Are Fuel Economy Standards Regressive?

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Abstract

Despite widespread agreement that a carbon tax would be more efficient, many countries use fuel economy standards to reduce transportation-related carbon dioxide emissions. We pair a simple model of the automobile automakers' profit maximization problem with unusually-rich nationally representative data on vehicle registrations to estimate the distributional impact of U.S. fuel economy standards. The key insight from the model is that fuel economy standards impose a constraint on automakers which creates an implicit subsidy for fuel-efficient vehicles and an implicit tax for fuel-inefficient vehicles. Moreover, when these obligations are tradable, permit prices make it possible to quantify the exact magnitude of these implicit subsidies and taxes. We use the model to determine which U.S. vehicles have been most subsidized and taxed since 2012, and we compare the pattern of ownership of these vehicles between high- and low-income Census blocks. Finally, we compare these distributional impacts with existing estimates in the literature on the distributional impact of a carbon tax.

Key Words: CAFE Standards, Gasoline Tax, Carbon Tax, Distribution of Income
JEL: D31, D62, H23, Q38, Q41, Q48

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1 Introduction

Global oil consumption now exceeds 90 million barrels per day (EIA, 2015) fueling the more than 1.2 billion vehicles in use worldwide (BP, 2015). Total carbon dioxide emissions from road transportation exceed five gigatons annually (IPCC, 2015), approximately one-sixth of all anthropogenic emissions. Policymakers are increasingly turning their attention to this important sector, evaluating alternative approaches for reducing carbon dioxide emissions. Economists agree that the most cost-effective approach would be a carbon tax, or equivalently, taxes on gasoline and diesel. Carbon dioxide emissions are proportional to fuels consumption, so either approach would be first-best for reducing carbon dioxide emissions from driving.

Despite widespread agreement that a carbon tax would be more efficient, many countries instead use fuel economy standards. The United States and Japan have long histories with fuel economy standards, and similar policies have also been recently implemented by the European Union, China, India, and elsewhere (Anderson and Sallee, forthcoming). The exact format differs between countries, but many programs follow the U.S. Corporate Average Fuel Economy (CAFE) standards in requiring automakers to meet a minimum sales-weighted average for their vehicle fleets.

It can be easier politically to introduce fuel economy standards than taxes, but the two are not equivalent, partly because of concerns about the regressivity of energy taxes (Knittel, 2014). Probably the single biggest limitation of fuel economy standards is that they don't achieve the efficient level of vehicle *usage*; to efficiently reduce gasoline consumption you need people to buy more fuel-efficient cars and to drive them less. But economists have pointed out other disadvantages as well. For example, Jacobsen and van Benthem (2015) show that fuel economy standards reduce the incentive for drivers to retire old vehicles, leading fuel-inefficient vehicles to stay on the road longer. Overall, studies have found that fuel economy standards are three to six times more costly than a carbon tax (Austin and Dinan, 2005; Jacobsen, 2013).

In this paper we ask a different but related question. Are fuel economy standards regressive? We pair a simple model of the automakers' profit maximization problem with unusually-rich nationally representative data on vehicle registrations to estimate the distributional impact of U.S. fuel economy standards. The key insight from the model is that fuel economy standards impose a constraint on automakers which creates an implicit subsidy for fuel-efficient vehicles and an implicit tax for fuel-inefficient vehicles. Moreover, when these obligations are tradable as they are under new CAFE rules, the permit prices make it possible to quantify the exact magnitude of these implicit subsidies and taxes.

We find that CAFE standards are mildly progressive when we consider both new vehicle sales and the stock of vehicles. We compare these distributional impacts with existing estimates in the literature on the distributional impact of a carbon tax. In general, this literature has found that the regressivity or progressivity of such a tax strongly depends on what is done with the collective revenue. CAFE standards are more regressive than carbon taxes that recycle the revenue through uniform transfers, but more progressive than taxes that either do not recycle the revenue or use the revenues to reduce progressive taxes such as labor and payroll taxes. Thus, we do not find a trade off between regressivity of the two types of policies and efficiency.

This paper fills an important gap in the literature. Previous studies of fuel economy standards have focused almost exclusively on efficiency and overall cost-effectiveness, but the distributional impacts of fuel economy standards have received little attention. An important exception is Jacobsen (2013) which studies the distributional impacts of CAFE using microdata from the 2001 National Household Travel Survey. The paper finds that CAFE is regressive, with low-income households suffering proportional welfare losses three times as large as high-income households. Our results are a valuable complement to this important earlier work.

Before proceeding we want to be clear about several important limitations of our analysis. First, our maintained assumption throughout is that these impacts are borne entirely by vehicle buyers rather than automakers or retailers. This is a reasonable assumption in market segments that are highly competitive and consistent with at least one study of subsidy incidence in the U.S. automobile sector (Sallee, 2011), but is a strong assumption that we are not going to be able to verify empirically.

Second, our calculations implicitly assume that these taxes and subsidies do not change buyers' vehicle decisions. This is, of course, incorrect and, indeed, part of the purpose of fuel economy standards is to move buyers toward more fuel-efficient vehicles. We might see, for example, someone who owns a vehicle that is subsidized under CAFE and conclude they are a "winner" when in fact, without CAFE they would have purchased a different vehicle that because of CAFE is taxed. This buyer is not a winner at all and despite buying a subsidized vehicle might have suffered a significant welfare loss. We are not going to estimate a fully-specified demand model so our analysis is silent on this substitution behavior and on the broader welfare impacts of CAFE.

Third, our approach for modeling the impact of CAFE on used vehicles is *ad hoc* and only a rough approximation. Fuel economy standards apply only to new vehicles but have significant indirect impacts on used vehicle prices. We model this using a strong simplifying assumption that we argue describes the general pattern of impacts but cannot capture all of the complicated cross-price effects. Fourth, our analysis is short-run in that we are not going to attempt to model the impact of CAFE rules on innovation and/or the development of entirely new vehicle models that might have disproportionate impacts across income groups. There has been some recent work on fuel economy standards and innovation (Klier and Linn, forthcoming), but we are not aware of any work examining the potential long-run distributional impacts.

2 Background

The Corporate Average Fuel Economy (CAFE) program was introduced in the United States in 1975 with the objective of reducing gasoline consumption. Under CAFE, automakers are required to meet a minimum sales-weighted average fuel economy for their vehicle fleets. These requirements have been tightened several times, most recently with a significant revision to the program resulting in new program rules which took effect starting in 2012. For a complete regulatory history, see Anderson et al. (2011), Knittel (2012), and Leard and McConnell (2015).

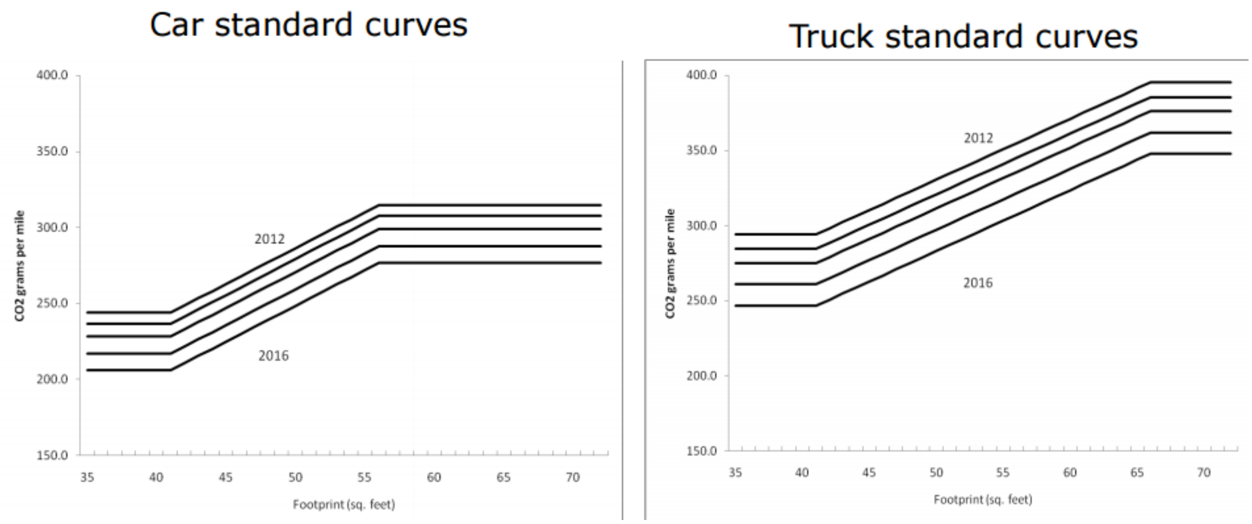
Our analysis is particularly timely because policymakers are gearing up for a required midterm review that will determine what form the program takes for vehicle model years 2022-2025. The review formally kicks off in June 2016 when the Environmental Protection Agency will release its Draft Technical Assessment Report for public comment (EPA, 2015). Based on the midterm review the EPA could decide that the standards are appropriate or update the standards making the more or less stringent.

