Fleet Turnover and Old Car Scrap Policies

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Abstract

This paper incorporates owners' decisions to keep, repair or scrap their old vehicles into a simulation model of fleet emissions. This decision depends critically on the owner's perceived value of the vehicle, so we examine the factors affecting owners' valuations of their old vehicles using a unique longitudinal dataset. Willingness to accept for the vehicle is well predicted by mileage and condition of the car, and declines systematically with its age. Our estimated model of vehicle value is used as an input into a simulation model of a 1,000-car fleet representative of California's fleet. Other inputs into the simulation models are the estimated distributions of emissions in the fleet, and two equations that link emissions reductions to the cost of repairs. The simulation model is used to examine the role of scrap policies alone and combined with other policies for reducing emissions, such as current I/M programs and proposed emissions fees, and the welfare implications of combining such programs. The model incorporates both technical and behavioral relationships, and assumes that of all possible options (repairing the car, scrapping the vehicle, or paying the emissions fee without repairing the vehicle) the owner chooses the one with the least cost. We find that old car scrap programs may increase net welfare under a regulatory program like I/M in practice today, but that a stand alone scrap program is unlikely to provide very much in the way of emission reductions.

Key Words: mobile source, inspection and maintenance, I/M, scrappage, emission fees

JEL Classification No.: Q25

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Anna Alberini, Winston Harrington,
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1. INTRODUCTION

Despite dramatic reductions in "new car" emissions standards over the past 20 years, vehicle emissions continue to be a major source of urban air pollution in the U.S. The reasons for this are complex and numerous, but two important factors are the deterioration in performance of emissions control equipment as vehicles age, and the number of older cars with less effective pollution controls which are still on the road. Because new cars are cleaner than older cars, sometimes dramatically so,[2] policies that encourage turnover of the fleet or early scrappage of older vehicles have at least the promise of significant emission reductions.

Not only have newer model year vehicles become less polluting since the early 1970s, there is new evidence that stricter warranty regulations on the post 1991 vehicles have resulted in vehicles whose emissions equipment is less likely to deteriorate over time than before. This is likely to shift the policy focus even more in the direction of reducing old car emissions and increasing the pace of fleet turnover.

Among the most politically attractive of policies that encourage fleet turnover are old vehicle scrappage programs. These programs pay a bounty (usually $500 to $1,000) to owners of older vehicles who turn their vehicles in to be scrapped, thus removing the vehicle's emissions from the road over what would have been its remaining life time.[3] These programs are voluntary and appear to politicians and the public to be low-cost, especially when public tax monies are not used to finance them. Most scrap programs so far have in fact been privately financed, usually by companies seeking emissions offsets or relief from other regulations. All have been of short duration, primarily designed to demonstrate the feasibility

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[2] For example, we found in an earlier study (Alberini, Edelstein, Harrington and McConnell, 1994) that some pre-1980 model year vehicles had emissions of hydrocarbons (HC) as high as 25 grams per mile, while a new 1992 model year car on the road at the same time would have HC emissions less than .4 grams per mile.

[3] Alberini, Harrington and McConnell (1996) show that the extent of the emissions reductions depends crucially on how much longer those old vehicles would have been kept in use in the absence of the scrappage program, on the miles driven every year, and on the age of the replacement vehicle.

of the idea.[4] In 1994, however, California included as part of its State Implementation Plan (SIP) a provision to allow for the scrappage of 75,000 older vehicles per year for ten years, using as a scrappage inducement a bounty of up to $1,000 per vehicle. However, the State has yet to come up with the funding to implement the program.

Accelerated scrappage programs suffer from some severe limitations. While several studies have shown them to be at least moderately cost-effective, their emissions reduction potential is small unless the scrap bounty is very large, which substantially reduces their cost effectiveness (Alberini, Harrington and McConnell, 1996; Hahn, 1995). A large-scale scrappage program might also have large price effects in used car markets, raising the cost of purchasing older vehicles and thus reducing the cost-effectiveness of the program. In addition, some observers are skeptical of the perverse incentives that might accompany a long-term scrappage program (Alberini et al., 1994; Hahn, 1995).

The main policy currently in place directed at in-use vehicle emissions is a fully regulatory approach, inspection and maintenance (I/M) in which a vehicle's emission control equipment is tested and, if necessary, repaired. I/M policies have at least the potential for very large emission reductions, but these programs have been hampered by hostility from some motorists. First implemented in the early 1980s, I/M programs produced at best modest results, and in 1990 Congress directed the EPA to develop regulations for an "Enhanced" I/M program that would correct the presumed deficiencies of the existing state programs. An effective I/M program, in addition to repairing emissions equipment on some cars, would encourage retirement of others which might be too expensive or difficult to fix. The Enhanced I/M regulations, however, have proved to be extremely controversial, with a great deal of public opposition in some areas of the country.

Given the shortcomings of "pure" scrappage programs on the one hand and "pure" I/M on the other, some observers have suggested combining the two. A motorist facing a $450 repair bill to get an inspection certificate for his 1974 Dodge Dart is not likely to be a supporter of I/M. A scrap bounty of $500 might mollify him. However, little is known about the properties of such hybrid programs. In fact, there is not much empirical data on motorist scrap decisions in the first place, let alone how those decisions might operate in an environment containing both I/M and scrappage inducements.

In this paper we model the decision to scrap a car at the household level and estimate its determinants using longitudinal data on the actual decisions of owners of older vehicles. We use the empirical results to incorporate the scrappage decision into a model of fleet emissions and examine the emissions reductions and welfare implications of various policies directed at mobile source emissions reductions. These policies include pure scrappage,

[4] See Alberini et al. (1994) for a survey of accelerated vehicle retirement programs conducted in various parts of the country, and Lodder and Livo (1994) for a report on the design and attainments of the program sponsored by Total Petroleum in the Denver metro area. The first scrappage demonstration project in the U.S. was conducted by UNOCAL in 1990. For further information about the UNOCAL program see Dickson (1991) and Tatsutani (1991). A description of a scrappage program in Illinois can be found in Illinois Environmental Protection Agency (1993).

scrappage combined with I/M and scrappage combined with vehicle emissions fees. Emissions fees are an alternate policy that require motorists to pay fees based on their vehicle's emissions reading. Our results suggest that emissions fees are a possible cost-effective alternative to either scrappage programs or existing I/M, and ways to implement them should be explored.

Our work differs from Hahn's (1995) analysis of old car scrap programs in that we introduce emissions fees and we incorporate behavioral components that allow vehicle owners to predict emissions reductions and compare the costs of alternative ways of reducing emissions. Furthermore, we exploit the *distributions* of emissions, vehicle value, repairs and post-repairs emissions estimated from empirical studies, rather than relying on emissions inventory models, on average blue book values, and on EPA's assumptions about the average cost of repairs as does Hahn's (1995).

This paper is organized as follows. We first derive a theoretical model of vehicle ownership and scrappage in section 2. In section 3, we describe a simulation model of fleet emissions that incorporates the decision rules of the theoretical ownership model. Section 4 describes the empirical model of vehicle value using survey data from the Delaware Vehicle Retirement Program which will be used in the simulation. We show the results of the simulations for the different policies in section 5. Section 6 concludes.

2. A MODEL OF THE DECISION TO SCRAP A VEHICLE

Despite the importance of fleet turnover for policies to reduce vehicle emissions, surprisingly little is known about the behavior that underlies car ownership decisions, particularly the decision to scrap. There is little evidence about which cars are scrapped and why, or about the distribution of vehicle prices or values as cars age. Statistics are available only for *average* vehicle values and *average* vehicle scrap rates by vehicle model year (US Department of Energy (1995) or AAMA (1995)), and most existing models of fleet emissions make simple assumptions about the impact of policies or changes in prices on the number of vehicles scrapped and their underlying characteristics, such as their expected remaining life.[5]

However, to evaluate the costs or welfare implications of policies that encourage fleet turnover, it is important to know how vehicles differ even within a model year. Cars that are scrapped early are likely to be those whose value to their owners is the lowest, because, for example, they are in poor condition. If these cars also have high emissions, removing them

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[5] The most notable model is EPA's MOBILE emission factor model. The current version of the model assumes the distribution of age in the fleet stays constant over time, meaning that scrappage rates are constant. With the increased interest in old car scrap programs in the early 1990s, EPA designed regulations which allow states or others who initiate scrap programs to get "credits" or emissions reductions on the basis of a three year average remaining life for the scrapped vehicles (EPA, 1993). A model developed by EEA (1994) to be used with EPA's MOBILE model does allow the user to change scrappage rates as a result of an I/M or old car buy-back policy. In the EEA model, all vehicles within any given vintage are assumed to be identical, i.e., they have the same value, same remaining emissions, etc., so the impact of scrappage programs on emissions will change depending on which model years are scrapped.

from the road may be cost-effective. Hence, for evaluating scrap policies it is important to know the characteristics of vehicles most likely to be scrapped.

We model the decision to scrap a vehicle drawing from our earlier work (Alberini, Harrington and McConnell, 1995) and from models of rational scrappage by Parks (1977), Manski and Goldin (1983) and Gruenspecht (1982) adapted to a dynamic optimization framework (Kohlas, 1977). We assume that once a year the owner of a used vehicle must decide whether to keep the vehicle or get rid of it. In making this decision the owner compares the net present value (NPV) p_t of owning the vehicle with the NPV A_t of the best alternative (which could be either the ownership of no vehicle or acquiring ownership of any other vehicle). Let $J_t = \max\{A_t, \mathrm{p}_t\}$, the NPV of the optimum decision in year t.

