Stranded Vehicles: How Gasoline Taxes Change the Value of Households' Vehicle Assets

Meghan Busse, Christopher R. Knittel, and Florian Zettelmeyer^{*}

November 2012

Abstract

Economists tend to favor Pigouvian taxes or cap-and-trade programs to correct the negative externalities of climate change and local pollution caused by the burning of fossil fuels. Arguments against energy taxes, and gasoline taxes more specifically, often include concerns about the regressivity of the tax. Other concerns relate to the geographic incidence of the tax. We study the effect of a gasoline tax using changes in vehicle values. We construct three measures of households' capital loss from a gasoline tax and show how they vary across income, geography, and political party. We show that that the capital loss from the tax varies considerably across states; the Midwestern states bear a much higher burden than states in the Northeast. This geographic variation is also correlated with political affiliation; census tracts with a higher share of residents voting for President Bush in the 2000 election experience a higher loss in the value of their vehicles. We find that gasoline taxes are initially progressive; the loss in capital value as a share of income is increasing with income over the first three deciles, but then steeply decreases after the fourth decile. However, if tax revenues are equally distributed to households, the policy is highly progressive for the first four income deciles and largely income neutral thereafter.

** Preliminary – do not cite **

^{*}This paper has benefited from Severin Borenstein, Dick Schmalensee and Joseph Doyle. *Busse:* Associate Professor of Management and Strategy, Kellogg School of Management, Northwestern University and NBER, *email:* m-busse@kellogg.northwestern.edu. *Knittel:* William Barton Rogers Professor of Energy Economics, Sloan School of Management, MIT and NBER, *email:* knittel@mit.edu. *Zettelmeyer:* Nancy L. Ertle Professor of Marketing, Kellogg School of Management, Northwestern University and NBER, *email:* f-zettelmeyer@kellogg.northwestern.edu.

1 Introduction

Economists tend to favor Pigouvian taxes or cap-and-trade programs to correct the negative externalities of climate change and local pollution caused by the burning of fossil fuels.¹ While energy taxes are typically met with strong opposition from a number of groups, the "fiscal cliff" appears to have put a number of revenue-generating options back on the table.² Arguments against energy taxes, and gasoline taxes more specifically, often include concerns about the regressivity of the tax. Other concerns relate to the geographic incidence of the tax. In this paper, we study how the incidence of increases in gasoline prices varies across income, geography, and political affiliation.

One standard approach used in the literature is to measure how the share of expenditures on energy, as a fraction of income, varies across demographic groups or geography. However, if expenditures on energy arise from using a durable good, an energy tax not only affects energy expenditures, it can also change the value of the durable good itself. This is because the durable good becomes less attractive if it is more expensive to operate. In fact, recent work by Busse, Knittel, and Zettelmeyer (2013) and Allcott and Wozny (2011) show that changes in gasoline prices can have sizable effects on the market value of vehicles.

In this paper, instead of focusing on energy expenditures, we analyze how the value of household capital stocks respond to changes in energy prices in the light-duty transportation sector. That is, we estimate how changes in gasoline prices affect the value of the vehicles that people own and how this varies across demographic groups and geography.

We justify doing so based on the results in Busse, Knittel, and Zettelmeyer (2013), which shows that the relative change in vehicle values of two vehicles, as a result of a change in gasoline prices, represents the change in the relative present discounted value of fuel costs between these two vehicles. These results imply, for example, that the relative change in the prices of a used Honda Civic and a used GMC Yukon induced by a change in gasoline prices is equal to the present discounted value (at standard discount rates) of the relative change in lifetime fuel costs of these vehicles implied by the same change in gasoline prices.

We focus on three different measures. First, we estimate the effect of gasoline prices on the value of used vehicles, controlling for the odometer, and therefore the remaining life, of these vehicles. By applying these estimates to each vehicle registered in the United States, we can predict, for the

²See, for example, *Bloomberg*, November 16, 2012: "Carbon Fee From Obama Seen Viable With Backing From Exxon"; *Washington Post*, November 9, 2012: "With 'fiscal cliff' looming, carbon tax getting closer look"; *Business Insider*, November 14, 2012: "A Modest Carbon Tax Could Solve A Lot Of Problems".

average household in each census tract, how gasoline taxes would change the value of the household's current vehicles. We refer to this measure as the "current-capital loss." We derive our second measure by dividing the current-capital effect in each census tract by the tract's median household income. We refer to this measure as the "current-capital loss as share of income."

In these two measures, the effect of a gasoline tax on asset values is determined by both fuel economy and vehicle odometer. This is because gasoline prices, as we will later show, affect the values of vehicles with a high odometer less than those of vehicles with a low odometer. This captures, as our first two measures intend to, the effect of a gasoline tax on the value of households' *current* assets. However, focusing on current assets assumes that consumers in each tract are only affected for the remainder of the life of their current vehicle. As a result, when we calculate the loss in asset value in different tracts, we will calculate lower capital loss in tracts that contain older vehicles, all else equal. This will especially affect measures of regressivity since income and vehicle age are negatively correlated. This leads us to a third measure, "lifetime-capital loss as a share of income." With this measure we compare how a gasoline tax would affect households with vehicles of different fuel economy, under the assumption that all vehicles have the same remaining lifetime. We do this by calculating capital loss as a share of income based on estimates from recent vintage used vehicles only. This measure is also more directly comparable to the standard approach of estimating incidence as current fuel consumption divided by income (see the appendix for the implications of this approach and how it compares to Poterba (1991)).

In summary, while all three measures are related, each provides a different picture of how consumers are affected by changes in gasoline prices, and thereby gasoline taxes. The first two are measures of how changes in gasoline taxes would affect the value of households' current vehicles. Consumers may be concerned about the value of their vehicles regardless of the impact of the tax on lifetime fuel costs. The last measure, lifetime-capital loss as a share of income, is a closer analog to the existing approach of measuring incidence of a tax through changes in fuel expenditures over the life of the consumer.

To estimate how values of vehicles of different fuel economies respond to changes in gasoline prices, we use data on roughly 90 percent of all transactions at wholesale automobile auctions in the United States. We combine these results with vehicle registration data at the census tract level. This allows us to estimate how the value of the vehicle capital stock in different geographic areas is affected by gasoline prices. We also correlate these changes with demographics and political affiliations.

We find that all three measures vary considerably across states. Losses are concentrated in the Midwest, with the Northeast harmed the least from gasoline taxes. While this is partly driven by income differences, the main driving force is geographical variation in the average fuel economy of registered vehicles.