2.1 Footprint-Based Standards

As has always been the case with CAFE standards, automakers are required to meet a minimum sales-weighted average fuel economy for their vehicle fleet. Since 2012, however, this target now depends on the footprint of vehicles in the fleet. Calculated as the product of a vehicle's wheelbase (i.e. length) and track width (i.e. width), the footprint is a simple measure of the overall size of the vehicle.

Each vehicle has a different emissions target based on its footprint and on whether it is a

Figure 1: Emissions Targets, 2012 to 2014



car or truck. Figure 1 shows the emissions targets (in grams of carbon dioxide per mile) for cars and trucks produced during the first phase between 2012 and 2016. The rules establish increasingly strict requirements on fuel economy for each vehicle model year. Larger vehicles receive larger emissions targets and trucks receive preferential treatment in the form of higher emissions targets for any given footprint and model year.

Just because a vehicle is small does not ensure that it meets the emissions target. For example, the Mini Cooper with a footprint of 39 square feet in 2012 received an emissions target of 244 grams of carbon dioxide per mile. Actual emissions are 296 grams per mile, significantly above the emissions target. Thus, even though this car is one of the smallest on the road weighing only 2,500 pounds and with 115 horsepower, it is less fuel-efficient than its footprint-based target. Thus if BMW wants to sell more Mini Coopers, it also needs to sell more of some other vehicle that is below its target and/or BMW needs to buy permits from some other automaker.

Herein lies the central problem with footprint-based targets. For a given vehicle footprint, the standards encourage automakers to make their vehicles as fuel-efficient as possible. However, the footprint-based standards create no incentive for buyers to choose smaller vehicles. This may make sense from a political perspective in the United States because domestic automakers produce large numbers of SUVs, crossovers, and pickups, but it does not make sense from the perspective of reducing greenhouse gas emissions.[1]

Another significant distortion with the standards is the preferential treatment for trucks.

[1] See Ito and Sallee (2014) for a broader discussion of the economic costs of attribute-based regulation.

For a given footprint, trucks have a less stringent carbon emissions standard than cars, so the standards encourage automakers to sell more trucks and fewer cars. The preferential treatment for trucks also encourages automakers to classify as many vehicles as possible as "trucks".[2] Today "trucks" include not only pickup trucks but also SUVs, crossovers, and minivans. These are some of the largest and fastest growing segments in the U.S. automobile market.[3]

2.2 Permit Trading Rules

Each vehicle sale generates a small "surplus" or "deficit" for the automaker depending on whether the vehicle is below or above its target emissions value. The total balance is then evaluated separately for each model year and each automaker. If a automaker is below the total target emissions value, then it has a surplus for the year and receives permits. If instead a automaker is above the total target emissions value, then it has a deficit and must buy permits.

Permits are denoted in tons of carbon dioxide. This is an important and not immediately obvious feature of the CAFE program so is worth briefly elaborating on this point. Fuel economy is measured as grams of carbon dioxide per mile. There are 8.887 kilograms of carbon dioxide per gallon of gasoline and 10.180 kilograms of carbon dioxide per gallon of diesel, so there is a simple mapping between carbon dioxide emissions per mile and vehicle fuel economy. Finally, an assumption is made about vehicle lifetime miles traveled in order to denote the standard in tons; in particular, cars are assumed to travel 150,922 total miles whereas trucks are assumed to travel 172,552 total miles.

Automakers can bank permits for up to five years, and borrow permits for up to three years into the future. This flexibility is intended to help automakers smooth over year-to-year fluctuations in demand driven by macroeconomic shocks, changes in gasoline prices, and other factors. The banking and borrowing also provides stability for the permit market, helping to avoid permit price spikes and crashes, and mitigating concerns about market

[2] The classic example of this is a vehicle Chrysler manufactured called the PT Cruiser. In the early 2000s, Chrysler was making large profits on its Dodge Ram pickups, and wanted to sell more, but was running up against the CAFE constraint. Ingeniously, Chrysler responded by introducing the PT Cruiser which looked like a car but was built on a truck platform, thus raising Chryslers average fuel economy for trucks and allowing Chrysler to sell more fuel-inefficient pickups.

[3] The biggest year ever for the U.S. auto industry was 2015 with 17.5 million total vehicle sales nationwide including large year-on-year increases for trucks, SUVs, and crossovers. See Automotive News, "U.S. Auto Sales Break Record in 2015," January 5, 2016.

power in permit markets.[4]

Permits may also be traded between automakers. Permit trading increases the efficiency of fuel economy standards. Just as with any cap-and-trade policy, trading equalizes marginal cost across agents, achieving the targeted aggregate level of emissions reductions at lowest total cost. These efficiencies are likely substantial with fuel economy standards because opportunities for improvements in fuel economy vary widely across automakers. For some automakers there is low-hanging fruit, for example, because they already have relative expertise in producing and marketing fuel-efficient vehicles whereas for other automakers it can be much harder.

All automakers have an incentive to improve fuel economy, including those who are well above the fuel economy standard. This was not the case under the old CAFE rules that did not allow trading. Toyota and Honda tend to sell relatively fuel-efficient vehicles, so were perennially well above the minimum MPG requirement. For automakers in this position under the old CAFE rules, it was as if the standard did not exist. There was no penalty, but also no incentive to make further improvements in fuel economy. In fact, these automakers had an incentive to make larger vehicles to pull market share away from other automakers who were constrained by CAFE. Now with permit trading any improvement in fuel economy generates CAFE credits, and thus profit.

Automakers trade permits through bilateral trades. There is no central clearing house for permit trading, nor is there any system in place for making permit prices made publicly-available. Leard and McConnell (2015) nonetheless manage to infer permit prices based on information from two different sources: (i) a Department of Justice settlement with Hyundai and Kia resolving overstated fuel economy labels and (ii) Tesla Motors' SEC Filing Form 10-K from 2013 and 2014 reporting earnings from permit sales. These sources yield a permit price of between \$35 and \$40 per ton. We adopt these permit price values in the empirical results that follow but it would be straightforward to incorporate updated permit prices as newer information becomes available.

Interestingly, these inferred permit prices are close to recent median estimates of the social cost of carbon (see, e.g. Interagency Working Group on Social Cost of Carbon, 2013). Thus, on the margin, automakers would appear to be facing an incentive similar to an, e.g., \$40 per ton tax on carbon dioxide. (Future carbon dioxide emissions are not discounted under CAFE, so it would actually be equivalent to a somewhat higher tax per ton.) Much unlike a carbon tax, however, fuel economy standards do not encourage drivers to use their vehicles

[4]See Borenstein et al. (2014) for a discussion of similar issues in cap-and-trade programs for carbon dioxide.

less intensively. To efficiently reduce gasoline consumption you need people to buy more fuel-efficient cars and to drive less, and fuel economy standards can never address this second margin.

2.3 Alternative Fuel Vehicles

This section reviews a couple of significant CAFE loopholes which cause the standards to further depart from a first-best tax on carbon dioxide. In particular, the rules provide preferential treatment for several different types of alternative fuel vehicles.

