Market Mechanisms and Incentives: Applications to Environmental Policy

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Resources for the Future
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Market Mechanisms and Incentives: Applications to Environmental Policy

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October 17th – 18th, 2006

October 17, 2006: Market Mechanisms in Environmental Policy

8:00 a.m. – 8:45 a.m.	**Registration**	
8:45 a.m. – 11:45 a.m.	**Session I: Brownfields and Land Issues** Session Moderator: **Robin Jenkins**, EPA, National Center for Environmental Economics	
	8:45 a.m. – 9:00 a.m.	Introductory Remarks: **Sven-Erik Kaiser**, EPA, Office of Brownfields Cleanup and Redevelopment
	9:00 a.m. – 9:30 a.m.	Environmental Liability and Redevelopment of Old Industrial Land **Hilary Sigman**, Rutgers University
	9:30 a.m. – 10:00 a.m.	Incentives for Brownfield Redevelopment: Model and Simulation **Peter Schwarz** and **Alex Hanning**, University of North Carolina at Charlotte
10:00 a.m. – 10:15 a.m.	**Break**	
	10:15 a.m. – 10:45 a.m.	Brownfield Redevelopment Under the Threat of Bankruptcy **Joel Corona**, EPA, Office of Water, and **Kathleen Segerson**, University of Connecticut
	10:45 a.m. – 11:00 a.m.	Discussant: **David Simpson**, EPA, National Center for Environmental Economics
	11:00 a.m. – 11:15 a.m.	Discussant: **Anna Alberini**, University of Maryland
	11:15 a.m. – 11:45 a.m.	Questions and Discussion
11:45 a.m. – 12:45 p.m.	**Lunch**	
12:45 p.m. – 2:45 p.m.	**Session II: New Designs for Incentive-Based Mechanisms for Controlling Air Pollution** Session Moderator: **Will Wheeler**, EPA, National Center for Economic Research	
	12:45 p.m. – 1:15 p.m.	Dynamic Adjustment to Incentive-Based Environmental Policy To Improve Efficiency and Performance **Dallas Burtraw, Danny Kahn,** and Karen Palmer, Resources for the Future

	1:15 p.m. – 1:45 p.m.	Output-Based Allocation of Emissions Permits for Mitigating Tax and Trade Interactions **Carolyn Fischer**, Resources for the Future
	1:45 p.m. – 2:00 p.m.	Discussant: **Ann Wolverton**, EPA, National Center for Environmental Economics
	2:00 p.m. – 2:15 p.m.	Discussant: **Arik Levinson**, Georgetown University
	2:15 p.m. – 2:45 p.m.	Questions and Discussion
2:45 p.m. – 3:00 p.m.	**Break**	
3:00 p.m. – 5:30 p.m.	**Session III: Mobile Sources** Session Moderator: **Elizabeth Kopits**, EPA, National Center for Environmental Economics	
	3:00 p.m. – 3:30 p.m.	Tradable Fuel Economy Credits: Competition and Oligopoly **Jonathan Rubin**, University of Maine; **Paul Leiby**, Environmental Sciences Division, Oak Ridge National Laboratory; and **David Greene**, Oak Ridge National Laboratory
	3:30 p.m. – 4:00 p.m.	Do Eco-Communication Strategies Reduce Energy Use and Emissions from Light Duty Vehicles? **Mario Teisl**, **Jonathan Rubin**, and **Caroline L. Noblet**, University of Maine
	4:00 p.m. – 4:30 p.m.	Vehicle Choices, Miles Driven, and Pollution Policies **Don Fullerton**, **Ye Feng**, and **Li Gan**, University of Texas at Austin
	4:30 p.m. – 4:45 p.m.	Discussant: **Ed Coe**, EPA, Office of Transportation and Air Quality
	4:45 p.m. – 5:00 p.m.	Discussant: **Winston Harrington**, Resources for the Future
	5:00 p.m. – 5:30 p.m.	Questions and Discussion
5:30 p.m.	**Adjournment**	

October 18, 2006:

8:45 a.m. – 9:15 a.m.	**Registration**	
9:15 a.m. – 12:20 p.m.	**Session IV: Air Issues** Session Moderator: **Elaine Frey**, EPA, National Center for Environmental Economics	
	9:15 a.m. – 9:45 a.m.	Testing for Dynamic Efficiency of the Sulfur Dioxide Allowance Market **Gloria Helfand**, **Michael Moore**, and **Yimin Liu**, University of Michigan
	9:45 a.m. – 10:05 a.m.	When To Pollute, When To Abate: Evidence on Intertemporal Use of Pollution Permits in the Los Angeles NOx Market **Michael Moore** and **Stephen P. Holland**, University of Michigan

10:05 a.m. – 10:20 a.m.	**Break**	
	10:20 a.m. – 10:50 a.m.	A Spatial Analysis of the Consequences of the SO_2 Trading Program **Ron Shadbegian**, University of Massachusetts at Dartmouth; Wayne Gray, Clark University; and Cynthia Morgan, EPA
	10:50 a.m. – 11:20 a.m.	Emissions Trading, Electricity Industry Restructuring, and Investment in Pollution Abatement **Meredith Fowlie**, University of Michigan
	11:20 a.m. – 11:35 a.m.	Discussant: **Sam Napolitano**, EPA, Clean Air Markets Division
	11:35 a.m. – 11:50 a.m.	Discussant: **Nat Keohane**, Yale University
	11:50 a.m. – 12:20 p.m.	Questions and Discussion
12:20 p.m. – 1:30 p.m.	**Lunch**	
1:30 p.m. – 4:35 p.m.	**Session V: Water Issues** Session Moderator: **Cynthia Morgan**, EPA, National Center for Environmental Economics	
	1:30 p.m. – 2:00 p.m.	An Experimental Exploration of Voluntary Mechanisms to Reduce Non-Point Source Water Pollution With a Background Threat of Regulation Jordan Suter, Cornell University, Kathleen Segerson, University of Connecticut, Christian Vossler, University of Tennessee, and Greg Poe, Cornell University
	2:00 p.m. – 2:30 p.m.	Choice Experiments to Assess Farmers' Willingness to Participate in a Water Quality Trading Market **Jeff Peterson**, Washington State University, and Sean Fox, John Leatherman, and Craig Smith, Kansas State University
2:30 p.m. – 2:45 p.m.	**Break**	
	2:45 p.m. – 3:15 p.m.	Incorporating Wetlands in Water Quality Trading Programs: Economic and Ecological Considerations **Hale Thurston** and Matthew Heberling, EPA, National Risk Management Research Laboratory, Cincinnati, Ohio
	3:15 p.m. – 3:35 p.m.	Designing Incentives for Private Maintenance and Restoration of Coastal Wetlands **Richard Kazmierczak** and **Walter Keithly**, Louisiana State University at Baton Rouge
	3:35 p.m. – 3:50 p.m.	Discussant: **Marc Ribaudo**, USDA, Economic Research Service
	3:50 p.m. – 4:05 p.m.	Discussant: **Jim Shortle**, Pennsylvania State University
	4:05 p.m. – 4:35 p.m.	Questions and Discussions
4:35 p.m. – 4:45 p.m.	**Final Remarks**	

4:45 p.m. **Adjournment**

Tradable Fuel Economy Credits:
Competition and Oligopoly[1]

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Abstract

Corporate average fuel efficiency (CAFE) regulations specify minimum standards for fuel efficiency that vehicle manufacturers must meet independently. We design a system of tradeable fuel economy credits that allows trading across vehicle types and manufacturers with and without considering market power in the credit market. We perform numerical simulations to measure the potential costs savings from moving from the current CAFE system to one with stricter standards, but that allows vehicle manufacturers various levels of increased flexibility. We find that the ability for each manufacturer to average credits between its cars and trucks provides greater savings than the ability to trade credits across manufacturers in separate vehicle markets. As expected, the greatest savings comes from the greatest flexibility in the credit system. Market power lowers the potential cost savings to the industry as a whole. However, loss in efficiency from market power does not eliminate the gains from credit trading.

Key Words: GHG, Credits, Cost-Benefit, Socio-Economic, Energy Conservation

JEL codes: Q25, Q28, Q30, Q48, Q40

1 Introduction

1.1 Fuel Economy Standard Policy Context

Corporate average fuel efficiency (CAFE) standards established by the US Energy Policy and Conservation Act of 1975 (PL94-163) specify minimum fleet average standards for fuel efficiency that U.S. light-duty vehicle (car and light-truck) manufacturers must meet. Light-duty vehicles produced 59% of transportation CO_2 emissions in 2003 (USEPA, 2005, p. 57) and consume 36% of the oil used in the U.S. (Davis and Diegel, 2004, Tables 1.13, 2.3, 2.4.)

The effectiveness of CAFE standards in raising the light-duty vehicle fleet's fuel efficiency, and other effects of CAFE regulations, have been discussed in a large body of literature. It was debated whether the improvements in average fuel efficiency realized from 1978 (the first year that the CAFE standards went into effect) through 1987 were attained at a reasonable economic cost and whether the CAFE regulations induced undesirable changes in vehicles that could lower their safety (Greene (1990), Crandall and Graham (1989), Nivola and Crandall (1995), Greene (1998)).

Thorpe (1997) found that the CAFE standards have led to a shift toward larger, more luxurious models in the imported Asian fleet and may have led to a decrease in the fleet's average fuel efficiency. In addition, the CAFE standards themselves, by being less restrictive for trucks than for cars, may have had the unintended effect of encouraging the shift in market share from cars to light-duty trucks. The light-duty truck share of new vehicle sales has grown from 9.8% in 1979 to 42.8% in 1997 (Godek, 1997; NHTSA, 1998a, p. 16627). Parry, et al. (2004) examine the social welfare of raising CAFE standards taking into consideration existing externalities. They find that higher CAFE standards can produce anything from moderate welfare gains to substantial welfare losses, depending on how consumers value fuel economy technologies and their opportunity costs.

In 2002 the National Research Council's comprehensive review of the effectiveness and impact of CAFE standards concluded that while the CAFE program has clearly increased fuel economy, certain aspects of the CAFE program have not functioned as intended. These include indirect consumer and safety costs, a breakdown in the distinctions between foreign and domestic fleets, and between minivans, SUVs and cars in the calculation of fuel economy standards, and the artificial creation of fuel economy credits for multi-fuel vehicles.[2] Moreover, the National Research Council concluded that technologies exist that, if applied to light-duty vehicles, would significantly reduce fuel consumption within 15 years (Finding 5).

The availability of improved technologies for fuel economy alone is not sufficient to encourage their widespread adoption. The National Research Council concluded that raising the CAFE standard would reduce future fuel consumption, but that other policies could accomplish this same end at lower cost and greater flexibility. The National Research Council concluded (Finding 11): “Changing the current CAFE system to one featuring tradable fuel economy credits and a cap on the price of these credits appears to be particularly attractive. It would provide incentives for all manufacturers, including those that exceed the fuel economy targets, to continually increase fuel economy, while allowing manufacturers flexibility to meet consumer preferences.”[3]

We investigate the potential cost savings from the implementation of a system of tradable fuel economy credits coupled with higher fuel economy standards. These benefits include the economic cost savings from reduced fuel use, reductions in fuel use and reductions in US GHG emissions from the light-duty vehicle sector.

1.2 Current CAFE Regulations and Standards

Current legislation and regulation requires that each manufacturer of passenger cars or light trucks with a gross vehicle weight rating of 8,500 lbs. (3636.4 Kg) or less manufactured for sale in the US

[2]The majority of members of the Committee on the Effectiveness and Impact of CAFE standards found that down-weighting and down-sizing, in part due to CAFE standards, increased traffic fatalities. Dissenting minority committee members, including David Greene, concluded that the statistical evidence for such safety effects is not conclusive.

[3] Similar views are also expressed by the the National Commission on Energy Policy (NCEP, 2004) and the Pew Center on Global Climate Change (2006).

attain a minimum corporate average fuel efficiency standard (PL 94-163, 49 U.S.C. §32902). Regulations adopted in March, 2006 change the structure of the corporate average fuel economy for light trucks and establishes higher CAFE standards for model year 2008-2011 light trucks (49 CFR Parts 523, 533 and 537). Starting in MY 2011, the CAFE program will include trucks that have a gross vehicle weight up to 10,000 lbs (NHTSA, 2006, p. 17).[4]

The CAFE standard for each manufacturer, *m*, is defined as the sales-weighted harmonic average fuel economy, defined in terms of miles per gallon: E^*_{vo} (49 U.S.C. §32902, §32904). There are separate standards for each vehicle class *v* (passenger car or light truck) and origin of manufacturing for cars, *o* (domestic or foreign).[5] Thus, S_{mvi} are manufacturer *m's* sales in vehicle class *v,* all models *I.* The form of the harmonic average standard is given below. [6]

$$E^*_v \le \frac{S_{mv}}{\sum_i \frac{S_{mvi}}{E_{mv}}}, \quad where \quad S_{mv} = \sum_i S_{mvi} \tag{1}$$

If a manufacturer does not meet the standard, it is liable for a civil penalty of $5.5 for each 0.1 mile per gallon (or $55/MPG) its fleet average falls below the standard, multiplied by the number of vehicles it sold in a given model year in each fleet. Credits are earned when a manufacturer more than attains the standard in any model year. These credits may be carried forward (banked) or carried back (borrowed) for

[4]There are additional other specific rules and guidelines given in the final rule. NHTSA estimates that expanding the truck category will add an additional 240,000 vehicles into the CAFE program in 2011.

[5]For simplicity we do not separate out foreign and domestic car fleets.

[6]New CAFE regulations for light-duty trucks due to be phased in are based on a measure of vehicle size called "footprint," the product of multiplying a vehicle's wheelbase by its track width. The form of the standard is as given in the formula above, except that the standard S_v or target T, for trucks is given as: $T = \dfrac{1}{\frac{1}{a} + \left(\frac{1}{b} + \frac{1}{a}\right)\frac{e^{(x-c)/d}}{1+e^{(x-c)d}}}$ where a, b, c and d are parameters representing maximum and minimum fuel economy targets, footprint values and rates of change targets (NHTSA, 2006, p. 178).

three years on a rolling basis. Important limitations of the current system are that fuel economy credits are not tradable amongst manufacturers nor subclassification for a given manufacturer.[7]

Level of current standards and proposed regulations

The current level of fuel economy standard for passenger cars is 27.5 mpg. The standard is set at 21.0 mpg for light-trucks produced through MY 2005. This rises to 22.2 mpg for MY 2007 (Federal Register, 49 CFR Part 533), and the new standards promulgated by NHTSA raise the standard for light-trucks to 24 mpg by MY 2011 and allow compliance based upon a reformed CAFE standard based on a manufacturer's vehicles footprint.

In their report, the National Research Council determined that the cost-effective average fuel economy could be increased by 12% for subcompact automobiles, up to 27% for large passenger cars and between 25% and 42% for light-duty trucks (depending on size) over the next 15 years (National Research Council, 2002; p. 66).[8] Given these benchmarks, we examine two alternative fuel economy levels, 30% and 40% improvements by 2015. Given a base year fuel economy standard of 27.5 for passenger cars, 30% and 40% improvements implies targets of 35.75 and 38.5 MPG, respectively. The corresponding targets for light trucks are 26.9 and 29.0 (compared to a base level of 20.7), and the combined light-duty fleet numbers are 31.4 and 33.8, versus a 2002 model year weighted average of 24.2. Note that these targets are relative to base year fuel economy standards, (using the MY light truck share of 48.9%) not the base year fleet fuel economy level actually attained (NHTSA, 2003, Table II-6).

2 Market Models of Producer and Consumer Behavior

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[7]An important aspect of the current CAFE system is the value of time flexibility to manufacturers. As shown by Rubin and Kling (1993) in the context of phasing in stricter standards for new vehicles for criteria emissions, a credit system can realize cost savings when firms are allowed to borrow and banking credits even if they do not trade. We examine the value of time flexibility in on-going work.

[8]Cost-effective technologies means combinations of existing and emerging technologies that would result in fuel economy improvements sufficient to cover the purchase price increases they would require holding size, weight, and vehicle performance characteristics constant.

2.1 The Fuel Economy Market Model - Perfect Competition

Given a market for tradable fuel economy credits, we formulate the objective from the perspective of a vehicle manufacturer which maximizes the net private value to consumers of vehicle fuel efficiency plus the revenues from fuel economy credits sold (or purchased) for each vehicle type. The net value of fuel efficiency is the consumer's valuation of vehicle-lifetime fuel savings minus the increase in vehicle cost due to fuel economy technology. We examine two cases of consumer valuation of fuel economy. In our high value case, the representative consumer carefully calculates the value of fuel savings over the full-expected life of the vehicle. Our alternative hypothesis assumes that consumers consider only the first three years of fuel savings but do not discount the savings. In general, this implies that consumers will place less than half as much value on fuel savings. In theory, failing to account for real future fuel savings would represent a market failure, in the sense that real-world consumers would not be acting like the fully informed, rational consumers of economic theory and, thus, the market for fuel economy would not be economically efficient.[9]

Manufacturers could use technology for improving fuel economy to increase performance or to cross-subsidize particular makes and models to alter their distribution of vehicle sales. We expect this latter behavior not to be significant, however, since Greene (1991) has shown that pricing strategies and mix changes are a relatively expensive means for a manufacturer to increase its corporate average MPG.

Other researchers, Parry, et al. (2004) have taken a different approach, one that looks at maximizing social welfare of a representative agent taking into consideration existing externalities (carbon emissions, oil dependency, accidents, and congestion) and preexisting fuel taxes. They find that

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[9]Certainly consumers are heterogenous with differing discount rates and annual vehicle miles of travel. Consumers use their vehicles differently, demand different rates of return, and have different preferences for fuel economy versus other vehicle attributes. To some extent, the differences amongst manufacturers' current fleet fuel economy levels can be explained by the different market segments they serve. No attempt is made here to account for such differences in consumer preferences across manufacturers. For this reason, it is most appropriate to interpret the predicted impacts of alternative standards on manufacturers as being generally indicative of the kinds of impacts the standards may have, rather than as a prediction of the impacts on a particular manufacturer.

raising CAFE could cause significant welfare losses largely (though not exclusively) by lowering the cost per mile driven and exacerbating mileage-related external costs such as congestion, accidents and local pollution. They argue that alternative policies such as broad-based oil and carbon taxes, higher fuel taxes, pay-as-you-drive auto insurance, subsidies for alternative fuel vehicles, and subsidies for R&D into carbon capture technologies are more likely to lead to social welfare improvements.

We agree with Parry et al. that other policies such as higher fuel taxes have desirable efficiency properties.[10] However, we do not agree with their conclusions about the potential negative welfare effects from raising CAFE standards, especially if reformed to allow for additional regulatory flexibility such as credit trading. Where we differ is in looking at the CAFE policy tool in the context of other policy initiatives. Since light-duty vehicle use has many externalities, our view is that this calls for multiple policy tools. In particular, asking fuel efficiency regulations to be responsible for congestion externalities is too much.[11]

2.2 Market Power in Tradable Credits

There are only 15 vehicle manufacturers to whom the fuel economy regulations apply. The top five firms accounted for 82 % of total U.S. sales in 2003, and 84% in MY2004.[12] Moreover, certain fundamentals of the automobile market are not likely to change. Given the economies of scale of automobile production, further consolidation seems more likely than an increase in the number of firms. Given the structure of the CAFE market where credits apply at the manufacturer level, it seems almost

[10] In addition we have informal evidence from discussion with vehicle manufacturers that consumers want a short, 3-5 year, payback on fuel economy technology. Thus, optimally correcting for this myopia via fuel taxes would require very substantial externality taxes given that new vehicles last about 14 - 16 years.

[11] Consider for example the congestion charging system of the City of London (UK). This congestion charging scheme levies a £8 daily charge for vehicles entering or parking within the city center during peak hours. The Department for Transport estimates that congestion has been reduced by 30%, the number of vehicles entering the zone has been reduced by 18%, air pollution from road traffic in the form of NO_x and particulates have been reduced by 12% and green house gas emissions by 19% since the program took effect in February 2003 (Transport for London, 2004a, p. 1, 2004b, p. 4)

[12] The largest manufacturers, in order of MY2004 sales in the U.S. light-duty vehicle market, were General Motors (4.3 million vehicles), DaimlerChrysler (3.2), Ford (2.9), Toyota (2.1) and Honda (1.3). All 10 other manufacturers sold 2.6 million vehicles (NHTSA, 2005)

inescapable that the market *in tradable credits* will be imperfectly competitive: an oligopoly versus an oligopsony with a competitive fringe.

2.2.1 Incentives for the Exercise of Market Power in Credit Markets

The issue of market power in tradable credit markets has been subject to extensive theoretical and empirical research that includes Hahn (1984), Sartzetakis (1997), Ellerman and Decaux (1998), Misiolek and Elder (1989), Malueg (1990), Innes, et al. (1991), Fershtman and Zeeuw (1995), Westskog (1996 and 2001), and Godby (2002). In these papers, either dominant buyers (monopsony or oligopsony) or sellers (monopoly or oligopoly) may be able to exert market power in the credit market or use their market power in the credit market to gain power in the product market.[13]

In the context of GHG emission credits, Westskog (1996) extends Hahn's (1984) model a monopoly with a competitive fringe to a group of nations as acting as Cournot-players with a competitive fringe. The Cournot players act as leaders deciding how many credits to buy or sell given the other Cournot countries' sales or purchases of credits and given the response function of the followers. The competitive fringe acts as followers who choose the optimal amount of credits to sell or buy given the market price of credits resulting from the first move of the leaders. Similar to Hahn, Westskog finds that the least-cost efficient solution will attain only when the countries with market power are given the number of credits that they want to have after credit trading has taken place.