We also find that the geographic variation in capital loss as a share of income is correlated with political affiliations. Using county-level data on voting behavior during the 2000 Presidential election, we find that, both current- and lifetime-capital loss as a share of income are positively related to the share of a county that voted for President Bush in the 2000 election: a 10 percentage point increase in the share of the population who voted for President Bush is correlated with a 0.16 percentage point increase in current-capital loss as a share of income and a 0.31 percentage point increase in lifetime-capital loss as a share of income. This relationship continues to holds, albeit smaller in magnitude, when we control for ethnicity, commute times, income, population density, and state fixed effects.

We find that gasoline taxes are initially *progressive*; lifetime-capital loss as a share of income is increasing with income over the first three deciles before steeply decreasing after the fourth decile. This is consistent with Poterba (1991) who finds, using data from the Consumer Expenditure Survey, that the gasoline expenditures as a share of total expenditures increases initially but then tends to fall.

We also find that if the loss in value generated from the tax, proxying for the revenues that would be generated from a gasoline tax, were equally distributed to households, then the policy would be highly progressive for the first four income deciles and then largely income neutral thereafter. This result suggests that fairly simple revenue choices can make gasoline taxes progressive throughout the entire income distribution. These results are broadly consistent with Bento et al. (2009) which estimates incidence of gasoline taxes by estimating a structural model of vehicle and miles-driven choice. They find that when tax revenues are recycled "flatly," the bottom quartile of the income distribution benefits, incidence increases between the first and second, and the second and third quartile, and then is largely constant between the third and fourth quartiles.

The remainder of the paper proceeds as follows: Section 2 discusses the data used in the analysis. Section 3 summarizes the estimated effects of changes in gasoline prices on vehicle values. Section 4 summarizes the three measures of capital loss across census tracts. Section 5 correlates our capital loss measures with geography, political affiliation, and demographics. Section 6 investigates the regressivity of our measures. Finally, Section 7 concludes.

2 Data

To perform our analysis we need to answer two basic questions. First, how are the asset values of different used vehicles affected by gasoline prices? Second, what is the distribution of ownership of these different used vehicles across the United States.

In prior work we have relied on transaction data from franchised new car dealerships to estimate how the value of vehicles changes with gasoline prices (Busse, Knittel, and Zettelmeyer (2012, 2013)). Because new car dealerships mostly sell low-mileage, recent model year used cars, this data is not suitable for estimating the change in asset values across the full spectrum of cars owned in the United States. As a result, in this paper we use a large dataset of transaction at used vehicle wholesale auctions. This data stems from "AuctionNet," a partnership between the National Auto Auction Association (NAAA) and then National Automobile Dealers Association (NADA) Used Car Guide. The data collects 140,000 to 200,000 auction transactions per week from over 150 auctions nationwide, including the two largest wholesale auction companies, Manheim and ADESA. Overall, the data list about 90% of all wholesale auction transactions in the US. The data identifies each vehicle at the "VIN prefix" level.³ The VIN prefix defines the make, model, model year, engine type, drive train, and in most cases the trim level of the vehicle. For each transaction the data record the week of sale, the sale price, the mileage, the "sale type," and the region of sale. The "sale type" identifies whether a vehicle was sold by a manufacturer (e.g. BMW), by a fleet or lease operator (e.g. Hertz, Bank of America), or by a dealer, and whether the vehicle was declared as "salvage," was repossessed, or sold "as-is." We exclude the last three sale type categories since these vehicles either cannot be resold at retail or require major repair and reconditioning work before any sale. There are either 10 or 20 regions identified in the data, depending on whether the transaction occurred before or after 4/1/2003, respectively. Our final dataset consists of 55,447,043 wholesale auction transactions from 1/1/1998 to 6/30/2008.

We supplement these auction data with weekly gasoline price data from the Energy Information Administration (EIA). This data is collected by calling about 900 retail gasoline outlets each week. We use data on the price of regular gasoline in each of seven areas called PADDs (Petroleum Administration for Defense Districts): New England, Central Atlantic, Lower Atlantic, Midwest, Gulf Coast, Rocky Mountain, and West Coast.

 $^{^{3}}$ Each vehicle sold in the US has a unique vehicle identification number (VIN) number. The first eight and the tenth digit of the number describe the manufacturer, vehicle details, and model year. This is what we refer to as the "VIN prefix." The ninth digit is a check digit to detect errors in the VIN. The eleventh digit identifies the plant that manufactured the vehicle. The last 6 digits are a sequential number that identifies individual vehicles.

We also add the Environmental Protection Agency (EPA)'s "Combined Fuel Economy" rating to each vehicle transaction in the auction data. This rating is the weighted geometric average of the EPA Highway (45%) and City (55%) Vehicle Mileage. We use the rating that corresponds to the new 2008 EPA rating process.⁴

To answer our second basic question about the distribution of ownership of different vehicles across the United States, we use the Polk "Vehicles in Operation" database. This data reports for each census trace the number the number of vehicles registered in that tract by VIN prefix at the beginning of each calendar year. The data cover 100 percent of registered vehicles. For this paper we use registration data from 2006.

3 Price Effect by Fuel Economy and Mileage

We estimate the effect of gasoline prices on the auction price of used vehicles in two different ways. First, we allow the estimates to differ by the odometer of vehicle. This forms the basis for calculating the current-capital effect and incidence. Second, we restrict our sample to recent vintage vehicles. These estimates are used to calculate lifetime-capital incidence.

3.1 Estimates for the current-capital measures

We would like to allow for the possibility that cars with high mileage may be affected by changes in gasoline prices differently than the same type of cars with low mileage. To do so we split the transactions in our data into transactions for which the odometer readings at the time of sale falls into 20,000 mile intervals, i.e. we create datasets of vehicles with odometer readings of 0 to 20,000, 20,001 to 40,000, 40,001 to 60,000, and so on up to 199,999.⁵ For each of these datasets we estimate the following specification:

$$P_{irjt} = \lambda_0 + \lambda_1 (\text{GasolinePrice}_{at} \cdot \text{MPG Bin}_j) + \delta_j + \mu_{rt} + \tau_{rsT} + \lambda_3 (\text{Mileage}_{irjt} \cdot \nu_{sr}) + \epsilon_{ijt}.$$
(1)

 $^{^{4}}$ We merge the fuel economy data by VIN prefix. Since there was no standard for VINs before 1982, we cannot merge the fuel economy data for cars that were produced before 1982. As a result, we omit these vehicles from our analysis (these observations represent less that 2.0 percent of registrations).

⁵An alternative approach is to estimate gasoline price effects separately for vehicles of different age. We prefer mileage for a number of reasons: First, mileage is measured with more granularity than model year and thus varies across most individual vehicles. Second, mileage is less collinear with gasoline price than car age is because it does not move together with calendar time, thus making it easier for us to identify gasoline price effects. Finally, we find that car age does not contribute much to explaining depreciation once odometer is controlled for (in the sense of increasing R^2).