We can break the NPV of keeping the vehicle into two parts: the net value of vehicle services during the coming year plus the expected discounted present value of the optimum decision in the next year t+1:

$$\mathrm{p}_t = V_t + \mathrm{b}E(J_{t+1}), \qquad (1)$$

where b is the discount factor and E expected value. The net value of vehicle services is the difference between the benefits of using the vehicle for a year and the costs:

$$V_t = B(D_t, Q_t(Q_{t-1}, M_{t-1})) - C(D_t, EM_t), \qquad (2)$$

where D_t is the mileage driven during year t and Q_t a measure of vehicle condition during year t. M_{t-1} and EM_t are, respectively, the amount the individual spent on maintenance in the past year and the amount he expects to spend during the coming year. As shown, vehicle condition depends on both the condition and the maintenance expenditure in the previous period.

The NPV of replacing the vehicle with another vehicle over all possible alternatives, *a*, is:

$$A_t = \max_a \{p_t - (p_t^a + c) + V_t^a + \mathrm{b}E(J_{t+1}^a)\}. \qquad (3)$$

The first term represents the selling price of the current vehicle, and the second term, in parentheses, is the cost of each alternative including the transactions costs, *c*, associated with the purchase of a replacement vehicle. V_t^a is the net value of a year's worth of driving services for vehicle *a*, and the last term in (3) is the net present value of owning vehicle *a* in period t+1.

People decide to trade or scrap their vehicles for many different reasons, but for our analysis here we are interested two possible responses to environmental policies. First, how is the decision to scrap a vehicle affected by the presence of a scrappage bounty, and, second, how does the prospect of a costly repair required or encouraged by an I/M policy or some other vehicle emission policy affect the scrappage decision? Let us suppose, then, that the individual has made a preliminary decision to keep the vehicle, so that $\mathrm{p}_t > A_t$, but now the vehicle is subjected either to I/M or a scrappage bounty or both. The potential effect of these policies is, in the first case, to decrease the expected value of the current vehicle, and in the second, to increase the expected value of the best alternative.

Consider first a scrappage bounty of *S*. If the individual accepts the scrap offer, the following must be true from (3) above and the definition of J_t:

$$p_t < \pi_t - (\pi_t^a - (p_t^a + c)) < S \,, \tag{4}$$

Where $\pi_t^a = V_t^a + \beta E J_t^a$ is the gross value of the best alternative. The first inequality in (4) follows from the supposition that, in the absence of scrappage, the owner would keep the vehicle, while the second follows from the acceptance of the scrap offer. Expression (4) implies that the scrap decision depends not only on the characteristics of the vehicle currently owned but on the characteristics of the best alternative. If an individual has his eye on a particular alternative vehicle, it is easy to imagine how he might accept a scrap offer greater than the market value of his vehicle, even if it is not equal to the subjective worth of the vehicle to him. If the individual's tastes resemble those of everyone else, however, and if the market in new and used vehicles is efficient, so that there are no real "bargains" to be had, then the NPV of the best alternative will approach zero, $\pi_t^a - (p_t^a + c) = 0$, in which case the decision rule is to scrap the vehicle if the scrap offer *S* exceeds π_t, the individual's current valuation of his vehicle. This is the decision rule in the model by Parks (1977), for example.

Now suppose the vehicle fails an I/M test and is required to make emission repairs with an expected cost of *R*. This unanticipated cost reduces the NPV of owning the vehicle from π_t to $\pi_t - R$; however, it will probably also reduce the market value of the vehicle from p_t to $p_t - R$. (A potential buyer will almost certainly require the vehicle to pass inspection as a condition of sale. The owner may be able to avoid the associated loss of value if the vehicle is sold outside the area where I/M is required. But selling elsewhere entails costs, and so we assume vehicles are sold locally). The repair cost can be avoided if the vehicle is scrapped, so as in the preceding case the owner will scrap the vehicle if its new value is less than the scrap value, or $\pi_t - R < S$. Here *S* may or may not include a scrap bounty. We use the decision rules derived here in the simulation model below to predict the impact of scrappage and I/M policies.

According to the model described here, the decision to scrap the vehicle in any period depends critically on the vehicle's value to the owner relative to its scrap value and the cost of maintenance and repair. The model also suggests that the value of a used car should be predicted by variables capturing the quality of the car, and the benefits and cost of driving it. The condition of the vehicle, its make and age, how heavily it has been used in the past and how well it has been maintained in the past are likely to be strongly correlated to its current value. Below, we include an econometric estimation of vehicle values that incorporates these components, and use the results as vehicle values in the simulation. We first describe the structure of the simulation model, and then the estimation of vehicle values. The paper concludes with the simulation results.

3. SIMULATION MODEL OF VEHICLE REPAIR AND SCRAPPAGE

To evaluate policies designed to encourage fleet turnover in order to reduce emissions, we apply the model of rational scrappage developed above to owners of a fleet of vehicles and simulate the effects of various policies on the decision to repair or scrap old vehicles. This model is quite different in structure from the simulation model used by Kazemi (1997), but is not inconsistent with it. In section 5 below, we look at both the emissions reductions and economic impacts resulting from different policy options. The model simulates the decisions of motorists under the following three policies:

- *Accelerated Vehicle Retirement*. A stand alone scrap program in which old cars are purchased at a specified offer price. In the simulation model below, the offer price is allowed to vary from $100 to $1,000;
- *Regulatory Program (with and without scrap program).* A regulatory program which represents the current generation of state "enhanced" inspection and maintenance programs. Owners must test vehicles on a regular basis, and failing vehicles must be repaired up to some cost limit.[6] As part of that program, there can be a standing offer to buy old vehicles at a specified offer price, e.g. $500 per car.
- *Emissions fee policy (with or without scrap program).* The emission fee we use in this analysis requires that emissions of all cars be tested, and owners pay a fee based on the gram per mile emissions test results.[7] Two types of fees are considered. The first type has no exempt emissions (i.e., owners must pay the fee on all emissions, or "baseline=0"), whereas in the second type ("baseline=1") owners must pay the fee only on emissions greater than some allowed level, which we set equal to the average emissions level of the fleet. A scrap program can be added to the fee program, giving owners an alternative to repairing the car or paying the fee.[8]

The simulation model represents emissions from a fleet of vehicles, and includes stochastic and behavioral elements of emissions measurement and repair. The decision rule for vehicle owners in the simulation is based on the theoretical model above: scrap the vehicle if its value to the owner net of the cost of repair is less than the scrap offer. The scrap offer is the amount of the bounty offered in an old car scrap program operating either in isolation or in conjunction with an I/M program or vehicle emissions fee. In the absence of an old car scrap program, the scrap value is simply the value of scrap metal and old car parts, and the simulation model effectively analyzes I/M or vehicle emissions fee policies alone.

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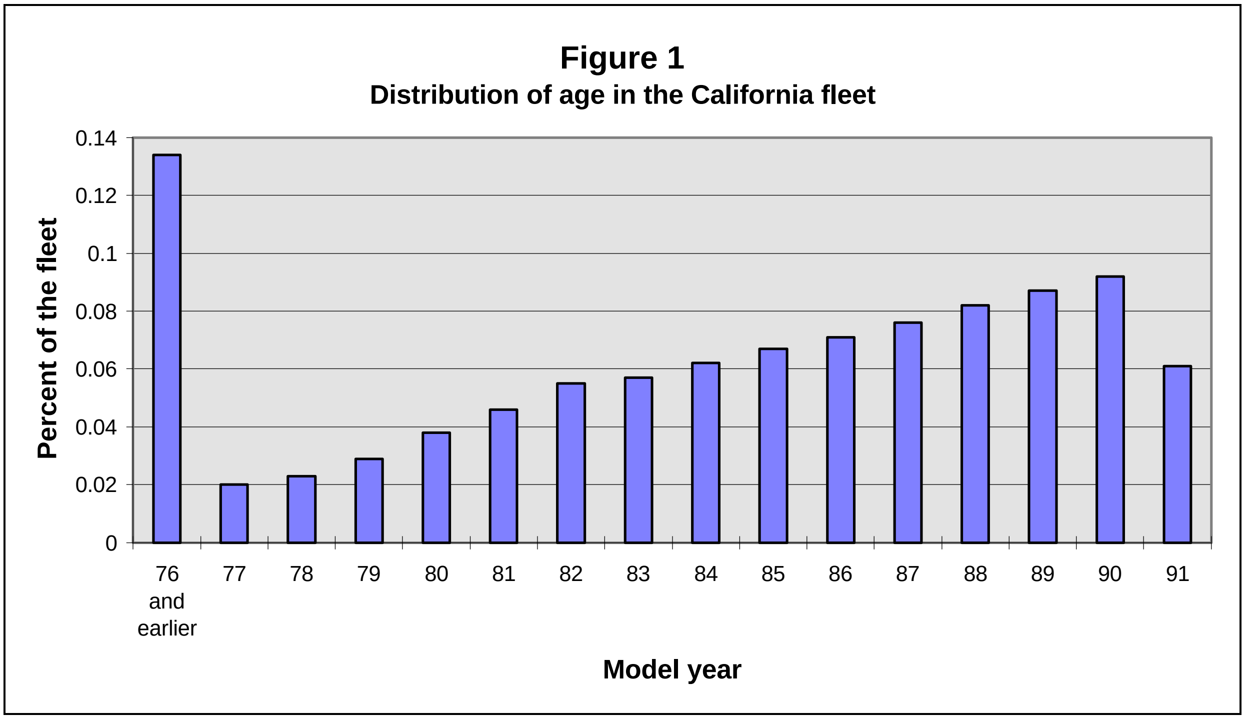
[6] In most I/M programs vehicles can get a "waiver" after they have spent some amount on repairs and the vehicle still does not pass. The waiver rate specified in the 1990 Clean Air Act for ozone nonattainment areas is $450.