First, electric vehicles (EVs), for compliance purposes, are assumed to be zero carbon. Recent empirical evidence shows that the actual carbon impact from EVs is quite varied depending on where and when the vehicle is charged, but that in many cases the carbon impact of EVs may actually exceed the carbon emissions from gasoline-powered vehicles (see, e.g. Holland et al., 2015). This treatment of EVs was meant as an explicit subsidy and not as an accurate description of the current carbon emissions from EVs.

Second, plug-in hybrids like the Chevrolet Volt and Toyota Prius plug-in also receive preferential treatment. These vehicles have both an electric drive train and internal combustion engine and thus can be operated using either electricity or gasoline. For CAFE compliance purposes, the gasoline component is treated normally but the electric component is assumed to be zero carbon. This is again not an accurate description of current emissions resulting from these vehicles. Even in parts of the country where electricity generation tends to be relatively low-carbon, the *marginal* source of electricity generation is virtually always some form of fossil fuel generation.

Third, the loophole which ends up being most importantly quantitatively during our sample period is the treatment of flexible-fuel (or "flex-fuel") vehicles which can run either on E85 (a blend of 85% ethanol and 15% gasoline) or on regular gasoline. Between 2012 and 2015 when calculating CAFE compliance, flex-fuel vehicles were assumed to be operated 50% using E85 and 50% with gasoline. Moreover, each gallon of E85 is assumed to have the carbon content of only 0.15 gallons of gasoline. That is, the ethanol component of E85 is assumed to be zero carbon.

These assumptions are overly generous to flex-fuel vehicles. Empirical evidence is not available on the fraction of flex-fuel vehicles that operate using E85, but the 50/50 assumption is a very optimistic assumption given that many sales of flex-fuel vehicles occur in parts of the country where there is limited E85 availability (Anderson and Sallee, 2011). But the assumption about carbon content is even more optimistic, and hard to reconcile with a substantial scientific literature on the carbon emissions from ethanol. Quantifying the lifetime carbon impacts of ethanol is challenging because of land use effects and other complications, but most studies find that, at best, ethanol is only marginally less carbon-intensive than gasoline (Knittel, 2012).

As we show later in the paper, these overly generous assumptions lead flex-fuel vehicles to be treated by CAFE as if they were extremely fuel-efficient. And not suprisingly, automakers have responded enthusiastically. For the 2014 model year, for example, there are more than 100 different models of flex-fuel vehicles for sale in the United States. Moreover, even though the preferential treatment for flex-fuel vehicles ended with model year 2015, the loophole was so lucrative that many automakers were able to generate large stores of surplus credits (U.S. Environmental Protection Agency, 2015). Under CAFE rules these credits can be banked until 2021, so these banked credits will allow automakers to produce lower-MPG vehicles for years to come.

3 Conceptual Framework

In this section we write down the vehicle automakers' profit-maximization problem subject to the CAFE constraint. From this problem we derive a first-order condition that quantifies the implicit subsidy and tax for each vehicle which we can then take to the empirical analysis. We first consider the case of perfect competition. The degree to which this is a reasonable assumption varies across vehicle segments from some highly-competitive segments like compact sedans and mid-size SUVs, to other segments like sportscars where some automakers can influence price considerably. We then relax the perfect competition assumption in the following subsection and show that the first-order condition is similar in both cases.

3.1 Perfect Competition

The automobile chooses quantities to maximize profits,

$$\max_{q_1, q_2 .., q_J} \sum_{j=1}^{J} \left[q_j p_j - c_j(q_j) \right]. \tag{1}$$

Here q_j is total sales of vehicle model j. Revenues are the product of sales (q_j) and prices (p_j), summed over all vehicle models. Profits are total revenues minus total costs, where the cost of producing q_j units of vehicle model j is denoted $c_j(q_j)$. Here we allow production costs to vary between vehicle models but rule out complementarities between models, though this restriction is not necessary.

The fuel economy standard can be expressed as follows,

$$\sum_{j=1}^{J} \left[(emissions_j - target_j) * VMT_j * q_j\right] \leq 0. \tag{2}$$

In this equation $emissions_j$ is carbon dioxide emissions in grams per mile for vehicle model j. Depending on its footprint, each vehicle model is assigned a target emissions level, $target_j$, based on its footprint, also measured in grams per mile. Thus the first part of equation (2) in parenthesis reflects whether each vehicle model is either above or below its target. These deviations are then weighted based on assumed lifetime miles traveled and vehicle sales. In particular, vehicles are assumed to travel VMT_j total miles over their lifetime. Finally, q_j is total sales of vehicle model j in a given year.

The automaker maximizes profits subject to the CAFE constraint. The lagrangean can be written as follows,

$$\mathcal{L} = \sum_{j=1}^{J} \left[q_j p_j - c_j(q_j)\right] - \lambda \sum_{j=1}^{J} \left[(emissions_j - target_j) * VMT_j * q_j\right] \tag{3}$$

where λ is the lagrangean multiplier on the CAFE constraint. Differentiating with respect to q_j yields the following first order condition,

$$p_j = c_j'(q_j) + \lambda \left[(emissions_j - target_j) * VMT_j\right]. \tag{4}$$

In the first-order condition λ is the shadow value of the CAFE constraint. With permit trading this shadow value equals the permit price. This the relevant opportunity cost for all automakers, regardless of whether they have a surplus or a deficit. automakers have two margins to adjust in meeting the CAFE constraints: (1) adjusting quantities and (2) buying/selling permits. Profit-maximization requires that the marginal returns from these two margins be equated. In addition, none of this is changed by banking or borrowing of permits. For example, we could have included banked permits from previous years in the CAFE constraint, but this is not a function of q_j, and thus would not have entered the first-order-condition.

The first-order condition has an intuitive interpretation. Consider first the extreme case in which the permit price equals zero. In this case the shadow value λ is zero, and the automaker maximizes profit by increasing the quantity sold of each vehicle up until price equals marginal cost. For non-zero permit prices, the automaker maximizes profit by adjusting quantities to reflect both marginal cost and the additional cost (or benefit) which accrues because of the standard.[5] For vehicle models that emit *more* than their target emissions level there is an additional cost for each unit sold, so the optimal quantity is lower. Symmetrically, for vehicle models that emit *less* than their target emissions level there is an additional *benefit* for each unit sold so the optimal quantity is higher.

In short, the fuel economy standard creates a tax for fuel-inefficient vehicles and a subsidy for fuel-efficient vehicles. In the empirical analyses that follow we use this insight to calculate the taxes and subsidies borne by different vehicle models sold in the United States. We focus on the period since 2012 which allows us to use permit prices to measure the shadow value of the constraint. In principle, however, it would be relatively straightforward to take parameter estimates from studies like Anderson and Sallee (2011) and Jacobsen (2013) to infer the shadow value of λ and use this general approach to perform analogous calculations for the pre-2012 period.

3.2 Imperfect Competition

The problem for an oligopolist automobile automaker is similar except they face a downward sloping demand curve, $p_j(q_j)$ and in the first order condition price is replaced with marginal revenue,

$$p_j'(q_j) * q_j + p_j = c_j'(q_j) + \lambda \left[(emissions_j - target_j) * VMT_j \right]. \tag{5}$$

Here we have assumed that cross-price elasticities are zero. See Jacobsen (2013) for the first-order condition with non-zero cross-price elasticities. With the full matrix of price elasticities the problem is more complicated because in thinking about vehicle model j the automaker takes into account implications not only for the price of vehicle model j, but also for the price of all other vehicle models. However, even with the full set of cross-price elasticities the first-order condition takes on this same basic form on the right-hand side.

Thus pricing behavior with imperfect competition is similar but not identical to pricing under perfect competition. Fuel-efficient vehicles will still be priced lower than they would have otherwise, and fuel-inefficient vehicles will still be priced higher than than would have otherwise, but with imperfect competition it becomes more difficult to say exactly how much

[5] See Kwoka (1983); Helfand (1991); Holland et al. (2009) for more related discussions.