 P_{irjt} , the auction price that buyer *i* pays for vehicle *j* purchased in region *r* at time *t*. We are interested in coefficients λ_1 , which measure the effect of a \$1 increase in gasoline prices (at the level of PADD *a* in week *t*) on the auction prices of vehicles of different fuel economies. Since gasoline prices may affect high fuel economy vehicles differently from low fuel economy vehicles, we split cars into five fuel economy bins and interact indicators for each of these bins with *GasolinePrice*. The bins are created on the basis of the EPA Combined Fuel Economy rating and were chosen to divide the sample into rough quintiles. Table 1 shows how the bins are defined and reports the average share of transactions in our data for each bin.

| | Vehi | cles in bin | |
|-----|----------|---------------|----------|
| | have | e MPG of | Share in |
| Bin | at least | but less than | sample |
| 1 | 0 | 16 | 17.7% |
| 2 | 16 | 19 | 24.1% |
| 3 | 19 | 21 | 18.4% |
| 4 | 21 | 24 | 19.4% |
| 5 | 24 | ∞ | 20.5% |

 Table 1: MPG Bin Definitions

We control for "vehicle type" fixed effects (δ_j) that are defined as the interaction of make, model, model year, trim level, body style (sedan, coupe, hatchback, etc.), doors, drive type (2WD, 4WD), fuel type (gasoline, diesel), cylinders, and displacement.

In our specification we allow average price levels to differ seasonally. Since vehicle prices in different regions may exhibit different seasonal patterns, we interact the 10 geographic regions in which the vehicle was auctioned with month-of-year (μ_{rt}) fixed effects. In addition, to allow for changing tastes over time in different regions for different vehicles segments, we control for regionand segment-specific year fixed effects (τ_{rsT}).⁶

Finally, we want to take into account that used vehicles depreciate with increasing mileage, even within the 20,000 mile ranges we separately estimate. In addition, mileage may affect the resale value of cars in different segments and regions differently. Hence, we interact mileage with segment × region fixed effects (Mileage_{irit} · ν_{sr}).

The gasoline price coefficients from estimating the price specification for different odometer ranges are reported in Table 2. The results show a consistent pattern across fuel economy bins. For a \$1 increase in gasoline prices, auction prices tend to decrease for vehicles in the 2-3 bins of lowest fuel economy and tend to increase for vehicles in the 2-3 bins of highest fuel economy. We also find that the higher the mileage range of vehicles, the more attenuated are the absolute price effect associated

⁶There are seven vehicle segments: Compact, Midsize, Luxury, Sporty, SUV, Pickup, and Van.

| Odometer Range | Fuel Economy | Coefficient | SE | p-value | Average Price |
|-----------------------|--------------|-------------|----------------|---------|---------------|
| 0-19,999 miles | 0-15 MPG | -933 | 78 | 0.00 | \$20,177 |
| 0-19,999 miles | 16-18 MPG | -728 | 66 | 0.00 | \$18,436 |
| 0-19,999 miles | 19-20 MPG | -326 | 61 | 0.00 | \$15,675 |
| 0-19,999 miles | 21-23 MPG | 93 | 54 | 0.09 | \$12,568 |
| 0-19,999 miles | 24- MPG | 552 | 52 | 0.00 | \$10,406 |
| 20,000-39,999 miles | 0-15 MPG | -904 | 67 | 0.00 | \$17,207 |
| 20,000-39,999 miles | 16-18 MPG | -723 | 59 | 0.00 | \$15,590 |
| 20,000-39,999 miles | 19-20 MPG | -386 | 57 | 0.00 | \$13,561 |
| 20,000-39,999 miles | 21-23 MPG | 103 | 41 | 0.01 | \$10,910 |
| 20,000-39,999 miles | 24- MPG | 456 | 37 | 0.00 | \$9,118 |
| 40,000-59,999 miles | 0-15 MPG | -836 | 56 | 0.00 | \$14,592 |
| 40,000-59,999 miles | 16-18 MPG | -596 | 46 | 0.00 | \$12.576 |
| 40,000-59,999 miles | 19-20 MPG | -331 | 39 | 0.00 | \$11.148 |
| 40,000-59,999 miles | 21-23 MPG | 13 | 38 | 0.72 | \$8.929 |
| 40.000-59.999 miles | 24- MPG | 277 | 34 | 0.00 | \$6.858 |
| 60.000-79.999 miles | 0-15 MPG | -658 | 47 | 0.00 | \$10.804 |
| 60.000-79.999 miles | 16-18 MPG | -333 | 33 | 0.00 | \$8.432 |
| 60.000-79.999 miles | 19-20 MPG | -168 | 26 | 0.00 | \$6.934 |
| 60.000-79.999 miles | 21-23 MPG | 41 | $\frac{1}{24}$ | 0.09 | \$5.861 |
| 60.000-79.999 miles | 24- MPG | 202 | 26 | 0.00 | \$4.553 |
| 80.000-99.999 miles | 0-15 MPG | -528 | 38 | 0.00 | \$7.881 |
| 80.000-99.999 miles | 16-18 MPG | -217 | 24 | 0.00 | \$5.718 |
| 80.000-99.999 miles | 19-20 MPG | -90 | 20 | 0.00 | \$4.569 |
| 80.000-99.999 miles | 21-23 MPG | 32 | 17 | 0.07 | \$4,001 |
| 80.000-99.999 miles | 24- MPG | 126 | 20 | 0.00 | \$3,192 |
| 100.000-119.999 miles | 0-15 MPG | -447 | 32 | 0.00 | \$6.059 |
| 100.000-119.999 miles | 16-18 MPG | -174 | 20 | 0.00 | \$4.213 |
| 100.000-119.999 miles | 19-20 MPG | -40 | 18 | 0.03 | \$3,288 |
| 100.000-119.999 miles | 21-23 MPG | 31 | 14 | 0.03 | \$3.002 |
| 100,000-119,999 miles | 24- MPG | 88 | 17 | 0.00 | \$2,445 |
| 120.000-139.999 miles | 0-15 MPG | -386 | 28 | 0.00 | \$4.830 |
| 120.000-139.999 miles | 16-18 MPG | -135 | 17^{-0} | 0.00 | \$3.286 |
| 120.000-139.999 miles | 19-20 MPG | -4 | 15 | 0.78 | \$2.564 |
| 120.000-139.999 miles | 21-23 MPG | 27 | 13 | 0.03 | \$2.404 |
| 120.000-139.999 miles | 24- MPG | 65 | 15 | 0.00 | \$1.996 |
| 140,000-159,999 miles | 0-15 MPG | -331 | 24 | 0.00 | \$3,917 |
| 140.000-159.999 miles | 16-18 MPG | -109 | 15 | 0.00 | \$2.649 |
| 140.000-159.999 miles | 19-20 MPG | 14 | 14 | 0.31 | \$2.070 |
| 140.000-159.999 miles | 21-23 MPG | 36 | 12 | 0.00 | \$2.008 |
| 140.000-159.999 miles | 24- MPG | 59 | 13 | 0.00 | \$1.678 |
| 160.000-179.999 miles | 0-15 MPG | -302 | 21 | 0.00 | \$3.328 |
| 160,000-179,999 miles | 16-18 MPG | -99 | 14 | 0.00 | \$2,255 |
| 160,000-179,999 miles | 19-20 MPG | 44 | 14 | 0.00 | \$1,750 |
| 160.000-179.999 miles | 21-23 MPG | 55 | 12 | 0.00 | \$1.743 |
| 160,000-179,999 miles | 24- MPG | 73 | 13 | 0.00 | \$1,464 |
| 180,000-199,999 miles | 0-15 MPG | -253 | 19 | 0.00 | \$2,908 |
| 180,000-199,999 miles | 16-18 MPG | -85 | 14 | 0.00 | \$1,966 |
| 180,000-199,999 miles | 19-20 MPG | 52 | 13 | 0.00 | \$1,509 |
| 180,000-199,999 miles | 21-23 MPG | 59 | 12 | 0.00 | \$1,541 |
| 180,000-199,999 miles | 24- MPG | 64 | 13 | 0.00 | \$1,294 |