[7] The fee is expressed in cents per gram/mile and for this analysis has been set equal to the marginal damages of emissions in California as measured by Small and Kazimi (1995): 0.3 cents per gram mile for HC and 1 cent per gram per mile for Nox. Also, to keep the model manageable, in this paper we rule out the possibility that drivers may limit their driving to reduce their liability under the emissions fee program. In the simulation, we assume that cars are driven a constant 10,000 miles a year.

[8] Emissions fees on vehicles have been suggested by many economists and policy makers (White, 1982; Kessler and Schroeer, 1993; and Harrington, McConnell and Alberini, 1996), but have yet to be implemented.

The simulation model, described in more detail in Harrington, McConnell and Alberini (1996), creates a "virtual" fleet consisting of 1000 vehicles with an age distribution similar to the age distribution of vehicles observed in use in California in 1991 as shown in Figure 1 (EEA, 1994). Each of these vehicles has been assigned an initial "true" rate of hydrocarbons, carbon monoxide, and NOx emissions, expressed in grams per mile (g/mile) as earlier discussed. Emissions are, however, measured with error since no emissions test is perfectly accurate. We account for the error by using existing empirical evidence on the accuracy of current tests. Repair effectiveness assumptions in the model are also based on empirical evidence from several repair studies. The model is summarized in detail in the Appendix.



Notes for Figure 1

Our information about the distribution of age in the California passenger vehicle fleet is based on data from a 1991 remote sensing study (EEA, 1994), as shown in Figure 1. The distribution indicates that the average model year is 1984, and that about 20 percent of the fleet is comprised of pre-1980 vehicles.

Simulation of the pure scrap program

We consider the case of a pure scrap program, in which a bounty is offered for old vehicles regardless of emissions. Owners decide to scrap or keep their vehicle based on their valuation of the vehicle relative to the bounty offered. In the simulations below the bounty varies from $100 to $1,000.

Simulation of the regulatory program: I&M (see Figure 2)

The I/M program is characterized by a set of model year-specific cutpoints, one for each of the three pollutants, HC, CO and NOx, which determine whether the vehicle passes the test; these cutpoints also vary with whether the vehicle is a car or light-duty truck.[9] Each simulated "vehicle" proceeds through the simulation in the following steps:

1. *Initial vehicle emission measurement*. Because emissions tests measure true emissions with some measurement error, we generated emissions measurements using the formula: $\hat{E} = E^* + (1\text{-}\kappa)\cdot e$ where E* are the true emissions of a specified pollutant, $\hat{E}$ are the observed emissions, and e is a normal variable with mean zero and standard deviation equal to the standard error of the regression in Table 1 of Appendix 1, representing the measurement error. We simulate a somewhat, but not excessively, imperfect test accuracy by multiplying the standard error by the parameter κ, equal to 0.5.[10] A vehicle fails the emissions test if measured emissions $\hat{E}$ are greater than vintage-specific cutpoints.

2. *Owner response*. Any vehicle that has measured emissions exceeding any cutpoint is subjected to repair, or, at the owner's option, retirement. The simulated cost of each repair, R^1 is a random draw from a log-normal distribution estimated from the reported repair costs in the 1100-car study by the California I/M Review Committee (1993).[11] We also use the data from this study to estimate post-repair emissions as a function of pre-repair emissions and repair costs (see Tables 2 and 3 of Appendix 1). Owner reservation prices, V , used to determine whether to scrap the vehicle, are drawn from vintage-specific log-normal value distributions with parameters estimates as shown in Table 2, column (C), below. The model terminates here if the vehicle is scrapped. If the vehicle is repaired, post-repair emissions are determined by applying to the true emissions the coefficients in Table 2 of Appendix 1, plus a random error distributed as the errors in that table.

3. *Retest*. A second draw is made from the post-repairs emission test distribution (Table 2 of Appendix 1).

4. *Second repair*. If any cutpoint is still exceeded, the "vehicle" proceeds to the second repair. This second repair is allowed to be more extensive than the first repair. The simulated costs and emission reductions are parameterized using data from a vehicle repair study conducted by the Sun Oil Company (Table 3 of Appendix 1).[12] Again, the owner has the option of scrapping the vehicle instead of repairing it.

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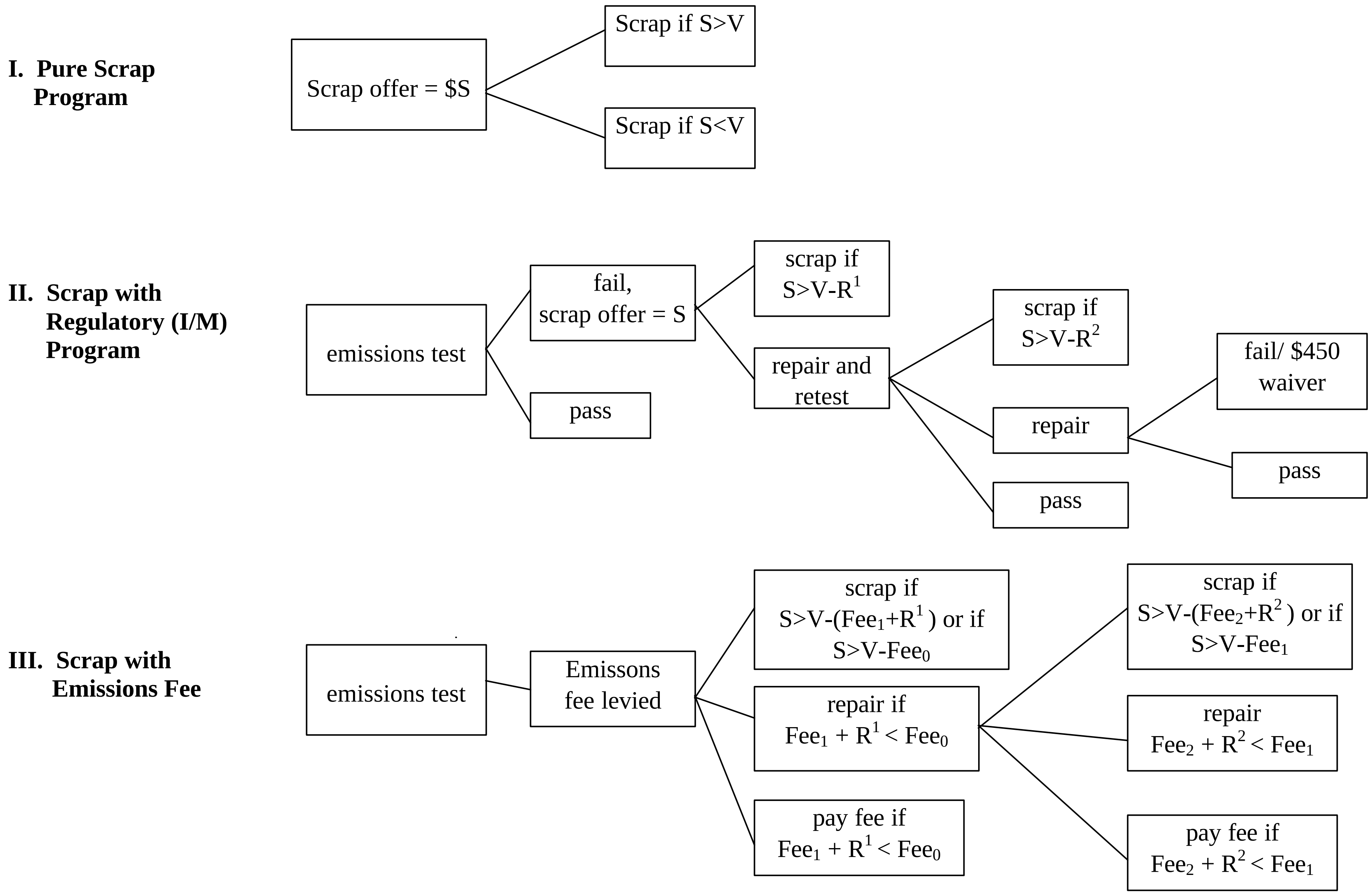
[9] We use the cutpoints in actual use in California in 1992, as reported by Klausmeier et al. (1994).

[10] For comparison, κ=1 represents perfect accuracy.

[11] The average repair costs from the California study were approximately $89 per vehicle and are held down by a model year-dependent cost cap designed to prevent exceptionally large impacts on particular motorists.

[12] We assume that motorists would first implement relatively inexpensive repairs, much like the ones observed in the California repairs dataset. If the vehicle still fails the emissions test, the owner would switch to more expensive repairs, like those reported in the Sun Co. study dataset.

Figure 2. Driver Decisions under Different Policies



5. *Stop*. If the vehicle remains unable to pass the test after the second repair, it is allowed to be operated even though it is in violation.

Simulation of the economic incentive program: emissions fee (see Figure 2)

The emissions fee policy uses many of the same elements as the regulatory program. The main difference is in the importance of predicting the reduction in emissions, since the decision to repair the vehicle is based on this prediction. The following steps are developed:

1. Initial vehicle emission measurement and calculation of initial fee:

$$Fee_0 = \max\left\{0, \sum t_i \left(\hat{E}_i - Baseline_i\right)\right\}$$

where t_i is the fee rate for each pollutant, $\hat{E}_i$ the measured emission rate (which gives total liability under the emissions fee program after it is multiplied by miles and fee rate), and *Baseline* the level of "free" (tax-exempt) emissions granted each vehicle, if there are any.

2. Prediction of emission reductions and estimation of post-repair fee:

$$EstFee_1 = \max\left\{0, \sum t_i \,(10{,}000 \cdot \tilde{E}_i - Baseline_i)\right\}$$

where $\tilde{E}$ is predicted emissions using the repair cost and effectiveness from the California I/M Review Committee study. The predicted repair is based on the regression whose results are reported in Table 2 of Appendix 1 -- i.e., post-repair emissions are a function of pre-repair emissions, estimated repair cost, and vehicle model year. We assume that owners have a reasonable, but not perfect, ability to predict the emissions reduction attained through the repairs.[13]

3. Compare Fee_0, Repair cost + $EstFee_1$ and Owner's Value *V*, net of scrap value. If Fee_0 is the smallest, do nothing. If Repair cost + $EstFee_1$ is smallest, repair. Otherwise, scrap. "Scrap value" is replaced by the bounty offered to owners of older cars as an inducement to vehicle retirement when we consider emissions fees combined with a scrappage program.

