Cost-Effective Policies to Reduce Vehicle Emissions

By Don Fullerton and Li Gan*

To compare "cost-effectiveness" of different abatement methods, many studies estimate production or cost functions and plot the marginal cost curve for using each method to achieve more abatement. Normally the cost is additional outlay by the firm (e.g., added equipment, process changes, or fuel switching). Each method may have diminishing returns, however, so the marginal cost of abatement (MCA) may start at different points and rise at different rates.[1] Then efficiency requires the planner to pursue each method to the point where all have the same MCA. Or, as pointed out by Arthur C. Pigou (1920), an emissions tax gives incentive for firms to pursue each method until its MCA equals the tax rate, which achieves the same efficiency.

For vehicle emissions, the list of usual suspects similarly includes the purchase of pollution-control equipment, process changes such as driving at low and uniform speeds, and fuel switching from leaded to unleaded gasoline and to cleaner fuels. Perhaps the MCA curves for those techniques could all be plotted to undertake the same sort of analysis. Yet this analysis for vehicle emissions faces four problems. First, the abatement decisions are made by many different agents: manufacturers can include equipment to achieve required rates for emissions per mile (EPM), but consumers get to choose whether to buy a car or sports utility vehicle (SUV), whether to drive at low or uniform speeds, and how many miles to drive. Second, heterogeneity means that the efficient mix differs across drivers: some can switch from an

SUV to a car, others can buy a new vehicle with low emission rate, others may change driving style, and still others could change driving amounts. The planning solution is not feasible, and so policy must rely on incentives. Third, however, the tax on emissions is not feasible either, since the measurement technology is not yet available.[2] Fourth, while some of the costs of abatement are extra outlays for equipment included by manufacturers, or for the higher cost of cleaner fuel, many costs would instead come in the form of lost consumer surplus from driving fewer miles and from driving in the "wrong" vehicle: a car instead of an SUV, or a newer car instead of an old car.

This paper deals with all four of these issues: we use an estimated demand system that accounts for heterogeneity to calculate the lost consumer surplus from *feasible* policies such as a higher tax on gasoline, a tax on distance, or a subsidy for buying a newer car.[3] To do this, we introduce a somewhat new view of cost-effectiveness, comparing policies instead of technologies. A policy such as the gasoline tax, for example, might induce some consumers to drive less, some to switch from two vehicles to one, some to buy a car instead of an SUV, and some to do "all of the above." Our model captures these behaviors. For each rate of tax, we simulate the changes in all such choices and how the new choices affect emissions. We also calculate the lost consumer surplus, or equivalent variation (EV), and subtract tax revenue to get deadweight loss (DWL). Finally, we take the added DWL over the additional abatement

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[1] For the example of greenhouse gas (GHG) abatement, see figures 20–21 of U.S. EPA (2001 p. 23), where the highest MCA curve is for U.S. CO_2 emission reduction, followed by U.S. other GHG reduction, U.S. sequestration, and then other countries' CO_2, other GHG, and sequestration.

[2] On-board diagnostic equipment is too costly because millions of vehicles would need to be retrofitted (Winston Harrington et al., 1994). Remote sensing is less expensive and can measure *average* emissions, but it cannot distinguish emissions clearly enough to tax each car separately (Sierra Research, 1994). And any tailpipe device would entirely miss evaporative emissions.

[3] Fullerton and Sarah West (2000) consider combinations of gas taxes and car taxes that maximize welfare when an emissions tax is not available, but they assume substitution elasticities and calibrate other parameters. Here we use estimated parameters.

as the social marginal cost of abatement (MCA), and we plot this curve for several different tax policies.

Current policies state maximum emission rates for new vehicles. These have become more stringent over time, and they are more stringent for cars than for SUVs.[4] We do not simulate changes in these mandates; indeed they are reflected in our data showing how newer cars have lower EPM than older cars or SUVs. Instead, we simulate additional policies that would use incentives to get consumers to buy those newer cars or to reduce their miles.