Table 2: Equilibrium price response to gasoline prices by mileage range^{\dagger}

[†] Full results are available upon request from the authors.

| Fuel Economy | Coefficient | SE | p-value | Average Price |
|--------------|-------------|----|---------|---------------|
| 0-15 MPG | -1058 | 69 | 0.00 | \$17,384 |
| 16-18 MPG | -825 | 64 | 0.00 | \$15,766 |
| 19-20 MPG | -350 | 64 | 0.00 | \$13,806 |
| 21-23 MPG | 227 | 52 | 0.00 | \$11,033 |
| 24- MPG | 662 | 41 | 0.00 | \$9,146 |

Table 3: Equilibrium price response to gasolineprices for recent vintage vehicles[†]

[†] Full results are available upon request from the authors.

with a gasoline price increase. However, as a percentage of the average selling price we find that the effects are fairly similar across mileage ranges, with a slight increase in the percentage decrease for the lowest fuel economy bin as mileage increases (from approximately 5% to 9%).

3.2 Estimates for the lifetime-capital measure

We now estimate the effect of gasoline prices on the auction price of used vehicles, restricting the sample to vehicles that three years old or less. We estimate Equation 1 on this restricted sample without distinguishing between odometer bins. The gasoline price coefficients are reported in Table 3.

The results are a little larger in magnitude than the lowest-odometer results in Table 2. We find that a \$1 increase in gasoline prices decrease the value of low fuel economy vehicles by \$1058 while increasing the value of high fuel economy vehicles by \$662.

4 Geographic variation in capital loss

We now use our estimates to calculate how the vehicle values in different census tracts change as gasoline prices change. To do so we combine the price effect estimates in Tables 2 and 3 with our data on vehicle registrations across the United States. For each census tract we observe the number of vehicles registered in the tract at the level of the VIN prefix. For example, for a given census tract in a given year, we observe how many 2006 Honda Accord, V-6, four door, front-wheel drive cars are registered. We focus on registrations in 2006. The results are extremely similar if we repeat the estimates with registrations from other years.

By merging registration data with our price estimates, we compute the average change in the value of the census tract's vehicle stock from a \$1 change in gasoline prices. To aggregate this to a household effect, we multiply the average change by the average number of vehicles per household, as reported by the 2000 Census.

We present these calculations visually. Figure 9 maps the average census tract fuel economy. The cut-offs roughly correspond to the quartiles of the tract-level fuel economy distribution (19 MPG,



Figure 1: Histogram of census tract-level current-capital loss

19.75 MPG, 20.3 MPG). This graph explains many of the later results. Average fuel economy is higher along the two coasts and in urban areas suggesting that asset values will be more negatively affected in rural areas. As a result, we will also find that the incidence of a gasoline tax will be higher in rural areas.

Our estimates of the price effect in Table 2 imply not only that fuel economy is an important predictor of the effect of changes in gasoline prices on vehicle value, but vehicle mileage is as well. If the low fuel economy areas in Figure 9 also own vehicles with higher miles, then, because the magnitude of the price estimates are smaller for vehicles with higher miles, the effect of gasoline prices on asset values should be lower than indicated purely by the average fuel economy of registered vehicles.

Figure 1 shows the distribution of the middle 98% of our census tract-level current-capital loss measure, based on the fuel economy and odometer-bin specific estimates in Table 2. We use the negative of the price effect, so that the greater the size of the estimate, the greater the *loss* in vehicle value from changes in gasoline prices.

The per household current-capital loss of the median census tract is \$245, slightly lower than the average current-capital loss of \$269. Ten percent of census tracts experience a per household current-capital loss of \$457 or more (see column 1 of Table 4 for key percentiles of the distribution).



Figure 2: Histogram of census tract-level current-capital loss as share of income

Figure 10 shows how the current-capital loss is distributed across the United States. The figure maps current-capital loss by census tract. The cut-offs in Figure 10 correspond approximately to the quartiles of the distribution of current-capital loss. Because this map looks similar to the map of census tract average fuel economy in Figure 9, the effect of fuel economy differences appear to dominate the effect of differences in the average odometer readings across tracts. This is consistent with a correlation coefficient of 0.87 between average tract fuel economy and current-capital loss.

We now turn to our second measure, current-capital loss as a share of income, where we use median household annual income in the census tract as our income measure. As before, this measure relies on the fuel economy and odometer bin specific estimates in Table 2. Figure 2 shows the distribution of the middle 98% of this measure. The capital loss experienced by households in the median census tract corresponds to 0.55% of household median income in the census tract. On average, households lose 0.67 of their annual income in asset values from a \$1 increase in gasoline prices. The variation is considerable: Ten percent of census tracts experience a current-capital loss as a share of income of 1.2% or more while ten percent of census tracts experience a loss of 0.23% or less (see column 2 of Table 4).

Figure 11 maps current-capital loss as a share of income across census tracts in the United States.



Figure 3: Histogram of census tract-level lifetime-capital loss as share of income from a \$1 increase in gasoline prices

The cut-offs correspond directly to the quartiles of the distribution of this measure.⁷ We find that a gasoline price tax would lead to lower current-capital loss as a share of income along the coasts and in urban areas than in the middle of the country and in rural areas.