4. Repeat 2 and 3, using the Sun Oil Co. repair cost and effectiveness (see Table 3 of Appendix 1).

The decision rules for all three cases are summarized in the flow chart in Figure 2.

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[13] We simulate improvement in repair-effectiveness prediction with a parameter λ defined in the unit interval, with λ=0 representing the predictive ability shown in Table 4 and λ=1 representing perfect predictability. For the simulation model of this paper, λ is set to 0.5. We allow both λ and κ to vary in a related paper (Harrington, McConnell, and Alberini, 1996) in which we discuss changes in technical parameters of the model, the precision of the emissions measurement (variations in κ) and the ability to predict repair effectiveness (variations in λ), and use the simulation model to examine the effect on emission reductions and costs of changes in the fee rates, cutpoints and other policy parameters. Harrington and Walls (1996) use a similar model to examine the distributional implications of various in-use vehicle emission policies.

4. THE DISTRIBUTION OF VEHICLE VALUES

A critical component of the decision to scrap is the value of the current vehicle, and vehicle values vary with the condition and quality of the vehicle. The simulations, as described above require a distribution of vehicle values across the fleet. In his study of scrappage Hahn (1995) used blue book values for each make and model year, distinguishing between two categories of vehicles, those in good condition and those in fair condition. This method neglects the range of differences that are likely to occur between individual vehicles and the group average. Our analysis attempts to address this problem by estimating the entire distribution of vehicle values. However, because data are not available documenting individual vehicle condition and value for California which serves as the empirical bases for the simulated fleet, we draw on available evidence from a survey of old car owners conducted as part of the Delaware Vehicle Retirement Program of 1992, and then "transfer" these vintage-specific distributions to the simulated California fleet.

The Delaware dataset is comprised of a random sample of older (pre-1980) vehicles in Delaware, some of which were scrapped in the Delaware Vehicle Retirement Program, and some of which owners elected not to scrap. The data includes information about both vehicle characteristics and owner characteristics, and is described in detail in Appendix 2. Using the data, we estimate a model that relates the price at which the owner would be willing to scrap his vehicle (willingness-to-accept (WTA)) -- our best measure of the value of a vehicle to its owner -- to condition, use and repair information. The dependent variable in our regression model is, therefore, WTA. The estimated coefficients in the WTA model are used to determine the distribution of vehicle values used in the simulation model.

The theoretical model described in Section 2 above of vehicle scrappage and ownership implies that the value of a vehicle, reflects the present and future benefits and costs of driving it. We assume that the benefits (B in our theoretical equations) depend on individual and household characteristics, such as household income, age of the owner, size of the family, how many cars the household owns relative to the number of household members or licensed drivers, and the need to use the car for work-related purposes. Other variables, such as the age of the vehicle, its condition, past repairs, the total miles on the vehicles, the miles driven in the most recent period, and factors describing emissions, such as the vehicle's waiver status, proxy the cost of maintenance and repairs (C in our theoretical equation).[14]

Among car characteristics, we expect higher odometer mileage, older age and poor condition to decrease the value of the car. Waiver status may also decrease the value of the car, whereas the effect of past maintenance and repairs is uncertain a priori: high maintenance expenditures in the past may imply that this vehicle has been taken good care of, but may also signal a poor quality car.

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[14] Note that all of these variables are predetermined (they are the results of decisions and repair expenditures undertaken in the past, but not the object of current decisions) or are outside of the owner's control (such as the age of the vehicle). This ensures that the regressors in our econometric model of WTA are not simultaneously determined with the dependent variable, WTA.

Econometric Results

We initially ran regressions that included both the vehicle characteristics (affecting costs) as well as individual/household characteristics, which are assumed to be the main determinants of the benefits of owning the vehicle. However, individual and household characteristics were never significant in the models of WTA that included both these and vehicle attributes,[15] so we report results for those regressions that only include determinants of costs among the regressors.

Table 1. WTA model: Dependent variable: log WTA

(T statistics in parentheses)

Independent variable	(A)	(B)	(C)
Intercept	12.6836 (9.057)	2.9667 (2.353)	7.4719 (25.311)
Age of car in yrs	-0.0540 (-1.734)	0.0078 (0.299)	-0.0333 (-1.957)
Log miles	-0.3491 (-2.895)		
Log miles driven, past yr	-0.1279 (-1.700)	-0.0363 (-0.665)	
Condition dummy	-0.8264 (-6.013)	-0.7683 (-7.926)	
Log blue book value		0.5847 (5.506)	
Log of $ spent on repairs	0.0999 (0.987)	0.0915 (1.186)	
I/M waiver status	-0.1000 (-0.706)	0.0252 (0.216)	
Num. Veh owned by hh		0.0068 (0.199)	
stand devn of error	1.1729 (14.833)	1.0247 (17.313)	1.2048 (20.301)
sample size	344	404	632
log L	-216.33	-267.64	-458.02

Table 1 shows the results for various specifications of the econometric model. Column (A) includes age and condition of the vehicle, recent and cumulative miles driven, recent maintenance expenditure and waiver status among the independent variables. As shown in Column (A), as we expected, age tends to depress the value of the vehicle (the

[15] These results are consistent with those reported by Morey (1996), who analyzes willingness to accept data from the Total Petroleum scrappage program. In our case the result may be due to the collinearity between individual characteristics and vehicle attributes/expenditures.

coefficient of age being negative and significant at the 10 percent level), but the effect of age is dominated by that of odometer miles (which tend to be correlated with age, and have a negative and highly significant coefficient) and condition of the car. The miles driven in the previous year also tends to correlate negatively with WTA (the coefficient being significant at the 10 percent level). Waiver status does not seem to affect the value of the car. The coefficient of past maintenance is positive, but not significant at the conventional levels.

In Column (B) we eliminate odometer reading and include blue book value at the time of the first survey.[16] Blue book value and condition are two of the strongest predictors of WTA. This suggests that the owner-assessed value of the vehicle tends to follow the market average for vehicles of that model year, the difference relative to this average being explained by the condition of the vehicle "for its age." In the span of time covered by our surveys (about two years) the present condition of the vehicle is sufficient to explain the decline in value relative to the initial-survey blue book value: the miles recently driven and age have no additional explanatory power, suggesting that miles and age are correlated with condition.

These regressions confirm our priors on the relationship between use, condition and value of a vehicle, and indicate that value does systematically decline with the age of the vehicle. Column (C) of Table 1 isolates the effect of vintage alone, which is we use for the simulations discussed in the remainder of the paper. Age *is* a significant predictor of WTA, its coefficient being negative and significant at exactly the 5 percent level.[17] When the mean and variance of log WTA within each model year are estimated, the dispersion around the vintage-specific mean increases slightly with age. Because we have only age of the California fleet, we use this simple equation to predict vehicle values be used in the simulation.

5. RESULTS OF THE SIMULATION MODEL

To illustrate the interaction of scrappage bounties with other regulatory policies for in-use emissions we use the empirical results on vehicle value as inputs to the simulation model developed above. Owners of the 1,000 car fleet make decisions to either keep, repair or scrap their vehicles under different policy regimes, using the simulation process described in Section 3 above. Here, we examine the regulatory policy (I/M) and emission fee policies both with and without the option to scrap an old vehicle. The I/M program examined has cutpoints set at a level of about twice the mean emission rate of all vehicles, a level that is lenient relative to the new-car emission standards, but probably is representative of the "transitional" cutpoints used in the first year of some Enhanced I/M programs. We compare these policies to a pure scrap program. The various policies can be evaluated in a number of different ways

[16] Blue book value is predicted from age and odometer reading. We include current age and miles driven most recently to proxy for what the blue book value would be at the time of the second and third round surveys.

[17] We also ran regressions in which WTA at the time of the previous round of survey was included among the independent variables. We found that today's value is strongly correlated with the vehicle value reported by the owner in the immediately preceding round of surveys, all other variables (miles driven between the two surveys, present condition of the car, etc.) offering no additional explanatory power.

including the impact on scrappage and repair, on emissions reduction potential, on cost-effectiveness, and on net economic benefits.

We examine only the results of the first year of the program, After the first year, presumably, fewer vehicles would be scrapped because the worst vehicles would have been removed. We assume the remaining life of a vehicle sent to the scrapyard by a scrap or I/M policy would have been one year in the absence of a policy.[18] We also assume that repairs required to bring the vehicle in compliance with the I/M program are effective for one year: Should a vehicle be scrapped, its replacement is assumed to be the average vehicle in the fleet.

We first examine the results of the regulatory program (I/M) and emissions fees on scrap and repair rates. Figures 3a and 3b show the results of including a scrap program with an I&M program and an emissions fee. First, with no structured old car scrap program (bounty equal to $0), about 2 percent of the fleet is scrapped due to both average fleet turnover and the presence of the I/M program and its required repairs. With the emissions fee policy (no baseline) set at the level of marginal damages ($3,000 per ton of hydrocarbons and $10,000 per ton of NOx)[19], with no scrap offer, about 7 percent of the fleet is scrapped. In both cases, when a scrap program is introduced, increases in the scrap offer cause drivers to elect to scrap instead of repair. Those cars that are scrapped will be the ones that have the highest expected repair cost relative to the driver's valuation of the car.