Table 1: Vehicle and Tract Summary Statistics in 2012

	Mean	Standard Deviation	Min	Max
Tract population	5,049.6	2,207.5	36	39,143
Mean tract income	84,981.8	43,749.3	5,229	605,007
Median tract income	67,279.6	31,409.6	2,500	250,000
Median tract earnings	40,409.4	15,774.1	2,500	213,594
Vehicle footprint	48.0	6.1	26.8	77.6
CO_2 grams per mile emissions standard	296.5	39.3	244	395
CO_2 grams per mile	272.3	70.8	0	628.3
Miles per gallon	34.82	8.9	14.2	70.8
Tax/subsidy (footprint based)	-203.7	491.9	-2,460.3	2,333.5
Tax/subsidy (non-footprint based)	-451.3	549.4	-2,258.1	2,336.3

these markups/markdowns would be. As with any question about incidence, it depends on the relative elasticities. If demand is relatively elastic (i.e. $p'_j(q_j)$ close to zero), then the automaker has little market power and the outcome is close to the perfect competition case.

4 Data

The key insight from the previous section is that fuel economy standards create an implicit subsidy for fuel-efficient vehicles and an implicit tax for fuel-inefficient vehicles. In this section we pair this insight with rich microdata from the U.S. automobile market 2012-2015 to estimate the distributional impact of fuel economy standards. We proceed in several steps. First, we show how each vehicle model compares to its target emissions level. Second, we use the automaker's first-order-condition to quantify the implicit tax (or subsidy) for each vehicle model. Third, we use national data on vehicle registrations by zip code to see how the average impact of CAFE standards varies between high- and low-income zip codes.

Microdata on the U.S. automobile market from 1979 to 2014 are from DataOne Software and Polk Automotive. The DataOne sample provides a rich set of car and truck characteristics used in analysis, including each vehicle's truncated vehicle identification number (VIN). The VIN provides information about the vehicle's make, model, model year, body style, engine type, fuel tank size and driveline. DataOne also provided the wheelbase, front track and rear track measurements used to calculate a footprint for each vehicle, as well as fuel type and vehicle category. We divided fuel type into four categories—gasoline, electric, electric hybrids and flex-fuel—where gasoline includes vehicles fueled by gasoline, ethanol, natural gas or diesel. Following the EPA guidelines, vehicles listed as sports-utility vehicles, pickup trucks, minivans or vans were coded as trucks and compact, large, midsize, minicompact, and subcompact cars, two seaters and station wagons were coded as cars.

In addition to vehicle specifications, we observe each vehicle's sales in a given census tract for the years 2008 to 2014 using the Polk Automotive dataset. Vehicles are distinguished by a series of specifications including make, model, model year, engine size, cylinders, and fuel type. As a result, the data allow us to identify and compare the number of registrations of flexible-fuel 2012 Toyota Tundra trucks with 5.7L V8 engine with the number of registrations of 2012 Toyota Tundra trucks with a 5.7 V8 engine. A limited number of vehicles were further differentiated by various trim levels, such as the Mercedes-Benz C1550 which is manufactured in both standard and "4Matic" models. However the data do not distinguish between all the available model options which can be installed, such as leather upholstery. Merging DataOne vehicle specifications with census-tract level vehicle registration data from Polk, we were able to assemble a detailed makeup of the automobile market across each census-tract.

Sociodemographic county and census-tract-level data (income, population, race) come from the 2009 and 2014 American Community Survey (ACS). Finally, fuel economy data for each vehicle was obtained from the EPA. Each vehicle's actual emissions comes from the same source. For CAFE compliance purposes, the relevant vehicle fuel economy comes from the EPA's City and Highway test procedures (referred to as the 'two-cycle" tests), not the measures used for vehicle labels.

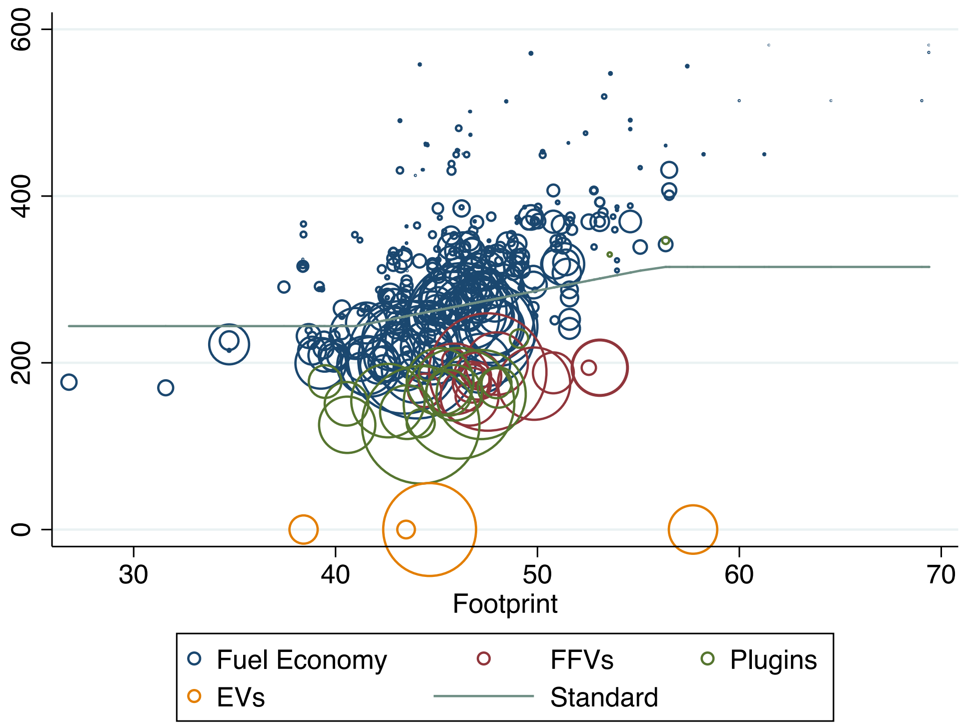
5 Results

5.1 Comparing Actual Emissions to Targets

We first calculate how actual emissions for each vehicle model compares to its footprint-based target. Our data describe all vehicles from the 2012 model year. These data provide each vehicle's footprint as well as whether it is a truck or a car, and we can calculate its emissions target using the official formula from Administration (2010), Table III.B.2.

Figure 2 shows how each car from vehicle model year 2012 compares to its emissions target. Observations are scaled by each vehicle model's total sales in 2012. The x-axis is each vehicle's footprint, measured in square feet. The green solid line indicates the emissions target in grams of carbon dioxide per mile. Most cars are within the upward sloping part of the emissions target function though there are a sizable number of cars below 41 square feet in the flat portion of the function. Actual emissions vary significantly from the targets. This is particularly above the line with a non-negligible fraction of vehicles which emit more than twice as much carbon dioxide per mile as is targeted.

