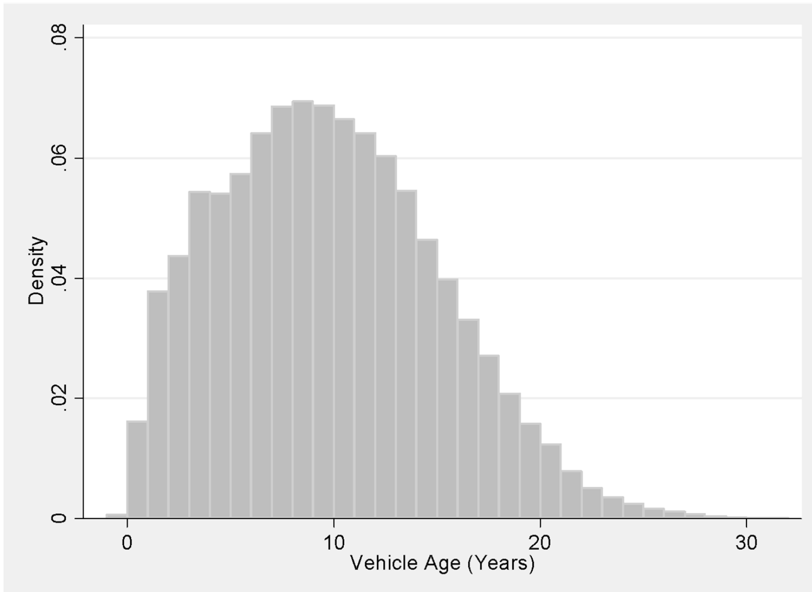
When relative vehicle prices change, some subset of owners will re-optimize their vehicle choice; the change in prices is large enough to overcome the transaction cost for a group on the margin. Since these people are changing to a different vehicle, the choice for the old one becomes sell or scrap. This reduces the number of excess repairs (since scrap will be preferred if the cost of repairs exceeds the car's value). For a vehicle whose price has increased, this effect works against the price-scrap effect we are trying to measure and mutes the elasticity. For a vehicle whose price has decreased, in contrast, the two effects work in the same direction. Therefore, to the extent transaction costs are important in our context, we expect the scrap elasticity to be muted (exaggerated) for vehicles that experience an increase (decrease) in resale value in any given period.

Table B.1 presents an empirical test of this asymmetry. We split the sample into vehicles whose price is expected to increase based on the first stage estimates and vehicles whose price is expected to decrease. We then estimate the IV and OLS specifications allowing separate elasticities for the two groups of observations. The direction of the effect in the table is as would be expected from transactions costs (elasticities are larger in magnitude for vehicles whose price has fallen) but the size of the difference is very slight, suggesting that transaction costs have a limited influence in our setting.

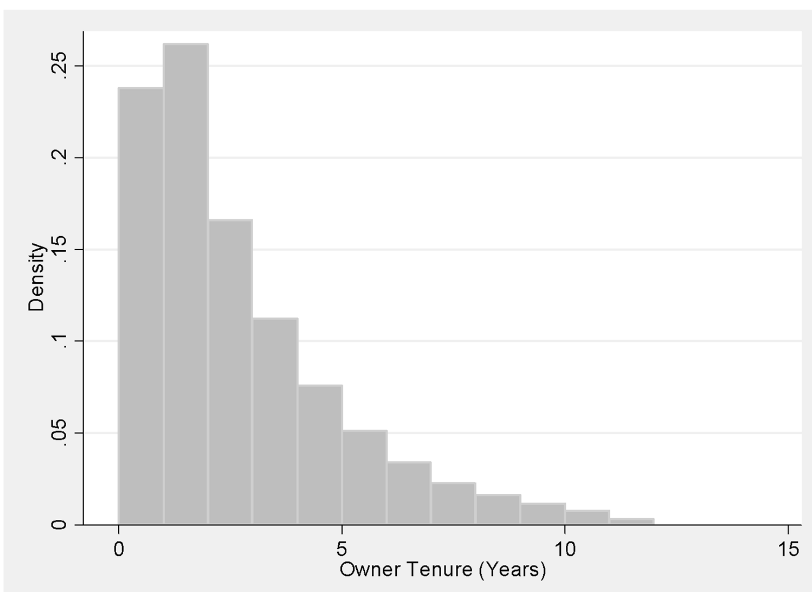
Appendix C Elasticity Estimates from Alternative Models

We first consider an alternative instrumenting strategy using the intuition of the quartile model in Equation (5). Table C.1 reports IV results – analogous to the estimates in Table 3 of the main paper – that directly import the estimates appearing in Table 2 as the first stage. The elasticity estimates are generally similar to the main specification, although the elasticity is somewhat larger for older used vehicles.