Figure 4 addresses the broader issue of the net benefits under different policies as the scrap offer varies from 0 to $1,000. Benefits are calculated as the emissions reductions under each policy times a constant marginal damage function. We use marginal damages estimates from Small and Kazimi (1995) of $3,000 per ton of hydrocarbons and $10,000 per ton of nitrogen oxides. We examine cases where the fees vary between half and twice the marginal damages, but the results reported here refer to the case where the fees equal the assumed marginal damages.[20]

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[18] Both EPA guidelines (1993) and Hahn (1995) assume that the remaining life would have been 3 years. In our earlier work we find, based on the owner planned vehicle retirement, that the average remaining life of a vehicle participating in a scrap program that offers up to $1000 per car is generally well below 3 years.

[19] The damages from vehicle emissions include the increased morbidity from ozone formed by HC and NOx emissions and the increased mortality caused by some types of particulates including some NOx particulates. Small and Kazimi (1995) find that the mortality effects from nitrogen oxides are about 3 times higher than the damages from hydrocarbons. This estimate, especially for NOx emissions, is high relative to other estimates of air pollution damages (see Krupnick and Portney, 1991).

[20] The costs of each program are calculated as the repair cost, plus the cost of scrapping cars early (the value of the cars that get scrapped). To keep costs comparable across policies, we do not count the fee payment as part of the social cost in the case of the emissions fees, assuming that taxes will be reduced by an equal amount elsewhere. Similarly, with the scrap program bounty, we assume that taxes must be raised elsewhere to raise the money to make the bounty offers, so there is simply a redistribution of funds. The costs and subsidies are, however, very real to drivers. Finally, we do not include the testing costs under the regulatory or fee policy, because we assume these costs would be the same under either policy. Testing costs depend more than anything else on test frequency, which is beyond the scope of our one-year comparison.

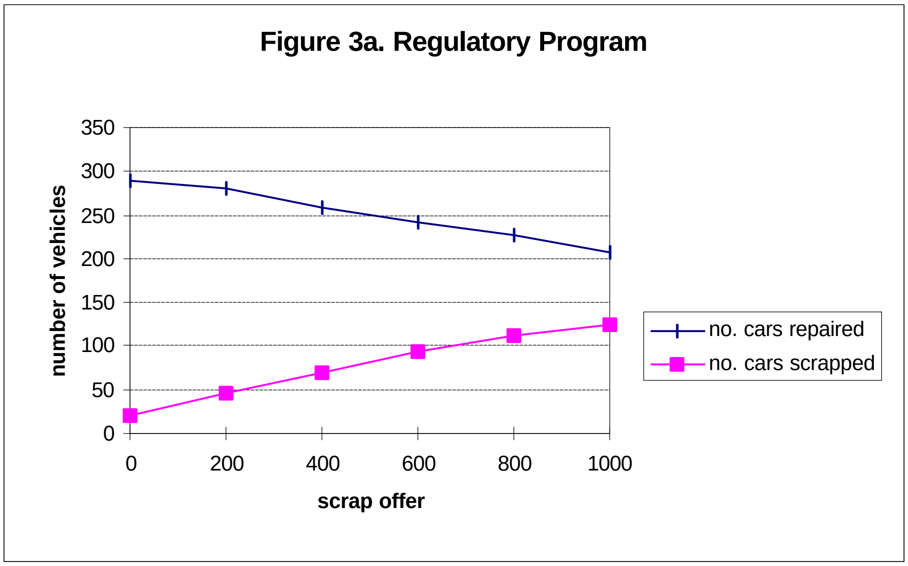


Figure 3a. Regulatory Program
number of vehicles
350
300
250
200
150
100
50
0
0
200
400
600
800
1000
scrap offer
no. cars repaired
no. cars scrapped

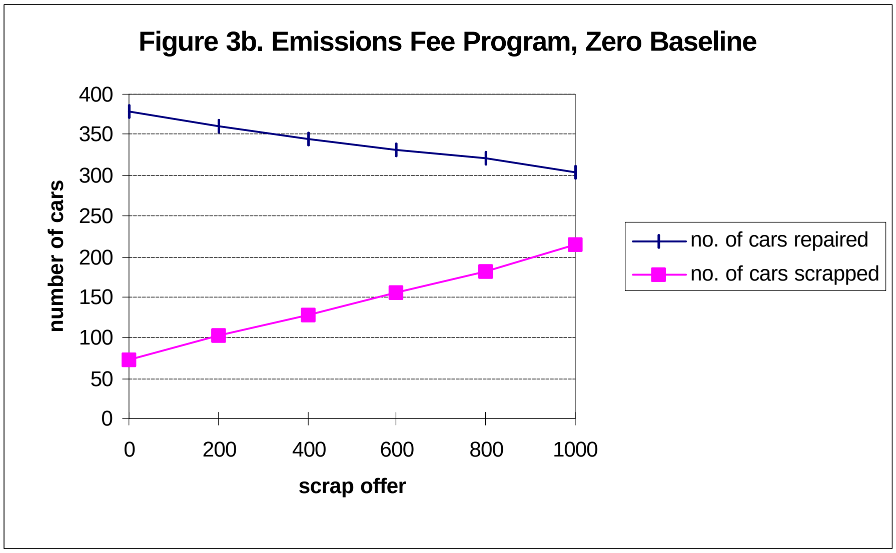


Figure 3b. Emissions Fee Program, Zero Baseline
number of cars
400
350
300
250
200
150
100
50
0
0
200
400
600
800
1000
scrap offer
no. of cars repaired
no. of cars scrapped

Figure 4.
Net benefits for different policies - with varying scrap offers

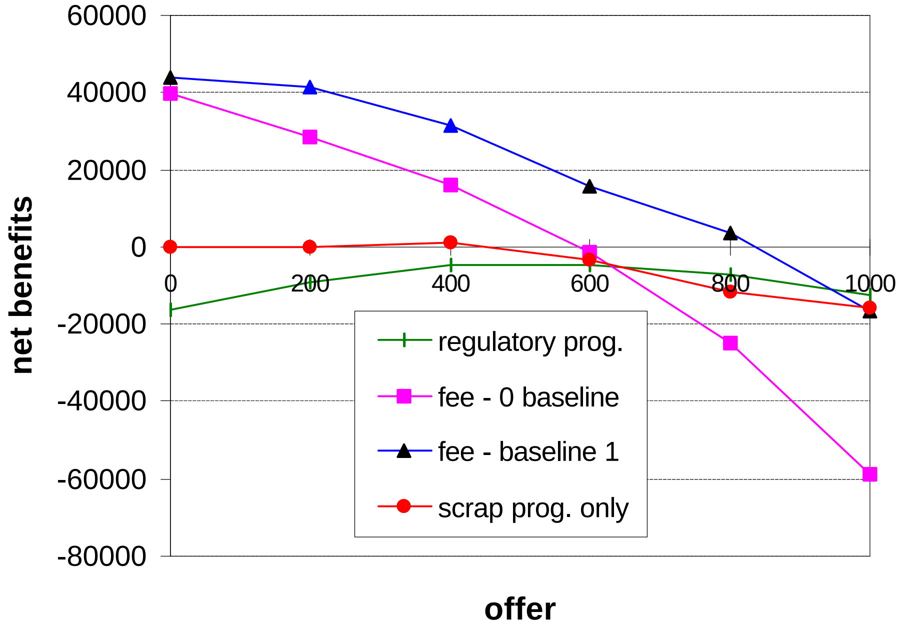


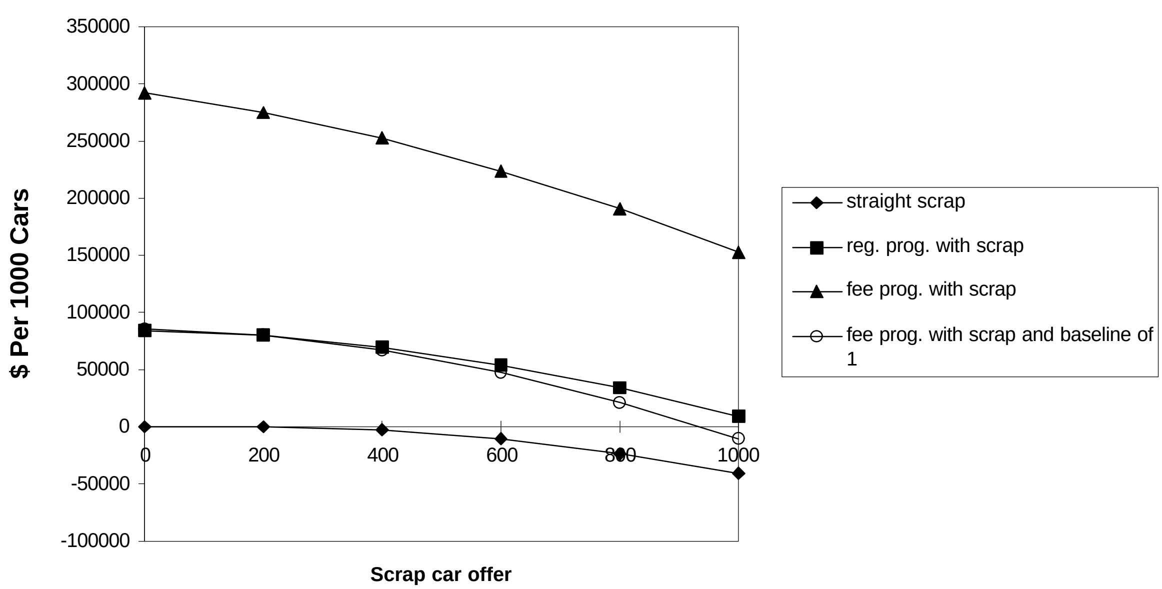
Figure 4 shows that, as we would expect, the regulatory and simple scrap programs have net benefits well below the fee policies. It is of interest that the policy with the highest net benefits is not the "pure" effluent fee, but the effluent fee with a baseline. Although the pure fee would be the most efficient policy under assumptions of perfect information in this setting, it is no longer necessarily the most efficient or cost effective policy once measurement errors or repair uncertainty is introduced (Harrington, McConnell and Alberini, 1996).