Figure 2: Each Vehicle Model Relative to Target, Cars

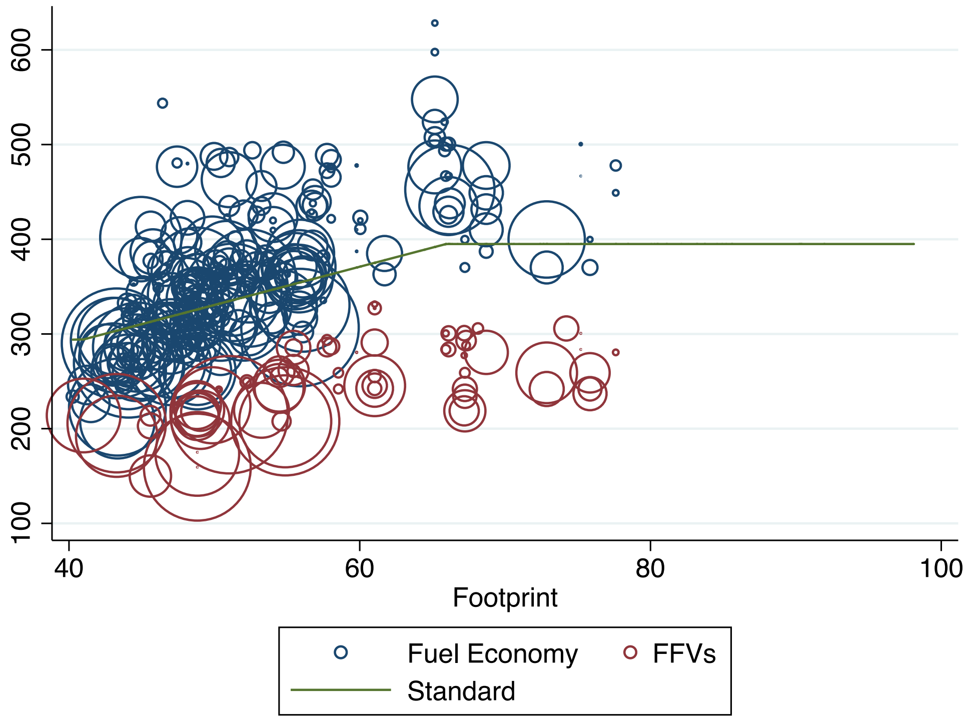


Note: Figure based on fuel economy from the EPA's City and Highway test for the 2012 model year and NHSTA standards. Fuel economy for plug-in hybrids assumes a 50-50 gasoline and electricity split and flex-fuels assumes a 50-50 gasoline and E85 split. Circle sizes correspond to national sales for each vehicle model.

Clearly, alternative fuel vehicles play a substantial role. The figure uses colors to indicate different types of alternative fuel vehicles. As of 2012, there were only two electric vehicles and three plug-in hybrids widely sold in the United States. What is striking, however, about Figure 2 is the large number of flex-fuel cars. This includes several high selling vehicle models including the Ford Focus FFV (subsidy of $1,000), Chrysler 300 FFV ($865), and Dodge Charger FFV ($865). We calculated emissions for these vehicles using CAFE's optimistic assumptions so these vehicles show up as some of the most low-carbon vehicles in circulation.

Figure 3 is the analogous figure for trucks for model year 2012. Most vehicles are within the upward-sloping part of the emissions target function, and again, there is a great deal of

Figure 3: Each Vehicle Model Relative to Target, Trucks



Note: Figure based on fuel economy from the EPA's City and Highway test for the 2012 model year and NHSTA standards. Fuel economy for plug-in hybrids assumes a 50-50 gasoline and electricity split and flex-fuels assumes a 50-50 gasoline and E85 split. Circle sizes correspond to national sales for each vehicle model.

variation in emissions for any given footprint. There were no mass-marketed electric or plug-in hybrid trucks. What is again striking, however, is the large number of flex-fuel vehicles. Flex-fuel vehicles are particularly common among trucks with very large footprints; virtually every truck above the 66 square foot kink is flex-fuel. Many of these flex-fuel trucks sell in high volumes. The three best selling flex-fuel trucks in 2012 were the Ford F150 (subsidized by as much as $1592), Chevy Silverado ($1438), and Mercury Mariner ($1314).

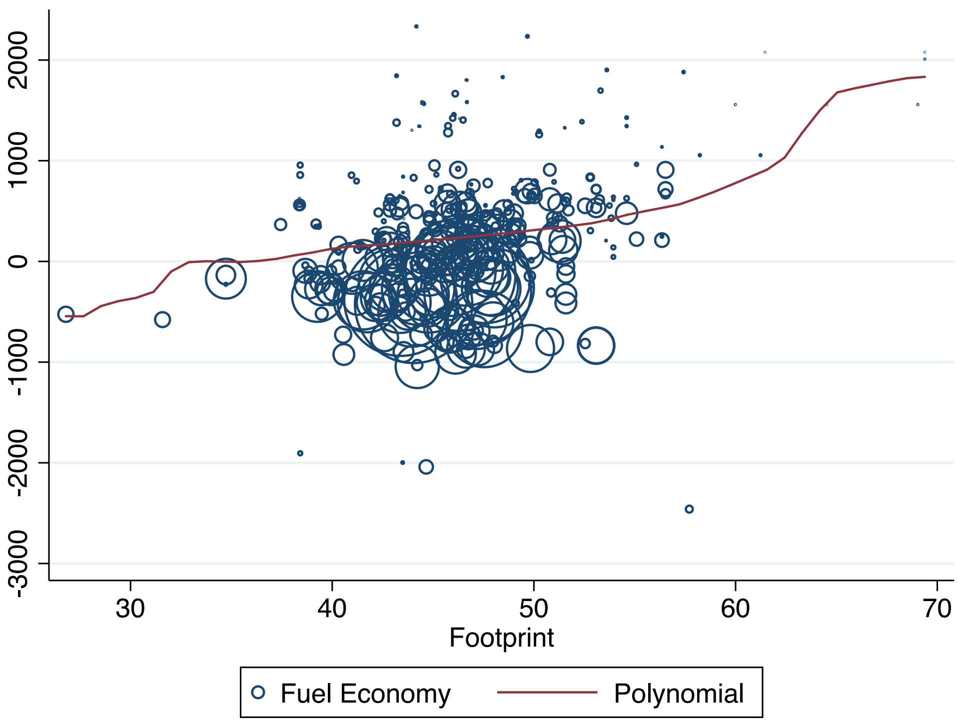
5.2 Implicit Taxes and Subsidies

Moreover, when these obligations are tradable as they are under new CAFE rules, the permit prices make it possible to quantify the exact magnitude of these implicit subsidies and taxes. Following from the first-order condition in Equation (4), we calculate the implicit tax or subsidy imposed by the CAFE constraint as

$$t_j = \lambda \left[(emissions_j - target_j) * VMT_j \right] \tag{6}$$

where t_j is the tax or subsidy borne by vehicle j. We equate the λ with the permit price and adopt the expected lifetime mileage, VMT_j, used by the EPA for trucks and cars, 225,865 miles and 195,264 miles, respectively.

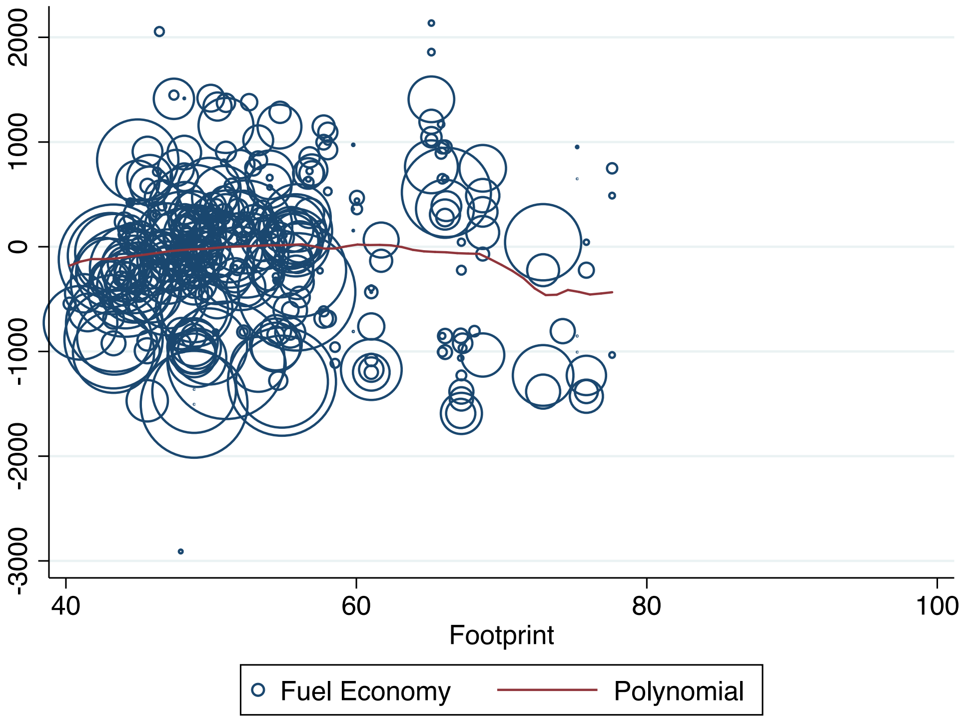
Figure 4: Implicit Taxes and Subsidies, Cars



Note: Implicit tax and subsidy calculations are based off of fuel economy data from the EPA's City and Highway test for the 2012 model year, 2012 trading permit price and vehicle expected lifetime mileage. Implicit taxes and subsidies are measured in 2012 dollars. Circle sizes are proportional to national sales.