Figure B.1: Summary Statistics: (a) Vehicle Age and (b) Owner's Tenure.



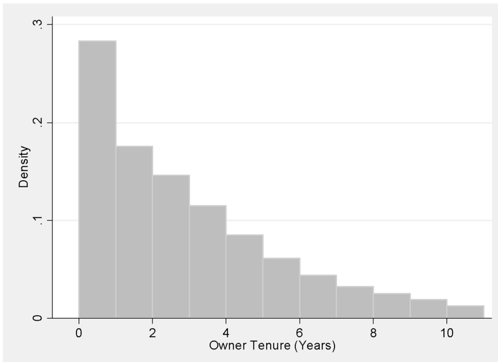
(a) Histogram of Used Vehicle Age at the Time of Transaction.



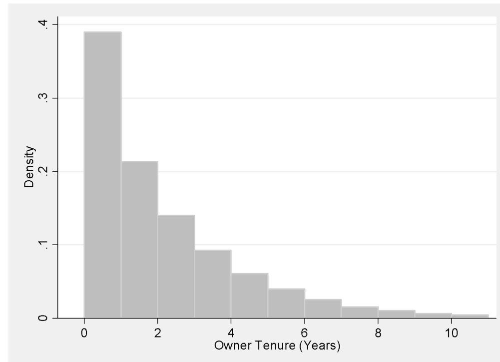
(b) Histogram of Used Vehicle Tenure.

Notes: Sample restricted to used vehicles that transacted at least once during the period 2001-2002.

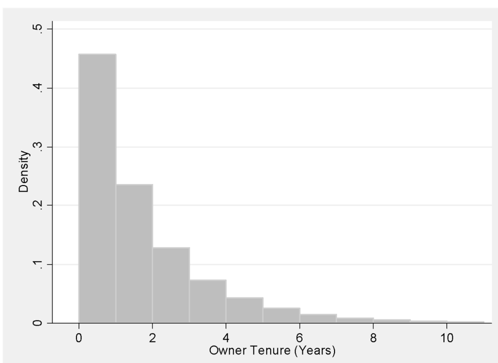
Figure B.2: Summary Statistics for Used Vehicle Tenure by Vehicle Age.



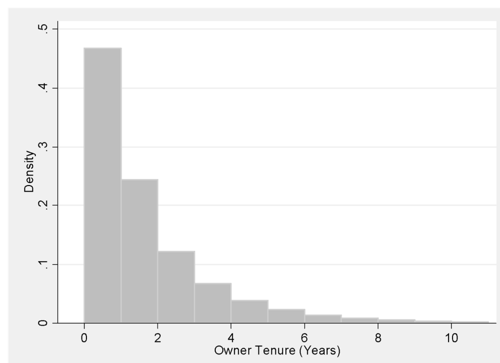
(a) Vehicle Age up to 5 Years.



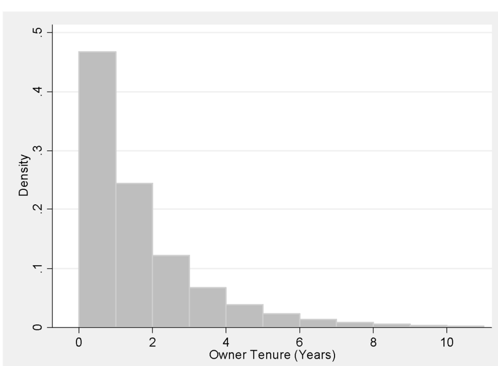
(b) Vehicle Age 6-10 Years.