2.3 Defining CAFE Credits

In much of credit literature, the total sum of credits is set by an environmental regulator. With fuel use credits, however, the total number of credits is determined based on a performance standard set

[13]In addition, firms with market power the credit market may engage in exclusionary manipulation to make gains in the product market (Misiolek and Elder, 1989; Godby, 2002, Innes, et al., 1991). Output market manipulation by vehicle manufacturers who also have market power in a CAFE credit market may be a real possibility. At the corporate nameplate level, this type of manipulation would seem likely. At the same time, however, market power in the vehicle output market is not likely to be maintained at the level of specific makes and models where vehicles compete. Moreover, we do not believe it is practical to characterize accurately market power in the vehicle market, especially as it may relate to reactions to CAFE credit market manipulations. We therefore, do not consider further this potential line of inquiry.

by the NHTSA and the number and sales mix of vehicles chosen by manufacturers. Because the CAFE constraint applies to a harmonic average of MPGs, the exposition is much clearer and the analysis is simplified when the standard is written in terms of fuel intensity (gallons per 100 miles, or GPHM) than fuel economy (miles per gallon).[14] Written in fuel intensity G_{mvi} with the standard (maximum fuel intensity) for vehicle class v denoted by G^*_v, the CAFE regulatory constraint on each manufacturer m is linear:[15]

$$G_{mv} \equiv \sum_i \frac{S_{mvi}}{S_{mv}} G_{mvi} \leq G_v^* \tag{2}$$

The market that will emerge, if credit trading is allowed, is a market for fuel-use credits. Credit quantities will be in units of vehicle-GPHM and credit prices will have units of $/veh-GPHM.

2.4 Private Market Model: Perfect Competition

Formally, the manufacturer is assumed to maximize (on behalf of the consumer) the net present value (NPV) of future fuel savings per vehicle minus the incremental cost per vehicle of fuel economy technology. Following the lead of Ahmad and Greene (1993) we simplify by assuming that each vehicle design is essentially fixed except for its fuel intensity. If the initial level of fuel intensity is G^0_{mvi}, and the fractional change in fuel intensity is X_{mvi}, then the firm objective for each vehicle i in class v can be written as a linear expression for fuel savings minus a quadratic function for fuel economy technology cost:

$$\begin{aligned} NPV(X_{mvi}) &= K_v \cdot [G^0_{mvi} - G^0_{mvi}(1.0 + X_{mvi})] - [b_{mv} X_{mvi} + c_{mv} X^2_{mvi}] \\ &= -K_v \cdot G^0_{mvi} X_{mvi} - [b_{mv} X_{mvi} + c_{mv} X^2_{mvi}] \end{aligned} \tag{3}$$

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[14]Thus, a car achieving the 27.5 mpg standard is equivalently using 3.64 gallons per hectomile. A light truck achieving the 20.7 mpg standard is using 4.83 gallons per hectomile.

[15]In this equation and elsewhere we suppress the model index i when referring to the sum over all vehicle models i in class v for manufacturer m, with the understanding that $S_{mv} \equiv \sum_i S_{mvi}$. We also write $G_{jv}* = G_v*$, since all manufacturers face the same fuel intensity (performance) standards.

where parameter K_v is the estimated present value of fuel savings over the lifetime of a typical vehicle in class v for a unit change in fuel intensity (the units of K_v are ($/veh)/GPHM)).

The number of credits produced (number sold net of purchases) Z_{mv} by a manufacturer m is equal to the credit allowance minus the credit demand.[16] That is, the difference between the fuel intensity standard G_v* and the achieved average fuel intensity of its new vehicle fleet G_{mv}, times the total number of vehicles it produced, $S_{mv} = \sum_i S_{mvi}$ in class v. We write the achieved fuel intensity G_{mvi} as the original fuel intensity G^0_{mvi} times one plus the fractional change in intensity X_{mvi}. Let P_v be the price of a fuel use credit for vehicle type v denominated in units of dollars per vehicle-gallons per 100 miles ($/veh-GPHM). That is, P_v is the price per vehicle of relaxing the fuel economy constraint by 1 gallon per 100 miles of travel. The competitive manufacturers problem is:

$$\begin{aligned} &\underset{X_{mvi},Z_{mv}}{Max} \ \sum_i NPV(X_{mvi}) \cdot S_{mvi} + P_v Z_{mv} \\ &s.t.: \ Z_{mv} = S_{mv} \cdot G_v^* - \sum_i S_{mvi} \cdot G^0_{mvi}(1 + X_{mvi}) \end{aligned} \tag{4}$$

Under credit trading, each manufacturer m produces a set of vehicles indexed by i that are in regulated class v, adjusting their fuel intensities to maximize the net value of fuel use reductions *plus* the revenues from fuel use credits sold (or purchased) in credit market v. Note that each credit market v, that is each group of vehicle models, classes and manufacturers that may pool and exchange credits, will have its own credit price P_v.

To solve for the outcomes for all manufacturers, the set of problems for each firm as stated above must be supplemented by overall market constraints on credit balances. The scope and nature of the credit trading market can be represented by sign restrictions on credit production or various sums of credit production across vehicle classes or manufacturers, as shown in Table 1. Finally, because a positive

[16]We use the sign convention that when $Z_{mvi} > 0$ net credit production is positive.

market price for credits can only be sustained if the market constraint on credit balances is actually binding, the market solution, including the determination of credit prices, also requires complementary slackness conditions

Table 1: Summary of Trading Cases and Solution Conditions

Case	Description	Trade Among Veh Classes ?	Trade Among Firms ?	Credit Constraint	Complementary Slackness Cond.
1	No trading among firms or vehicle classes, with a separate standard G_v^* for each vehicle class (corresponds to the current class-based CAFE standard)	N	N	Z_{mvi} *u.i.s.* (*unrestricted in sign*). $Z_{mv} \equiv \sum_i Z_{mvi} \geq 0 \ \forall m,v$	$P_{mv} \cdot Z_{mv} = 0$; $P_{mv} \geq 0 \ \forall m,v$
2	Class Averaging: trading among vehicle classes within each firm, but not between firms. Corresponds to eliminating the vehicle class distinction from current CAFE standard.)	Y	N	Z_{mvi}, Z_{mv} *u.i.s.*, but $Z_m \equiv \sum_v Z_{mv} \geq 0 \quad \forall m$	$P_m \cdot Z_m = 0$; $P_m \geq 0 \quad \forall m$
3	Firm trading within classes (separate standard G^*_v for each vehicle class)	N	Y	Z_{mvi}, Z_{mv} *u.i.s.*, but $Z_v \equiv \sum_m Z_{mv} \geq 0 \quad \forall v$	$P_v \cdot Z_v = 0$; $P_v \geq 0 \quad \forall v$
4	Full (Firm & Class) Trading	Y	Y	$Z_{mvi}, Z_{mv}, Z_m, Z_v$ *u.i.s.*, but $Z \equiv \sum_{m,v} Z_{mv} \geq 0$	$P \cdot Z = 0$; $P \geq 0$

Consider first Case 3, credit trading in separate markets for each vehicle class v (other cases follow analogously). The first order conditions for this problem yield, for manufacturers behaving competitively in the credit market (i.e., for firms behaving as if $dP/dZ_m = 0$):

$$\frac{\partial NPV_{mv}}{\partial X_{mvi}} = P_v G^0_{mvi}, \qquad \forall \ m,v,i \tag{5}$$

The left hand side of **(5)** is interpreted as the marginal net present value per vehicle of a change in fuel use of a particular manufacturer's vehicle model. This must be equal to the price of a credit for fuel use weighted by the base fuel use for that model. We expect that at the optimum d*NPV*/d*X* will be positive: the CAFE constraint is binding and relaxing fuel intensity yields greater avoided technology costs than increased fuel costs. Vehicle production (S_{mvi}) drops out of the optimality condition because both the marginal value of fuel intensity and the marginal cost of credits are proportional to vehicle production.

For a competitive manufacturer, the credit price will equal the marginal cost of producing a credit. The credit price will be non-zero if the credit constraint (the aggregate fuel economy constraint for members of the credit market) is binding. Note that $-G^0_{mv}$ is the marginal change in credit supply per unit increase in fuel intensity, that is $\partial Z_{mv}/\partial X_{mvi} = -S_{mvi}G^0_{mvi}$. Thus

$$P_v = \left(\frac{\partial NPV_{mvi}}{\partial X_{mvi}}\right) \Big/ G^0_{mvi} = -\left(\frac{\partial S_{mvi}NPV_{mvi}}{\partial X_{mvi}}\right) \Big/ \left(\frac{\partial Z_{mvi}}{\partial X_{mvi}}\right) = -\left(\frac{\partial S_{mvi}NPV_{mvi}}{\partial Z_{mvi}}\right) \quad \forall m,v,i \qquad \textbf{(6)}$$

Stated another way, we see that at the optimum, each *competitive* manufacturer adjusts the fuel intensity of its vehicles *i* to balance the marginal cost of producing another credit with the credit price. If the aggregate fuel intensity constraint over the whole tradeable credit market is non-binding, the credit price will fall to zero. Manufacturers will then alter their fuel intensity until their marginal net benefit is zero.[17]

In summary, we can state that with a competitive market for fuel economy credits it is optimal for manufacturers to sell or buy credits as long as the market price is higher or lower than their own marginal cost of providing any given level of net fuel economy benefit. In competitive equilibrium, marginal net fuel economy benefits are equalized across all manufacturers.

[17] Some manufacturers may be expected to increase fuel intensity in this case.

2.7 Private Market Model with Market Power in Credits

Cournot-Nash Strategy for CAFE Credits

Models of oligopoly require specific assumptions on the behavior of the actors. Well known analytical solutions exist for the special case of the duopoly: the Cournot solution, in which the two suppliers act simultaneously by anticipating the other's reaction function, and the Stackelberg solution in which one supplier takes the price leadership in anticipating the other's reaction function. In the Stackelberg case, the oligopolist offers thereafter a maximum profit supply quantity. Based on market projections on the supply side, we anticipate that Japanese manufactures are potential Stackelberg actors. Technically, Japanese manufacturers would reduce their quantity of credits sold to the market to achieve maximum profits. Other oligopolistic approaches are n-actor cooperative and non-cooperative games. In all cases, solutions depend critically on behavioral characteristics that are difficult to determine.

In the models of imperfect competition and credit trading, it is typical for the market price of credits to be a function of the difference between the total allotment of credits, exogenously set by a regulator, and those used by the dominant firm.[18] With fuel use credits, however, the total number of credits is determined based on a performance standard set by the NHTSA and sales S_{jvi} and fuel economy X_{jvi} of vehicles chosen by vehicle manufacturers. The price of credits, will nonetheless, still be a function of the level of net credit sales Z_{kv} (sales less purchases) by the dominant firms k.

We partition the set of manufacturers M into a subset of oligopolists, M_o, and a subset of competitive ("fringe") firms, M_F. Following the approach of Westskog (1996), we let each Cournot oligopolist player $j \in M_O \subset M$, take as given the net supply Z_k of fuel economy credits by other Cournot players (for $k \neq j$) and recognize the competitive firms' price taking behavior.[19] The price-taking behavior of the competitive fringe implies that the market price of credits is a function $P(Z_O)$ of the total

[18] See for example, Hahn (1984), Innes et al. (1991) and Westskog (1996).

[19] This assumes that there are no negotiations between manufacturers, i.e., no cooperation.

net supply of credits by oligopolistic firms Z_O.

The profit-maximizing problem for a non-competitive firm j is then to determine the change X_{jvi} in fuel intensity for each of its vehicles, and the total supply of fuel economy credits Z_{jv} to maximize vehicle value plus credit sales revenue:

$$
\begin{aligned}
&\underset{X_{jvi},Z_{jvi}}{Max} \sum_i [NPV(X_{jvi}) \cdot S_{jvi} + P_v Z_{jvi}] \\
&st: \\
&P_v = P_v\left(\sum_{k \in M_O} Z_{kv}\right) = P_v(Z_{jv} + Z_{\sim jv}) \quad \forall\ v,\ j \in M_O \\
&Z_{jvi} = S_{jvi} \cdot G_v^* - S_{jvi} \cdot G_{jvi}^0 (1 + X_{jvi}) \\
&Z_{jv} \equiv \sum_i Z_{kvi} \\
&Z_{\sim jv} \equiv \sum_{k \in M_O, k \neq j} Z_{kv} = fixed\ if\ Cournot
\end{aligned}
\qquad \mathbf{(7)}
$$

Assuming vehicle production quantities S_{jvi} (and therefor shares) are fixed, but initial fuel intensity G_{jvi}^0 is varied by the fractional change X_{jvi}, the Lagrangian first order conditions yield the non-competitive analog to Eq. **(21)**:

$$
MV\ Permit_{jv} = \frac{\partial NPV_{jv} / \partial X_{jvi}}{G_{jvi}^0} = \left[P_v + \frac{\partial P_v}{\partial Z_{jv}} Z_{jv}\right] \quad \forall\ j,v,i \qquad \mathbf{(8)}
$$

The left hand side of **(8)** can be interpreted as the marginal net present *economic* value of an fuel intensity credit for a manufacturer j's vehicle class v. That is, it is the marginal economic value of a fractional change in fuel intensity of all models of class v ($dNPV_j/dX_{jvi}$) divided by the marginal number of credits needed per unit-change in fuel intensity ($dZ_{jv}/dX_{jvi} = G_{jv}^0$). For a net credit seller, $Z_{jv} > 0$, this marginal value of a credit must be equal to the marginal revenue from selling an additional fuel use credit times the market share of that vehicle model and it's original fuel use (intensity). Since $[P_v + (\partial P_v/\partial Z_{jv})Z_{jv}] < P_v$ for credit sales from a firm with market power, this means that there is less incentive to decrease the fuel intensity of a manufacturer's fleet of vehicles (and thereby earn credit revenues) as compared to a competitive credit market. For a net credit buyers, $Z_{jv} < 0$, the opposite result obtains for price, $[P_v + (\partial P_v / \partial Z_{jv}) Z_{jv}] > P_v$. Here, vehicle manufacturers face higher prices of fuel use credits than under a competitive market and thereby purchase fewer fuel use credits. Thus, market power in the fuel use credit market causes both oligopolistic buyers and sellers to produce and consume fewer fuel intensity credits as compared to the competitive market situation.

This result is similar to those of Hahn (1984) and Westskog (1996). One important difference is that in their models, the total number of credits is set by a regulator. They note that, in principle, a regulator could ameliorate market power by assigning firms with market power the number of credits that the firms would want to hold after trading takes place. A variation of this solution is available in this market, regulators could assign different fuel intensity requirements on manufactures. This is because there is no set number of credits issued in this market; the credits are defined in terms of intensity, not an absolute number per period. The result is the regulatory structure which regulates efficiency, and leaves the number of vehicles sold by each manufacturer unregulated.

Implementation of the Cournot-Nash Solution

We implement the Cournot-Nash solution extending the approach of Westskog (1996). In her model there is a residual demand for credits from competitive fringe firms, $f \in M_F \subset M$, that take credit prices as given. With this distinction between the sets of fringe firms M_F and Cournot oligopoly firms M_O we have $M_F \cup M_O = M$, and total fringe demand for credits is:

$$Z_{Fv}(P_v) = \sum_{f \in M_F} Z_{fv}(P_v), \quad where\ P_v = P_v(Z_{Fv}) \tag{9}$$

From **(5)**, we know that a competitive fringe firm *f* will change fuel intensity until the marginal net cost of generating a credit is equal to the credit price. Taking the derivative of the net benefit function per-vehicle, we get the fringe's inverse demand curve for credits

$$P_v(Z_{fv}) = -[k_{1v} G_{fv}^0 + b_{fv} + 2c_{fv} X_{fvi}] / G_{fv}^0 \tag{10}$$

where, k_{1v} represents the effective discounted vehicle lifetime value of fuel use of vehicle class v. Parameters b and c represent a quadratically increasing cost of fuel technology as fuel intensity is reduced via adding more efficient vehicle technologies.[20] Solving for X_{fv} yields fringe firm f's optimal fuel intensity change (percentage increase) for vehicle i class v, as a function of credit price.

$$X_{fvi}(P_v) = -\frac{b_{fv} + [k_{1v} + P_v]G_{fv}^0}{2c_{fv}} \quad \textbf{(11)}$$

Then, using our expression for the net supply of credits **(3)** we can solve for each fringe firm f's demand for credits Z_{fv} for vehicles of class v in terms of the credit price set via the Cournot firms. Summing over the individual fringe firms and vehicle classes yields an aggregate demand for credits from the fringe.

$$Z_{Fv}(P_v) = \sum_{f\in M_F} Z_{fv}(P_v) = \sum_{f\in M_F}\left[G_v^* S_{fv} - \sum_i G_{fv}^0 \cdot S_{fvi}\left[1 - \frac{b_{fv} + [k + P_v]G_{fv}^0}{2c_{fv}}\right]\right] \quad \textbf{(12)}$$

The units for fuel intensity are gallons per hundred miles and the units for credits are vehicle-gallons per hundred miles (veh-GPHM). We can group terms and simplify to highlight that the total fringe supply is a linear function of price,

$$\begin{aligned}
Z_{Fv}(P_v) &= Z_{FSv}^* - Z_{FD0v} + \Delta Z_{Fv}(0) + \alpha_v P_v \\
Z_{FSv}^* &\equiv \sum_{f\in M_F} G_v^* S_{fv} \\
Z_{FD0v} &\equiv \sum_{f\in M_F}\sum_i G_{fv}^0 \cdot S_{fvi} \\
\Delta Z_{Fv}(0) &\equiv \sum_{f\in M_F}\sum_i G_{fv}^0 \cdot S_{fvi}\left(\frac{b_{fv} + kG_{fv}^0}{2c_{fv}}\right) \\
\alpha_v &\equiv \sum_{f\in M_F}\sum_i G_{fv}^0 \cdot S_{fvi}\left(\frac{G_{fv}^0}{2c_{fv}}\right)
\end{aligned} \quad \textbf{(13)}$$

The newly-defined terms in this equation correspond for vehicles of class v to the total credits allocation to the fringe Z_{FSv}^*, total initial credit demand (at base intensity) for the fringe Z_{FD0v}, fringe net

[20] We drop the subscripts on the b and c cost parameters for notational ease. In the simulations, b and c are manufacturer and vehicle class specific.

supply if credit price were zero $\Delta Z_{Fv}(0)$, and the rate of credit supply increase with price, α_v.

We invert the linear supply function to yield the price function for credits from the totality of fringe firms:

$$P_v(Z_F) = \frac{\beta_v}{\alpha_v} + \frac{1}{\alpha_v} Z_{Fv}, \quad where, \qquad \beta_v \equiv -(Z^*_{FSv} - Z_{FD0v} + \Delta Z_{Fv}(0)) \tag{14}$$

In the oligopoly-with-competitive fringe model, each oligopolistic firm *j* anticipates the effect of its production on total supply, and thereby on market price. Oligopolist firms know the credit supply response of the fringe, Z_F, and make a conjecture about the response of other oligopolistic firms, $Z_{o\sim j}$. Each oligopoly firm *j* recognizes the balance constraint for the market in credits (all Z's represent *net* supply from firms in the credit market):

$$Z_{Fv} + Z_{jv} + Z_{O\sim j,v} = 0, \quad \forall \quad v, j \in M_O \qquad \text{where,} \quad Z_{Fv} \equiv \sum_{f \in M_F} Z_{fv} \qquad Z_{O\sim j,v} \equiv \sum_{k \in M_O,\, k \neq j} Z_{kv} \tag{15}$$

From the balance equation the oligopolist *j* can infer how fringe supply must vary for an increase in his supply Z_j:

$$\frac{dZ_{Fv}}{dZ_{jv}} = -1 - \frac{dZ_{o\sim j,v}}{dZ_{jv}} \tag{16}$$

A critical assumption of any oligopoly model is the "conjectural variation" cv_j or assumed response of other oligopoly firms to a change in supply from firm *j*, denoted $cv_j \equiv \partial Z_{o\sim j}/\partial Z_j$. In the Cournot oligopoly model the hypothesized conjectural variation is zero, hence $dZ_{Fv}/dZ_{jv} = -1$, and

$$\frac{dP_v}{dZ_{jv}} = \frac{dP_v}{dZ_{Fv}} \frac{dZ_{Fv}}{dZ_{jv}} = -\frac{dP_v}{dZ_{Fv}} \tag{17}$$

Using this Cournot anticipated price response, and the fringe inverse supply curve **(12)** in the oligopolist's first order conditions for profit maximization, **(8)**, we get the following necessary condition for each oligopolist.

$$-\frac{[k_{1v}G_{jv}^{0} + b_{jv} + 2c_{jv}X_{jv}]}{G_{jv}^{0}} + \left[\frac{1}{\sum\limits_{f\in M_F}\sum\limits_{i}\left(\frac{(G_{fv}^{0})^{2}S_{fvi}}{2c_{fv}}\right)}Z_{jv}\right] = P_v, \qquad \forall\ v, j\in O \tag{18}$$

This establishes the optimal behavior of Cournot oligopolists with respect to price.

Thus, a Nash solution to the Cournot oligopoly problem is to simultaneously satisfy the equations in **(18)** and **(10)** by equating all of the left-hand sides to one-another, and the credit balance equation $\sum\limits_{m\in M} Z_{mv} \geq 0.$ Additionally, we impose the complementary slackness conditions shown in Table 1 to address the cases in which the credit price collapses to zero.

3 Model Parameterization

3.1 Parameterization for Fuel Savings

We need to estimate the parameter K_v, that represents the consumer's present discounted value of fuel economy of vehicle class *v*. Given that vehicles have a relatively short lifespan for a major capital expenditure, we assume that consumers treat fuel economy technology as a depreciating asset. This implies that the consumer will demand a higher rate of return for an investment in fuel economy than for an investment in a non-depreciating asset. The rate of return consumers will demand for fuel economy improvements will be primarily determined by the expected life of the vehicle, L_v, and the rate of decline in use of the vehicle.[21] Although higher rates of return on fuel economy investments could be argued for,

[21]Data from Oak Ridge National Laboratory show that the median lifetime for a 1990 vintage car or truck is 16.9 and 15.5 years respectively (Davis and Diegel, Tables 3.6 and 3.7). National survey data indicate that new private automobiles and trucks travel 15,000 and 17,500 miles, respectively, in their first year of operation (Davis and Diegel, Tables 3.6 and 3.7). However, these same data shows that vehicle use (miles driven) declines with vehicle age, which implies declining annual fuel savings. We take as a reasonable approximation in the rate of decline in use for cars and trucks to be 4.0 and 3.0 percent respectively (USDOT, 2004, Davis and Diegel).