Figure 4 shows the dollar amount of implied tax (subsidy) per car. The x-axis is each vehicle's footprint, measured in square feet. The red line is a non-parametric estimation of the relationship between a vehicle's footprint and its implied tax using a local polynomial kernel-weighted regression. In general, cars with small footprints are more likely to be subsidized, while those with large footprints are likely to be taxed. For cars with footprints between 40 and 60, the polynomial line is near flat around zero with a slight upwards trend for cars, although the majority of cars lie under the polynomial line and are subsidized for being in compliance. The mean tax/subsidy for cars is -\$78 (a subsidy) across all model years and -\$217 for model year 2012 cars. This suggests over-compliance in model year 2012 which is consistent with anecdotal evidence that manufacturers are building up credits in expectation that the constraint will become more binding in the future.

Figure 5: Implicit Taxes and Subsidies, Trucks



Note: Implicit tax and subsidy calculations are based off of fuel economy data from the EPA's City and Highway test for the 2012 model year, 2012 trading permit price and vehicle expected lifetime mileage. Implicit taxes and subsidies are measured in 2012 dollars. Circle sizes are proportional to national sales.

Cars with higher national sales are also more likely to be subsidized. Circle sizes in the figure reflect total vehicle registrations and the largest circles are slightly subsidized and between the 40 and 50 square foot footprint. Sales for cars with a tax greater than a $1000 are low, as denoted by the small circle sizes. The top three selling cars in 2012 have relatively high rates of subsidy; the Toyota Camry 2.5 liter version is subsidized at $260, Honda Civic1.8 liter is subsidized at $395 and the Nissan Altima 2.5 liter is subsidized at $161.

Figure 5 is the corresponding plot for trucks. Unlike cars, trucks at lower footprint sizes are not more likely to be subsidized, while trucks at higher footprint sizes are only slightly more likely to be taxed. The roughly flat polynomial approximation throughout the vehicle footprint reflects this more even distribution between subsidized and taxed trucks. The mean tax/subsidy for trucks is -$43 (a subsidy) across all model years and -$299 for model year 2012 trucks. As with cars, larger circles correspond to higher grossing vehicle models and tend to lie around or under zero. The top three selling trucks are the Honda CR-V AWD is subsidized at $380, Chevy Silverado is subsidized at $1312, while the Dodge Grand Caravan subsidized at $1314.

5.3 Distributional Impacts

Table 2 displays the mean distributional impact of CAFE standards on each income decile. Welfare impacts are measured as the equivalent variation (EV) of the policy in dollars in the first column, as well as the EV as percentage of income in the second and third columns. The second column reflects EV as a share of income for auto-owners only, while column (3) captures distributional impacts across all individuals within a decile group. Negative values correspond to subsidies and reflect gains to income, while positive values correspond to taxes and reflect deductions.

Table 2: Mean Welfare Impacts from CAFE Standards in 2012 by Decile

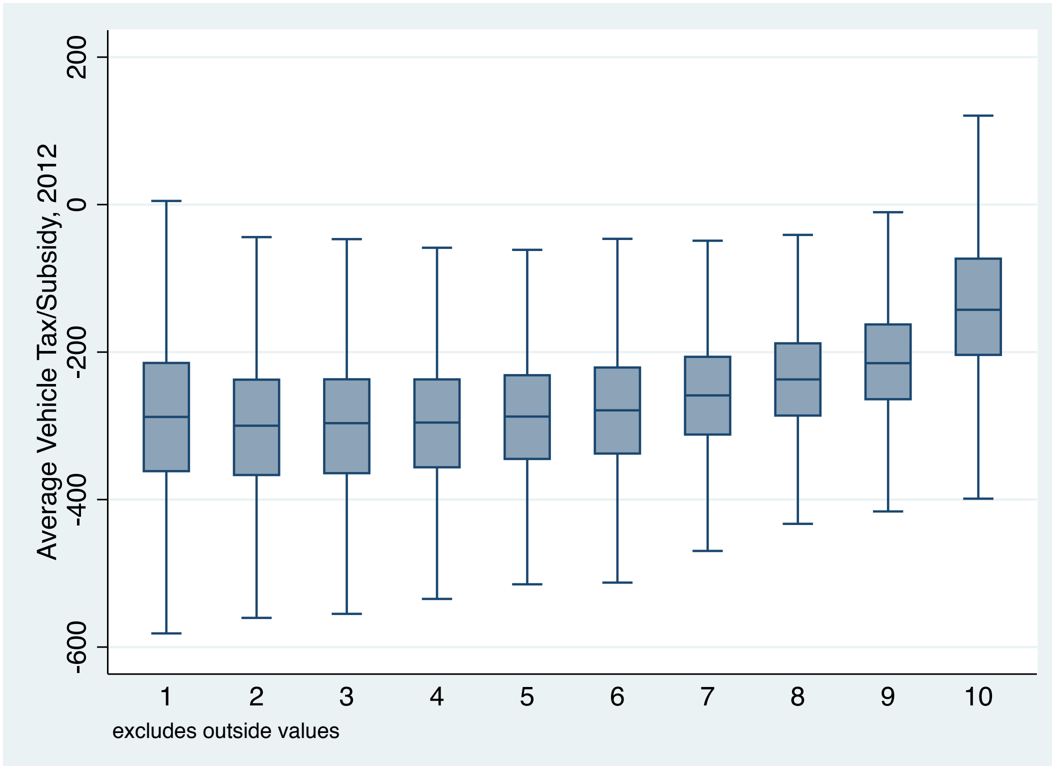
Decile	EV ($) (1)	Share of income (%) (2)	Per capita share of income (%) (3)
1	−289.06	−1.087	−0.469
2	−303.13	−0.817	−0.326
3	−303.53	−0.703	−0.228
4	−298.61	−0.614	−0.319
5	−290.49	−0.537	−0.190
6	−280.07	−0.465	−0.304
7	−258.35	−0.382	−0.150
8	−235.62	−0.304	−0.143
9	−211.22	−0.231	−0.162
10	−133.44	−0.114	−0.053

Note: Distributional welfare impacts expressed in 2012 dollars. Share of income corresponds to expected variation from CAFE standards as a fraction of median income for vehicle owners within a tract, while per capita share reflects expected variation as a fraction of median income for all individuals within a tract. Negative values reflect gains to income.

All income groups see a welfare improvement under CAFE standards with low-income households experiencing the greatest gains and high-income households experiencing the smallest. The range of mean subsidy levels are limited, and households in the highest income decile receive a subsidy roughly 54% smaller than those in the lowest income decile. Except for a difference between the first and second decile, the direction of changes in subsidy level align. Overall, mean subsidy levels are proportional throughout the lower half of income groups and become more progressive in the upper half.

Figure 6 shows the boxplot of the average tax per vehicle. The marked 37% decrease between the ninth and tenth income groups also suggests sharper contrasts in automobile markets between the top ten percent and the remainder of households and may be a result of low-mpg, luxury vehicle purchases being clustered within this top decile. The inner-quartile range

Figure 6: Average Tax Per Vehicle, by Income Decile



(IQR) for each income decile group is wide, with the IQR for the tenth decile spanning XXX and YYY. The "whiskers" of the plot, outlier values within 1.5 times the IQR of the nearest quartile, emphasize that income decile groups experience a much larger range of taxes and subsidies than those suggested by their group averages. The boxplots suggest that there may be significant variation within income decile groups that are obscured by focusing on the means. Notably, lower income groups experience a wide range of subsidies and some tracts in the highest income group are actually worse off under the CAFE standards.