Our third measure—the lifetime-capital loss as a share of income—is based on the estimates of gasoline prices on vehicle prices for recent vintage vehicles only (see Table 3). Because these vehicles experience greater losses and gains than older vehicles as gasoline prices change, the distribution of this lifetime-capital measure in Figure 3 is shifted to the right relative to that of the current-capital measure in Figure 2. The average lifetime-capital loss as a share of income is 1.1%. Ten percent of census tracts lose over 2.2 percent of their income.

Figure 12 shows the results for this measure across all census tracts in the United States. This figure looks extremely similar to Figure 11; the correlation in the two measures is 0.97. The key difference, however, is that the lifetime measure shifts the capital loss as a share of income upward for each census tract. The high correlation suggests that this shift upward is relatively constant across tracts.

⁷There are a few outliers driven by very low or very high median incomes. We omit these from map.



Figure 4: Average current-capital loss across states from a \$1 increase in gasoline prices

5 Capital loss by state, political affiliation, and demographics

While the maps provide a general picture of how capital loss varies across the country, in this section we provide more specific measures of how capital loss varies across geography, political affiliation, and demographic characteristics.

5.1 States

First, we discuss how the measures differ by states. Figures 4 and 5 plot the average value for all three capital loss measures by state. There is considerable variation across states. Turning first to the current-capital loss implied by a \$1 increase in gasoline taxes, households in the District of Columbia lose only \$51, on average, while households in South Dakota lose over \$760. As the earlier maps suggested, the current-capital loss is strongly correlated with a state's region of the country. The five largest losers are all in the Midwest (South Dakota, Nebraska, Kansas, Iowa, and Minnesota); in all five states households would experience losses that exceed \$650, on average. The five states with the smallest current-capital losses are all, with the exception of Hawaii, in New England (New York, Rhode Island, Massachusetts, Connecticut, Hawaii); households would experience losses below \$200, on average.

The same holds for the two capital loss measures scaled by income. Using the loss in current-



Figure 5: Average current- and lifetime-capital loss as share of income across states from a \$1 increase in gasoline prices

capital value as a share of income, households in the five states with the largest loss all lose more than 1.7 percent of median income, on average, and are located in the Midwest (South Dakota, Nebraska, Kansas, North Dakota, and Iowa). The five states with the smallest average loss are in New England (Connecticut, New York, Massachusetts, New Jersey and Rhode Island). Households in these states all lose less than 0.37 percent of their median income, on average.

The lifetime-capital loss as a share of income is larger than the current-capital measure for all states except for the District of Columbia. The conclusion about which states would be most affected by a gasoline tax, however, is similar to that of the current-capital measure. The largest losses are all in the Midwest. Households in the top five states all lose more than 2.49 percent of their median income (South Dakota, Nebraska, Kansas, Iowa, Wyoming); households in the bottom five states lose less than 0.49 percent of their income (Connecticut, Massachusetts, New York, Rhode Island, New Jersey).

The increase in loss when focusing on the value of lifetime capital stock as opposed to current capital stock is also is strongly correlated with the region of country. Southern states see the largest increase, reflecting the fact that the average vintage of vehicles is older in the South (and in Alaska).

5.2 Political affiliation and demographics

Next, we correlate our measures with the political affiliation, ethnicity, income, population density and commute patterns in each tract. Tables 5 through 7 report the results of univariate regressions of all three measures on these variables.

For each tract we measure political affiliation as the share of voters who voted for President Bush in 2000 in the county that contains tract. The current-capital loss, both in levels and as a share of income, is strongly correlated with political affiliation. Moving from a county that voted 40% for President Bush to a county that voted 60% for President Bush is correlated with an a average household loss of \$110 (0.2*552.1) in the value of current household vehicles. This is a 0.32 (0.2*1.6) and 0.61 (0.2*3.1) percent increase in the current- and lifetime-capital loss as a share of income. These estimates exceed the mean of each measure by roughly a factor of three.

Moving to demographics, census tracts with a higher share of African Americans, Asians, and Hispanics relative to whites, on average, have smaller drops in asset values across all three measures. Higher income tracts have a higher loss in the *level*, but a smaller drop in asset values as a share of income (we come back to this below). We also find that population density and commute time are negatively correlated with all three measures of capital loss.⁸ In the univariate regressions, population density explains nearly 31 percent of the variation in the drop in asset values. This is more than any other variable and suggests that rural areas are harmed more than urban areas by changes in gasoline prices.

Our results have clear implications for the political economy of gasoline and, by extension, carbon taxes. The univariate results suggest that gasoline taxes should opposed most among predominantly Republican and rural regions. Ethnically diverse areas may be more receptive to taxes. Most of findings persist when we include all of the correlates in the same regression (Column 6 in Tables 5 through 7) and when we control for state fixed effects (Column 7 in Tables 5 through 7).

6 Regressivity

As discussed in the introduction, the regressivity of energy taxes are often a concern. We analyze the regressivity of both our current- and lifetime-capital loss measures. Given the strong correlation between the two, the general patterns are the same, but the effects are magnified when focusing on

⁸Comparing population densities across tracts highlights a limitation of our analysis since we focus on asset values rather than consumption. tracts with longer commute times will experience a smaller drop in asset values because they, on average, own more fuel efficient vehicles, but are likely to consume more fuel because they, on average, drive more miles.



Figure 6: Average current- and lifetime-capital loss as share of income across household income deciles from a \$1 increase in gasoline prices

the lifetime-capital effect. Figure 6 plot the average census tract capital loss as a share of income across income deciles. Both measures initially increase, and then fall.

This suggests that gasoline taxes are not uniformly regressive, but progressive for the lowest income deciles. Poterba (1991) found very similar results using a completely different empirical strategy.

We would like to investigate the effects of redistributing the revenue from a hypothetical \$1 gasoline tax. Regrettably, because we focus on the change in vehicle values, our empirical exercise does not yield estimated tax revenues. Nonetheless, we can mimic a gasoline tax and apportion the revenues if we assume that the tax is revenue-neutral. We do this by first aggregating the total loss in vehicle values across all households and then calculating the average household loss. If we assume that each household receives a transfer equal to the average loss, this implies that the average effect across households is zero. Clearly, we cannot say anything about the magnitude of the transfer each household receives because, in contrast to an approach that directly estimates tax revenues, the average household loss depends on how much gasoline prices change vehicle values, whereas tax revenues do not. Nonetheless, this approach does yield a measure of regressivity under a regime where tax revenues are apportioned equally among all consumers.