I. The Model

Each consumer has a discrete choice about the number and types of vehicles and continuous choices about vehicle miles traveled (VMT). To capture all such choices simultaneously, and the way all such choices affect emissions, we use estimated parameters from Ye Feng et al. (2005). In their model, each household first chooses the number of vehicles (0, 1, or 2) and then for each vehicle chooses a car or SUV. The result is six "bundles" (no vehicle, one car, two cars, one SUV, two SUVs, one of each). We have no need to model the choice among hundreds of vehicle types, as in prior studies of manufacturer product differentiation. All cars in a given year are made to meet a single emission rate standard, so the only important choices for emissions are between car and SUV and the age of the vehicle. We model age as a continuous choice and estimate the emission rates for cars of different age. After the discrete choice among bundles, then, a two-vehicle household makes four continuous choices (the age of each vehicle and the miles to drive each vehicle). The marginal price per mile is

$$(1) \qquad p_i = \left[\frac{p_\mathrm{g} + t_\mathrm{g}}{\mathrm{MPG}_i} + t_\mathrm{e} \mathrm{EPM}_i + t_\mathrm{d} \right]$$

where i indexes the vehicle bundle, p_g is the price of gasoline, t_g is the gas tax in dollars per gallon, MPG_i is miles per gallon, and EPM_i is grams of emissions per mile. The imposition of

a distance tax t_d in dollars per mile would add directly to the cost per mile. If an emissions tax *were* feasible, at rate t_e in dollars per gram, then $t_\mathrm{e}\mathrm{EPM}_i$ would be the extra cost per mile.

Estimation requires a price for each good that is independent of the amount chosen, just as the price per mile above is independent of miles chosen. We also have a choice of vehicle age, but the "price" of holding a new car for one year is higher than the price of holding an old car for one year. We therefore make a nonlinear transformation of age to define a quantity with a linear price. If depreciation is exponential at rate δ per year, then $(1 - \delta)^{\mathrm{age}}$ is the fraction left, and we can define $\mathrm{Wear} \equiv 1 - (1 - \delta)^{\mathrm{age}}$ as the fraction depreciated. Consumers holding a new or used car effectively make a continuous choice about the amount of Wear, and they receive a constant "reimbursement price" q_i per unit Wear accepted. Since this choice is separate from the discrete choice, we define the annualized price of bundle r_i as the cost of a brand new vehicle.

The household's direct utility is a positive function of VMT and another consumption good c_i, and it is a negative function of Wear. Given income y, the budget constraint is

$$(2) \qquad p_i \mathrm{VMT}_i - q_i \mathrm{Wear}_i + c_i = y - r_i$$

where the price of c_i is normalized to 1. The indirect utility for bundle i is a function of household income and prices, denoted as $V(y - r_i, p_i, q_i)$. We use a standard log-linear demand for VMT as a function of prices, income, and observed demographic variables $\mathbf{x}$:

$$(3) \quad \ln(\mathrm{VMT}_i) = \alpha_V^i + \alpha_p^i p_i - \alpha_q q_i$$
$$- \beta y + \beta_1 k_i + \mathbf{x}'\boldsymbol{\gamma} + \eta$$

where the coefficient on the price per mile is bundle-specific, η is an agent-specific error term, and k_i is the capital cost of the bundle (related to annual cost by $\beta_1 k_i = \beta r_i$). Then the implied indirect utility function is

$$(4) \quad V_i = \frac{1}{\beta} \exp(-\alpha_0^i + \beta y - \beta_1 k_i - \mathbf{x}'\boldsymbol{\gamma} - \eta)$$
$$- \frac{1}{\alpha_p^i} \exp(\alpha_p^i p_i - \alpha_q q_i) + \varepsilon_i.$$

[4] For an overview of vehicle pollution policy, see Harrington and Virginia McConnell (2003).

Using Roy's Identity, this form for indirect utility further implies that the demand for Wear is:

$$(5) \quad \ln(\text{Wear}_i) = \alpha^i_W + \ln(\alpha_q/\alpha^i_p) + \alpha^i_p p_i - \alpha_q q_i$$

$$- \beta y + \beta_1 k_i + \mathbf{x}' \boldsymbol{\gamma} + \eta.$$

Finally, for two-vehicle households, direct utility is $U(\text{VMT}_{i1}, \text{VMT}_{i2}, \text{Wear}_{i1}, \text{Wear}_{i2}, c_i)$. The budget constraint contains all those quantities (with prices p_{i1}, p_{i2}, q_{i1}, and q_{i2}). Indirect utility and all four continuous demands have more terms but are analogous to equations (3)–(5).