12%/year will be used as a base case assumption for this analysis.

Clearly, consumers do not know what future fuel prices will be. We model consumers as having static expectations over fuel prices. That is, consumers will assume that the future price of fuel will be the same as the current price at the of vehicle purchase. We use the Energy Information Administration's 2012 reference case 2012 forecast price of $1.51 and "high B" forecast of 1.84 cents per gallon (EIA, 2005, Table 12). The price of fuel *P* is unaffected by choices about vehicle fuel economy, and average vehicle economy for the fleet of new vehicles.

We make the additional assumption that the utilization of each vehicle (vehicle miles traveled per year) *M* is fixed for each vehicle class, regardless of choice of fuel economy F. If vehicle owners drive more with a higher fuel efficiency vehicle then we are underestimating the value of fuel economy purchased.

Given these estimates we are now able to estimate K_v the consumer's present discounted value of fuel economy of vehicle class *v* as the lifetime discounted miles driven, M_v, times the current fuel price in year y, P_y, applying the declining use rate γ_v and the discount rate ρ_v. Note that we divide the number of miles through by κ=0.85 to discount test-value mpg numbers to reflect real-world performance.[22]

$$K_v = \frac{PM_v}{\kappa}\left(\frac{1.0}{\gamma_v+\rho_v}\right)\left(1.0 - e^{-(\gamma_v+\rho_v)L_v}\right). \qquad \textbf{(19)}$$

Only the monetary costs and benefits of fuel economy will be considered since fuel economy technologies are assumed hedonically neutral. That is, except for their impacts on fuel economy and vehicle price, they do not enter into a consumer's purchase decision or affect a consumer's satisfaction with a vehicle. Thus, our base case cost curves do not include diesel and hybrid technology. While this may understate the fuel economy technology available, the NAS technologies are nearly invisible to the

[22]Consumers typically achieve lower fuel economy in actual on-road driving than the EPA dynamometer test MPG numbers (e.g., Hellman and Murrell, 1984). Although there is evidence that the shortfall for trucks may be larger than that for passenger cars (Mintz et al., 1993), the average shortfall of 15% implied by EPA official correction factors is used here for both vehicle types.

consumer. This is not necessarily true for diesels and hybrids. These technologies may penetrate the market in different ways in terms of consumer tradeoffs. Diesel and hybrid technologies can be added to the NAS list, but they will be disruptive, superior, to the other technologies on this list. Changes in the hedonic value due to changes in vehicle attributes are not only difficult to predict, but difficult to value, as well. [23]

3.2 Fuel Intensity Cost Curves

We use data for MY 2003 vehicles sold in the United States, obtained from the National Highway Traffic Safety Administration (NHTSA) Manufacturer's Fuel Economy Reports. These give us vehicle manufacturers sales and fuel economy by vehicle class (8 cars and 7 truck) and country of origin (foreign or domestic). Not all manufacturers have product offerings in all vehicle type categories. Moreover, examination of the weight and horsepower, and fuel economy data also confirms that manufacturers' product offerings differ somewhat even within vehicle size/class categories. For example, the average fuel economy of a compact car from BMW is lower than that of Ford.

The National Research Council's presents low and high retail equivalent price estimates for a low and high range of incremental fuel efficiency gains by individual technologies for 4 car and 6 truck classes (NRC, Tables 3.1 -3.4) .[24] In particular, we use National Research Council's "emerging" (path 3) technologies . Except for camless valve actuation and variable compression ratio technologies, the rest of the technologies are either implemented on some vehicles now or are capable of being implemented in the time frame of the National Research Council's analysis. This is conservative assumption because it does

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[23] Beyond these practical reasons, we also do not include hybrid and diesel vehicles since they are still expected to make up only a small amount of the market in the time frame of our analysis. The EIA's Annual Energy Outlook 2005 reference case projects hybrid car and diesel new car sales to be 5.8% and 0.3% by 2016 (EIA AEO, p. 29). The EIA notes that regulations pending implementation in California would regulate the greenhouse gas emissions of light-duty vehicles in California. If this legislation is also adopted by other states that have adopted California vehicle emission standards (New York, Maine, Massachusetts, and Vermont), this could lead to a 11.0% and 0.9% of total new car sales to be hybrid and diesel by 2016 (EIA AEO, p. 29). These regulations are currently being challenged in federal court.

[24]For cars and trucks these include: subcompact, compact, midsized, large, (trucks) SUV-Small, SUV-Mid, SUV-Large, Minivan, Pickup-Small, Pickup-Large.

not include diesel or hybrid technology.

We use the National Research Council's high and low retail costs with low and high efficiency gains to generate low, average and high retail costs of fuel efficiency improvements that encompass the full range of cost and performance uncertainty. Before mathematical functions are fitted to the data, the technologies are ranked by a cost-effectiveness index, equal to the percent improvement in fuel economy divided by the price increase. This procedure ensures that technologies are implemented in order of increasing marginal cost, in accordance with economic theory. Engineering knowledge and judgment is also employed to ensure that combinations of technologies do not violate technological feasibility. The technology cost curves we develop, therefore, represent an aggregate description of the industry's ability to supply fuel economy, rather than a technical plan for improving the fuel economy of a particular vehicle. This generates low, average and high cost curves for 4 car and 6 truck class of vehicles.

A recent review of the technology cost literature indicated that two-parameter quadratic curves fit data from all studies reasonably well (Greene and DeCicco, 2000). The two-parameter quadratic cost function is shown in **(20)**.

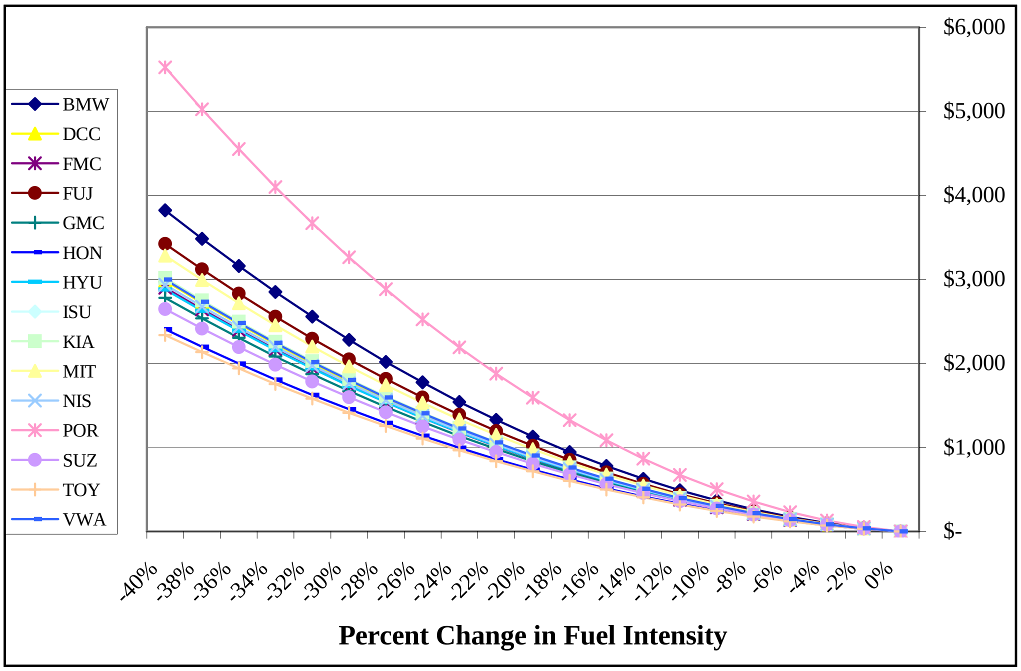
$$P(X) = bX + cX^2 \tag{20}$$

P(x) is the retail price (cost) increase to the percentage decreases in gallons per 100 miles over a base level, G^o , and b and c are parameters to be estimated. By construction, the curves pass through the origin (0% improvement has $0 cost). The parameter estimates are intended to be curve fits and not statistical estimations. The important point is that the fitted curves accurately reflect the rate of increase in retail price for a percent decrease in fuel intensity for the full range of fuel economy improvements being considered. This generates a high, average and low cost curve for each the National Research Council's 10 vehicle types. The two-parameter quadratic functions fit the data very well, with adjusted R-squared values exceeding 0.98 in all instances.[25]

[25]For a few of the low cost, high decrease in fuel intensity cases we dropped a outlier data points at the high end to improve the fit of the curves for low decreases in fuel intensity range.

We then generate manufacturer-specific cost curves by weighting both of the estimated coefficients for the 10 size classes and vehicle types by the manufacture specific sales-weighed average of vehicles and fuel intensities. For example, to generate a particular vehicle manufacturer's cost curve for cars, we combine the sales-weight average of the parameters for the 4 size classes produced by that manufacturer and weighted by fuel intensity of that manufacturer. We show of estimates for the average cost and performance case in Figure 1.

Figure 1: Fuel Intensity Costs by Manufacturer (Average of Costs for Cars and Trucks)



4 Results

4.1 Percentage Cost Savings

In order to explore the potential cost savings from allowing more regulatory flexibility by credit trading we examine 4 possible credit trading scenarios. These scenarios reflect increasing amounts of flexibility, starting from the base case that does not allow any credit trading by manufacturers consistent with current CAFE regulations (see Table 2).

Table 2: Credit Trading Scenarios

Scenario Name	Credit Trading Among Firms	Credit Trading Among Vehicle Classes	Scenario Description
Base (No Trading)	No	No	Firms must independently meet separate standards for cars and trucks
Class Averaging	No	Yes	Firms trade credits across vehicle classes (but not among firms)
Class Trading	Yes	No	Credits trade amongst firms but in separate car and truck markets
Firm & Class Trading	Yes	Yes	Firms can trade credits in a single a single market

In addition, for those scenarios that allow credit trading among manufactures, we allow varying degrees of competition, from an assumption of perfect competition to the case where we assume that our 5 largest competitors (General Motors, Ford, DaimlerChrysler, Toyota and Honda) each act as independent oligopolists. To test the sensitivity of our parameter assumptions we also examine each of these cases assuming low and high valuation of fuel economy by consumers, base and high projects of gasoline prices, and low, medium and high costs and effectiveness of the fuel economy technology. Given the large number of permutations of cases, we focus on deviations from our base case: no credit trading among vehicle type or manufacturers, low valuation of fuel economy cost savings by consumers, average costs of fuel economy technology and base projections of fuel prices. This scenario is closest to representing the current CAFE regulations with conservative assumptions concerning the valuation of fuel economy and average cost assumptions. One minor point in which we differ from the current regulatory outcome, is that we insure that each manufacturer does comply with the CAFE regulations rather than fall short and pay the fines as noted earlier.[26]

[26]Historically, only BMW, Porsche and the manufacturers of a few other specialty high-performance cars actually have paid fines rather than meet the standard (NHTSA, 2005)

Table 3: Percentage Cost Savings due to Trading
(Base Case with Perfect Competition - High Fuel Economy Target*)

Scenario Name	Base Case	Low Cost of Fuel Economy Technology	High Cost of Fuel Economy Technology	High Future Gasoline Prices
No-trading Cost ($/vehicle)	*+$44*	*-$374*	*+$806*	*-$44*
Class Averaging	90%	1%	14%	86%
Class Trading	56%	1%	8%	50%
Firm & Class Trading	128%	1%	19%	119%

*Base case: no credit trading among vehicle type or manufacturers, low valuation of fuel economy cost savings by consumers, average costs of fuel economy technology and base projections of fuel prices, all firms joint net benefits and a 40% increase in fuel economy by 2015. Savings are percentage cost reductions relative to the cost of increasing fuel economy under the no-trading baseline (current policy).

Shown in data column 1 of Tables 4 and 3 are the percentage costs savings to all manufacturers taken together from allowing trading of fuel economy credits under our base case assumptions and assuming perfect competition. The difference between the two tables is the level of increased fuel economy required; Table 4 assumes and increase of 30% and Table 3 assumes an increase of 40% by 2015. What stands out, as expected, is that the highest level of regulatory flexibility, firm and vehicle class trading, yields the greatest savings. Given the construction of our cost curves and the market shares of the vehicle manufacturers, we find that “class averaging” (allowing vehicle manufacturers to trade fuel economy credits across their vehicle classes) provides the next greatest level of savings. This is followed by class trading among manufactures where manufacturers can sell or buy a car and truck credits with other manufacturers in separate car and truck markets.

That a significant portion of the total savings available is from class averaging within firms is of particular importance in term of possible non-competitive behavior. This portion of savings will not be affected by the possible oligopolistic or oligopsonistic withholding of credit trades from the market in order to drive credit prices up or down. Note that adding the percentage saving between class averaging and class trading yields a greater level of savings than complete flexibility that allows both of these trades to occur simultaneously. This shows that the regulatory flexibility of class averaging and class trading are, to some extent, substitutes. However, the magnitude of the substitution effect does not appear great.

As shown in data columns 2-4, the magnitude of the percentage savings depends substantially on the particular scenario under examination, but the same pattern of savings across the trading systems remains unchanged. What is clear is that if our base scenario assumptions are correct, the cost savings from fuel economy credit trading are quite substantial, possibly in excess of 100% of the net costs of increasing fuel economy by 30% or 40% under the current regulatory regime.

Table 4: Percentage Cost Savings due to Trading
(Base Case with Perfect Competition - Low Fuel Economy Target*)

Scenario Name	Base Case	Low Cost of Fuel Economy Technology	High Cost of Fuel Economy Technology	High Future Gasoline Prices
No-trading Cost ($/vehicle)	*-$21*	*-$377*	*+$495*	*-$94*
Class Averaging	127%	0%	15%	25%
Class Trading	99%	0%	13%	18%
Firm & Class Trading	187%	0%	23%	36%

*Base case: no credit trading among vehicle type or manufacturers, low valuation of fuel economy cost savings by consumers, average costs of fuel economy technology and base projections of fuel prices, all firms joint net benefits and a 30% increase in fuel economy by 2015. Savings are percentage cost reductions relative to the cost of increasing fuel economy under the no-trading baseline (current policy).

Looking at the cost savings under alternative assumptions, a few points stand out. First, there is a very large range in the retail cost and the technological effectiveness presented in the NRC's data. As a result the low and high cost cases present very different views. In the low cost/high technological effectiveness case (data column 2), there are effectively no cost savings from trading because the imposed higher CAFE standards are essentially not binding on the industry as a whole. Similarly, the percentage gains from trading are significantly less under the high fuel economy cost/less effective technology case (data column 3) than the base case. This is because the manufacturers as a group have less ability to find savings through averaging and trading. They all must significantly increase the use of fuel economy technology. Thus, the added flexibility is still valuable in absolute terms, but the savings, as a percentage of overall costs from the no-trading baseline, are much reduced. The magnitude of the savings, not surprisingly, is therefore highly dependent upon the accuracy of the NRC's estimates of the costs and effectiveness of the fuel economy technology. Similarly, looking at the final column we see that higher future gasoline prices increase the value of additional regulatory flexibility (trading) by enhancing the value to consumers of the additional fuel economy technology.

As discussed earlier, given the large proportion of vehicles produced by the 5 largest manufacturers, the effect of market power in the price and availability of fuel economy credits needs to be examined explicitly. In Tables 6 and 5 we show the percentage cost savings from 3 different cases of imperfect competition relative to two different baselines, given the base case assumptions used earlier. The first column of each table repeats the savings shown above assuming perfect competition in the credit markets. The 3 non-competitive cases make different assumptions about which manufacturers act as oligopolists: all 5 major manufacturers, only Honda and Toyota, or only (what was formerly called) the big three US firms (Ford, General Motors, DaimlerChrysler). As before, the cost savings shown are for all manufacturers jointly. Now especially, since we examine the impact of market power, the gains to individual manufacturers from credit trading will vary. Individualized impacts are examined later.

Table 5: Percent Cost Savings Due To Trading

(Comparison Across Various Non-Competitive Cases - High Fuel Economy Target)

	Perfect Comp	All 5 Majors		Honda & Toyota		US Big 3	
Scenario Name	Relative to Base	Relative to Base	Relative to PC Case	Relative to Base	Relative to PC Case	Relative to Base	Relative to PC Case

Class Averaging	90%	90%	0%	90%	0%	90%	0%
Class Trading	56%	47%	-21%	55%	-2%	55%	-3%
Firm & Class Trading	128%	124%	-13%	128%	-1%	127%	-1%

For each case of imperfect competition, the first column indicates the cost savings relative to its *own baseline of no averaging or trading*, while the second column shows the cost savings *relative to the equivalent trading scenario under perfect competition scenario*. For example in Table 6 we see that when the big five each act as independent Cournot oligopolists, the savings from being able to average and trade is 69% compared to the no trading baseline. This is a reduction in savings of 15% from averaging and trading when the credit market is perfectly competitive.[27] Note that the savings due to class averaging (trading among classes within each firm) are not affected by non-competitive behavior; this is shown in the table by the zeros relative to the perfectly competitive case.

Since this scenario posits oligopoly sellers and oligopoly buyers with a competitive fringe, determining who is able to extract the most gains is a numerical question. As is seen in Tables 6 and 7, when only Toyota and Honda or only the US big three act as oligopolists, the losses in efficiency are quite small. As we see below, gains and losses from imperfect competition are larger for individual companies compared to the market as a whole.

Table 6: Percent Cost Savings Due to Trading

(Comparison Across Various Non-Competitive Cases - Low Fuel Economy Target)

	Perfect Comp	All 5 Majors		Honda & Toyota		US Big 3	
Scenario Name	Relative to Base	Relative to Base	Relative to PC Case	Relative to Base	Relative to PC Case	Relative to Base	Relative to PC Case

[27] Since the baselines are different in the two columns, the percentage changes should not add across columns.

Class Averaging	127%	127%	0%	127%	0%	127%	0%
Class Trading	99%	69%	-15%	97%	-1%	93%	-3%
Firm & Class Trading	187%	174%	-5%	187%	-0%	186%	-1%

4.2 Firm Compliance Costs

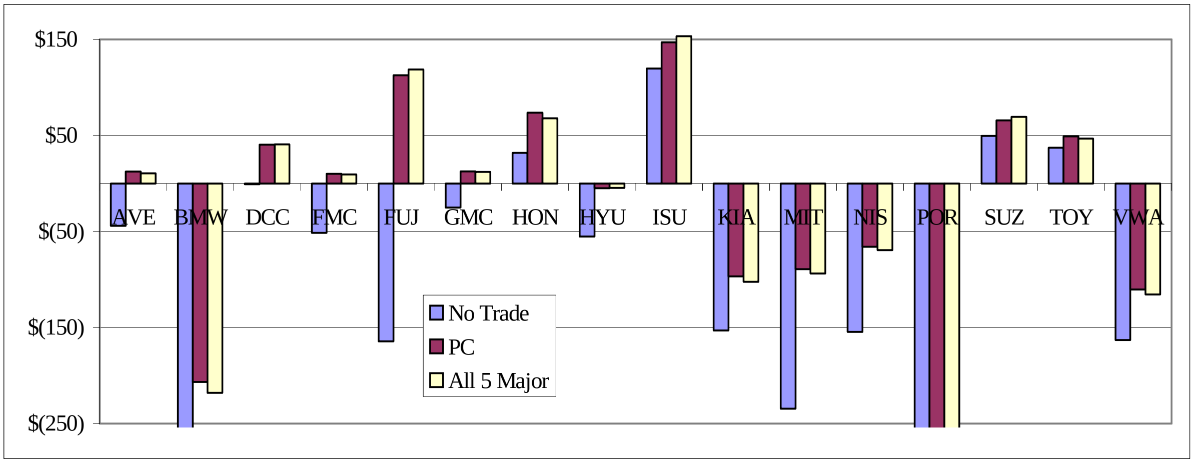


Figure 2: Net Present Value per Vehicle including Net Credit Sales (Base Case)

What matters from an individual firm's perspective is the net cost of compliance. Apart from technology costs and consumers perceptions of the value of future cost savings, these cost are determined from the degree of regulatory flexibility available and from the possible effects of non-competitive behavior in the market place. In Figure 2 we show the net revenues (positive and negative depending on manufacturer) of credit sales to the net technology and fuel costs. This figure captures our estimate of the average net total cost of compliance to a 40% increase in CAFE standards given the base case assumptions detailed above. For all manufacturers we see that allowing vehicle manufacturers to average and trade fuel economy credits lower the cost of compliance. As is seen in this figure, the magnitude of savings can be quite substantial for some manufacturers, less so for others. Importantly, for all manufacturers, both net sellers and net buyers, oligopolistic behavior, as we have modeled it, by the big five manufacturers does not substantially diminish the savings from being able to trade fuel economy credits.

Beside lowering the potential gains from credit trading, market power also affects the price of credits. Using the base case assumptions, with credit trading across classes and manufacturers yields the following credit prices for different scenarios of imperfect competition. These include assuming that all firms act perfectly competitively (PC), and the following groups act as Cournot oligopolists: Honda and Toyota (H&T), Ford, GM DaimlerChrysler (US 3), and Honda, Toyota, Ford, GM and DaimlerChrysler (All 5).