Figure 7: Average combined effect from lifetime-capital loss plus recycled revenue as share of income across states from a \$1 increase in gasoline prices

Our results suggest that \$267 would be recycled to each household. The dollar value is smaller than the annual revenue that would be generated from a \$1 gasoline tax, however, it is internally consistent with our calculations of the capital loss as a share of income and thus yields a valid measure of regressivity (see the appendix for more details).

First we show how this policy—apportioning tax revenue equally to households—changes the lifetime-capital loss as a share of income across states. Figure 7 plots the state-level winners and losers from such a policy. Under such a policy 18 states lose, on average, while the remaining states gain from such a policy. Once again, the losses are concentrated in the Midwest and parts of the South.

While such a policy does not change the geographic incidence of the tax, it does change the regressivity of the tax. Figure 8 plots the average combined effect from lifetime-capital loss plus recycled revenue as share of income across household income deciles. Because each household receives the same revenue, we expect the policy to reduce the regressivity of the tax. In fact, the policy leads to a tax that is progressive over the first four deciles and essentially neutral thereafter.

These results are consistent with Bento et al. (2009) which estimates incidence of gasoline taxes using a more structural approach. They first estimate a structural model of vehicle choice and miles-



Figure 8: Average combined effect from lifetime-capital loss plus recycled revenue as share of income across household income deciles from a \$1 increase in gasoline prices

driven choice and then analyze the equivalent variation required to make consumers indifferent between the tax policy and no change. They find that when tax revenues are recycled "flatly," the bottom quartile of the income distribution benefits, incidence increases between the first and second, and the second and third quartiles, and then is largely constant between the third and fourth quartiles.

7 Conclusions

In this paper we estimate the effect of gasoline taxes through the lens of changes in vehicle values. Our empirical approach differs from two common methods for assessing incidence. The first common method uses current expenditures on the product as a proxy for welfare changes in the presence of a tax. The second common method estimates a structural model of demand for both the taxed product (e.g., vehicles) and the intensive margin related to the taxed product (e.g., miles driven).

Our empirical approach differs considerably from these. Drawing on our work that suggests that the effect of gasoline prices on used vehicle prices reflects the present discounted value of changes in lifetime fuel costs, we estimate the effect of gasoline taxes by focusing on how the value of households' vehicle assets change. This approach allows us to take advantage of a rich data set that reports vehicle ownership at the census tract level down to the detail of a vehicle's make, model, model year, engine type, drive train, and in most cases the trim level. This allows us to assess the incidence of a gasoline tax across more dimensions that is possible with data from the Consumer Expenditure Survey used by Poterba (1991).

We find that capital loss varies considerably across states. Losses are largest in the Midwest, and smallest in the Northeast. We also find that the geographic variation in capital loss is correlated with political affiliation. Using county-level data on voting behavior during the 2000 Presidential election, we find that all our capital loss measures are positively related to the share of a county that voted for President Bush. This relationship holds, but is smaller in magnitude, when we control for ethnicity, commute times, income, population density, and state fixed effects.

We find that gasoline taxes are progressive over the first three income deciles and regressive thereafter. This is consistent with Poterba (1991) who finds that gasoline expenditures as a share of total expenditures increases for the first three deciles, but then tends to fall. However, a revenueneutral policy that recycles revenues equally across households is highly progressive for the first four income deciles and then largely income neutral thereafter. This is broadly consistent with Bento et al. (2009) who find that when tax revenues are recycled "flatly," the bottom quartile of the income distribution benefits, incidence increases between the first and second, and the second and third quartiles, and then is largely constant between the third and fourth quartiles.

References

- Allcott, Hunt and Nathan Wozny. 2011. "Gasoline Prices, Fuel Economy, and the Energy Paradox." Working paper, New York University.
- Bento, Antonio M., Lawrence H. Goulder, Mark R. Jacobsen, and Roger H. von Haefen. 2009.
 "Distributional and Efficiency Impacts of Increased US Gasoline Taxes." American Economic Review 99 (3):667–699.
- Busse, Meghan, Christopher R. Knittel, and Florian Zettelmeyer. 2012. "Who is Exposed to Gas Prices? How Gasoline Prices Affect Automobile Manufacturers and Dealerships." Working paper, Northwestern University and MIT, Evanston, IL and Cambridge, MA.
- Busse, Meghan R., Christopher R. Knittel, and Florian Zettelmeyer. 2013. "Are Consumers Myopic?Evidence from New and Used Car Purchases." American Economic Review 103 (1).
- Poterba, James M. 1991. "Is the Gasoline Tax Regressive." *Tax Policy and the Economy* 5:pp. 145–164.



Figure 9: Average fuel economy













| | (1) | (2) | (3) |
|-----------------|-----------------|------------------|------------------|
| Point of the | Current-capital | Current-capital | Lifetime-capital |
| Distribution | loss (\$) | incidence $(\%)$ | incidence $(\%)$ |
| 10th Percentile | 79 | 0.23 | 0.25 |
| 25th Percentile | 148 | 0.36 | 0.51 |
| 50th Percentile | 245 | 0.55 | 0.90 |
| Mean | 269 | 0.67 | 1.10 |
| 75th Percentile | 349 | 0.84 | 1.50 |
| 90th Percentile | 457 | 1.20 | 2.20 |

 Table 4: Distribution of measures

| | (1) | (6) | (6) | (4) | | (8) | (1) |
|--------------------------------------|------------------|------------------|------------------|---------------------------|---------------------|---------------------|------------------|
| VARIABLES | (1) Perc Bush | (2) Ethnicity | (3) Income | (4) Population Density | (5) Commute Time | (0) All | All & State FEs |
| Percent voting for Bush | 552.1^{***} | | | | | 138.2^{***} | 125.4^{***} |
| | (4.7) | ***** | | | | (4.5) | (3.4) |
| Fercent Airican American | | -295.9^{+++} | | | | -30.0^{+++} (2.6) | (1.8) |
| Percent Asian | | -510.7^{***} | | | | -132.1^{***} | -164.2^{***} |
| | | (8.6) | | | | (7.4) | (5.3) |
| Percent Hispanic | | -181.6^{***} | | | | 64.6^{***} | 29.2^{***} |
| | | (3.3) | | | | (2.9) | (2.2) |
| Log of Median Census-Block HH Income | | | 123.3^{***} | | | 135.1^{***} | 126.7^{***} |
| | | | (1.5) | | | (1.4) | (0.0) |
| Log of Population Density | | | | -47.7*** | | -43.4^{***} | -36.4^{***} |
| | | | | (0.2) | | (0.3) | (0.2) |
| Log of Average Commute Time | | | | | -83.3*** | -63.3*** | 24.3^{***} |
| | | | | | (2.4) | (2.0) | (1.3) |
| Constant | 10.1^{***} | 347.1^{***} | $-1,037.3^{***}$ | -100.7^{***} | 536.1^{***} | $-1,357.9^{***}$ | $-1,554.1^{***}$ |
| | (2.3) | (0.0) | (15.7) | (2.0) | (7.8) | (14.9) | (11.4) |
| Observations | 63.996 | 64.739 | 64,499 | 64,671 | 64.512 | 63.734 | 63.734 |
| R-squared | 0.2 | 0.2 | 0.1 | 0.4 | 0.0 | 0.5 | 0.8 |
| | | | | | | | |