Following McFadden's random utility hypothesis, vehicle bundle i is chosen if and only if $V_i \geq V_j$ for all $j \neq i$. We let the random variable ε_i have a generalized extreme value distribution, so that the discrete-choice part becomes the familiar nested logit model. Prior literature estimates discrete and continuous demands sequentially, using the predicted shares from the discrete part to correct for endogeneity of vehicle choice in VMT demands.[5] As pointed out by Feng et al. (2005), however, the same α and β parameters enter both the indirect utility for estimation of discrete choices and in the continuous demands. In the sequential procedure, estimated parameters of continuous demands are not constrained to match the same parameters in the estimated discrete-choice model. Often they are quite different.

Feng et al. (2005) introduce a procedure to estimate both parts simultaneously, and they obtain a single set of α and β parameters. They also use the estimated parameters to calculate various elasticities, for interpretation, but they do not undertake any simulations or welfare analysis. Here, we use the estimated parameters from Feng et al. in the indirect utility function to measure the dollar value of utility changes from simulated changes in tax rates.

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[5] Jeffrey A. Dubin and Daniel L. McFadden (1984) introduce the sequential procedure for a logit model with two appliances (and continuous usage hours). It is used for vehicle choice and miles by Fred Mannering and Clifford Winston (1985), Kenneth Train (1986), Pinelopi K. Goldberg (1998), and West (2004). W. Michael Hanemann (1984) estimates discrete and continuous choices simultaneously, but without unobserved heterogeneity.

Data from the 1996–2001 Consumer Expenditure Survey (CEX) for 9,027 households include demographic characteristics, total expenditures, gas expenditure, vehicle type, make, and year. Fuel prices for each year and region are taken from the ACCRA cost-of-living indices. Assuming 20-percent depreciation per year, Wear is calculated by the formula above, and current market value of each vehicle (k_i) is calculated from original purchase price and year. Hedonic regressions are used to impute missing values, and to calculate q_i (the price of Wear). Data from the California Air Resources Board (CARB) on 672 vehicles of various types and ages are used to estimate MPG_i and EPM_i as functions of vehicle type, age, and number of cylinders. Estimated parameters are used to impute MPG_i and EPM_i for each vehicle in the CEX. Then for each vehicle, VMT is calculated by MPG times gallons (gas expenditure over price p_g).

II. Results

The estimates for price and income coefficients in Feng et al. (2005) all have the expected signs, though they differ in magnitude and significance. Because the coefficients themselves are difficult to interpret, we turn to elasticities. A 1-percent increase in the price per mile affects all discrete vehicle shares, but the largest shifts are 0.8 percent less for the car-and-SUV bundle and 0.7 percent more for the two-car bundle. For any given bundle, this 1-percent higher price per mile also reduces miles, but to small extents ranging only from 0.02 percent to 0.07 percent. A 1-percent higher reimbursement price for Wear changes bundle shares slightly; given a bundle, desired Wear and VMT each rise by 0.12–0.14 percent. Higher income raises the fraction of households with both a car and an SUV. Some capital cost elasticities seem too large. For example, a 1-percent increase in the cost of an SUV leads to a 7-percent reduction in the one-SUV share and 14-percent reduction in the car-and-SUV share (which means that this share falls from 14.5 percent to 12.5 percent of all households).

Here, we calculate implications for emissions. For simplicity, calculations are based on the average household with average income and demographic characteristics, but this consumer holds the predicted shares of all six bundles. We

first calculate total emissions in the baseline as the sum over all vehicles of EPM $\times$ VMT. We then calculate the changes in behavior from successive increases the gas tax t_g, from the introduction of a distance tax t_d, or from an emissions tax t_e. This last tax is not realistic, but it is useful for comparison. Equation (1) shows how those taxes affect the price per mile. We also simulate a Wear tax t_q (which might shift consumers into new vehicles with low EPM). We calculate the dollar value of changes in utility.