Figures 7 and 8 show the boxplots for the average tax per vehicle as a share of median tract income under two scenarios; Figure 7 considers tax burdens for vehicle owners only, while Figure 8 considers the per-capita share. In both figures, CAFE standards are moderately progressive, although the per-capita scenario is slightly less progressive than the per-capita outcome. In comparison to the tax levels in Figure 6, the IQRs are narrower. The spread of the share value is decreasing in decile since the median income in each decile increases significantly more than the mean value of the tax; in higher income groups, the range of the tax or subsidy is less significant. This variation is especially evident in the lowest income-decile group, where the complete spread of the welfare impact ranges from a subsidy of around -6% to a tax of nearly 2% of income. Meanwhile, the spread of the highest income-decile

Figure 7: Average Tax Per Vehicle as Share of Median Income, by Income Decile

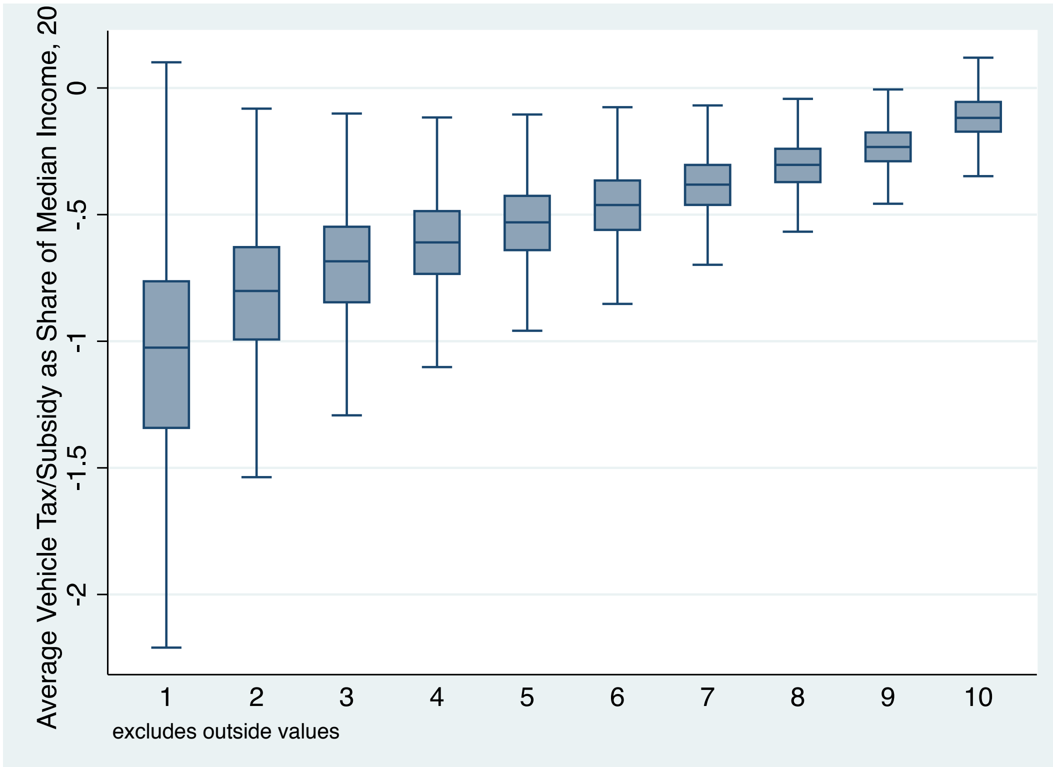
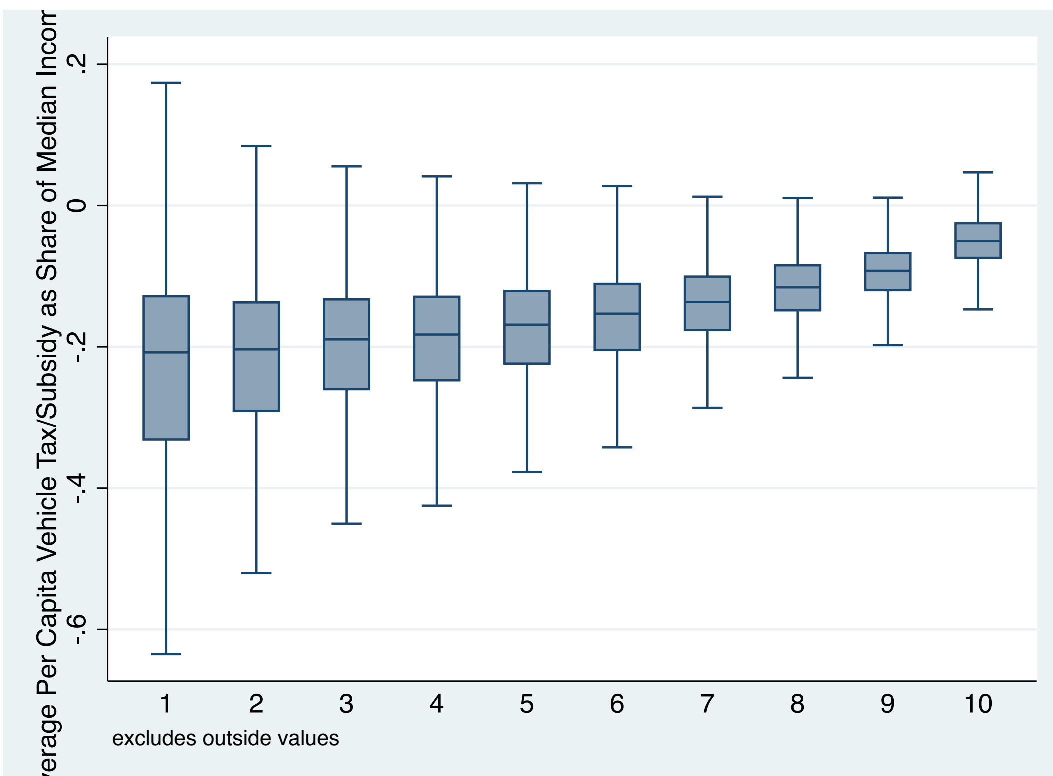


Figure 8: Average Per-Capita Tax Per Vehicle as Share of Median Income, by Income Decile



group is between -0.18% and 0.5% of total income. The boxplots show that CAFE standards are progressive, however they emphasize that there is large variation in distributional impacts in lower-income deciles.

5.4 Comparison to Gasoline Tax

We can now compare the distributional impacts of CAFE with previous estimates in the literature on the distributional impacts of a gasoline or carbon tax.

Previous studies have examined the distributional effects of gasoline taxes (Poterba, 1989, 1991; West, 2004; Bento et al., 2009) and carbon taxes (*e.g.* Hassett et al., 2009; Burtraw et al., 2009; Williams et al., 2015), but CAFE standards have received far less attention.

Not surprisingly, a common message in these papers is that the distributional effects of gasoline and carbon taxes largely depend on how additional revenue from the tax is recycled. For example, gasoline taxes are significantly less regressive when revenues are used to cut labor tax rates than when revenue is discarded (West and Williams, 2004; Williams et al., 2015). Bento et al. (2009) show that if returned lump sum-on a per-capita basis, a gasoline tax could make the bottom four income deciles better off on average, even without incorporating external benefits. Burtraw et al. (2009) analyze five different uses for revenues raised from cap and trade auction, including lowering income and payroll taxes, and finds significant differences in progressivity. Similarly, (Rausch et al., 2010) simulate the distributional effects of carbon taxes under two redistribution bundles with varying amounts of revenue set aside for deficit reductions or cuts for other taxes. They find all scenarios to be progressive in lower income deciles and proportional in upper deciles, however the degrees of incidence exhibit significant differences over time. Meanwhile, Metcalf (2009) proposes a distributional-neutral carbon tax by offsetting price increase with capped income tax credit.