| VARIARI ES | (1) Dorro Buich | (2) Ethnicitu | (3) Incomo | (4) Domilation Doneity | (5) | (9) VII | $\begin{array}{c} (7) \\ \Lambda 11 \ \ell_{\tau} \ C_{\tau \ o \ t \ o} \ FF_{c} \end{array}$ |
|--------------------------------------|--------------------|-----------------|-----------------|---------------------------|-----------------|-----------------|--|
| CHITCHINE | | AUDITION | | I uputation memory | | ΠV | CT J DIVIC N IIV |
| Percent voting for Bush | 1.5979^{***} | | | | | 0.2768^{***} | 0.1864^{***} |
| 1 | (0.0153) | | | | | (0.0160) | (0.0158) |
| Percent African American | | -0.4198^{***} | | | | -0.2156^{***} | -0.2297^{***} |
| | | (0.0091) | | | | (0.0093) | (0.0084) |
| Percent Asian | | -1.8553^{***} | | | | -0.0609** | -0.1828^{***} |
| | | (0.0297) | | | | (0.0262) | (0.0247) |
| Percent Hispanic | | -0.1646^{***} | | | | 0.1681^{***} | 0.0269^{**} |
| | | (0.0113) | | | | (0.0104) | (0.0104) |
| Log of Median Census-Block HH Income | | | -0.3118^{***} | | | -0.3125^{***} | -0.3371^{***} |
| | | | (0.0048) | | | (0.0048) | (0.0041) |
| Log of Population Density | | | | -0.1418^{***} | | -0.1296^{***} | -0.1104^{***} |
| | | | | (0.0008) | | (0.0010) | (0.0009) |
| Log of Average Commute Time | | | | | -0.4475^{***} | -0.2153^{***} | -0.0023 |
| | | | | | (0.0076) | (0.0069) | (0.0061) |
| Constant | -0.0801^{***} | 0.8080^{***} | 3.9763^{***} | -0.4291^{***} | 2.1002^{***} | 3.5498^{***} | 3.2187^{***} |
| | (0.0075) | (0.0030) | (0.0514) | (0.0067) | (0.0245) | (0.0524) | (0.0536) |
| Observations | 63,761 | 64,499 | 64,499 | 64,499 | 64, 472 | 63,734 | 63,734 |
| R-squared | 0.1456 | 0.0835 | 0.0603 | 0.3095 | 0.0506 | 0.4055 | 0.5998 |
| | | | | | | | |

Table 6: Correlates of the loss in current capital value as share of median income

| | | (0) | 101 | | 11 | | Ĩ |
|--------------------------------------|------------------|-----------------|-----------------|---------------------------|---------------------|-----------------|------------------------|
| VARIABLES | (1) Perc Bush | (2) Ethnicity | (3) Income | (4) Population Density | (5) Commute Time | (6) All | (7) All & State FEs |
| Percent voting for Bush | 3.0709^{***} | | | | | 0.7637^{***} | 0.4302^{***} |
|) | (0.0259) | | | | | (0.0261) | (0.0274) |
| Percent African American | ~ | -0.6999*** | | | | -0.2483^{***} | -0.3409^{***} |
| | | (0.0156) | | | | (0.0152) | (0.0145) |
| Percent Asian | | -3.6733^{***} | | | | -0.3335^{***} | -0.5566^{***} |
| | | (0.0508) | | | | (0.0427) | (0.0428) |
| Percent Hispanic | | -0.2518^{***} | | | | 0.4142^{***} | 0.1381^{***} |
| | | (0.0194) | | | | (0.0169) | (0.0180) |
| Log of Median Census-Block HH Income | | | -0.5422^{***} | | | -0.5108^{***} | -0.5426^{***} |
| | | | (0.0084) | | | (0.0078) | (0.0072) |
| Log of Population Density | | | | -0.2687^{***} | | -0.2441^{***} | -0.2138^{***} |
| | | | | (0.0014) | | (0.0016) | (0.0015) |
| Log of Average Commute Time | | | | | -0.6779^{***} | -0.2416^{***} | 0.0578^{***} |
| | | | | | (0.0133) | (0.0113) | (0.0106) |
| Constant | -0.3388*** | 1.3497^{***} | 6.8518^{***} | -0.9798*** | 3.2692^{***} | 5.0393^{***} | 4.6400^{***} |
| | (0.0127) | (0.0051) | (0.0887) | (0.0111) | (0.0426) | (0.0856) | (0.0927) |
| Observations | 63,761 | 64,499 | 64,499 | 64, 499 | 64, 472 | 63,734 | 63,734 |
| R-squared | 0.1810 | 0.0981 | 0.0613 | 0.3732 | 0.0389 | 0.4671 | 0.5979 |
| | | | | | | | |

 Table 7: Correlates of the lifetime-loss in capital value as share of median income

Appendix: A discussion of regressivity measures

The incidence of a tax is the loss in the present discounted value of utility resulting from the tax. If we ignore the use of the tax revenues, we can write the incidence as:

$$Incidence = \sum_{t=0}^{T} \delta^t \left[u(q_{gt}, X|p_{gt} + \tau) - u(q_{gt}, X|p_{gt}) \right].$$
(2)

An upper bound on this is the change in the present discounted value of fuel expenditures under the assumption that consumers do not adjust their miles driven or the fuel economy of their vehicles, yielding:

$$\overline{Incidence} = \sum_{t=0}^{T} \delta^t \left[(p_{gt} + \tau)q_{gt} - (p_{gt})q_{gt} \right].$$
(3)

$$=\sum_{t=0}^{T}\delta^{t}\cdot\tau\cdot q_{gt} \tag{4}$$

Studies interested in the regressivity of a given tax often use only the current-year expenditures as a fraction of some static measure for lifetime wealth (e.g., current-year income or expenditures). For example to assess the regressivety of a gasoline tax, Poterba (1991) calculates:⁹

$$\frac{\tau \cdot q_{gt}}{Total \ Household \ Expenditures_t}.$$
(5)

The regressivity of the tax depends on:

$$\frac{\partial \frac{\tau \cdot q_{gt}}{Total \ Household \ Expenditures_t}}{\partial Total \ Household \ Expenditures_t}.$$
(6)

When Poterba (1991) plots equation 5 across expenditure deciles, he finds a positive slope for the first three deciles and a negative slope thereafter.