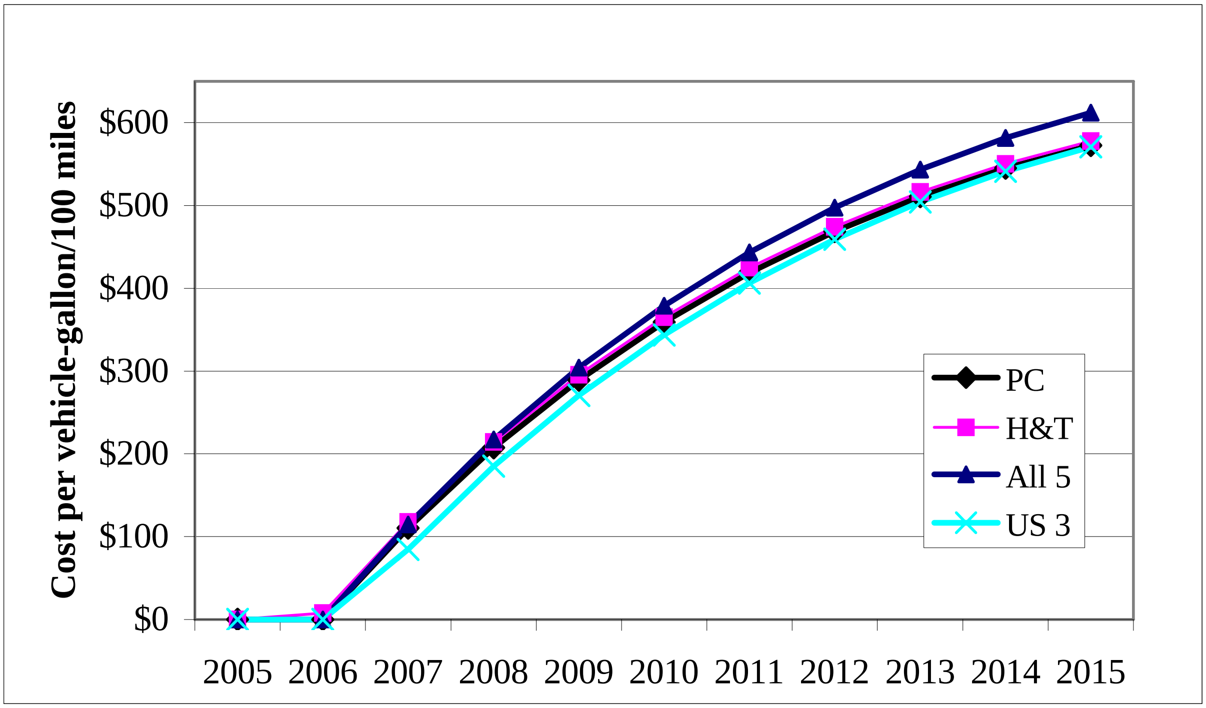


Figure 3: Credit Prices for Different Levels of Imperfect Competition

As is seen, the credit price is zero for the first year under all scenarios reflecting the gradually phased in stricter standards. As credit prices rise reflecting tighter standards, the divergence between the perfectly competitive price (PC) and the oligopoly prices grows. As expected, the credit price is slightly below competitive level when the net buyers (“US 3") act non-competitively, and slightly above the non-competitive price when the net sellers (“H&T”) act non-competitively. The largest divergence occurs when the big five sellers each act as independent oligopolists (All 5).

Besides the market price of credits, however, is the behavior of firms, and therefore application of fuel economy technology, based on their marginal value of an additional credit. Fringe firms equate their marginal value of a credit to the price of credits. Cournot firms, however, following **(18)**, regardless of whether they are net buyer or sellers, anticipate the effect of their own purchases and sales on the market price. This divergence between the market price of credits and the marginal value to Cournot firms is the source of inefficiency that reduces the gains from trade available in a perfectly competitive market.

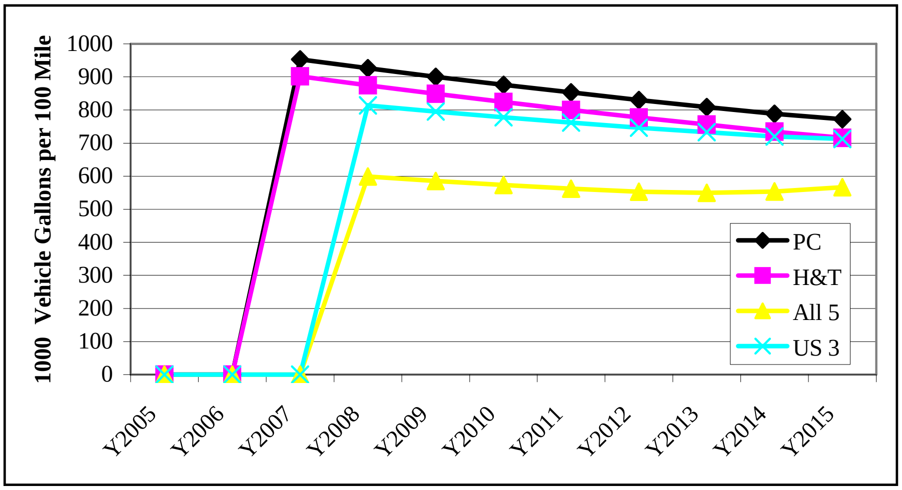


Figure 4: Credit Volume by Levels of Competition, Base Case

While the market price for credits could be higher or lower under oligopoly-verses-oligopsony trading than under perfect competition, depending on the relative market power of buyers and sellers, theory tells us the net effect of non-competitive supplier and demander behavior is always to reduce trade volumes. This is because both non-competitive buyers and sellers reduce their market transactions to limit their anticipated adverse effects on the market price of credits. This phenomenon is seen in Figure 4. Here in the most extensive case of market power we explore, all 5 major manufacturers behaving non-competitively, the credit volume drops about 35% compared to the perfectly competitive benchmark. Note credit volumes are zero for the first year or two reflecting a zero price for credits given that the standards are not initially collectively binding.

5. Final Comments

Depending upon the case, the net cost of tightened fuel economy standards to the industry as whole may be quite large or small. This uncertainty reflects the large range of possible costs of fuel economy technology, uncertain future gasoline prices, and ambiguity regarding how consumers value future fuel economy savings. The results in this paper show how the net costs also depend on the level of future fuel economy standards, the flexibility of the standards, and the degree to which a tradable credit market is affected by non-competitive behavior. Resolving uncertainty over the engineering costs of increasing fuel economy at the firm and industry level and improving our understanding of consumers' valuation of fuel economy is clearly needed.

For cost scenarios that impose significant costs on individual vehicle manufacturers, we find the savings from averaging and trading credits to be quite substantial. The greatest proportional savings exceeded 100% in some cases, reflecting the fact that, to the industry as a whole, average costs per vehicle went from a net negative to a net positive value. The scenarios that show large percentage gains from trade generally reflected the middle range of net costs - where there were substantial imposed costs on some, but not all, manufacturers from increased fuel economy standards. In cases where the net costs were lower (low cost of fuel economy technology or high consumer valuation of fuel economy improvements), the gains from trading were small or non-existent reflecting the largely non-binding nature of increased fuel economy targets. At the other extreme, when fuel economy improvements were expensive, the percentage gains from being able to average and trade credits were considerably smaller (while the absolute gains in dollars-per-vehicle were greater). For many of the scenarios, the ability of each manufacturer to average credits between its car and truck classes provides greater savings than the ability to only trade credits between manufacturers in separate vehicle class markets. As expected, the greatest savings comes from the greatest flexibility, when manufacturers are able to average and trade fuel economy credits.

Given the high concentration of vehicle sales by the five largest firms, we explicitly examined the potential impact of market power in the credit markets. We modeled the largest firms as Cournot oligopolists facing a competitive fringe. The theoretical effect of imperfect competition on fuel economy credit price (compared to a perfect competition benchmark) is ambiguous since firms with market power are both sellers and buyers. Our numerical simulations show that there is a small increase in the price of credits when all five of the largest firms act as oligopolists, and seek a Cournot-Nash equilibrium. However, both sellers and buyers of credits have an incentive to reduce their net credit transactions in order to influence to the credit price. We find that the volume of credit sales can be up to 35% less compared to the perfectly competitive benchmark.

As expected, the existence of market power did lower the potential cost savings to the industry as a whole. However, the magnitude of the potential losses in efficiency from the market power were not large, less than 25% of the potential savings from trade in all cases when considering the industry as a whole. Since some firms are net sellers and some net buyers, individual firms experienced greater gains or losses from trading when taking market power into consideration than did the industry as a whole. Importantly, every firm was still better off from credit trading with imperfect competition compared with our no trading baseline. Imperfect competition in credits does not appear to eliminate all the gains from trading at the firm level and has relatively modest impacts on the industry as a whole.

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Do Eco-Communication Strategies Reduce Energy Use and Emissions from Light Duty Vehicles?

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Abstract

The widespread use of eco-marketing and labeling strategies suggests they are perceived effective in promoting eco-conscious buying. However, some have been skeptical about the touted environmental and economic benefits of these programs. We present results from an ongoing study designed to test the effectiveness of a voluntary eco-communication program in the light-duty passenger vehicle market. Our results indicate consumers do value the benefits of greener vehicles but that the current state of eco-communication in this market is limited. We find that producers are reluctant to participate. It thus remains an open question whether a voluntary eco-communication program in the light-duty vehicle market will lead to an environmentally sustainable outcome.

Introduction

The environmental characteristics of products have become increasingly important to consumers. Firms have responded by placing information on existing products that highlight the product's environmental attributes and by introducing new, or redesigned, "green" products. Governments and non-governmental organizations have also responded by organizing, implementing, and verifying environmental labelling and marketing programs (hereafter, eco-information programs) that cover thousands of products in more than 20 countries [1]. Recently, the State of Maine has implemented the *Maine Clean Car Campaign* (hereafter the Campaign) - a cooperative effort of Maine's Department of Environmental Protection (DEP), the Maine Automobile Dealers Association (MADA) and the Natural Resources Council of Maine. The goal of the Campaign is to educate Mainers about the effects of vehicle air pollution and to inform them about differences in vehicle emissions. From a policy perspective, one aim of eco-information programs is to educate consumers about the environmental impacts of product consumption, thereby leading to a change in purchasing behavior, and ultimately, to a reduction in environmental impacts.

In the light-duty vehicle (cars, truck, minivans, SUVs) market, product regulation, while very effective in cases where consumers have no impact on outcomes, such as the elimination of lead in gasoline, are less effective when consumers can choose vehicles with different levels of environmental performance. This is seen most dramatically in the market shift from cars to light-duty trucks in the United States since 1975 when light-duty trucks had a market share of 21% to 2004 when their market share rose to 55% of all new passenger vehicles [2, Table 4.6]. This may well reflect that consumers' were unaware of the differences in the environmental performance of cars and trucks. Effective implementation and regulation of eco-information programs may allow customers to make choices that clearly reflect their environmental preferences while simultaneously achieving policy objectives (e.g., reductions in fossil fuel use and air emissions). Finding policy tools complementary to, or as a substitute for, command-and-control regulations is important. Indeed, the success of voluntary agreements, such as the Memorandum of Understanding between the Government of Canada and the Canadian automobile industry to limit GHG emissions from new vehicles, depends, in part, on the ability of vehicle manufacturers to sell consumers more fuel efficient vehicles [3].

Eco-communications programs may not achieve their objectives unless consumers are willing to pay for the underlying improvements in the production practices specified by the program. Earlier work has indicated that there is a portion of consumers who state they are willing to pay a premium for environmentally better vehicles. [4] [5] [6]. However, in addition to being willing to pay, consumers must also notice, understand and believe the information presented to them by the product manufacturer. Because the promise of improved production practices is impossible for most consumers to verify, the success of eco-labeling uniquely hinges on companies being able to credibly communicate to the consumer that some vehicles are environmentally better than others.

Although studies indicate a demand for 'greener' vehicles, no one has studied whether an eco-information program is effective in *altering* consumers' attitudes toward, or purchases of, environmentally preferred vehicles. It is, thus, an open question whether informed customer choice in the light-duty market will lead to these outcomes. Recent implementation of the Campaign provides an excellent opportunity to identify whether eco-information programs are effective. This study focuses on documenting the ability for eco-information to alter consumer attitudes because these are important antecedents to environmentally preferred behavior. We focus on the vehicle market because this market is of particular concern to policy makers. This concern arises in part from the fact that nationally, light-duty vehicles produce 62 percent of transportation CO2 emissions (including international bunker fuels). Combustion of fossil fuels to power transportation was the single largest source of greenhouse gas emissions in the U.S. economy in 1999 [7]. Light-duty vehicles are also responsible for 18 percent of nitrogen oxide (NOx), 45 percent of carbon monoxide (CO), and 26 percent of volatile organic compounds [7]. This is also true in Maine where on-road vehicles are the largest source of in-state created air pollution.

Design of the Maine Clean Car Campaign

There are two main parts to the Campaign. One part (eco-labeling) focuses on providing information to vehicle shoppers at the point-of-purchase (car and truck dealerships); although providing some educational benefit, the primary purpose of the eco-labeling is to provide information to improve consumers' ability to make cross-product comparisons. This dealer-based information consists of brochures explaining the Campaign, and placement of Clean Car stickers (Figure 1) in the window of new, environmentally better vehicles. The label indicates the vehicle:

- has a highway fuel economy rating of 30 miles per gallon or better; and
- is classified as a low emission vehicle by the U.S. Environmental Protection Agency.

Although the Maine Auto Dealers Association is an active partner in this Campaign, we should emphasize that active participation of individual dealers is solely voluntary. Indeed, one aspect of this research is to measure the level of participation among dealers, and the level of knowledge or awareness among sales people at the dealership.

The second part of the Campaign primarily focuses on educating Mainers about Maine's air quality,[1] its link to motor vehicles and to heighten awareness of the Campaign. This is important as research has shown that the credibility and effectiveness of an eco-labeling program is dependent upon consumer familiarity with the program [8].

The eco-marketing has several components. First, is the Campaign website (www.LEVforME.com) that provides detailed information about vehicles and their contribution to air quality problems. In addition, the Campaign uses newspaper and radio advertisements[2] that provide eco-information messages including information about the Campaign and the Campaign website. The eco-marketing portion of the Campaign started on January 31st and, except for the weeks of March 7, April 18 and May 30,[3] ran continuously until June 13th in several Maine newspapers and on radio stations of various formats (e.g., light rock, classic hits, and country music). Newspaper ads ran three times a week (Thursday, Friday and weekend editions) as banners (Figure 1) and were located on the third page of the front section. In total there were 20 different versions of the newspaper banner ads that where rotated within, and across weeks, to enhance repetition of messages across weeks while remaining 'fresh' (i.e., we did not run the same add on all three days of the week). All of the banner ads were designed to look similar, all carried a general environmental message related to vehicle emissions and all carried a representation of the eco-label. In aggregate, the 20 banner ads were displayed in the newspapers 153 times during the marketing treatment period.

Because one purpose of the research component of the project is to document the effects of the Campaign, the above eco-marketing program was only administered to one portion of the state. Hereafter, the portion of the state where the eco-marketing was administered is referred to as the treatment group and the remaining portion of the state is referred to as the control group.

[1] Both in terms of criteria pollutants and global warming gases.
[2] The marketing materials (brochure, website, radio and newspaper advertisements) were designed with a Portland-based firm - BFT International LLC©.
[3] The weeks of March 7 and April 18 were school vacation weeks and May 30 was the week of Memorial Day holiday weekend.

Design of the University of Maine Study

The goal of the project is to determine whether the eco-labeling and marketing program had any impact on producer (vehicle dealers and sales personnel) knowledge and behaviors, and consumer knowledge, perceptions and behaviors. To determine impacts on producers we analyzed observational data collected from vehicle dealerships in Maine. To determine impacts on consumers we collected and analyzed two sources of data. First, we examined the level of activity being generated by the Campaign's website. Second, we analyzed changes in survey responses to a mail survey administered twice (before and after the marketing program) to independent samples of individuals residing in and out of the marketing treatment areas. Thus, our survey-based research design is quasi-experimental, with pre- and post-test measures from a treatment and a control group. This design helps isolate the impact of the eco-information program. Currently, we are almost through analyzing the survey data and are beginning the analysis of the market data; in turn, this paper will focus on only the survey results.

Literature Review

Economic theory suggests demand for a product or service is a function of a number of factors; one of these being the tastes and preferences of consumers. Traditionally, economists have been rather ill-equipped at incorporating tastes and preferences in their models (often proxied by socioeconomic characteristics). Yet, social psychologists have a rich literature focusing on what constitutes tastes and preferences.[4] This literature suggests a person's eco-behavior is positively influenced by their level of environmental involvement, perceived consumer effectiveness, and their faith in the eco-behavior of others. Barriers to environmentally friendly consumption include when individuals perceive that purchasing eco-products entails some increased inconvenience, cost or risk, or entails accepting a decrease in product quality. Teisl also finds that the amount of information can alter the perceived credibility of a label [10]. In general, adding information increases a label's credibility; however, adding some types of information could actually decrease it.

Methods

Observational study of vehicle dealers

To determine the level of dealer participation in the eco-marketing, we had several student employees attempt to visit all car and truck dealers who were members of the Maine Automobile Dealers Association (MADA) during the previous year. Visits to dealers were performed from June 24 to July 22, 2005; this was toward the end of the marketing treatment. Of the 134 eligible dealers, 105 were visited for a 78 percent visitation rate.

During a visit, the students would indicate to dealers that they were interested in purchasing a vehicle and were interested in an environmentally friendly vehicle. Students would mention the Maine Clean Car Campaign by name, and indicate they had learned of the program via radio or newspaper ads. They would then request additional information from the dealer including: a) looking for vehicles displaying the vehicle sticker, b) a brochure and c) where additional information regarding this program may be obtained (i.e. websites). Students would also enter the showroom to ascertain whether brochures or stickers were displayed in the showroom at each dealership. Additionally, students would look at vehicles on the lot which qualify for the program to confirm whether stickers were present on these vehicles.

For each visited dealership, students recorded whether the dealership displayed the Campaign's stickers on qualifying vehicles, and whether the Campaign brochure was available (displayed in the showroom or provided by a salesperson when requested). Students also recorded whether the

[4] See [9] for a more complete review of this literature.

salesperson knew about the Campaign's or DEP's websites where information about qualifying vehicles is listed. Finally, the students recorded qualitative information about the apparent level of knowledge exhibited by the salesperson.

Analysis of these data is along two fronts. First, we want to document the level of dealer participation in the Campaign to help us determine the relative importance of dealer-based eco-labeling versus non-dealer provided eco-marketing. Second, we want to analyze the factors that influence dealer participation in the Campaign, and the factors influencing sales personnel knowledge of the Campaign. In this paper we will use descriptive statistics to provide some analysis supporting the first objective.

Campaign website activity

All of the eco-marketing materials (brochures, newspaper and radio advertisements) related to the Campaign contained a website address. This website address was included for two reasons. First, previous research has indicated that the presence of a website address can increase the credibility of an eco-label [10]. Second, the website allowed us to reduce the level of detail presented in the marketing materials; this provided more interested consumers the ability to seek out more information while simultaneously reducing the potential for information overload occurring for less interested consumers.

The website (www.levforme.com) consists of a home/welcome page, and several content and ancillary pages. One content page ("What's the problem?") presents information about the environmental problem and its link to vehicle emissions whereas another page ("What can you do?) presents suggestions on how to be a more environmentally conscious driver/vehicle owner. Others pages are devoted to presenting background information about: the project partners ("Who are we?"), the sticker (eco-labeling) program, the components of the eco-marketing program ("See & hear the campaign") and more academic reports generated by the project ("Want more info?").

To determine the quantity and quality of website activity we collected the following daily web statistics; number of unique visitors to the site, number of hits, length of visit and pages visited. We use descriptive statistics to analyze these data.

Consumer mail survey

In May of 2004 and 2005, approximately 1.4 million vehicle registration records were obtained from the Maine Bureau of Motor Vehicles; the records (our sampling frame) represent everyone who registered a vehicle in Maine within the previous 12 months. A random sample of approximately 2,000 was generated each year from the frame with approximately 800 records removed because they were inappropriate or contained incomplete information. For example, records were rejected if the: primary address was outside the state, vehicle was listed as homemade, registration was for a non-passenger vehicle (e.g., utility trailers) or records did not have a valid vehicle identification number. Multiple registrations were also removed.

Between June and August of each year, we administered a mail survey to final random samples of 1,148 and 1,163 (2004 and 2005 surveys respectively) Maine adults who had registered vehicles in Maine. In total, 620 Maine residents responded to the 2004 survey and 691 responded to the 2005 survey, for responses rates of 60 and 64 percent, respectively. In general, our respondents are similar to the characteristics of the Maine adult population as measured by the recent U.S census, except in terms of gender. Although our survey respondents are more likely to be males, relative to the U.S. census, the proportion of males correctly reflects the underlying percent of males in the vehicle registration data.

The survey instrument consisted of seven sections with forty-one questions. Sections I and II solicited respondents' opinions on air quality in Maine, the relationship between motor vehicles and air pollution, and environmental protection in general. Section III asked respondents about their current vehicle, including the type of vehicle and the importance of various attributes considered during the purchase decision. Section IV respondents were asked about their search and use of environmental information in the vehicle purchase decision. Sections V and VI incorporated an experimental label test and a vehicle choice experiment, respectively. The final section of the survey, Section VII, collected demographic characteristics.

To evaluate the success of the eco-marketing program we need to examine whether the Campaign altered people's environmentally-related knowledge and perceptions as these have been shown to be important antecedents to supporting eco-behaviors. To determine whether the eco-marketing program affected these psychological variables we estimated a series of models which differ in their dependent variables but were of the general form of:

$$DEP = \alpha + \beta_1 YEAR + \beta_2 MKT + \beta_3 GEN + \beta_4 AGE + \beta_5 ENV + \beta_6 ED + \beta_7 INC + \Sigma_k \beta_{8k} REC_k + \beta_9 NOREC$$

where DEP denotes the dependent variable which varies across equations (see Table 1 for definitions of all variables). The dependent variables included one variable to measure exposure to the Campaign information (SEE), one behavioral variable (SEARCH) and various perceptual/psychological measures (WANT, DLR, IMP, CONC, AQUAL, LSTYLE, 2HARD, MOST, WTP, LAWS, TRST, ALLS, LPERF, and COST). SEE is our most basic measure of the campaign's success as an information program cannot succeed unless it is first noticed and recognized. WANT, DLR and IMP denote whether respondents want information that helps them identify vehicles that produce less pollution when driven, find auto dealers are good at providing this type of information and measure the importance a respondent places on eco-label information. We asked a series of questions (CONC, AQUAL) to determine Mainers' opinions of Maine's current level of air quality;[5] increased levels of concern should indicate an increased likelihood for the Campaign to succeed.