The scrap program alone generates modest benefits up to a bounty of a little over $400. Higher bounty offers result in the scrappage of vehicles that have higher in-use value than the value of eliminated emissions, making the losses larger than the emissions reduction benefits. When a scrap program is combined with regulatory I/M program the net benefits increase as the scrap bounty increases, up to $400 -$600 per car, and then decrease. With low bounty offers, some cars will get scrapped whose value net of repair cost is lower than the emission reduction benefits, and net benefits will rise. Eventually, at higher bounty levels, vehicles will be scrapped whose value in use net of repair costs is greater than the emission reduction benefits from scrapping, and overall net benefits fall. Under the assumptions of the model regarding measurement accuracy and cost of repair, net benefits for the regulatory program are *negative* at all bounty levels, implying that the social costs are not worth the emissions reduction benefits.

Figure 4 also shows that a scrap program decreases the net benefits of either emissions fee program. This is because fees were set at the optimal level to begin with, so increasing the bounty for old cars will cause less than optimal decisions to be made -- some vehicles will be scrapped whose value in use exceeds the emission reduction benefits. Generally, however, Figure 4 shows that emissions fee policies prove superior to the other alternatives considered, especially for the variant without exempt emissions.

Figure 5 shows the driver costs associated with the alternative policies. Driver costs are calculated as the emissions fee, plus the cost of repairs and the lost value of the vehicle if the owner elects to scrap the vehicle, minus the bounty received for turning in the vehicle to a scrap program. Clearly, a pure scrap program is most favorable to drivers: as the bounty increases, drivers actually receive a net surplus from the program. For an offer of $1000, the surplus is about $40,000 per 1000 vehicles. And, the drivers who benefit most from scrap programs are likely to be those who face the highest costs for repairing or maintaining the emission control equipment on their vehicles (vehicles in the worst condition) -- these are the drivers who otherwise would be hardest hit by or unwilling to participate in emission reduction programs.

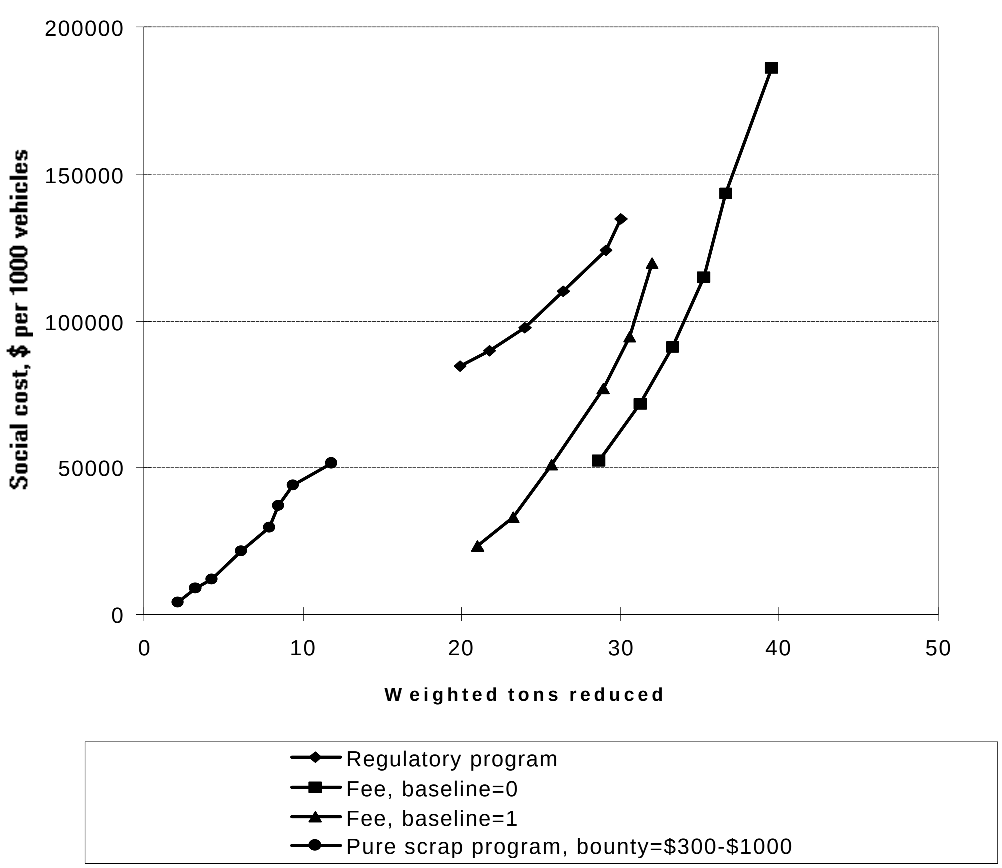
Figure 5. Driver Costs under Different Policies



The least attractive policy from the drivers' point of view is the emissions fee policy with zero baseline, in which the emissions fee paid into the system and the repairs well exceed the aggregate bounty received by those vehicle owners who turn in their vehicles. With no overlapping scrap program, drivers incur costs of about $292,000 per 1000 vehicles. As expected, however, driver cost are attenuated as the bounty increases: a $1000 bounty brings driver costs down to about $170,000 per 1000 vehicles.

Figure 6 shows the total social cost functions for reducing emissions under the alternative policies, for different scrappage offer prices. Each point on the line for I/M and emissions fees represents a different offer price, from 0 to $1,000 in $200 increments. The line for the pure scrap program is based on bounty levels ranging from $300 to $1000 in $100 increments. Emissions reduced are given in terms of weighted tons reduced, where tons are weighted according to the marginal damages from HC and NOx (NOx emissions are weighted 3 times higher than HC).[21]

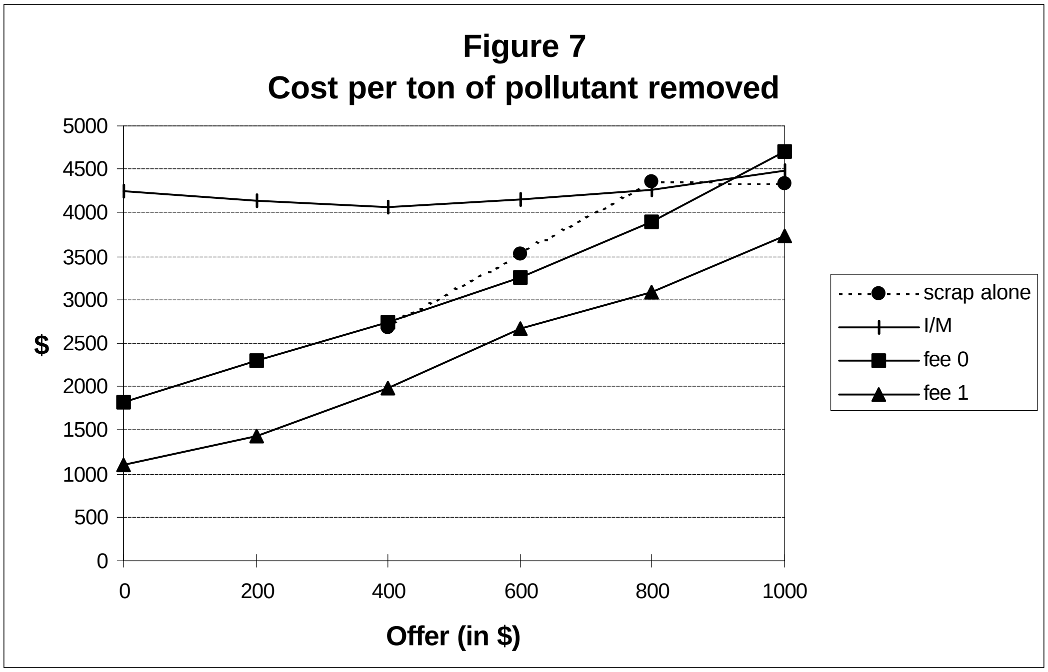
Figure 6. Social costs and tons reduced



For all of the policies we examine, the emissions reductions do increase with the bounty offered by the companion scrap program. The stand alone scrappage program is relatively low cost, but provides relatively few emissions reductions, a finding that confirms the evidence from other analyses (Alberini et al., 1994). Based on social costs, the cost effectiveness of a pure scrappage program (shown in Figure 7) is about $1900 per weighted

[21] For comparison, Hahn (1995) assigns weights of 1 and 1.8 to HC and NOx emissions, respectively.

ton of the pollutants when the bounty is $300. Cost-effectiveness deteriorates as the scrap offer increases: at $1000 scrap price, the cost effectiveness is $4700 per weighted ton. The total weighted tons of pollutants reduced range from only 2.3 (at $300) to about 12 (at $1000).



The regulatory program, on the other hand, attains a much higher level of emissions reductions (20 to 35 tons), albeit at a higher cost. Its cost-effectiveness, however, is relatively insensitive to the scrap offer, since it is at $4200 per weighted ton in the absence of a formal scrap program, about $4070 per weighted ton at a bounty of $400, and about $4500 at a scrap offer of $1000. These figures are relatively close to the cost-effectiveness calculations in Hahn (1995).

Of the two emissions fee programs, the one with exempt emissions has emissions reduction potential comparable to that of the regulatory I/M program (21 to 32 tons), but is much less costly. Its cost-effectiveness is about $1100 per weighted ton with no scrap offer, and worsens to about $3700 when the scrap offer is $1000. Adding a scrap program with successively higher scrap offers raises cost more quickly with the fee policies than with the I&M policy. This is because the low-valued high emitting cars have already been scrapped under an emissions fee policy, so scrapping additional cars will bring in higher valued cars.