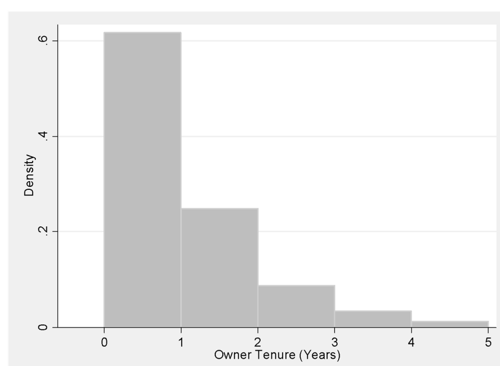
(c) Vehicle Age 11-15 Years.



(d) Vehicle Age 16-20 Years.



(e) Vehicle Age 21-25 Years.



(f) Vehicle Age over 25 Years.

Notes: Sample restricted to used vehicles that transacted at least once during the period 2001-2002.

Table B.1: Empirical Test for Asymmetry in the Effect of Transactions Costs on the Scrap Rate.

	IV		OLS	
	All ages	Age 10-19	All ages	Age 10-19
	(1)	(2)	(3)	(4)
Scrap elasticity	-0.696**	-0.656**	-0.581**	-0.479**
(predicted price increases)	(0.043)	(0.041)	(0.032)	(0.037)
Scrap elasticity	-0.709**	-0.681**	-0.584**	-0.482**
(predicted price decreases)	(0.043)	(0.041)	(0.032)	(0.037)
R^2	0.232	0.276	0.237	0.314
Observations	36,665	20,648	36,665	20,648
Number of make-model-age FEs	5,657	3,197	5,657	3,197

Notes: All models include fixed effects for each make-model-age combination, and a linear time trend for each age. R^2 is reported for within-group variation. Standard errors clustered by make-model-age. *,** indicate significance at the 5% and 1% level, respectively.

Table C.1: The Used Vehicle Price Elasticity of Scrappage with MPG Quartiles in the First Stage.

	IV - First stage: quartile regressions				
		By age category			
	All ages	Age 2-5	Age 6-9	Age 2-9	Age 10-19
	(1)	(2)	(3)	(4)	(5)
Scrap elasticity (γ)	-0.886**	-1.134**	-0.608**	-0.924**	-1.243**
	(0.094)	(0.195)	(0.150)	(0.127)	(0.124)
R^2	0.196	0.189	0.198	0.189	0.184
Observations	31,082	7,792	8,189	15,981	15,101
Number of make-model-age FEs	5,466	1,226	1,234	2,460	3,006
First stage F-statistic	52.07	50.01	53.77	58.41	40.08

Notes: Fixed effects are for each make-model-age and each age-year combination. Standard errors are clustered by make-model-age. R^2 is reported for within-group variation. *,** indicate significance at the 5% and 1% level, respectively.

Table C.2 presents estimates from several additional alternative specifications of the model. We find that the scrap elasticity estimates are robust:

Small vs. large increases/decreases in gasoline price: The point estimates are similar for years in which the (absolute value of the) change in the gasoline price is above or below the median change. Hence, the elasticity estimates do not seem to be driven by years with large vehicle price shocks and consumer response seems relatively consistent through the range.

WLS weighted by registration counts: Weighting by registration counts gives more weight to common models in the elasticity estimation. The effect on the point estimate is small.

Make by model by year fixed effects: Allowing flexible patterns in scrappage by make-model-year (rather than make-model-age in our preferred specification) has little effect on the elasticity results. *Controls for accident rate:* We include annual accident rates at the make-model-age level on the right hand side of equation (2). We use data from the NHTS Fatal Accident Reporting System and so assume that accidents causing scrap are proportional to this measure. The estimated elasticity is not significantly changed.

Table C.2: Additional Elasticity Estimates from Alternative Models.