The variables of LSTYLE, 2HARD, MOST, WTP, LAWS, TRST, LPERF, and COST are coded from respondents reactions to a set of perceptual statements aimed at measuring their general perceptions regarding their personal environmental impact, others' willingness to work to improve the environment, whether science or the state can effectively reduce air pollution. Responses to the first set of questions (LSTYLE, 2HARD) provide information about whether individuals see themselves as being able to improve the environment through the choices they make. Presumably, individuals who see their choices as having an environmental impact are more likely to take notice of Maine's Clean Car Campaign. The second set of questions (MOST, WTP) is meant to measure individuals' perceptions of others' level of environmental involvement; responses to these questions have several possible interpretations. Individuals who perceive that other people are environmentally involved may feel increased pressure to act similarly (a 'peer-pressure' effect). Alternatively, these individuals may think that, since others are doing their share for the environment, they do not need to do anything to improve the environment (a 'free-rider' effect). The third set of questions (LAWS, TRST) is meant to measure individuals' perceptions about whether they think the state is capable of improving or safeguarding environment quality. The last set of questions (LPERF, COST) was aimed at seeing what people view as some of the perceived tradeoffs when buying a greener vehicle. Individuals who see greener vehicles as being inferior substitutes are less likely to respond positively to the Campaign.

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[5] The question only asked about general air quality concerns and did not differentiate between criteria pollutants and global warming gases. However, other research indicates that vehicle buying decisions are driven more by a concern with global warming gases [9].

ALLS measures whether respondents think all vehicles pollute about that same when driven; eco-labeling, dependent upon the idea there are significant eco-differences across products, should be less important to individuals holding priors that there are no environmental differences across vehicles.

Results

Participation by vehicle dealers

Of the 89 dealerships, only 10 (11 percent participation) displayed the Campaign sticker on its vehicles and only 10 (11 percent) had the Campaign brochure available; only four dealerships (four percent) provided both the labels and the brochure. Sales personnel knowledge of the Campaign or DEP websites was also low; only two (two percent) of the contacted salespeople knew about the Campaign website and only four (four percent) knew about the DEP website. In terms of a general knowledge on the environmental characteristics of vehicles, sales people did rather better; 22 (25 percent) exhibited some awareness or knowledge of the Campaign and 13 (15 percent) knew about vehicles meeting California's emission standards. In terms of a willingness to assist the customer, five of the contacted salespeople used their computer to link to the Campaign or DEP websites.

Overall, we find these results from dealerships particularly disappointing. Perhaps, however, we should not be surprised. In our discussions with the Maine Auto Dealers Association we stressed that all full-line vehicle manufacturers would have some vehicles that qualified for the label. Hence the label could be used as a positive selling point to consumers who value the environmental performance of their vehicles. This positive approach presumes that dealers are indifferent to which vehicles they sell. This may not be borne out in practice. For purposes of inventory management or because of differences in per vehicle profits, dealers may prefer to sell low scoring vehicles (or not draw attention to the fact that some of their vehicles score low). This may lead dealers to consciously choose not participate in the sticker program and not educate their sales staff. Whatever the cause, the low-level awareness of sales people at the dealerships in the sticker program shows that a voluntary approach to vehicle labeling may not be effective in promoting a positive sales approach to clean vehicles. It would be interesting to test whether a mandatory approach to vehicle labeling would be more effective in selling environmentally friendly vehicles.

Campaign website activity

Descriptive statistics indicate there was a relatively strong increase in website activity once the newspaper and radio advertisements began at the end of January (Figure 2). Before the Campaign there were only 10 visitors/122 hits during the month of January. After the Campaign, this rose to 85 visitors/3,000 hits (during February); which settled to an average of 150 visitors per month and 2,200 hits per month over the next few months. Initially there were a greater numbers of hits to the site relative to the number of visitors. This difference declined after the first few months of the campaign. This would seem to indicate that initially, there were a greater number of visitors making repeated hits to the site. Interestingly, the level of website activity was maintained for about six months after which it began to increase (except for a decline in activity during the summer of 2006) – this was occurring months *after* cessation of radio and newspaper advertising. Apparently, the website continued to attract attention and it is currently unclear why this occurred. It could be that 'word-of-mouth' advertising (either by previous website users or by sales personnel at dealerships) began generating its own stream of new visitors. It could also be an artifact of how internet search engines operate; as sites generate more hits they move up the ranking of most search engines – leading to a future increased level of traffic. We are continuing to examine the data to try and explain what caused this phenomenon;

however, we have noticed that a percentage of our visitors are from outside the state (in fact, some of our visitors are from outside the US). This may indicate that news of the website may be spreading from among eco-conscious web-users.

The number of visitors/hits seems to indicate a positive eco-marketing effect; however, the data on length of visit (average visit length was 4 ½ minutes) indicates that most visits lasted for less than half a minute (Table 2). This may indicate that many visitors were simply searching for some quick information to establish the legitimacy of the campaign or link to another site (e.g., using the website to link to Maine DEP site which lists the vehicles qualifying for the eco-label). Alternatively, it could mean that many visitors only stumbled onto the site by accident and then left immediately. We do not know which explanation is more likely, however, data on which pages were being visited suggests that many visitors were indeed searching for some more information. Most visitors went beyond the welcome/home page of the site and visited other pages. The most popular page (54 percent of visits) was the one presenting information about the environmental problem and its link to vehicle emissions ("What's the problem?"). Three pages ("What can you do?, "Who are we?" and "See & hear the campaign") were tied for the second most popular; each being visited by 11 percent of visitors.

Regression analysis: Changes in consumer perceptions and norms

We begin this section by presenting the results from the regressions, starting with some general observations of the impacts of individual characteristics, followed by a discussion focusing on the impact of the marketing treatment. Although we present the parameter estimates related to an individual's participation in outdoor recreation activities due to paper length we will not discuss these results.

<u>Respondents' perceptions and experiences with environmental information</u>

Males are less likely to want environmental information about vehicles; probably because they see this information as being less important (Table 3). In contrast, older individuals are more likely to search for information about how much pollution the vehicle generate and desire this information. More educated individuals and environmentalists are the most positive about the value of environmental information; they both tend to see the information as important and desirable, and search for this type of information when they are looking to buy or lease a vehicle.

<u>Respondents' perceptions of the environmental problem</u>

Males are generally less concerned about Maine's air quality relative to females (Table 4). They are less likely to think that their lifestyle has an impact on the environment and are more likely to think that it's too hard for someone like them to do much about the environment. However, males tend to think that most others are doing their part to protect the environment. Interestingly, males tend to think that current air pollution laws are strong enough but are less likely to trust the state government to protect the environment.

Older individuals are more concerned about Maine's air quality and tend to rate Maine's current air quality as poor. Similar to males, older respondents are more likely to think that its too hard for someone like them to do much about the environment and that most other people are willing to pay higher prices to protect the environment. Unlike males, older respondents tend to think that current air pollution laws are too weak but they are more likely to trust the state government to protect the environment.

Individuals who claim to be environmentalists are more concerned about Maine's air quality and tend to rate Maine's current air quality as poor. They are more likely to think that their lifestyle has an impact on the environment and less likely to think that it's too hard for someone like them to do much about the environment. Interestingly they have a more negative view of others' environmental behaviors. Not surprisingly they tend to think that current air pollution laws are too weak.

More educated individuals are generally less concerned with Maine's air quality. They are less likely to think that it's too hard for someone like them to do much about the environment. More educated individuals have a more negative view of others' and the state's environmental behaviors.

Respondents' perceptions of vehicles

Males, older and more educated individuals are less likely to hold the view that all vehicles pollute about the same when driven (Table 5). Older individuals tend to think that environmentally better vehicles suffer from poorer performance but are less likely to think that these vehicles are more expensive. Environmentalists are more positive about environmentally better vehicles; they are less likely to think that these vehicles suffer from poor performance or are more expensive.

Impacts of the marketing treatment

In each equation, the intercept parameters measure the average baseline (2004) level of the dependent variable (both for the treatment and control groups). The parameter on YEAR measures the change in the average responses of individuals who were not exposed to the eco-marketing campaign (the control group) during 2005 whereas the parameter on MRKT provides similar measures for individuals who were exposed to the marketing (treatment group) in 2005.Thus, to measure whether there was any impact on consumer perceptions and experiences we need to examine both the parameters on YEAR and MRKT (Tables 3, 4 and 5) and test whether there are significant differences between these parameters (Table 6). We use linear hypotheses tests to indicate whether the parameters on YEAR and MRKT are statistically different from each other.

In total we have 16 equations and we find that responses from individuals exposed to the marketing treatment are in the desired direction in 15 of them, and significant in five of the equations. Importantly, individuals exposed to the marketing treatment are significantly more likely to recognize the Campaign eco-label, a minimum requirement of the eco-marketing program. Additionally, we find that individuals exposed to the eco-marketing have a more pessimistic view of Maine's current level of air quality and are more likely to view current air pollution control laws as weak. Movements in these variables should increase the effectiveness of the eco-labeling portion of Campaign.

We also find that individuals exposed to the eco-marketing place a greater faith on the state's abilities to protect Maine's environment and in other people's willingness to pay for environmental protection. This is consistent with Bamberg's [11] contention that normative expectations of others may be a positive factor in an individual's behavior and by Gould and Golob's [6] work, where they indicate the positive behavior of others influences drivers' sense of personal responsibility for vehicle air pollution.

That the other "correct" effects of the marketing program are insignificant does not necessarily indicate a general ineffectiveness of eco-marketing programs. Analyzing responses to any marketing program is similar to analyzing a dose-response function. The potential magnitude of the effect is related to the size of the 'dose'. On several fronts, our marketing effort was of a relatively low dose: the entire program cost less than $125,000, did not use other available media (e.g., television) and ran for only about four and a half months. In addition, the low level of participation among dealers and the low level of awareness and knowledge among sales personnel likely limited the overall impact of program. Finally, some of our perceptual measures are more general and are likely to be ones that are less amenable to a significant marketing effect. The fact that we find correct impacts in all but one equation suggests a stronger marketing effort would be associated with more significant, positive responses.

Conclusions

The flow of information among market participants can play a critical role in the efficient operation of markets. In a broad sense, eco-information programs have the ability to convert a market in which all goods feature an attribute that consumers can't observe, or may not know about, into one in which consumers can or do. From a policy perspective, these programs allow consumers to make choices which match personal preferences and may provide information that actually changes people's preferences. From a business perspective, these programs may allow firms using particular techniques to gain market share.

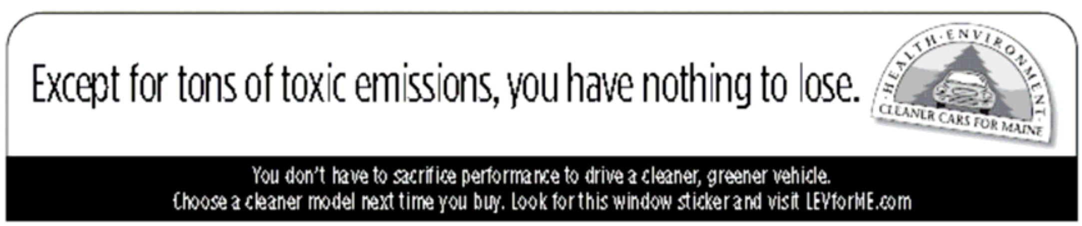
The results indicate the potential importance of well-designed eco-labeling and marketing strategies. The ability of eco-marketing information to alter the underlying psychological factors (both social and personal norms) shown to be important in eco-buying behavior suggests a strong (or perhaps new) role for the long-run provision of information through eco-marketing or eco-education programs. Providing eco-labels without an eco-marketing program to alter consumers' prior perceptions (especially when they are incorrect) may lead to less effective programs.

The reverse may also be true; providing eco-marketing without a strong eco-labeling component can also limit the programs effectiveness. For example, one of the prime messages of the eco-marketing portion of the Campaign was that vehicles are significantly different in their environmental characteristics. However, more than half of the respondents (approximately 60 percent) stated they thought most vehicles pollute about the same; in stark contrast to the reality of car and truck pollution. The success of an eco-information strategy in the vehicle market is contingent on people understanding that the choices they make in buying a vehicle can have significantly different impacts on the amount of air pollution generated. Yet even after exposure to the eco-marketing campaign, respondents have an imperfect appreciation for the large differences in the amount of air pollution produced by different types of vehicles. This continuing misperception is probably due to the lack of vehicle-specific emissions information (eco-labeling) present in the market. According to our survey results, almost half of our respondents (47 percent) visited a car or truck dealership within the last year; however, most of these consumers were never exposed to vehicle-specific emissions information because only a minority of dealerships participated in the Campaign. Presumably, if more dealers participated (or were made to participate) then consumers would be more familiar with the eco-labels and be more cognizant of the differences between vehicles.

Figure 1. Example of the Maine's Clean Car sticker (eco-label), placed on all new vehicle models meeting the Clean Car Program standards, and an example of a newspaper banner advertisement.

Eco-label

Newspaper banner ad



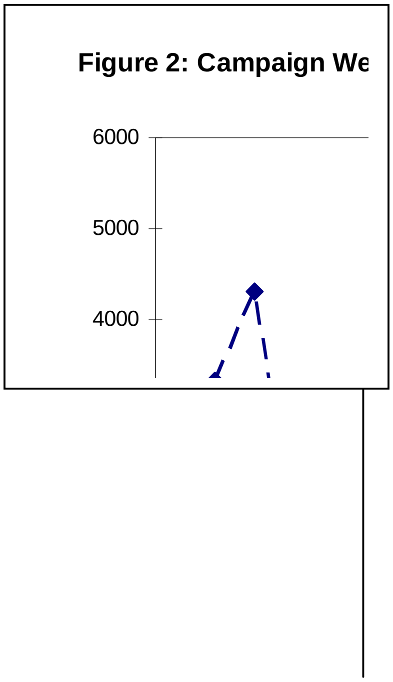


Figure 2: Campaign We
6000
5000
4000

Table 1. Variable names and descriptions

Name	Description
Dependent variables	
SEE	Coded 1 if respondent saw the campaign's eco-label; 0 otherwise
SEARCH	Coded 1 if respondent stated before buying or leasing a new vehicle they searched for information about how much pollution the vehicle produces
WANT	Coded 1 if respondent wants information helping them identify vehicles that produce less pollution; 0 otherwise
DLR	Coded 1 if individuals find auto dealers are good at providing information about how much air pollution a vehicle makes; 0 otherwise
IMP	The importance a respondent places on eco-label information (1 = 'not at all important' to 5 = 'very important')
CONC	The individual's concern over the amount of air pollution in Maine (1 = 'not at all concerned' to 5 = 'very concerned')
AQUAL	The individual's rating of Maine's air quality (1 = 'very bad' to 5 = 'very good')
LSTYLE	Respondent agrees[a] with the statement: My lifestyle can have an impact on the environment
2HARD	Respondent agrees[a] with: It is too hard for someone like me to do much about the environment
MOST	Respondent agrees[a] with: Most people do their part to protect the environment
WTP	Respondent agrees[a] with: Most people are willing to pay higher prices to protect the environment
LAWS	Respondent agrees[a] with: Air pollution laws are already strong enough
TRST	Respondent agrees[a] with: I trust the state government to protect Maine's environment
LPREF	Respondent agrees[a] with: Vehicles that produce less pollution have lower performance
COST	Respondent agrees[a] with: Vehicles that produce less pollution are more expensive
ALLS	Coded 1 if respondent thinks all personal vehicles pollute about the same when driven; 0 otherwise
Independent variables	
YEAR	Coded 1 if data was collected during 2005; 0 if during 2004
MKT	Coded 1 if respondent lived in the eco-marketing treatment area; 0 otherwise
GEN	Coded 1 if respondents is male; 0 if female
AGE	The respondent's age in years
ENV	Coded 1 if the respondent belonged to an environmental organization; 0 otherwise
ED	The respondent's education level in years
INC	The respondent's income in dollars
NOREC	Coded 1 if respondent did no outdoor recreation in the past year; 0 otherwise
BIKE	Coded 1 if respondent mountain or road biked; 0 otherwise
WATCH	Coded 1 if respondent wildlife watching; 0 otherwise
SNOW	Coded 1 if respondent snowmobiling; 0 otherwise
PHOTO	Coded 1 if respondent participated nature photography; 0 otherwise
BOAT	Coded 1 if respondent boated/canoed; 0 otherwise
HUNT	Coded 1 if respondent hunted; 0 otherwise
ATV	Coded 1 if respondent participated in ATV or dirt biking; 0 otherwise

a 1 = 'strongly disagree to 5 = 'strongly agree'

Table 2. Distribution of length of visit to the website; in minutes

Length of visit	Percent
Less than half a minute	78
Thirty seconds to two minutes	5
Two to five minutes	4
Five to fifteen minutes	5
Fifteen to thirty minutes	3
Thirty minutes to an hour	3
Greater than an hour	2

Table 3. Regression results: Respondent's perceptions and experiences with environmental information.[a]

	SEE	SEARCH	WANT	DLR	IMP
Intercept	-4.791***	-4.130***	-0.380	-3.316***	-1.783***
Intercept					-0.601*
Intercept					1.475***
Intercept					2.431***
YEAR	-0.806*	-0.130	-0.112	-0.067	-0.030
MKT	1.643***	0.179	0.071	0.284	0.033
GEN	-0.054	0.186	-0.482***	0.201	-0.920***
AGE	0.0043	0.028***	-0.002	0.023***	0.0035
ENV	0.427	0.647***	0.674***	0.183	0.976***
ED	0.041	0.045*	0.112***	-0.001	0.036*
INC	2.6E-6	5.2E-6**	-9.8E-7	2.7E-6	-4.4E-7
NOREC	-1.259*	-0.433**	0.135	-0.264	-0.099
BIKE	-0.620	0.160	0.238	0.274	0.261**
WATCH	0.405	0.142	0.522***	-0.248	0.349***
SNOW	0.561	-0.158	-0.240	-0.174	-0.340**
PHOTO	-0.906**	0.374**	0.144	-0.316	0.041
BOAT	0.010	0.228*	-0.077	0.404***	-0.072
HUNT	0.894***	-0.282	-0.389***	0.300*	-0.364***
ATV	-0.225	-0.287	0.052	-0.280	-0.097

[a] * denotes significant at the 10 percent level;** denotes significant at the five percent level;*** denotes significant at the one percent level

Table 4. Regression results: Respondent perceptions of: the environmental problem, their personal involvement in protecting the environment, others peoples participation in environmentally friendly behaviors and the state's ability to protect the environment.[a]

	CONC	AQUAL	LSTYLE	2HARD	MOST	WTP	LAWS	TRST
Intercept	-1.422***	-1.666***	-0.724**	-2.556***	-2.918***	-4.401***	-1.622***	-2.881***
Intercept	-0.371	0.444	1.625***	-0.693**	-0.625*	-1.443***	-0.215	-0.798**
Intercept	1.938***	2.992***	2.728***	0.175	0.255	-0.692**	0.831**	0.200
Intercept	2.865***	5.482***	4.014***	2.258***	2.348***	1.198***	2.255***	1.688***
YEAR	-0.042	0.440***	0.215*	0.0064	-0.153	-0.287***	0.162	-0.163
MKT	0.134	-0.327***	-0.009	-0.014	0.032	0.061	-0.250**	0.261**
GEN	-0.691***	0.086	-0.294***	0.292***	0.529***	0.029	0.320***	-0.275***
AGE	0.021***	-0.014***	-0.013***	0.0046	0.005	0.018***	-0.009***	0.0098***
ENV	0.615***	-0.381***	0.895***	-0.503***	-0.268*	-0.085	-0.595***	0.164
ED	-0.052***	-0.008	0.0092	-0.048**	-0.049**	-0.041**	-0.038**	-0.058***
INC	1.7E-6	6.1E-6***	5.7E-6***	-6.2E-6***	-4.2E-6**	6.9E-6***	1.9E-6	-9.0E-7
NOREC	-0.236*	0.093	-0.492***	0.629***	0.324**	0.303**	-0.032	0.433***
BIKE	0.356***	-0.214*	-0.022	-0.173	-0.301**	0.102	-0.231**	-0.185
WATCH	0.310***	-0.315***	0.273	0.341***	0.069	0.142	-0.362***	-0.280***
SNOW	-0.407***	0.779***	-0.003	-0.435***	0.006	0.060	0.386***	-0.0034
PHOTO	0.245*	-0.048	0.092	-0.418**	-0.195	0.219*	-0.126	-0.459***
BOAT	0.123	0.194*	0.255**	-0.280***	-0.150	-0.108	-0.184*	-0.070
HUNT	0.225*	0.087	-0.400***	0.358***	-0.052	-0.245**	0.249**	0.194*
ATV	0.034	-0.038	-0.446***	0.349**	0.083	0.116	0.127	0.214

[a] * denotes significant at the 10 percent level;** denotes significant at the five percent level;*** denotes significant at the one percent level

Table 5. Regression results: Respondent perceptions of vehicles.[a]

	ALLS	LPERF	COST
Intercept	2.120***	-2.821***	-0.363
Intercept		-1.010***	1.631***
Intercept		-0.040	2.496***
Intercept		1.478***	3.825***
YEAR	0.031	-0.189*	0.110
MKT	-0.052	-0.011	-0.016
GEN	-0.319***	0.115	-0.051
AGE	-0.008**	0.006*	-0.012***
ENV	-0.208	-0.427***	-0.253*
ED	-0.097***	-0.009	-0.023
INC	2.2E-6	2.0E-6	-2.4E-6
NOREC	-0.156	0.023	-0.143
BIKE	-0.152	-0.293**	-0.195*
WATCH	-0.297***	-0.049	0.171*
SNOW	-0.275*	0.323**	0.050
PHOTO	0.492***	0.058	-0.320**
BOAT	0.108	0.106	-0.092
HUNT	0.470***	0.201*	-0.046
ATV	0.603***	-0.152	-0.284**

[a] * denotes significant at the 10 percent level;** denotes significant at the five percent level;*** denotes significant at the one percent level

Table 6. Summary of marketing impacts[a]

Equation	Desired sign	Is sign met?	χ^2	p
Respondent perceptions and experience with environmental information				
SEE	+	Yes	7.744	0.005
SEARCH	+	Yes	1.096	0.295
LIKE	+	Yes	0.501	0.479
DLR	+	Yes	1.243	0.265
IMP	+	Yes	0.090	0.762
Respondent general environmental perceptions				
CONC	+	Yes	0.723	0.395
AQUAL	-	Yes	13.202	0.000
LSTYLE	+	No	1.093	0.296
2HARD	-	Yes	0.010	0.920
MOST	+	Yes	0.802	0.370
WTP	+	Yes	2.869	0.090
LAWS	-	Yes	4.122	0.042
TRST	+	Yes	4.281	0.038
Respondent perceptions of vehicles				
ALLS	-	Yes	0.128	0.720
LPERF	-	Yes	0.774	0.379
COST	-	Yes	0.380	0.538

a Degrees of freedom for all chi-square tests is equal to one

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VEHICLE CHOICES, MILES DRIVEN AND POLLUTION POLICIES

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Vehicle Choices, Miles Driven, and Pollution Policies
Ye Feng, Don Fullerton and Li Gan
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ABSTRACT

Mobile sources contribute large percentages of each pollutant, but technology is not yet available to measure and tax emissions from each vehicle. We build a behavioral model of household choices about vehicles and miles traveled. The ideal-but-unavailable emissions tax would encourage drivers to abate emissions through many behaviors, some of which involve market transactions that can be observed for feasible market incentives (such as a gas tax, subsidy to new cars, or tax by vehicle type). Our model can calculate behavioral effects of each such price and thus calculate car choices, miles, and emissions.