To understand these results, first note that the calculated EPM is 1.89 grams/mile for the average car and 3.56 for the average SUV. It also increases to 6.94 grams/mile for a very old vehicle (with Wear = 1). Thus, any shift from SUV to car or to a newer car will affect emissions, even with no change in miles. Second, note that the estimated elasticities for discrete choices are larger than for continuous choices. A higher gas tax raises the price per mile more in an SUV than in a car (because a car has higher MPG). It has small effect on miles but induces many consumers to switch from an SUV to a car (with lower EPM). Thus we expect that a gas tax can reduce emissions by more than a tax purely on distance.

For any tax, deadweight loss (DWL) generally starts at zero and rises with the square of the tax rate. The marginal cost of abatement (MCA) is defined as the change in DWL over the change in emissions, so one might expect the MCA to start at zero and to rise at an increasing rate. Figure 1 shows the MCA curve for each tax, and all curves are increasing as expected.[6] Perhaps surprisingly, the MCA curves do not start near zero. The explanation is that the baseline in our model starts with a gasoline tax of $0.374/gallon, so consumers already have DWL from reduced VMT and altered vehicle choices. Any additional tax that further changes those choices starts with positive costs. In Figure
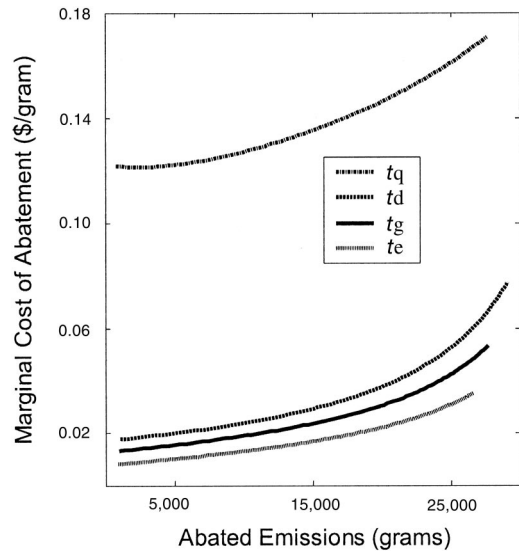

FIGURE 1. THE MARGINAL COST OF ABATEMENT (MCA) FOR EACH POLICY

1, the marginal cost of raising the existing gas tax is almost $0.02 for the first additional gram of abatement, and it rises as choices become further distorted.

Moreover, the cost of the existing gas tax is the consumer surplus lost from reduced driving, and that cost is exacerbated by *any* tax that further affects distance—such as the tax on distance (t_d) or on emissions (t_e). The MCA is lowest for the tax on emissions, as predicted by theory. Compared to the distance tax, the gas tax has lower MCA because it raises the price per mile more for any vehicle with low MPG (shifting consumers out of SUVs with high EPM).

Older cars have higher emissions rates, and the tax on Wear (t_q) discourages holding older cars.[7] Also, Feng et al. (2005) estimate that the elasticity of VMT with respect to the reimbursement price is 0.12–0.14, so the lower reimbursement price means driving fewer miles. Both those changes should reduce emissions. This tax has the highest MCA in Figure 1, however, so it is not very effective in reducing emissions. Overall, if a tax on emissions is not

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[6] Observed emissions are 52,228 grams per household per year, using weights from Fullerton and West (2000) to average over hydrocarbons, NO_x, and carbon monoxide. To get comparable abatement, one curve increases t_e from zero to $25 per 1,000 grams (collecting $483 per household per year); one increases t_g from $0.374 to $1.50 per gallon ($725); another raises t_d from zero to $0.10 per mile ($970); and one raises t_q from zero to $5,000 per unit of Wear ($2,565).

[7] It is equivalent to a subsidy for newer vehicles in our model, because it changes relative prices.

feasible, Figure 1 indicates that the gas tax is more cost-effective than these other taxes.

Figure 1 does not compare these taxes to other policies, however. Further research would be necessary to calculate costs of other taxes or even of further mandates like those already in place. For example, future requirements reduce emission rates for SUVs. Given the currently higher SUV emission rates, this model could be used to simulate the effects of an annual tax just on older sports utility vehicles (or subsidy for their retirement). More generally, a tax could be collected annually on any vehicle at a rate that is proportional to its emission rate. Finally, if the ideal emissions tax is not feasible, a cost-effective policy might combine this vehicle-EPM tax to change discrete choices of vehicles and a gas tax to change continuous choice of miles driven.

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