A second approach in the literature estimates a structural model of vehicle choice and milesdriven choice. The structural model then provides the primitives of consumers' utility functions which can be used to analyze the incidence of the tax. A nice example of this is Bento et al. (2009).

Our approach is different in that we estimate the change in the value of households' vehicle capital stock. Our previous work, Busse, Knittel, and Zettelmeyer (2013), argues that the relative change in vehicle values of two vehicles, as a result of a change in gasoline prices, represents the change in the relative present discounted value of fuel costs between these two vehicles.

⁹Poterba (1991) argues that total household expenditures is a better proxy for the present discounted of wealth. He does not address issues regarding changes in fuel consumption as a result of decreases in either miles driven or fuel economy.

To formalize this, consider the change in the relative prices of two vehicles, i and j:

$$\Delta V_i - \Delta V_j = \sum_{t=0}^{T_{veh}} \delta^t \left[\left[(p_{gt} + \tau) q_{gt,j} - (p_{gt}) q_{gt,j} \right] - \left[(p_{gt} + \tau) q_{gt,i} - (p_{gt}) q_{gt,i} \right] \right].$$
(7)

For example, Busse, Knittel, and Zettelmeyer (2013) illustrate that the relative change in the values of a used Civic and a used Yukon equals the relative change in lifetime fuel costs of the two vehicles for "reasonable" discount rates.

Two issues arise when using the change in vehicle values to calculate the regressivity of a gasoline tax. The first is that the calculation requires the upper bound of the summation to be the life of the individual, not the life of the vehicle. Second, the calculation requires the absolute, not just the relative change in fuel costs.

The first issue does not affect the *sign* of the relationship between this measure of incidence and income and will tend to reduce the size of the slope in absolute value. To see this, notice that:

$$\sum_{t=0}^{T_{veh}} \delta^t \left[\left[(p_{gt} + \tau) q_{gt,j} - (p_{gt}) q_{gt,j} \right] \right] = \alpha \sum_{t=0}^T \delta^t \left[\left[(p_{gt} + \tau) q_{gt,j} - (p_{gt}) q_{gt,j} \right] \right]$$
(8)

with $\alpha < 1$ when $T > T_{veh}$. Therefore we have:

$$\frac{\partial \frac{\sum_{t=0}^{T_{veh}} \delta^t[(p_{gt}+\tau)q_{gt,j}-(p_{gt})q_{gt,j}]}{\sum_{t=0}^{T} \delta^t Income_t}}{\partial Income} = \alpha \cdot \frac{\partial \frac{\sum_{t=0}^{T} \delta^t[(p_{gt}+\tau)q_{gt,j}-(p_{gt})q_{gt,j}]}{\sum_{t=0}^{T} \delta^t Income_t}}{\partial Income}.$$
(9)

This does imply, however, that if the focus is on the regressivity of a tax, when estimating the drop in asset value across census tracts, we do not want to differentiate by vintage of vehicles. That is, we do not want to use different T_{veh} even though census tracts vary in their average vintage. To see the intuition behind this, consider two census tracts that are otherwise identical except for in one of them the average vehicle age is 3 years, while in the other it is 12 years. The above calculations would imply that the tract with the older vehicle stock would experience a smaller decline in asset values. While this is true, if we are interested in the present discounted value of fuel costs, while the older tract will experience a smaller drop in asset values, they will have to buy new capital stock earlier. Under the maintained assumption that they continue to purchase the same fuel economy, their change in fuel expenditures will be the same; that is, if we apply the correct tract-specific α , the incidence in the two tracts will be identical. Alternatively, we can calculate the drop in asset values based only of fuel economy and not both fuel economy and vintage. Therefore, we can either apply the same coefficients estimates—not accounting for vintage—or, we can have tract-specific α s. We choose to apply the same coefficient estimates to reduce noise. The second issue implies that the change in asset values will be bounded from below by the change in the present discounted value of fuel costs. For notational ease, call the change in the fuel costs of vehicle j, ΔF_j . Also, abbreviate Income to I. The previous sections calculated incidence as:

$$\frac{\Delta V_j}{I} = -\frac{\Delta F_j}{I} + \frac{\Delta F_i}{I} - \left(-\frac{\Delta V_i}{I}\right) \tag{10}$$

We know that $\Delta V_i > -\Delta F_i$ since, for example, fuel efficient vehicles become *more* valuable when gasoline prices increase. In essence, this implies that the entire set of changes in vehicle values are shifted upward as they relate to the change in present discounted fuel costs. If this shift is equal across vehicle quintiles, then we have:¹⁰

$$\frac{\Delta V_j}{I} = -\frac{\Delta F_j}{I} + \frac{\Delta F_i}{I} - \left(-\frac{\Delta V_i}{I}\right) \tag{11}$$

$$= -\frac{\Delta F_j}{I} + \frac{X}{I} \tag{12}$$

Given the assumption that this is a constant shift, the derivative of this measure of incidence with respect to income is:

$$\frac{\partial \triangle V_j / I}{\partial I} = -\frac{\triangle F_j / I}{\partial I} + \frac{\triangle F_i}{I} - \left(-\frac{\triangle V_i}{I}\right)$$
(13)

$$= -\frac{\partial \triangle F_j / I}{\partial I} - \frac{X}{I^2} \tag{14}$$

Because both X and I^2 are positive, this implies that focusing on changes in asset prices will tend to understate the regressivity of the tax. The intuition behind this is that we are, in essence, reducing the incidence at each income level by a fixed amount. As a share of income, this is larger for lower incomes, making the tax look less regressive. We note, however, that Poterba (1991) argues that our use of current income to scale changes in asset values will tend to *over*state the regressivity of the tax. The intuition behind this is that there will be some households with low *current* income but these households expect higher income in the future. If these households smooth consumption, then their current fuel consumption, and automobile choices, will be greater than what their current income would suggest. Poterba (1991) argues that current total consumption is likely to be more strongly correlated with lifetime income than current income. He shows that using current consumption reverses the regressivity of a gasoline tax for the first three income deciles.

¹⁰ Notice that for all but one of the quintiles, the choice of the comparison vehicles, is arbitrary. Therefore, we can use the same comparison quintile for four out of the five quintiles leading to the identical shift upward. Specifically, assume that for quintiles one through four, we use quintile five as the comparison group. Then these four will shift by the same amount. We can repeat this procedure by using quintile one as the comparison group for quintiles two through five; these quintiles will then shift by the same amount.