A nested logit structure is used to model discrete choices among different vehicle bundles. We also consider continuous choices of miles driven and the age of each vehicle. We propose a consistent estimation method for both discrete and continuous demands in one step, to capture the interactive effects of simultaneous decisions. Results are compared with those of the traditional sequential estimation procedure.

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The standard case for market-based incentives requires a tax or price on each unit of emissions. Each form of abatement is then pursued until the marginal cost of reducing pollution matches the tax per unit of pollution, and the resulting combination of abatement technologies minimizes social costs (Pigou, 1920). For vehicles, a tax on emissions could induce drivers to: (1) buy a newer, cleaner car, (2) buy a smaller, more fuel efficient car, (3) fix their broken pollution control equipment, (4) buy cleaner gasoline, (5) drive less, (6) drive less aggressively, and (7) avoid cold start-ups.[1] Moreover, economic efficiency requires different combinations of these methods for different consumers: some lose little by switching to a smaller car, some could easily walk, and some just pay the tax.

Yet the technology is not available to measure each car's emissions in a reliable and cost-effective manner. On-board diagnostic equipment is imperfect, and it is costly to retrofit millions of vehicles (Harrington and McConnell, 2003). Remote sensing is less expensive and has been used to identify high-polluting vehicles, but it cannot measure emissions clearly enough to tax each car.[2] Moreover, vehicle emissions are important. In 2001, vehicles in the U.S. contributed 27 percent of volatile organic compounds (VOC), 37 percent of nitrogen oxides (NO_x), and 66 percent of carbon monoxide (CO) emissions.[3]

For these reasons, vehicle emission policies have relied almost solely on mandates: refineries must make clean gasoline, and new cars must meet required emission standards.[4] These command and control (CAC) policies miss the opportunity to reduce social costs by harnessing individual incentives, however, as the mandated combination of abatement methods is unlikely to match the combination that households would choose if faced with a tax on emissions. In fact, the cost of abatement using such mandates can be several times the minimum cost achieved by using an emissions tax (Newell and Stavins, 2003).

While the inability to measure emissions may preclude a vehicle emissions tax, it does not preclude any use of incentives. Those who sell new or used cars or light-trucks

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[1] Heeb et al (2003) find that cold start emissions rates (in g/km traveled) exceed stabilized emissions rates by a factor of two to five, depending on the pollutant. Sierra Research (1994) finds that a car driven aggressively has carbon monoxide emissions that are almost 20 times higher than when driven normally.

[2] See Sierra Research (1994). Remote sensing in Texas (http://www.tnrcc.state.tx.us/air/ms/vim.html#im3) and Albuquerque NM (http://www.cabq.gov/aircare/rst.html) is used in 2005 to identify polluting vehicles.

[3] See http://www.bts.gov/publications/transportation_statistics_annual_report/2004/. We focus on local pollutants, where emission rates depend on car characteristics. In contrast, CO_2 is linked directly to gas use.

[4] In the U.S., new cars face emission standards of .254 grams/km of HC's, 2.11 grams/km of CO, and .248 grams/km of NO_x. Light trucks face a variety of weaker standards, but all are scheduled to become more stringent. These figures pertain to a test in the U.S. with a cold start-up phase, a transient phase at different speeds, and a hot start phase, for a total distance of 18 km at an average speed of 34 km/h.

can collect tax on vehicle characteristics that are associated with emissions, or provide subsidy for vehicles with low emissions. Most states charge annual registration fees that can be made to depend on vehicle characteristics. Such policies might reduce emission rates, while changes in the gasoline tax can reduce miles driven.[5]

What vehicle characteristics or behaviors should be targeted by a tax or subsidy? How would consumers react to those new incentive instruments? How much would each tax reduce emissions? To address these questions, we build a general purpose model of discrete choices by households about how many cars to own and what types of cars to own, plus continuous choices about how far to drive. In our model, we embrace individual heterogeneity. We estimate all decisions simultaneously, and we use the estimated parameters to predict the effects of certain price changes on choices and on emissions.

Several existing papers explore market incentives that could be used in place of a tax on emissions.[6] In addition, several papers estimate models of the discrete choice among vehicle bundles (including number, size, and age categories).[7] Some models estimate the demand for gasoline or for vehicle miles traveled (*VMT*) as functions of price and income (as reviewed in Harrington and McConnell, 2003). As well, we note that other models predict emissions.[8] A major contribution of our research, then, is to include all such choices simultaneously. In general, we capture the effect of any price change on each household's choices about the number of vehicles to buy, the type and age of each, the consequent emissions rates, miles driven, and the consequent total emissions.

In a two-step procedure, Dubin and McFadden (1984) estimate a discrete choice model (for household appliances) and use the predicted shares to correct for endogeneity in the estimation of a continuous choice (usage hours). Others extend this model to the discrete choice among vehicle bundles and a continuous choice of miles (e.g. Goldberg, 1998, and West, 2004). Yet, a single set of parameters appear both in the indirect utility

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[5] A new higher gas tax may be politically unlikely, yet it is still worth studying to know its power as an emissions-reduction tool. And even if governments are unlikely to use tax dollars to pay for the various subsidies we study here, these incentives might instead be provided to drivers by private companies that want to purchase "offsets" – reductions in vehicle emissions to offset their increases from stationary sources. For all of these reasons, we find it important to study specific incentives to drivers.

[6] For examples, see Eskeland and Devarajan (1996), Innes (1996), Kohn (1996), Train et al (1997), Plaut (1998), Sevigny (1998), and Fullerton and West (2000, 2002).

[7] See McFadden (1979), Mannering and Winston (1985), Train (1986), Brownstone et al (1996), Goldberg (1998), Brownstone and Train (1999), West (2004), and other papers reviewed in McFadden (2001).

[8] For example, the U.S. Environmental Protection Agency (U.S. EPA, 1998, p.3-68) discusses the use of EPA's MOBILE5a model or California's EMFAC7F model.

function used to estimate discrete choices and in continuous demands. Using this sequential procedure, the estimated parameters of the continuous demand are not constrained to match the same parameters in the estimated discrete choice model.

Relative to this literature, we make a number of contributions. First, we capture the simultaneity of these decisions by proposing a method for consistent estimation of both discrete and continuous choices in one step, yielding a single set of parameters. In other words, whereas the Dubin-McFadden method corrects for selection of vehicle on the choice of miles, our simultaneous procedure also allows for heterogeneity in actual fuel demand to affect the choice of vehicle.[9] Second, we allow for two continuous choices of miles – in each vehicle of a two-vehicle household. These choices are bundle-specific.[10] Third, we allow for an additional continuous choice of the age of each vehicle. Fourth, we use the estimated parameters not only to predict changes in choices about vehicles and miles, but also how those choices affect emissions.[11]

For several reasons, we deviate from discrete vehicle types used in prior literature (including age and size categories). First, we have no need to model the choice among hundreds of vehicle types, as in prior studies of manufacturer product differentiation, since all cars in a given year are made to a single emission rate standard. Second, a different, weaker emission standard has applied to "sports utility vehicles" (SUV, for short, but defined here to include all light trucks and vans). Emission rules for new vehicles do not depend on engine size. We therefore model the choice between car and SUV, rather than engine size. Even for older vehicles, when we use data described below in separate regressions for cars and SUV's, we find that engine size is not an important determinant of emission rates. Third, those regressions find that vehicle age is very important for emission rates. We wish not to lose information by aggregation into finite age categories (e.g. new

[9] Hanemann (1984) proposes a method to estimate these demands simultaneously, but his method does not consider unobserved individual heterogeneity – a key factor in the Dubin-McFadden model. Our model captures the individual unobserved heterogeneity. Bento et al (2005) and Bhat (2005) are also working on models with simultaneous discrete and continuous choices.

[10] With a higher price of gas, some households might drive fewer miles in their SUV and *more* in their car. We do not estimate separately the miles in each vehicle, but we do estimate a change for the (Car, SUV) bundle that can differ from the (Car, Car) bundle. Other papers have estimated substitution between vehicles within the family, but they treat the vehicles as given rather than chosen. Greene and Hu (1985) find that this kind of substitution occurs to a large extent in some households, while Sevigny (1998) finds small effects.

[11] Our household responses represent market outcomes only if supply curves were horizontal. The simulation of a change in the price of getting a car that is one year newer can be interpreted as a new local tax or subsidy in a small open jurisdiction that can import more of those newer cars at a constant price. However, our demand system could be combined with some other estimates of supply to calculate equilibrium outcomes.

vs. old). Age is a continuous variable, and the choice of vehicle age is a continuous demand that affects emissions.[12] If a household in our model chooses to own two vehicles, then it has four continuous choices: age of each vehicle and miles to drive each vehicle.[13]

Age is normally measured in years, of course, but our model requires a price that does not depend on the amount demanded. The price of age is not linear, because owning a brand-new car costs more depreciation per year than owning an old car. Instead of using age in years, we therefore construct a continuous choice variable called "*Wear*" that measures the fraction of the vehicle that has depreciated (between 0 and 1). A constant rate of depreciation means that *Wear* is a nonlinear function of age, but then the price per unit of *Wear* does not depend on its amount. This constant price is estimated for each vehicle type using hedonic price regressions below. Next, in order to separate this choice of vehicle attribute from the choice of vehicle, we assume that the discrete choice is about a brand-new "concept vehicle." Then the household gets reimbursed by the price of *Wear* for accepting an older car. In other words, in our model, a household makes simultaneous decisions about which concept vehicles, how old, and miles to drive.

As it turns out, results for all continuous demands are broadly similar for the sequential and simultaneous models. For discrete choices, however, our simultaneous model finds substantially larger effects from a change in the gas price per mile, income, or vehicle-specific costs. Signs of some elasticities are reversed. In other words, household-specific heterogeneity does affect discrete choices.

The next section describes a behavioral choice model for one-vehicle households and then extends it to consider two-vehicle bundles. It also presents a new method designed for jointly estimating all discrete and continuous choices. Section II describes data sources and provides summary statistics, while III provides estimation results for both discrete and continuous demands. Section IV compares elasticities, and V concludes.

I. The Model and Estimation

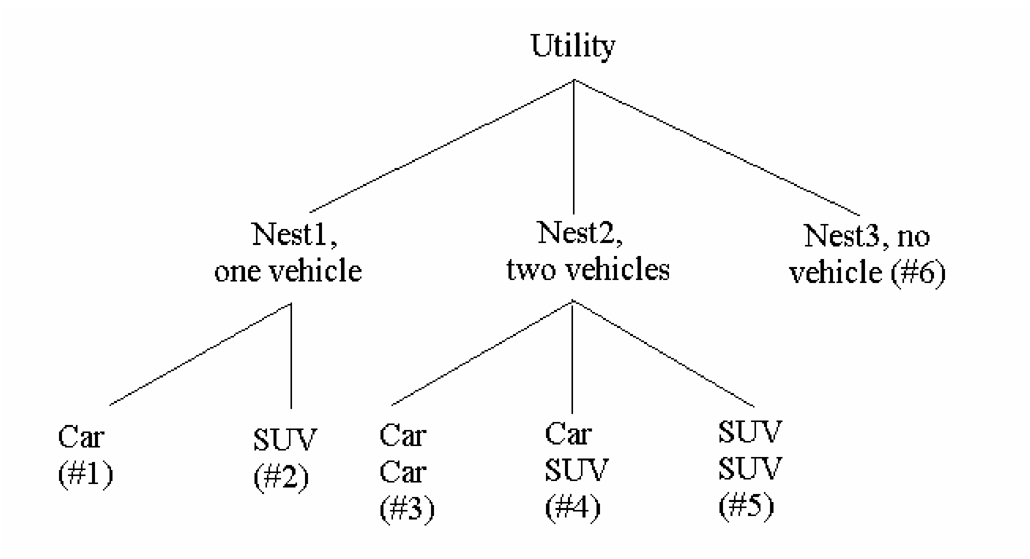
In our model, an agent representing each household faces a discrete choice among a finite number of vehicle bundles. The nesting structure is shown in Figure 1. One

[12] Older vehicles have higher emissions both because older vintages were produced to weaker standards and because pollution control equipment deteriorates with age. Panel data would be required to distinguish these.

[13] Fullerton and West (2000) also simulate effects of incentives in a model of heterogeneous households' continuous choices of car size, car age, and *VMT*, but they use calibrated rather than estimated parameters. That model avoids discrete choices, but it considers only one car per agent. In our model, we estimate discrete choices to consider the household's number of vehicles.

choice is the number of vehicles (0, 1, or 2), and another choice for each vehicle is the type of vehicle (a car or an SUV). We thus have six final bundles, as shown in the figure and listed in Table 1. Other choices important for emissions of each vehicle are the continuous choice about vehicle miles traveled (*VMT*) and vehicle age. To obtain a choice variable with a linear price, we construct "*Wear*" as the fraction of the vehicle used up by depreciation. It is calculated for each car in our sample by assuming 20% depreciation per year, so $Wear = 1 - (1 - 0.2)^{age}$. Thus, a new car has $Wear = 0$.

Figure 1: Nesting Structure for Choice among Vehicle Bundles



Then, since choice of age is considered separately, each discrete vehicle bundle must be defined in a way that is independent of age. For this reason, we define each "concept" vehicle as a bundle of attributes of a brand-new vehicle (car or SUV). The household must pay the price of that brand-new vehicle (the "capital cost"), but then it gets back some money for accepting *Wear* on that vehicle (the "reimbursement" price of *Wear*).

Our demand system now has several distinguishing characteristics. First, it incorporates all of these discrete and continuous choices simultaneously. Second, some unobserved characteristics might affect both kinds of choices. For example, an agent who lives far from work may drive more and thus prefer a larger, more comfortable car. Yet, a more comfortable car may increase the satisfaction of driving and thus induce the driver to drive more. Third, many households have two cars with multiple continuous choices. Consequently, the substitution structure in *VMT* and *Wear* among different vehicles is important in order to understand the effects of policy on driving behavior.

Since the discrete choice in Dubin and McFadden (1984) involves only two alternatives, that paper can use a simple logit model. Our model has six choices, however, and so we require a more general logit structure. We use the nested logit. The next sub-section describes the simple case for households with only one vehicle, and the second subsection considers multi-vehicle households. In the third and fourth sub-sections, we discuss the estimation procedure and elasticity calculations.

A. Our Model of Car Choice and Miles Driven

This description starts with the choices of *VMT* and *Wear*, assuming that a one-car household has already chosen vehicle number-and-type bundle i. Given bundle i, an agent's direct utility is a function of *VMT*, *Wear*, and another consumption good c. That is, $U = U(VMT_i, Wear_i, c_i)$. Given income y, the budget constraint is given by:

$$\frac{p_g}{MPG_i} VMT_i - q_i Wear_i + c_i = y - r_i \,, \tag{1}$$

where p_g is the price of gasoline (in dollars per gallon), and MPG_i is fuel efficiency (in miles per gallon), so that $p_i \equiv p_g/MPG_i$ is the marginal price per mile in the i^{th} vehicle bundle. The "reimbursement" price of *Wear* for vehicle type i is denoted as q_i. The price of the other consumption good is normalized to be 1. The annualized capital cost of the concept-vehicle bundle is r_i. Thus, gasoline is the only cost per mile, whereas capital cost is a fixed cost of each bundle.[14] The indirect utility for bundle i is a function of household income and prices, denoted as $V(y\text{-}r_i, p_i, q_{i,})$.

One common way to obtain the indirect utility function is to use parametric demand and then solve a system of partial differential equations using Roy's identity (Hausman, 1981). For comparability with other studies, we want *VMT* demand as a log-linear function of the price per mile p_i, available income $y - r_i$, and a vector of observed socio-demographic variables x. We then add the reimbursement price q_i to that equation to get:

$$\ln(VMT_i) = \alpha_V^i + \alpha_p^i p_i - \alpha_q q_i - \beta(y - r_i) + x'\gamma + \eta \,, \tag{2}$$

where η represents an agent-specific unobserved factor (see below). Also, we assume

$$r_i = (\delta + \rho) k_i, \tag{3}$$

[14] Time variation in gasoline prices may cause time variation in used vehicle prices. Our use of cross-section data helps avoid this problem.

where k_i is the total capital value of bundle i (depreciated or market value), δ is the annual rate of further depreciation in value, and ρ represents the interest and maintenance cost. When we plug (3) into (2) and integrate, the implied indirect utility is:

$$V_i = \frac{1}{\beta}\exp\left(-\alpha_0^i + \beta y - \beta_1 k_i - x'\gamma - \eta\right) - \frac{1}{\alpha_p^i}\exp(\alpha_p^i p_i - \alpha_q q_i) + \varepsilon_i\,, \tag{4}$$

where $\beta_1 = \beta(\delta+\rho)$.[15] This equation includes an extra additive error ε_i that is bundle-specific. As in the usual discrete choice model, this error term represents the difference between true individual utility at choice i and the calculated utility level.[16] For households who choose the no-vehicle bundle #6, continuous variables such as p_i, q_i, and VMT_i are unobservable. Implicitly, we assume that these households may purchase a bicycle or a fare card for public transportation with a fixed fee, similar to the capital cost k_i. With no cost per mile or of *Wear*, their second exponential term in (4) is 1.0. Their capital cost k_i is unobserved, so $\beta_1 k_i$ and α_0^6 are not separately identifiable. Since we allow for a choice-specific intercept, however, we combine both terms into one constant, α_0^6.

Note that the simple addition of $\alpha_q q_i$ to equation (2) dictates the form of indirect utility in (4). This indirect utility then implies specific forms for both demands:[17]

$$\ln(VMT_i) = \alpha_V^i + \alpha_p^i p_i - \alpha_q q_i - \beta y + \beta_1 k_i + x'\gamma + \eta \tag{5a}$$

$$\ln(Wear_i) = \alpha_W^i + \ln\left(\alpha_q / \alpha_p^i\right) + \alpha_p^i p_i - \alpha_q q_i - \beta y + \beta_1 k_i + x'\gamma + \eta \tag{5b}$$

This specification has pros and cons. One limitation is the use of specific functional forms, but these log-linear forms are comparable to prior literature and allow for two different demand functions (5a,b) that are consistent with a single indirect utility function (4). An advantage of this specification is that it allows the price of *Wear* (q_i) to enter the *VMT* demand, and price of *VMT* (p_i) to enter the *Wear* demand, but a

[15] Our model provides estimates of β and β_1, and these can be used to calculate $(\delta+\rho)$, but we do not provide separate estimates of δ and ρ. Some of our steps below require an assumption about δ, and we use 20 percent for this purpose. Estimates of the depreciation rate for automobiles range from 33% (Jorgenson, 1996) or 30% (Hulten and Wykoff, 1996) to 15%, the rate implicit in the vehicle depreciation schedule currently used by the Bureau of Economic Analysis. We use 20% because it falls between these bounds.

[16] Also, because of this integration, note that the intercept in (4) may be different from the intercept in (2).

[17] More general demand functions such as translog demand or the almost ideal demand system imply much more complicated indirect utility functions that could not be estimated. Also, note that no-vehicle households have zero marginal prices, so they have constant miles traveled (conditioned on observed socio-demographic variables and total income). Thus, no continuous demand equations are needed for these households.

limitation is that the expression $\alpha^i_p p_i - \alpha_q q_i$ enters both demands the same way.[18] Also, both continuous demands have the same income effect, β. A more general model could not be estimated. Note, however, that we have added generality where it matters most. In particular, the price per mile has a bundle-specific coefficient (α^i_p), to allow for different effects on the demand for miles in each type of vehicle. Thus a gas tax might decrease miles in an SUV more than in a car, in a way that depends on fuel efficiency, and the change in miles of a two-car household can differ from the change in miles of a household with two SUV's (or one car and one SUV).

B. Two-Vehicle Households

So far, the model above considers only one vehicle, but many households have two vehicles and thus two continuous choices of miles and two continuous choices of *Wear*. We have the observed *VMT* and *Wear* for each vehicle, so we can incorporate all four continuous choices.[19] The direct utility for a two-vehicle household choosing bundle i is $U(VMT_{i1}, VMT_{i2}, Wear_{i1}, Wear_{i2}, c_i)$. The budget constraint is given by:

$$\frac{p_g}{MPG_{i1}} VMT_{i1} + \frac{p_g}{MPG_{i2}} VMT_{i2} - q_{i1}(Wear_{i1}) - q_{i2}(Wear_{i2}) + c_i = y - r_i, \tag{6}$$

where q_{ij} are reimbursement prices for *Wear* in the two vehicles of bundle i (j = 1, 2). Also, $p_{ij} \equiv p_g/MPG_{ij}$ is the price per mile using the j^{th} car of bundle i. We consider the indirect utility function as follows:

$$V_i = \frac{1}{\beta}\exp\left(-\alpha_0^i + \beta y - \beta_1 k_i - x'\gamma - \eta\right) - \frac{1}{\alpha_{p1}^i}\exp(\alpha_{p1}^i p_{i1} + \alpha_{p2}^i p_{i2} - \alpha_{q1} q_{i1} - \alpha_{q2} q_{i2}) + \varepsilon_i \tag{7}$$

The indirect utility in (7) is similar to (4) except for two extra terms related to the second vehicle's gasoline price p_{i2} and reimbursement price q_{i2}. By Roy's identity, given that the household has chosen bundle i in (7), the four continuous demands are:

$$\ln(VMT_{i1}) = \alpha_{V1}^i + \alpha_{p1}^i p_{i1} + \alpha_{p2}^i p_{i2} - \alpha_{q1} q_{i1} - \alpha_{q2} q_{i2} - \beta y + \beta_1 k_i + x'\gamma + \eta \tag{8a}$$

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[18] Thus, a change in p_i must have the same effect on *Wear* that it has on miles. We tried other models, including one where indirect utility has separate terms $\exp(\alpha^i_p p_i)$ and $\exp(\alpha_q q_i)$, so that p_i would have no effect on *Wear*, and q_i would have no effect on *VMT*. That model would not converge, and anyway it is restrictive by assuming no cross-price effects. We also tried models with more coefficients, to relax these restrictions, and we tried many starting points, but only the model in (4) and (5) could be estimated simultaneously for discrete and continuous choices (especially for two-vehicle bundles considered below).