The greatest emissions reduction potential comes from the fee program with no emissions exemption, which can eliminate up to 39 tons of pollutants. Its cost-effectiveness ranges from $1800 to $4700 per ton removed, a performance that is inferior to that of the emissions fee without exemption but better than that of the I/M program for most of the bounty levels we examined.

6. CONCLUSIONS

We have included a model of the owner's decision to scrap or repair a vehicle in a simulation model of a vehicle fleet. This model has been used to evaluate the role of scrappage programs as an independent policy or in combination with an I/M or fee policy. A critical part of the model is the owner's valuation of his/her car. We examined the factors affecting owners valuations of their old vehicles using a unique longitudinal dataset. Willingness to accept is well predicted by the owner's valuation in last period, and on the mileage and condition of the car. Other inputs into the simulation models are the estimated distributions of emissions in the fleet, and the link between emissions reductions and the cost of repairs. We use empirical estimates of both of these in the simulations.

The simulation model is used to examine the role of scrap policies alone and combined with other policies for reducing emissions, such as current state I/M program and proposed emissions fees, and the welfare implications of combining such programs. The model assumes that of all possible options (repairing the car, scrapping the vehicle or turning it in to an old car scrap program, paying the emissions fee without repairing the vehicle) the owner will choose the one with the least cost.

We find that old car scrap programs may increase net welfare under a regulatory program like I/M in practice today, but that a stand alone scrap program is unlikely to provide very much in the way of emission reductions. Our simulations suggest that emissions fees are a cost-effective way to reduce emissions, and that their technical and political feasibility should be explored. Their cost-effectiveness is highest in the absence of an overlapping scrappage program, and ranges between $1100 and $1800 per ton of pollutants removed, depending on whether the policy allows for exempt emissions. Cost-effectiveness worsens -- while remaining still comparatively better than that afforded by the regulatory approach -- as a bounty is introduced, which considerably lessens driver costs.

APPENDIX 1. DESCRIPTION OF THE SIMULATION MODEL

Emissions in the California fleet

We fit joint log normal distributions to vintage-specific emissions rates of HC and CO as measured by remote sensing of over 90,000 vehicles in the Los Angeles region in 1991.[22, 23] Both HC and CO are expressed in grams per mile.

Nitrogen oxides readings are taken from a sample of 7234 vehicles given IM240 tests at EPA's Hammond, Indiana, test facility. Within each model year, NOx emissions are reasonably approximated by a log normal variable. When we artificially generate the data for our simulation exercise, we assume that NOx emissions rates are independent of HC and CO emissions rates.

Reliability of the BAR-90 test

Motorists and the state agency in California rely on the so-called BAR-90 test procedure to determine whether a vehicle is in compliance with the prescribed emissions rates. One important issue is whether this test procedure provides a truthful picture of vehicles' emissions. To answer this question, we use data collected by the California I/M Review Committee "undercover car" study (1993) and estimate statistical models of emissions *measurement* (as opposed to *true* emissions). It is *measured* emissions that form the basis for the owner decision to repair or scrap the vehicle.

The BAR-90 is a two-speed test that includes, in addition to the idle test, a test of emissions at an engine speed of 2500 RPM. It is usually regarded as inferior to tests involving the use of a dynamometer and the operation of a vehicle over many different driving modes, including acceleration, deceleration, stop and start. The Federal Test Procedure (FTP) is one such test and is currently considered by regulators and the automotive industry as the best method to produce an estimate of actual vehicle emissions.[24]

In an effort to assess the performance of the Smog Check program, the California I/M Review Committee study recruited a large number of vehicles in use which were given an

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[22] Remote sensing is a technology combining roadside monitors that send infrared beams from one side of the road to a detector on the other side, measuring a vehicle's emissions, with a video camera that obtains a photograph or electronic identification of the license plate. See Stedman, et al. (1994), for a discussion of remote sensing technology and the California data used in this study.

[23] We are here implicitly assuming that the distribution of emissions rates in the Los Angeles basin is representative of emissions rates in the whole state.

[24] The FTP is the test procedure currently used to certify new automobiles for compliance with the emissions requirements of the 1977 Clean Air Act. The test takes about an hour to complete and is quite expensive to perform (about $1000 per test). Enhanced inspection and maintenance programs generally rely on the IM240, a four-minute and much less expensive variant of the FTP. Recently, however, the FTP test has been criticized for not accurately reflecting true driving behavior and accompanying on-road emissions. Specifically, the FTP allegedly underrepresents high acceleration episodes (Ross et al., 1995). There is only limited empirical evidence confirming that the results of IM240 tests closely resemble those of the FTP tests.

initial FTP test. Those vehicles that failed the FTP were sent out to a sample of Smog Check stations in Southern California as if they were ordinary cars out to get their required Smog Check certificates. These "undercover" cars were given emission tests by the (presumably) unsuspecting Smog Check stations and, if failing, were repaired and retested. The cars were then given a post-repair FTP test. Of the 1100 vehicles originally included in the program, we work with a data set of 681 vehicles for which repairs were attempted and a second FTP completed.

The performance of the idle test was evaluated by regressing the FTP test results (before repairs) for a specific pollutant on the BAR-90 idle test results:

$$FTP = \alpha_0 + \alpha_1 IdleHC + \alpha_2 IdleCO + \varepsilon. \qquad \text{(A1.1)}$$

where *FTP* refers to the FTP test emissions for HC, CO and NOx, in grams per mile, *IdleHC* the HC idle test results in ppm and *IdleCO* the CO idle test results in percent CO. Because the idle test results are expressed in parts per million and percent, respectively, and the FTP test results are expressed in grams per mile, the regression coefficients are interpreted as conversion factors from one unit of measurement to the other.[25]

Results, with standard errors in parentheses, are given in Table A1 below. As shown, the idle test results are completely ineffective at explaining FTP results for NOx and explain about a third of the variation in emissions of HC and CO. The most important parameters are the standard errors of the regressions, for these are used to generate the random normal deviates that serve as emissions measurement errors in our simulation model.

Table A1. Ability of the Idle Test to Predict FTP Emissions

	Dependent Variable (grams/ mile)		
	FTP HC	FTP CO	FTP NOx
Constant	1.305 (0.314)	25.36 (1.90)	2.09 (0.074)
Idle HC (ppm)	0.00890 (0.00054)	0.0070 (0.0032)	0.37e-3 (0.12e-3)
Idle CO (percent)	0.279 (0.090)	9.93 (0.54)	-0.042 (0.021)
R-square	0.34	0.37	0.01
Standard error	5.86	35.52	1.38
N	669	669	669

Source: California I/M Review Committee, 1993. Standard errors in parentheses.

[25] Only HC and CO idle test emissions rates are included in the right-hand side of equation (4), as NOx rates are not measured by the BAR-90.

Cost-effectiveness of Repairs

Recent results suggest that vehicle emissions repair is not nearly as effective as had previously been assumed. In 1992 the EPA, in assessing the cost-effectiveness of the proposed Enhanced I/M regulation (EPA, 1992), assumed emission repairs to cost an average of $120 each and to be relatively effective at reducing emissions.

However, three recent studies indicate that vehicle emission repairs are much less successful and more expensive than assumed by the EPA. One of those studies produced the 681-car dataset described in the preceding section (California I/M Review Committee, 1993), which indicated that the average cost was low (less than $90 per vehicle), probably a result of waiver limits that restricted the amount spent on each vehicle. The average emissions reduction was also low: 25 percent for HC, 21 percent for CO, and 8 percent for NOx. Emissions reductions were also quite variable across vehicles, with nearly half the cars showing *higher* emissions after repair than before. Emissions reductions were not at all related to cost.

In two other recent repair studies the repairs were more effective, but far more expensive than assumed by the EPA. Both studies were conducted by oil companies searching for mobile source reductions to use as emissions offsets for stationary source emissions. In 1993 Sun Oil Company (Cebula, 1994) used remote sensing to identify gross-emitting vehicles owned by their employees as they left company parking lots in Philadelphia. Sun offered to repair these vehicles at its expense, and spent up to $450 on each vehicle. After an average expenditure of $338, the emissions reductions for HC, CO and NOx were 68 percent, 75 percent and 9 percent, respectively. While quite an improvement over the California results, the emissions reductions attained in the Sun program are still a far cry from the EPA assumptions. Moreover, fully 40 percent of the vehicles were not brought into compliance even after an expenditure of $450.

Another study was done by Total Petroleum in Denver. This was a combined scrap-repair study, in which gross-emitting vehicles were identified by several different means. This study found that emissions of HC and CO were reduced by about a third after an average expenditure of nearly $400.

Ideally, we would like to estimate a repair model that gives the emissions reductions following from making certain kinds of repairs.[26] Unfortunately, we have not been able to locate data that allow us to estimate the effectiveness of specific repairs. The three studies earlier discussed record initial and post-repairs emissions, and the cost of the repairs, but not repair *type*. Using the data from the California I/M Review Committee and the Sun Oil Co. studies we fit the following equation of repair effectiveness:

[26] Predictability of the emissions reductions associated with a given level of repair costs would be extremely useful in an I/M program, as mechanics would be able to select the combination of repairs that brings the vehicle into compliance with the emissions standards at the least cost. Repair predictability would be even more useful in an emissions fee program, since the mechanic could decide on the package of repairs that maximizes the expected net benefit of repair to the motorist -- that is, the expected reduction in emissions fees paid less the cost of repair. This choice can include the possibility of making no repairs at all if it is less costly to pay the fee.

$$E_i^1 = \beta_0 + \sum \beta_i E_i^0 + \gamma_1 Age + \gamma_2 Cost + \eta \tag{A1.2}$$

where $i, j = HC, CO, NOx$ are the pollutants of interest; E^0, E^1 refer to emissions before and after repair, respectively; *Age* is the vehicle age in years; *Cost* is the reported repair cost. The variable η is the disturbance term, which is assumed normal.