Several studies have shown that the regressive implications of carbon taxes can be overstated by overlooking index government transfer programs (Fullerton et al., 2012; Rausch et al., 2010; Dinan, 2012). Several government transfer programs, including Supplemental Security Income, are indexed to consumer price measures and thus increase alongside the price of carbon. For example, accounting for transfer program indexing, Rausch et al. (2010) use a computable general equilibrium model of the U.S. to show carbon taxes are moderately progressive, even ignoring distribution of after-tax revenue. They find that the lowest two income quintiles are made better off under a carbon tax. In addition, Fullerton et al. (2012) show that under partial indexing of transfer funds, a carbon tax is progressive for households in the bottom half of the expenditure distribution.

Rausch et al. (2010) also point out that higher prices caused by carbon taxes have effects on income. Using a CGE model, they show that a portion of the carbon price is shifted back to the owners of natural resources and capital, which lessens the regressivity of a carbon tax policy.

A thorough review of each of these studies focusing on the methods and underlying assumptions is beyond the scope of this paper. However, we attempt to summarize the literature by regressing each paper's incidence measure on the income decile number, where 1 is the lowest decile and 10 is the highest. A progressive policy would imply a positive slope in this regression. Furthermore the coefficient provides a rough idea of the average change in incidence when moving one decile.

Table 3 summarizes this exercise. Our results are listed in the first row. Each study is listed in the first column and studies are separated into three panels based on the type of recycling: no recycling, lump-sum transfers and tax cuts. Further information on the recycling treatment is listed in the Notes column. For example, under the lump-sum transfers panel, the notes indicate whether lump-sum transfer was uniform or proportional to household income. Similarly, within the tax cuts panel, the notes list whether income, labor or payroll taxes were lowered using tax revenue. We also track which studies use transfer indexing. The fourth and final column codes each carbon tax treatment as regressive (R), progressive (P), or a combination of the two if the direction of incidence switches. In the case of the latter, the parentheses by each letter contain which income groups are progressive and which are regressive.

We measure the relative progressivity or regressivity of the tax by the slope of the mean welfare impacts across household income group. We report slopes for welfare impacts measured as a per-capita share of income, as well as the level of incidence when available. The slope captures the direction of the incidence —negative slopes correspond to regressive taxes and positive slopes to progressive taxes —as well as the magnitude. We calculate the slope by running a linear regression of the welfare measure on decile, except Bento et al. (2009) which is measured in quartiles and (West and Williams, 2004) and (Williams et al., 2015) which are measured in quintiles. The significance level of each coefficient is also listed to determine whether the direction of incidence is statistically significant. Because slopes are calculated using a linear model, lower significance does not necessarily imply a lack of causation between decile and welfare burdens. If the direction of incidence changes for higher (or lower) deciles, a linear fit may be a weaker fit for a significant, yet polynomial, relationship.

We find this to be the case; apart from estimates from Bento et al. (2009), all statistically insignificant coefficients belong to tax burdens which shift directions. Despite strong trends of progressivity reported within the paper, share coefficients from Bento et al. (2009) are likely to be insignificant due to the fact that we have only four data points.

Comparing our results in the first row to the remainder of the tax incidence slopes, CAFE standards are more moderate than carbon tax estimates and CAFE is more regressive than carbon taxes with uniform recycling. CAFE is more progressive than carbon taxes that either do not recycle the revenue or use the revenue to reduced progressive taxes, such as labor and payroll taxes.

More specifically, regressive slope estimates range from -0.214 to -0.444 and progressive estimates are between 0.163 and 0.662. While recycling method remains a significant factor in determining whether a tax is progressive or regressive, the magnitude of the slope remains in a similar range regardless of recycling. Our slope of 0.015 falls more in line with reported results for mixed-direction slopes which range from -0.288 to 0.040, although our result is progressive throughout. These results suggest that welfare impacts from CAFE standards are more proportional than carbon taxes.

6 Conclusion

Economists have long complained that fuel economy standards are an inefficient way to reduce gasoline consumption. In a survey of top economists, 90% answered that they would prefer a gasoline tax over fuel economy standards (IGM, 2016).[6]

CAFE continues to suffer from a couple of more fundamental problems which greatly reduce its effectiveness. These problems existed under the old CAFE standards and they continue to exist under the new CAFE rules. These are problems inherent in any policy aimed at trying to reduce GHGs through fuel economy standards for new vehicles. When comparing the progressiveness of CAFE to carbon taxes that recycle the revenue in a uniform way, we find that there is not a trade-off between regressivity and efficiency.

[6] There is a strikingly high degree of agreement among economists on this question. In this survey 51% and 39% of economists answered that they "strongly agreed" and "agreed", respectively, that a carbon tax would be a less expensive way to reduce carbon-dioxide emissions than would fuel economy standards. Only 2% of economists "disagreed" with the remaining 5% "uncertain". This is a remarkably high level of agreement compared to other questions in the same survey (Sapienza and Zingales, 2013).

Table 3: Slope of Welfare Effects from Carbon and Gas Tax Literature

Paper	Notes	Slope, Share	Slope, Level	R/P
Lucas and Knittel (2016)		0.015**	6.772***	P
	Recycling method: No recycling			
Burtraw et al (2009)	None	−0.299***		R
Fullerton et al (2011)	Partial transfer indexing	−0.217***		R
	Full transfer indexing	−0.214***		R
Hassett et al (2009)	None	−0.296***		R
West (2004)	None	−0.022		P(1:6), R(6:10)
West and Williams (2004)	None	−0.288		P(1:2), R(2:5)
	Recycling method: Lump-sum transfers			
Bento et al (2009)	Uniform	0.208	96.933**	P
	Proportional to income	−0.042	−16.134	P(1:8), R(8:10)
	Proportional to VMT	0.018	22.582***	P
Burtraw et al (2009)	Uniform	0.164***		P
	Uniform, taxed	0.360***		P
West and Williams (2004)	Uniform	0.662***		P
Williams et al (2015)	Uniform, full transfer indexing	1.233***		P
	Recycling method: Tax cuts			
Burtraw et al (2009)	Labor tax	−0.444***		R
	Payroll tax	−0.379***		R
	Expanded EITC	0.474***		P
West and Williams (2004)	Labor tax	−0.165***		R
Williams et al (2015)	Labor tax, full transfer indexing	0.040		R(1:2), P(2:5)
	Capital tax, full transfer indexing	−0.232***		R

Note: Slope, Share is the slope of mean EV as a share of income across decile and Slope, Level is the slope of mean tax amount across decile. R/P codes if the tax is regressive (R), progressive (P), or a combination of the two. The range is listed in parentheses if the slope is a combination. All slopes calculated using linear regression of welfare measure on income group. Significance: *p<0.1; **p<0.05; ***p<0.01.

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Table 4: Most Taxed and Subsidized Vehicles under CAFE

	Vehicle Model	Car or Truck	Footprint, in square feet	Emissions Per Mile, in grams	Target Emissions Per Mile, in grams	Lifetime Emissions Above (Below) Target, tons	Implied Tax (Subsidy) Per Vehicle, $
				A. Most Taxed Vehicles			
#1	Mercedes Benz G550	Truck	46.5	544	320	50.54	$2,021
#2	GMC Yukon	Truck	61.0	577	379	44.66	$1,787
				A. Most Subsidized Gas/Diesel Vehicles			
#1	Ford F-150 4x2	Truck	67.0	260.6	436.9	(39.8)	($2,451)
#2	Chevy Silverado 2WD	Truck	67.4	239.8	399.1	(36.0)	($2,395)
				A. Most Subsidized Vehicles Overall			
#1	Toyota Rav-4 EV	Car	44.9	0	28.32	(61.3)	($2,451)
#2	Tesla Model S	Car	53.6	0	28.98	(59.9)	($2,395)

Note: This table lists the two most taxed and subsidized gasoline and diesel vehicles under CAFE in 2012, among non-exotic manufacturers. Slight variants of each model are not listed separately. Emissions are carbon dioxide emissions, calculated based on 8.887 kilograms per gallon of gasoline and 10.180 kilograms per gallon of diesel. Lifetime emissions are calculated following EPA program rules which assume cars and trucks travel 150,922 and 172,552 lifetime miles, respectively. Implied taxes are calculated based on a permit price of $40 per ton of carbon dioxide from Leard and McConnell (2015).