[19] Another interesting question is about each household member's choice of miles driven (in either car), but we have no such data. As described below, we have only data on miles driven in each vehicle.

$$\ln(VMT_{i2}) = \alpha^i_{V2} + \ln(\alpha^i_{p2} / \alpha^i_{p1}) + \alpha^i_{p1} p_{i1} + \alpha^i_{p2} p_{i2}$$

$$- \alpha_{q1} q_{i1} - \alpha_{q2} q_{i2} - \beta y + \beta_1 k_i + x'\gamma + \eta \tag{8b}$$

$$\ln(Wear_{i1}) = \alpha^i_{W1} + \ln(\alpha_{q1} / \alpha^i_{p1}) + \alpha^i_{p1} p_{i1} + \alpha^i_{p2} p_{i2}$$

$$- \alpha_{q1} q_{i1} - \alpha_{q2} q_{i2} - \beta y + \beta_1 k_i + x'\gamma + \eta \tag{8c}$$

$$\ln(Wear_{i2}) = \alpha^i_{W2} + \ln(\alpha_{q2} / \alpha^i_{p1}) + \alpha^i_{p1} p_{i1} + \alpha^i_{p2} p_{i2}$$

$$- \alpha_{q1} q_{i1} - \alpha_{q2} q_{i2} - \beta y + \beta_1 k_i + x'\gamma + \eta \tag{8d}$$

These demands generalize those of a one-vehicle household in (5) by including terms for p_{i2} and q_{i2} (and so we refer to (8) for "all" demands). The demand for VMT_{i2} is symmetric to VMT_{i1} in explanatory variables, but it is non-linear in parameters of both p_{i1} and p_{i2}. The demands for $Wear_{ij}$ (j= 1, 2) are similarly defined.

C. A Procedure to Estimate Discrete and Continuous Demands Simultaneously

Note that the same parameters appear in both discrete and continuous choice functions, yet previous literature has estimated these choice models separately. Often the estimates for the same parameters are different not only in magnitude but also in sign. In this sub-section, we propose a procedure for simultaneous estimation of bundle choice, vehicle age, and miles driven. We start with separate discussion of car choice and miles driven, and then how we combine them in a single estimation procedure.

Following McFadden's random utility hypothesis, vehicle bundle i is chosen if and only if: $V_i \geq V_j$ for all $j \neq i$. The unconditional expected share for bundle i then is:

$$S_i = \int \Pr(V_i > V_j, \forall j \neq i \mid \eta) f(\eta) d\eta, \tag{9}$$

where S_i is the share choosing bundle i, and $f(\eta)$ is the probability density function of the agent-specific error η. We are now in a position to describe the importance of η. On the one hand, individual heterogeneity represented by η could directly affect the choice of bundle. On the other hand, observed demands for VMT and $Wear$ are conditional on that choice. Since the choice of vehicle bundle is endogenous, the estimated demands for VMT and $Wear$ could be biased if the influence of η in (9) is ignored. In the model of Dubin and McFadden (1984), the error term η can be cancelled out from the inequality $\{V_i>V_j, \forall j \neq i\}$, which simplifies the calculation of probabilities (that is, the integration over η in equation (9) is not necessary). In such a model, η appears only in the continuous demands, so this individual heterogeneity does not affect the choice of vehicle bundle directly. They can estimate the discrete model with error ε_i for each bundle, and then, given predicted bundle shares, they estimate the continuous choices with errors η.

Yet, our purpose here is to *retain* individual-specific heterogeneity η and its effect on bundle choice. Thus, the evaluation of probabilities in our model involves integration over all error components (ε, η), where $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_J)$, and where J is the number of possible vehicle bundles. In our model, the ε_i are assumed to be distributed with a generalized extreme value (GEV) distribution, and η follows an unknown distribution with a zero mean across individuals. Conditional on η, we integrate over the GEV distribution to obtain conditional choice probabilities as a general nested logit model:

$$\Pr\left(V_{ni} > V_{lm}, \forall m \neq i, \forall n, l \middle| \eta\right) = \frac{\exp(V_i/\lambda_n)\left(\sum_{j \in B_k} \exp\left(V_j/\lambda_n\right)\right)^{\lambda_n - 1}}{\sum_{l=1}^{K}\left(\sum_{j \in B_l} \exp\left(V_j/\lambda_l\right)\right)^{\lambda_l}} \quad , \tag{10}$$

where n and l represent nests, i is an alternative within nest n, m is an alternative within nest l, K is the total number of nests, and B_l ($l = 1, \ldots, K$) represents a nested subset of alternatives. Our nesting structure is illustrated in Figure 1.

We also integrate over the distribution of η to obtain unconditional probabilities. The literature offers no guidance on the distribution of the η.[20] To reduce the numerical difficulty in estimation, we let η be uniformly distributed in the interval [$-\xi, \xi$]. We search for the ξ that yields a likelihood function with the largest value.[21]

As pointed out by Dubin and McFadden (1984), the random error η does not have a zero mean conditional on each chosen bundle, due to the endogeneity of bundle choice. This can be seen clearly if we rewrite equations (8a-d) into a more convenient form for estimation (using just equation 8a, as an example):

$$\begin{aligned} \ln(VMT_{i1}) = {} & \sum_j \alpha_{V1}^j d_{ij} + \sum_j \alpha_{p1}^j p_{j1} d_{ij} + \sum_j \alpha_{p2}^j p_{j2} d_{ij} \\ & - \alpha_{q1} \sum_j q_{j1} d_{ij} - \alpha_{q2} \sum_j q_{j2} d_{ij} - \beta y + \beta_1 \sum_j k_j d_{ij} + x'\gamma + \eta \end{aligned} \tag{11a}$$

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[20] Dubin and McFadden (1984) assume η has a particular form of mean and variance, in order to derive an explicit conditional expectation.

[21] This search yields ξ equal to 0.65. Since the estimation of the logit model requires integration over the individual heterogeneity term η, our model is a mixed logit model (McFadden and Train, 2000).

where d_{ij} is a choice indicator variable equal to one when $i = j$, and where equations (11b-d) are analogous. The random error η is correlated with the choice indicators d_{ij}. Dubin and McFadden (1984) suggest sequential estimation to solve this endogeneity problem (a procedure later adopted by Goldberg (1998) and West (2004)). First, the discrete choice model is estimated and the predicted probabilities are calculated. They then suggest three alternative methods that yield consistent estimates of parameters for continuous demands: the instrumental variable method (IV), the reduced form method (RF), and the conditional expectation correction method (CE). They derive the correction terms in terms of probabilities for the CE method based on the assumption of an *i.i.d.* extreme value distribution of ε_i. However, since we assume a GEV distribution of ε_i, these correction terms cannot be used in our model. We want a method that can be used both for sequential estimation and for our simultaneous estimation, in order to compare them, and so we employ the RF method. Taking expectation of (11a) over η, we have:

$$\begin{aligned}\ln(VMT_{n1}) &= \sum_j \alpha_{V1}^j S_{nj} + \sum_j \alpha_{p1}^j p_{j1} S_{nj} + \sum_j \alpha_{p2}^j p_{j2} S_{nj} \\ &\quad - \alpha_{q1} \sum_j q_{j1} S_{nj} - \alpha_{q2} \sum_j q_{j2} S_{nj} - \beta y + \beta_1 \sum_j k_j S_{nj} + x'\gamma + u_{n1}\end{aligned}, \qquad (12a)$$

where S_{nj} is the probability of individual n choosing vehicle bundle j from (9), u_{n1} is an additional error to represent the difference between observed *VMT* and predicted *VMT*, and where (12b-d) are analogous (not shown here). The sequential RF method applies least squares to (12a-d), except that the shares S_{nj} are replaced by estimated shares $\hat{S}_{nj}$ from the discrete choice model. In contrast, we estimate (9) and (12a-d) simultaneously.

Since the same parameters appear in both discrete and continuous choice functions, we propose a joint estimation method to capture this simultaneity. In particular, we obtain a set of parameters that maximize the following objective function:

$$\begin{aligned}F(\Theta | y, p_1, p_2, q_1, q_2, k, x) &= -\Sigma_n (\ln(VMT_1) - f_1)^2 - \Sigma_n (\ln(VMT_2) - f_2)^2 \\ &\quad - \Sigma_n (\ln(Wear_1) - g_1)^2 - \Sigma_n (\ln(Wear_2) - g_2)^2 + \Sigma_n \ln L\end{aligned}, \qquad (13)$$

where f_1, f_2, g_1, and g_2 represent the right hand sides (without the random error u_{n1}) of the four equations (12a-d), $\ln L$ is the log likelihood function of the nested logit, and Θ represents the set of parameters to be estimated by maximizing equation (13).

As is consistent with Dubin and McFadden (1984) and other papers in this literature, the maintained hypotheses are that the utility functional form is correct and that consumers maximize it. Under these hypotheses, our procedure produces consistent estimates of parameters. The reasoning is as follows: if the components of (13) were maximized separately, and if some single set of parameters were the solution to all those separate maximizations, then this set of parameters would also maximize the combined objective function. To compare the results, we estimate our model by both the sequential method and the simultaneous estimation method.

D. Elasticities

Once we obtain the parameter estimates, we are ready to calculate elasticities. To see the marginal effects of prices on indirect utility, and therefore on bundle choice, we use equation (7) to obtain explicit formulas for those derivatives. First, define $\exp(\cdot) \equiv \exp(\alpha_{p1}^i p_{i1} + \alpha_{p2}^i p_{i2} - \alpha_{q1} q_{i1} - \alpha_{q2} q_{i2})$. Then:

$$\frac{\partial V_i}{\partial p_{i1}} = -\exp(\cdot) \;, \qquad \frac{\partial V_i}{\partial p_{i2}} = -\frac{\alpha_{p2}^i}{\alpha_{p1}^i}\exp(\cdot) \tag{14a}$$

$$\frac{\partial V_i}{\partial q_{i1}} = \frac{\alpha_{q1}}{\alpha_{p1}^i}\exp(\cdot) \,, \qquad \frac{\partial V_i}{\partial q_{i2}} = \frac{\alpha_{q2}}{\alpha_{p1}^i}\exp(\cdot) \tag{14b}$$

and the marginal effects of income or capital cost on utility take similar forms:

$$\frac{\partial V_i}{\partial y} = \exp(-\alpha_0^i + \beta y - \beta_1 k_i - x'\gamma - \eta) \tag{15a}$$

$$\frac{\partial V_i}{\partial k_i} = -\frac{\beta_1}{\beta}\exp(-\alpha_0^i + \beta y - \beta_1 k_i - x'\gamma - \eta) \tag{15b}$$

Then we derive the elasticity of choice i with respect to a change in variable z_j (where z_j may be any of the price variables, income y, or capital cost k_j):

$$\frac{\partial S_i}{\partial z_j} \cdot \frac{z_j}{S_i} = \frac{\partial S_i}{\partial V_j} \cdot \frac{\partial V_j}{\partial z_j} \cdot \frac{z_j}{S_i} \tag{16}$$

Since these formulas involve the unconditional probability of vehicle bundle i, calculating each bundle elasticity requires integration over η. In contrast, calculations of *VMT* elasticites do not involve integration over η. For bundle i (i = 1, …, 5), the own- and cross-price elasticities of *VMT* demand are calculated by:

$$e^i_{V1p1} = \frac{\partial \ln(VMT_{i1})}{\partial \ln p_{i1}} = \alpha^i_{p1} p_{i1} = e^i_{V2p1} \ , \qquad e^i_{V2p2} = \frac{\partial \ln(VMT_{i2})}{\partial \ln p_{i2}} = \alpha^i_{p2} p_{i2} = e^i_{V1p2} \tag{17}$$

The elasticities of demand for *Wear* with respect to its price have a similar form:

$$e^i_{W1q1} = \frac{\partial \ln(Wear_{i1})}{\partial \ln q_{i1}} = -\alpha_{q1} q_{i1} = e^i_{W2q1} \ , \quad e^i_{W2q2} = \frac{\partial \ln(Wear_{i2})}{\partial \ln q_{i2}} = -\alpha_{q2} q_{i2} = e^i_{W1q2} \tag{18}$$

We can also calculate the income elasticity, given by:

$$e^i_{Vy} = \frac{\partial \ln(VMT_{i1})}{\partial \ln y} = \frac{\partial \ln(VMT_{i2})}{\partial \ln y} = -\beta y \ , \tag{19}$$

and the total capital cost elasticity, given by:

$$e^i_{Vk} = \frac{\partial \ln(VMT_{i1})}{\partial \ln k_i} = \frac{\partial \ln(VMT_{i2})}{\partial \ln k_i} = \beta_1 k_i \ . \tag{20}$$

In equations (16) – (20), elasticities are typically evaluated at each bundle's mean values of y and k, the bundle average of gas prices per mile (p_1 and p_2) and the bundle average of reimbursement prices (q_1 and q_2).

II. Data and Summary Statistics

In order to analyze household choice of vehicles, miles driven, and vehicle *Wear*, we need micro-data on household characteristics, household income or expenditures, and detailed information about household-owned vehicles such as the number of vehicles, miles driven in each, and vehicle characteristics (including miles per gallon, MPG, and emissions per mile, EPM). No single data set contains all such information.

The Consumer Expenditure Survey (CEX) provides data on household income, characteristics, and household-owned vehicles.[22] For each household, we aggregate expenditures over four quarters, taking demographic data and detailed vehicle information from their last quarter in the survey. We use the CEX from 1996 to 2000, supplemented with the corresponding OVB file (Owned Vehicles Part B Detailed questions). This OVB file includes data on each vehicle type, make, year, number of cylinders, purchase expenses and financing, time since purchase, mileage, gasoline expenditure, and other information. We keep only households that satisfy several criteria. First, expenditures

[22] The CEX data are collected by the Bureau of Labor Statistics of the U.S. Department of Labor through quarterly interviews of selected households throughout the U.S. Each household is interviewed over five consecutive quarters. Each quarter, 20% of households complete their last interview and are replaced by new households. For CEX data, see http://elsa.berkeley.edu or http://www.icpsr.umich.edu/.

must be reported consecutively for four quarters in the CEX of 1996-2000. Second, the household must possess the same number of vehicles during these four quarters. Third, we remove households that own more than two vehicles.[23] We also remove households that have vehicles other than automobiles or SUV's (defined to include light trucks or vans). Finally, we are left with 9027 households, of which 2077 own no vehicles, 4211 own one vehicle, and 2739 own two vehicles. We use yearly total expenditure as a proxy for yearly income of each household. Table 2 defines all the variables used in estimations.

Summary statistics are shown in Table 3 for major household characteristics by vehicle bundle. This table shows significant variations in household characteristics across the number of vehicles and bundles. For example, larger households especially with more kids have more vehicles and prefer SUVs. Wealthier households (as measured by total yearly expenditures) possess more vehicles. Households with more workers or income earners have more vehicles. Households with male heads are inclined to have SUVs.

Next, fuel price data are obtained from the ACCRA cost-of-living index for 1996-2000. This index compiles quarterly data for approximately 300 cities in the United States. It also lists average gasoline price for each city for each survey quarter. Since the CEX reports region and state of residence instead of city for each household, we average the city gas prices to obtain a state price for each calendar quarter. For those states reported in the CEX, but not reported in the ACCRA index, we use the average region price as a substitute. Then we assign a gas price to each CEX household based on the state of residence, CEX quarter, and year.

Some of the variables in our model require calculations or additional sources of data. We now describe these extra calculations.

(1) Wear: The vehicle's age is derived by taking the year of the survey minus the year the vehicle was made. We then assume 20% annual depreciation, and calculate *Wear* as the percentage of the vehicle's value that has wasted away (given all the vehicle characteristics unchanged except vehicle age). *Wear* ranges from zero for a new car, to $Wear = 1$ for a very old car. Specifically, $Wear = 1 - (1 - 0.2)^{age}$.

(2) Capital value of the vehicle: The vehicle's year of purchase and reported purchase price (*pp*) are available in the OVB file, but we want an estimate of current

[23] In the CEX of 1996-2000, 18.4% of households own more than two vehicles. Some of these households may have a vehicle for business, whereas our model of household choice assumes utility maximization.

market value (*cmv*). We calculate the number of "years since purchase" (*ysp*), and we subtract depreciation for each year, again using 20% as the annual rate of depreciation. The formula is $cmv = pp \times (1-0.2)^{ysp}$. We then estimate a simple hedonic price regression:

$$cmv = a_0 + a_1 cyl + a_2 im + b_0(1 - Wear) + b_1(Wear \times cyl) + b_2(Wear \times im) \tag{21}$$

where a_0 through a_2, and b_0 through b_2 are parameters. The variable cyl denotes the number of cylinders, while im is a dummy variable indicating if the vehicle is imported.[24] $Wear$ is included in the regression to capture the effects of vehicle age on market value. Using a sub-sample of the CEX that has all necessary variables, we run separate regressions for cars and SUV's and report the results in Table 4. Then, for the value of each brand new "concept" vehicle (with $Wear = 0$), we use:

$$\hat{k} = \hat{a}_0 + \hat{a}_1 cyl + \hat{a}_2 im + \hat{b}_0 \quad . \tag{22}$$

where $\hat{a}_0$ through $\hat{a}_2$ and $\hat{b}_0$ are estimates of parameters in (21).

(3) The price of Wear: First, we calculate the extra amount paid for a car with no wear on it ($Wear = 0$) compared to a very old car with the same characteristics ($Wear = 1$). From (21), that difference is $\left(\hat{b}_0 - \hat{b}_1 cyl - \hat{b}_2 im\right)$. Then, q is the annual reimbursement price of $Wear$, that is, the amount saved during a year by an owner who accepts one whole unit of $Wear$ (an old car instead of a new car). Since a very old car does not depreciate any further, the amount saved is the depreciation during the year from holding a new car. Again assuming 20% depreciation, we have: $q = 0.2\left(\hat{b}_0 - \hat{b}_1 cyl - \hat{b}_2 im\right)$.

(4) Fuel Efficiency: The EPA reports miles per gallon (MPG) of new vehicles, but we need it for vehicles of all ages. The CEX does not contain this information, so we estimate MPG using data of the California Air Resources Board (CARB, 1997 and 2000).[25] Their first sub-sample is "series 13", from November 1995 to March 1997, in which the CARB tested a total of 345 passenger cars, light-duty trucks, and medium-duty vans. The second sub-sample is "series 14", from November 1997 to August 1999, which includes

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[24] The CEX does not include the vehicle's nation of origin, so we create the *im* dummy using information on manufacturer and model. We also tried other vehicle characteristics in the regression, such as indicators for automatic transmission, power steering, and air conditioning, but the estimates are not significant. Inclusion of these variables does not raise adjusted R^2 and can result in negative predictions of *cmv*.

[25] For MPG of new cars, http://www.fueleconomy.gov/feg/index.htm is a website of the US Environmental Protection Agency (EPA) and the Department of Energy. The EPA also provides the historical fuel economy of new vehicles at http://www.epa.gov/otaq/mpg.htm or at http://www.epa.gov/otaq/tcldata.htm.

332 vehicles (but which reports only 327 vehicles). In total, we use 672 vehicles. We regress MPG against vehicle characteristics in the CARB and then use those estimated coefficients to predict MPG for each vehicle in the CEX. The estimation results are shown in Table 5, where a 4-cylinder SUV is the omitted category. This table shows that fuel efficiency decreases with vehicle age and with engine size, both for cars and for SUV's. Given the same vehicle age and engine size, MPG is higher for cars than for SUV's.

(5) Emissions per mile (EPM): For the same sample of 672 used vehicles, the CARB tests for several pollutants. Following Fullerton and West (2000), we weight each pollutant by estimates of its damages, with the highest weight on nitrous oxides (NO_X, 0.495), followed by hydrocarbons (HC, 0.405), and carbon monoxide (CO, 0.10). Results appear in Table 5. Cars pollute less than SUV's because they were produced under stricter standards. Older vehicles pollute more, both because newer vintages faced stricter standards and because pollution control equipment deteriorates over time.[26]

(6) Vehicle Miles Traveled (VMT): The OVB file provides cumulative miles on each vehicle, but we need yearly miles driven. We had planned to match households across quarters, take the latest odometer reading minus the earliest one, divide by the number of quarters between readings, and multiply by four. Unfortunately, however, some later odometer readings are less than the earlier ones, and many readings are missing. Therefore, we propose a different procedure to get *VMT*. For a one-car household, we take observed annual expenditure on gasoline, divide by the price per gallon to get number of gallons, and then multiply by MPG to get miles. For a two-vehicle household, we only know the total gasoline expenditure, so we need to allocate it between the two vehicles. Only for this allocation do we use the difference in odometer readings between quarters.[27]

(7) Vehicle bundles: As listed in Table 1, vehicle choices are classified into six categories according to the number and type of vehicles. For bundle 4, with one car and one SUV, the car is always identified as the first vehicle. For bundles 3 and 5, the first vehicle is identified as the one with higher yearly *VMT*. If two vehicles have the same

[26] For vehicles in our sample, 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).