The results for California (Table A2) show that by far the most significant predictor of post-repair emissions of a pollutant are the pre-repair emissions of that same pollutant. The coefficients can be interpreted as the marginal effectiveness of repair at removing pollutants from vehicle emissions. The coefficient of 0.36 for HC, for example, means that repair in the California program removed 64 percent of the incremental HC emissions. The effects of other pollutants are not consistently related to post-repair emissions. *Cost* is significant for CO and NOx and has the correct sign for all three pollutants, but in all cases the numerical magnitudes are so small that cost has no practical importance. (For example, an expenditure of $100 reduces expected HC emissions by 0.1 grams per mile.) The coefficient of *Age* (not reported for consistency with Table 5) is positive and significant in the CO and HC equations, the positive sign suggesting either that older vehicles are more difficult to repair or that what must be considered the emission level for a fully repaired vehicle increases slowly with vehicle age. On average, a year of age increases post-repair emissions by 0.1 g/mi. for HC and 1 g/mi. for CO.[27]

Table A2. Predicting Repair Effectiveness: California I/M Review

	Dependent variable (grams per mile)		
	HC	CO	NOx
Constant	0.041	5.30	0.14
	(0.25)	(1.40)	(0.048)
HC_0	0.36	0.53	-0.0025
	(0.027)	(0.15)	(0.0051)
CO_0	0.026	0.62	0.0027
	(0.0045)	(0.024)	(0.00084)
NOx_0	0.32	0.60	0.73
	(0.13)	(0.72)	(0.025)
Cost	-0.00084	-0.011	-0.00027
	(0.00064)	(0.0034)	(0.00012)
Std. error	2.87	15.54	0.54
R-square	0.34	0.59	0.57
n	669	669	669

Standard errors in parentheses.

[27] Table 4 reports the results of a regression in which both the dependent variable and the independent variables are untransformed. We experimented with double-log, semi-log and quadratic models, as well as models for percentage changes in emissions, and found that the results were qualitatively similar: the cost of repairs is a statistically significant predictor of post-repair emissions, but has virtually no practical importance.

Similar regressions run on the Sun Co. data (Table A3) show even higher pollutant removal efficiencies, owing most likely to the greater repair expenditure. The age of the vehicle was insignificant and has been omitted from the model in the table.

Table A3. Predicting Repair Effectiveness: Sun Oil Company

	Dependent variable (grams per mile)		
	HC	CO	NOx
Constant	0.36	2.48	1.04
	(0.28)	(3.45)	(0.24)
HC_0	0.098	0.16	0.10
	(0.026)	(0.32)	(0.023)
CO_0	-0.0036	-0.00051	-0.0041
	(0.0015)	(0.018)	(0.0013)
NOx_0	0.0055	-0.26	0.011
	(0.020)	(0.24)	(0.017)
Cost	0.0013	0.023	0.00017
	(0.00075)	(0.009)	(0.00066)
R-square	0.11	0.05	0.12
Std. error	1.20	14.58	1.05
n	151	151	151

Standard errors in parentheses.

In the simulation model described in the next section we use the linear model because its coefficients are easier to interpret and because we are more interested in prediction of the value of the dependent variable than in the coefficients *per se*. Specifically, the results from the California I/M Review study are used to generate the repair size and emissions reductions following the first round of repairs; the results from the Sun Co. study are used to generated the repairs and emissions reductions after the second round the repairs, if the vehicle fails the second test.

APPENDIX 2. DATA SUMMARY: DELAWARE VEHICLE RETIREMENT PROGRAM

The Data

We obtained owner-assessed values for relatively old vehicles in the course of interviews of vehicle owners conducted in association with the Delaware Vehicle Retirement Program (DVRP; see Alberini et al., 1994). The DVRP targeted approximately 4200 owners of pre-1980 vehicles, who were offered $500 for their vehicles. The targeted owners received letters that spelled out the nature of the program, the bounty level and asked interested owners to call a toll-free number in order to make arrangements for scrappage.

One-hundred twenty-five vehicles were purchased, and 121 of the owners of those vehicles were interviewed at the scrapyard. A total of 365 non-participants (owners of pre-1980 vehicles who were sent letters soliciting participation in the program, but had chosen not to participate) were surveyed over the telephone, whereas the 48 "waitlisted" owners (owners who indicated they wished to participate, but had replied to the DVRP letters only after the goal of 125 vehicles had already been attained) were not interviewed in this first round of surveys.

Both participants and non-participants were asked similar questions. Specifically, we verified the information on make and model year, asked whether the car had been purchased new or used, inquired about the odometer reading, the miles driven in the previous year, the current use of the vehicles for commuting and non-commuting work-related purposes and errands, the present condition of the car and the maintenance expenditures in the previous year as well as those planned for the next year.

In addition, we asked how much longer the owner planned to keep the vehicle, and how he or she was planning to dispose of it at that time (by selling, trading or scrapping it). One of the most important questions elicited an estimate of the car value to the owner.[28] The survey ended with questions about the household's economic circumstances and demographics.

About a year later, we once again contacted over the telephone the non-participants who still had their pre-1980 vehicle and administered a survey questionnaire that was virtually identical to that in our first round of surveys. In addition, we contacted and interviewed most (42) of the "waitlisted" owners and interviewed them over the telephone about the current value of the vehicle and the value of the vehicle at the time of the DVRP letters.

Finally, another year later we re-contacted all of those non-participants and "waitlisted" owners who had reported owning the car at the time of the second round of surveys and repeated the standard version of our questionnaire.

[28] Most respondent provided responses that we interpret as point estimates of their willingness to accept (WTA) for their vehicle. A few indicated that their WTA figure was greater than $1000, but did not specify a point value. We developed special statistical models to accommodate for these responses.

Econometric Specifications

The three round of surveys enabled us to develop a unique longitudinal dataset that includes participants, non-participants who still owned their pre-1980 vehicle at the time of the first round of surveys, and "waitlisted" owners who still owned their pre-1980 vehicle when first surveyed. Non-participating and waitlisted owners provide, at regular intervals of one year, information on the most recent condition, use, value and planned ownership for their car.[29]

Formally, the model for willingness to accept is:

$$\log WTA_{it} = x_{it}\beta + \varepsilon_{it} \tag{A2.1}$$

where *i* indexes the individual (i=1, 2, ..., *n*), *t* indexes the round of surveys (t=1, …, T_i, where T_i may be equal to one, two or three, depending on the fate of the respondent's vehicle), *x* includes all exogenous variables thought to influence WTA (individual or vehicle characteristics), and ε_{it} is a normally distributed error term.[30] The error terms are assumed serially uncorrelated (within one owner) and independent across owners: Cov($\varepsilon_{it}, \varepsilon_{js}$) is zero for $t \neq s$ and all *i*'s and *j*'s.

The nature of some of the observations on the value of a vehicle prevents us from using least squares when estimating our models of willingness to pay. We resort to maximum likelihood techniques to accommodate those respondents who -- in one or more rounds of surveys -- declined to participate in the scrappage program at $1000 but never reported their exact WTA value. The log likelihood function is:

$$\log \mathrm{L} = \sum_{i=1}^{n} \sum_{t=1}^{T_i} \left[(1 - I_{it}) \cdot \log \phi(\log WTA_{it}; x_{it}, \beta, \sigma) + I_{it} \cdot \log \Phi\left(\frac{x_{it}\beta}{\sigma} - \frac{\log 1000}{\sigma} \right) \right] \tag{A2.2}$$

where $\phi(\bullet)$ and $\Phi(\bullet)$ denote the standard normal pdf and cdf, respectively; σ is the standard deviation of the error term, and I_{it} is an indicator that takes on a value of one for those respondent who would not have participated in the program for $1000, but do not report their exact WTA value, and zero for all others.

A description of the variables used in our regressions is provided in Table A2.1.

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29 Since owners drop out of our dataset as soon as it is ascertained that they do not hold their vehicles any longer, we have a minimum of one and a maximum of three observations per owner in the dataset. Those owners who still had their cars at the time of the most recent round of surveys contribute three observations.

30 We choose log WTA as our dependent variable because previous work with the data from the first-round surveys suggests that WTA is reasonably approximated by a log normal distribution (Alberini, Harrington and McConnell, 1995).

Table A2.1. Description of Variables from the DVRP Surveys

Variable	Description	mean	std devn	min	max	#valid
WTA	exact WTA value	1535.58	2791.27	100	20000	506
age2_ye	age of the car in years	17.13	2.95	13.5	32	848
miles	odometer miles	126,060	61,415.15	1000	430,467	457
pastyr	miles driven in the past year	4343.92	3504.57	1000	12,000	543
wvalue	Blue Book Value at time of first survey	1021.83	1046.61	100	9850	522
cond	1 if vehicle is in fair/poor condition; 0 if in excellent/good condition	0.55	0.50	0	1	861
spent	how much money was spent to keep the car running in the past year	217.91	137.18	100	600	537
spend	how much money is to be spent to keep the car running another year	187.52	143.66	100	600	537
income	household income	36,663.75	19,985.50	10,000	75,000	571
owned	number of vehicles owned by the household	2.77	1.42	0	16	805
liscdriv	number of licensed drivers in the household	2.09	0.90	0	6	856
waiver	1 if the vehicle has been granted waiver status; 0 otherwise	0.34	0.47	0	1	861
age	years of age of the owner	49.48	15.95	18	92	807

Other variables used in the WTA regressions: lmiles = log odometer miles; lpastyr = log miles driven in the past year; lwvalue = log Blue Book value; lspent = log(spent); lincome = log household income.

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