	Using large gas price changes (1)	Using small gas price changes (2)	WLS (3)
Scrap elasticity (γ)	-0.642**	-0.737**	-0.707**
(All ages)	(0.072)	(0.067)	(0.069)
Scrap elasticity (γ)	-0.615**	-0.614**	-0.679**
(Age 10-19)	(0.066)	(0.062)	(0.048)
R^2 (all ages)	0.302	0.165	0.285
Observations (all ages)	17,764	18,901	36,665
Number of make-model-age/time FEs (all ages)	5,539	5,648	5,657
	Make-model-year fixed effects (4)	**Controls for accident rate (5)**	
Scrap elasticity (γ)	-0.815**	-0.695**	
(All ages)	(0.049)	(0.043)	
Scrap elasticity (γ)	-0.588**	-0.647**	
(Age 10-19)	(0.053)	(0.040)	
R^2 (all ages)	0.698	0.236	
Observations (all ages)	35,276	36,665	
Number of make-model-age/time FEs (all ages)	4,201	5,657	

Notes: All estimates here are variations on the make-model-age level instruments reported in the third panel of Table 3. All include fixed effects for each make-model-age and each age-year combination and report R^2 for within-group variation. Standard errors are clustered by make-model-age. *,** indicate significance at the 5% and 1% level, respectively.

Appendix D Additional Simulation Model Output and Calculations

VMT Data

Table D.1 reports the average vehicle miles traveled measure that we use in simulation. The values are computed from the 2009 edition of the National Household Transportation Survey.

Simplified Leakage Calculation

Table D.1: Average Miles Driven by Vehicle Age, Type and Size.

	Car		Light truck			Car		Light truck	
Age	Small	Large	Small	Large	Age	Small	Large	Small	Large
0	12,980	12,927	12,768	13,129	10	9,451	8,633	9,616	8,251
1	12,459	13,273	13,775	14,222	11	9,827	9,320	8,933	9,596
2	12,171	12,936	13,556	13,827	12	8,020	8,188	9,860	7,455
3	11,796	12,057	12,878	13,166	13	7,334	7,716	8,445	7,342
4	11,955	11,787	12,337	12,673	14	7,962	8,138	7,626	6,621
5	11,827	11,525	12,212	12,589	15	7,677	7,012	6,517	6,479
6	10,352	11,093	12,166	11,932	16	7,039	7,685	6,982	5,931
7	10,761	10,593	9,962	12,266	17	8,417	6,692	5,902	5,703
8	9,857	9,855	10,724	10,759	18	7,456	5,288	6,158	6,288
9	9,839	9,715	10,821	10,329					

Notes: Source: National Household Transportation Survey, 2009 edition.

This section outlines a highly simplified version of our simulation model to provide a more intuitive calculation of the approximate leakage that we should expect. We then compare the results with the leakage results from the full simulation model. Additional details are available from the authors on request.

The calculation pools all used vehicle ages but maintains the division into four classes (car vs. truck and small vs. large). We use the following inputs:

- A fixed mileage for each vehicle of 10,450 miles per year.
- A scrap elasticity of -0.8 for all vehicles.
- Quantity-weighted average base scrap rates for the four types of vehicles: 9.1%-9.4%.
- Average annual used vehicle price increases of \$96, \$164, \$62 and \$92 (for small cars, large cars, small trucks and large trucks, respectively) under the new CAFE standards relative to the old CAFE standards.
- Fleet sizes and MPG for each vehicle class following the data used in the full simulation.

We first calculate how the used vehicle price changes in the policy run (new CAFE) translate to reduced scrappage relative to the reference case (old CAFE). The difference in annual scrap rates is 0.06-0.10 percentage points (on a base of 9.1%-9.4%). The size of the vehicle fleet is 0.7% larger under new CAFE than in a counterfactual "new CAFE without leakage" scenario. We then multiply by the number of vehicles in each class and average annual gasoline consumption (10,450 miles divided by the average MPG of each vehicle class) to calculate leakage as the *difference* (between the "actual" and "counterfactual no leakage" policy experiments) in gasoline consumption. Fuel economy under the new CAFE standard increases by 0.57-2.01 MPG on average.

Using only the simplified data and inputs above, and introducing a fixed scrap elasticity of -0.8, we find that leakage calculated using the simplified model (13.9%) is close to the leakage result from the full simulation model (14.7%). This suggests that most of the effect operates directly through price-induced changes in the scrap rate as opposed to more complex general equilibrium effects in the simulation model.