[27] If the difference in odometer readings is positive for both vehicles, then we divide it by MPG to obtain an estimate of each vehicle's gas consumption. Each gasoline amount divided by their sum gives *shares*, used to allocate the observed total gas consumption. Each vehicle's gallons divided by MPG yields *VMT*. If the difference in odometer readings is positive only for one vehicle, we use this figure as VMT_1 and calculate gasoline used in this vehicle. Then total gasoline minus gas used in this vehicle is residual gas, allocated to the other vehicle. Dividing this residual gas by MPG yields VMT_2. If the difference in odometer readings is positive for neither vehicle, then we do imputations based on households with similar characteristics.

yearly VMT, the identification is random. If VMT is missing, then the vehicle with an earlier purchase year is taken as the first vehicle. If the purchase year and miles-driven are both missing, the identification is random.

III. Estimation Results

The model described in Section I is estimated by both the sequential and the simultaneous estimation methods. The mean values of key variables are reported by bundle in Table 6. We average the values within each bundle for each bundle-specific variable except gas price per mile. Gas price per mile is calculated by dividing gas price per gallon by a bundle-specific MPG listed in Table 1. Thus, gas prices per mile vary both within and between bundles. The presence of collinearity between the fixed effects α_0^i (i = 1, …, 6) and the bundle-specific variables such as k_i (i = 1, …, 5) forces us to normalize the fixed effect of bundle one (α_0^1) to zero. To facilitate the estimation, we also normalize y in units of 10,000 dollars, k_i in units of 1,000, and q_1 and q_2 in units of 100 dollars. Accordingly, we multiply $Wear_1$ and $Wear_2$ by 100 to keep the total amount of reimbursement unchanged in the budget constraint.

Notice that bundle 3 and bundle 5 each contains two vehicles of the same type, while bundle 4 consists of one car and one SUV. When the retail gas price increases, all gas prices per mile are affected in bundle-specific ways because MPG depends both on vehicle age and type (car or SUV). As revealed by Table 1, MPG is more type-specific than bundle-specific. Thus, we expect that the gas price parameters of car bundles 1 and 3 are quite close to one another, as are those of SUV bundles 2 and 5. For a household with one car and one SUV (bundle 4), however, we wish to allow more substitution. In our estimation, we assign one parameter α_{C1} to the gas price of the only car in bundle 1 and first car in bundle 3 (and α_{C2} to the second car). We assign one parameter α_{S1} to the only SUV in bundle 2 and first SUV of bundle 5 (and α_{S2} to the second SUV). Then we assign two gas price parameters to bundle 4: $\alpha_{p1}^4 (= \alpha_{CAR}^4)$ for the car and $\alpha_{p2}^4 (= \alpha_{SUV}^4)$ for the SUV. Results from the sequential estimation are discussed first.

We follow the procedure suggested by Dubin and Mcfadden (1984), but at the first stage we estimate a nested logit structure instead of a multinomial logit model. The traditional ML method is employed. The RF method is adopted at the second stage because the correction terms derived by Dubin and Mcfadden are inappropriate for the

GEV error structure. In the second stage we estimate four continuous demand equations jointly (only two equations for the one-vehicle bundles), using an objective function similar to equation (13) except that the last term is removed. We constrain parameters to be constant across bundles except those for gas prices and constant terms. The estimation results are reported in the first two columns of Table 7, under "sequential estimation".

For the discrete choice model in the first column of Table 7, the estimates of α_{C1} and α_{S1} are significant at the 1% level, while those of α_{C2} and α_{S2} are not statistically significant. The estimates of $\alpha_{p1}^{4} (= \alpha_{CAR}^{4})$ and $\alpha_{p2}^{4} (= \alpha_{SUV}^{4})$ are both significant at the 0.01 level. All of them are negative as expected. The *Wear* coefficients α_{q1} and α_{q2} are also different from zero at the 0.01 level. The parameter λ_n $(n = 1,2)$ measures the degree of independence of the errors of alternatives in nest n. In our model, the estimates of λ_1 and λ_2 are 0.814 and 0.066, respectively, both significant at the 0.01 level.[28]

Since all the estimates of α_{p1} and α_{p2} are negative, equations (14) indicate that the marginal effects of gas prices per mile are negative. As consistent with expectation, an increase in gas price reduces household utility. Since the coefficient on the reimbursement price q_1 is negative, the marginal effect on utility is positive as expected. A higher reimbursement price means more money back to the household for accepting a given vehicle age or level of *Wear*. However, the coefficient on q_2 has unexpected sign. Since estimates of β and β_1 are both negative and significant, equations (15) indicate that the marginal effect of capital cost is negative while that of income is positive.

We then use those discrete choices from the first column to estimate the continuous demands shown in the second column. A glance down the second column indicates that most of estimated coefficients are quite different from the corresponding estimates in the first column. Yet the parameters in the second column are the same parameters as in the first column, even from the same model, as the continuous demands are supposed to be consistent with a particular indirect utility function. For example, the estimated coefficient on income is −1.408 in the first column and +1.134 in the second column. Both have small errors, and so they are significantly different from each other, even though they are the

[28] If $\lambda_n \; \forall n$ are within the range of zero to one, then "the model is consistent with utility maximization for all possible values of the explanatory variables" (Train, 2003, p.85). Since our λ are significantly less than one, the errors within each nest are correlated, evidence in favor of nesting rather than MNL.

same parameter of the same model. Many price coefficients also differ significantly in magnitude (and the two estimates of α_{q2} differ in sign).

Next, the model is estimated by the simultaneous estimation procedure proposed in Section I.C. The point of this procedure is to capture household-specific heterogeneity in both discrete and continuous choices. The two types of choices are connected by the same parameters and the same random error term η appearing in both.[29] In contrast, in the sequential procedure, the bundle choice affects continuous demands (and not vice versa). The simultaneous estimates are reported in the last column of Table 7.

All ten estimates of coefficients on key variables have the expected signs, and all but two are significantly different from zero. Yet, for many parameters, the estimate differs from *both* estimates obtained by sequential estimation. For example, the capital cost coefficient (β_1) from the simultaneous model (–0.405) is smaller in magnitude than either that of the logit model (–0.671) or the continuous demand model (–0.456). The estimates of coefficients on demographic variables vary with the estimation method, not only in magnitude but also in sign. For most price variables, however, the estimate from the simultaneous model is *between* the two estimates from sequential estimation, which suggests that the simultaneous model might provide more "reasonable" coefficients. These coefficients cannot really be compared directly, however, and so we turn to elasticities.

IV. Elasticity Comparisons

Bundle choice elasticities are presented in Table 8. The upper panel shows elasticities from the sequentially estimated model, but our discussion will start with the elasticities in the lower panel from the simultaneously estimated model. Each entry in the table is not an elasticity with respect to each price in the model, as it might be difficult to interpret an elasticity such as the change in the probability of holding bundle 3 (two cars) for a change in the price p_1 for gas in the first car only. Instead, we calculate the simultaneous effect on all choices for a change in the price of gasoline. In the lower part of Table 8, the first row shows that a 1% increase in the price of gas would decrease most the probability of holding bundle 4 with a car and an SUV (by 0.793%) while increasing the share holding bundle 3 with two cars (by 0.695%). In other words, these households

[29] The standard deviation for $x'\gamma$ is about 0.086 within a bundle, and for βy is about 0.78 within a bundle, so the finding that η has a range (-0.65,0.65) reflects a significant amount of individual heterogeneity. Therefore, introducing individual heterogeneity is expected to make a difference in parameter estimates.

sell the SUV for a second car instead. This change is driven by the high price of driving an SUV with low fuel efficiency.[30] In contrast, using results from the sequential method in the top panel, the price of gas has little effect on any bundle share.

Given vehicle age, a higher reimbursement price q for *Wear* of a particular bundle means more money back to the household and thus higher probability of choosing that bundle. Again, however, it is difficult to interpret a change in the price q_1 for the first car with no change in q_2 for the household's second car. Instead, we show effects of a change in q for all vehicles (or for all cars only, or all SUV's only). Rather than raising q, policymakers may want to reduce q by taxing old vehicles or by subsidizing the purchase of a new vehicle, in order to reduce emissions. Table 5 above shows that emissions per mile (EPM) are higher for SUV's than for cars, and rise with either vehicle's age.

For the simultaneous model in the lower part of Table 8, the second row shows that a 1% tax on *Wear* (lower q for all vehicles) would decrease the probabilities of holding all bundles except bundle 5 (SUV, SUV). In the next row, a tax on the age only of cars would decrease the reimbursement for wear on cars, q_{car}, and switch households out of cars and into bundle 2 with an SUV and bundle 5 with two SUV's. Conversely, the next row shows that a tax on the age only of SUV's that lowers q_{suv} would induce a switch out of bundles 2 and 5 with just SUV's, and into bundles with cars.[31]

The discrete-choice-only model in the top half of the table shows results for q where effects on SUV bundles are unreasonably large and sometimes the wrong sign. A tax that lowers q_{suv} would encourage the purchase of two SUV's.

Back to the lower panel for the simultaneous model, the choice elasticities with respect to y indicate that households with more income switch from holding no car (bundle 6) to one car (bundle 1), and those with a single SUV (bundle 2) seem to add a car (bundle 4). Additional income reduces the share with two cars (bundle 3). These results are inconsistent with the discrete-choice model, where the only bundle with a positive income elasticity is bundle 2 with one SUV.

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[30] This reasoning is confirmed by the choice elasticities with respect to p_1 and p_2 separately. For bundle 4, a 1% higher price per mile in the car reduces the probability of choosing that bundle by 0.37%, while a 1% higher price per mile in the SUV (p_2) reduces the probability of choosing that bundle by 0.81%. Thus, the gas consumption of the SUV has twice as much impact as that of the car.

[31] This tax on age of SUV's might actually cut emissions in two ways: by inducing a switch from SUV's to cars (Table 8), and by inducing a switch from older SUV's to newer SUV's (Table 9 below).

We next look at an increase in capital cost in the lower panel of Table 8. Since this change effectively reduces available income, we see that each capital cost elasticity has the opposite sign as that bundle's income elasticity. With higher capital costs, households seem to shift primarily out of two-vehicle bundles with at least one SUV (4 and 5) into bundles with two cars (bundle 3) or only one SUV (bundle 2). While it does not make sense to increase the capital cost only for the first car of a two-car household, it might make sense to increase the capital cost only of cars relative to SUV's or vice versa (to represent a vehicle-type tax). The next row of Table 8 shows that if the increase in capital cost pertains only to cars, then it decreases the shares of the two bundles that have only cars. If it pertains only to SUV's, however, then it has large effects that decrease the shares of all three bundles with SUV's. Such a policy could clearly reduce emissions (given the EPM in Table 5). The 1% higher cost of an SUV means 13.7% less of bundle 4, which seems too large, but it means that the share falls two percentage points (from 14.5% of all households in Table 6 to 12.5% of all households). The discrete-choice-only model in the top part of Table 8 produces elasticities with smaller magnitudes, except that the bundle 5 elasticity has the wrong sign (higher k_{suv} lead to more households with two SUV's).

The sequential model uses predictions of discrete choices to estimate continuous demands, for which elasticities are shown in the top half of Table 9. These are "short run" elasticities, in the sense that car choices are fixed and only continuous choices like driving distances may change (Goldberg, 1998).[32] Again, we focus primarily on simultaneously estimated elasticities in the bottom panel. In the first row, all elasticities for VMT_1 with respect to gasoline price are negative, as expected, for all bundles. (For this demand, the sequential model produces similar results.) The next row of Table 9 shows the effects of a 1% increase in the reimbursement price, q, on *Wear*. These elasticities are all positive, as expected: households choose older vehicles when they get higher reimbursement for holding an old vehicle. Conversely, a tax on vehicle age that reduces q by 10% would reduce desired *Wear* by about 1.2 to 1.4% (assuming the desired cars were available).[33] The table also shows similar effects of changing q just for cars, or just for SUV's.

Next, consider income and capital cost elasticities. Due to the symmetric specification of demand functions, a 1% change in y or k has the same effect on both

[32] Panel data would be required to distinguish the effects of lags from contemporaneous price changes.

[33] In Table 6, the average *Wear* of 0.75 corresponds to 6.2 years of age, so a 1.2% decrease in *Wear* means a decrease of about one month of age. In the sequential model, the same 10% lower q affects desired age of one-vehicle bundles by one-tenth as much, and desired ages of two-vehicle bundles by three times as much.

VMT and *Wear* (whether for the first vehicle or the second). In the simultaneous model, income elasticities are positive as expected. One percent more income would increase driving distances by about 1% to 1.5% for all bundles. In contrast, the sequential model implies income elasticities that are all negative and large (-2.6 to -4.0). The capital cost elasticities are negative as expected, for both models.

The specific form for utility in equation (4) means a specific form for demands in equations (5), where $\ln(VMT)$ and $\ln(Wear)$ both depend on $\alpha^i_p p_i - \alpha_q q_i$. In other words, the parameter that determines the important effect of gas price on miles (α^i_p) also necessarily drives the less-important effect of the gas price on choice of *Wear*. Similarly, the own-price effect of q on *Wear* also drives the cross-price effect of q on *VMT*. We note this fact, but we do not mean to emphasize these cross-price elasticities.

Finally, the last column in Table 9 reports the percentage change in total emissions when each variable increases by 1%. In the simultaneous model, for example, a 1% increase in all gasoline prices would reduce total emissions by 0.136%, while a tax on age that reduces q by 1% would reduce total emissions by 0.434%.[34] The largest elasticities are from income and capital cost: 1% higher income raises total emissions as expected, by 4.246% (but in the sequential model would reduce emissions by 11.47%!) A 1% increase in capital cost reduces total emissions by about 8% in either model.

In the simultaneously estimated model, the coefficients are affected by all discrete and continuous choices. The model imposes more constraints on the estimates. Thus, if those constrained estimates are plugged into the likelihood function for either part of the sequential procedure, then the likelihood is not as high as for that *portion* of the sequential procedure. However, the sequentially estimated model yields two sets of estimates for the same parameters. The finding that these estimates are not consistent with each other raises questions about whether the behavioral model is correctly specified.

V. Conclusion

This paper focuses on incentive effects of price changes that might be associated with policies to reduce vehicle emissions. We provide a model of household behavior that incorporates both the discrete choice of vehicle type, with different fuel efficiencies and

[34] These are also short run elasticities, with no change in the number or type of vehicles. Notice that the percentage change in emissions from a change in p is more than twice the change in driving distance, because the higher p also reduces demand for *Wear* (which also reduces emissions). The change in q also affects both *VMT* and *Wear* in the same direction, enlarging the effect on emissions.

emission rates, and continuous demands for miles driven. Because emission rates depend directly on vehicle age, we also model vehicle age as a continuous choice. To model the effect of prices on the choice of vehicle age, we establish a choice of "concept vehicle" that is separate from the choice of "*Wear*". Using hedonic price regressions, we quantify the price of *Wear*. Then, after the discrete choice among concept vehicles, both *VMT* and *Wear* become continuous variables that enter utility.

Yearly household data are obtained from the CEX of 1996 – 2000, supplemented with fuel efficiency estimates from the CARB, and gas prices from the ACCRA cost of living indexes. First, like many others, we follow the sequential procedure suggested by Dubin and McFadden (1984). This procedure generates two different sets of estimates for the same set of parameters, which we argue is inconsistent with maintained hypotheses about the utility function and utility maximization. We then propose and implement a simultaneous method for consistent estimation of both discrete and continuous choices in one step. Results from the simultaneous estimation differ significantly both in signs and magnitude from both sets of estimates obtained by sequential estimation.

We find that a higher price of gasoline would shift households out of the Car-SUV pair and into the bundle with two cars. It also would reduce miles driven. Both of these changes reduce emissions. A tax on vehicle age would induce shifts to newer vehicles with less "*Wear*", and would also shift families out of bundles with an SUV. Both of these changes also reduce emissions. Similarly, a tax on SUV's would shift families into cars and reduce emissions. The size of these shifts is important information for environmental policy. Rather than pin down the exact size of the important parameters, however, this paper points to important problems with existing methods and suggests an alternative approach with more internal consistency.

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Table 1. Vehicle Bundle Descriptions and Statistics

Bundle	# of Vehicles	First Vehicle	Second Vehicle	# of Households	MPG of First Vehicle	MPG of Second Vehicle
1	1	Car	--	3469	21.37	--
2	1	SUV	--	742	16.76	--
3	2	Car	Car	1181	21.88	21.55
4	2	Car	SUV	1305	21.51	16.53
5	2	SUV	SUV	253	17.04	16.50
6	0	--	--	2077	--	--

Note: The number of households is from the consumer expenditure survey (CEX), and miles per gallon (MPG) is calculated from CARB data described below.

Table 2. Variable Definitions

Variable	Definition
y	Household's yearly expenditure
k	Total capital cost of a vehicle bundle
p_1	Gas price per mile of the first vehicle
p_2	Gas price per mile of the second vehicle
q_1	Unit price of *Wear* of the first vehicle
q_2	Unit price of *Wear* of the second vehicle
VMT_1	Miles driven in the first vehicle
VMT_2	Miles driven in the second vehicle
$Wear_1$	Continuous variable to measure the wear of the first vehicle
$Wear_2$	Continuous variable to measure the wear of the second vehicle
Famsize	Number of members in a household
Earnr	Number of income earners in a household
Kids	Number of children less than 18 in a household
Drivers	Number of household members 16 years old and over
Metro	A dummy variable: one if the household resides inside a Metropolitan Statistical Area (MSA), and zero otherwise
Pop4	A dummy variable: one if the household lives in an area with a population of more than 4 million, and zero otherwise
Urban	A dummy variable: one if the household lives in an urban area, and zero otherwise.
Age	Age of household head
White	A dummy variable: one if the household head is white, and zero otherwise
Male	A dummy variable: one if the head is male, zero otherwise
Educ	A dummy variable: one if the head has education higher than high school, zero otherwise
Northwest	A dummy variable: one if in the Northwest, zero otherwise
Midwest	A dummy variable: one if in the Midwest, zero otherwise
South	A dummy variable: one if in the South, zero otherwise
West	A dummy variable: one if in the West, zero otherwise

Table 3. Summary of Household Statistics by Vehicle Bundles

Characteristics	Number of Vehicles					
	1		2			0
	1 (Car)	2 (SUV)	3 (C,C)	4 (C,S)	5 (S,S)	6 (none)
# of households	3469	742	1181	1305	253	2077
household size	1.92	2.30	2.65	2.94	3.44	1.98
% with kids	23.87	33.56	33.62	43.98	62.45	26.05
# of kids	0.44	0.73	0.56	0.89	1.42	0.55
# > 15 years old	1.52	1.63	2.13	2.12	2.13	1.48
# of workers	0.85	1.08	1.43	1.49	1.58	0.70
% heads male	40.10	63.07	65.54	71.80	77.47	33.22
age of head	55.24	48.22	51.84	49.45	45.24	55.66
% heads white	82.07	87.60	83.32	89.04	92.89	67.89
% heads educ > high school	52.15	52.29	66.05	57.01	57.31	34.33
% in area with pop.> 4 million	28.37	19.41	30.48	22.68	18.58	38.61
expenditures	22754.	24574.	35472.	33812.	34246.	17795.
total gas cost	648.	920.	1103.	1279.	1398.	--

Table 4. Hedonic Price Regressions

Dependent Variable: *cmv*	Cars		SUVs	
	Coefficient	Standard Error	Coefficient	Standard Error
constant (a_0)	1444.64	1806.08	-1220.52	2702.42
cyl (a_1)	3150.55	288.44	1993.56	411.23
import (a_2)	2371.11	894.32	1417.36	1584.27
1-Wear (b_0)	-2179.03	3272.66	8973.32	4996.71
Wear×cyl (b_1)	-3184.92	546.49	-1459.66	763.85
Wear×import (b_2)	-998.07	1719.28	-658.35	2800.80
R^2	0.49		0.51	
# of obs.	793		510	

Table 5: Estimation of Miles Per Gallon (MPG) and Emissions Per Mile (EPM)

Independent Variable	Dependent Variable: MPG Coefficient	MPG Standard Error	EPM Coefficient	EPM Standard Error
constant	24.021	0.496	-0.597	0.663
cyl6	-4.395	0.483	1.103	0.645
cyl8	-7.948	0.581	3.548	0.777
age	-0.419	0.049	0.285	0.065
age^2	0.006	0.002	0.003	0.002
car	4.262	0.410	-0.589	0.548
cyl6 × car	-1.439	0.560	-0.661	0.749
cyl8 × car	-1.149	0.655	-2.819	0.875
R^2	0.7598		0.4095	
F-value	299.997		65.775	
# of obs.	672		672	

Table 6. Mean Values of Key Variables Involved in Estimation

Variable	Bundle: 1 (Car)	2 (SUV)	3 (C,C)	4 (C,S)	5 (S,S)	6 (none)
% of households	38.43	8.22	13.08	14.46	2.80	23.01
VMT_1	11799.	12977.	15283.	10513.	16151.	--
VMT_2	--	--	5554.	10771.	5358.	--
price of gas 1 (p_1)	0.058	0.074	0.056	0.057	0.072	--
price of gas 2 (p_2)	--	--	0.057	0.075	0.075	--
vintage1	8.62	8.24	7.63	7.89	6.87	--
vintage2	--	--	9.02	8.50	8.78	--
$Wear_1$	0.76	0.73	0.72	0.73	0.68	--
$Wear_2$	--	--	0.77	0.73	0.75	--
price of $Wear_1$ (q_1)	15572.	18010.	15363.	15686.	18052.	--
price of $Wear_2$ (q_2)	--	--	15301.	18133.	18105.	--
expenditure (y)	22754.	24574.	35472.	33812.	34246.	17795.
capital cost (k)	17224.	20187.	34157.	37684.	40551.	--
capital cost 1	17224.	20187.	17125.	17337.	20232.	--
capital cost 2	--	--	17032.	20348.	20319.	--

Table 7. Estimation Results

Parameters	Sequential Estimation		Simultaneous Estimation
	Nested Logit	Continuous Demands	
p_{11}, p_{31} (α_{C1})	-0.246**	-0.460**	-0.433**
	(0.025)	(0.070)	(0.073)
p_{32} (α_{C2})	-0.045	-0.238*	-0.045**
	(0.033)	(0.143)	(0.008)
p_{21}, p_{51} (α_{S1})	-0.237**	-0.927**	-0.526**
	(0.028)	(0.054)	(0.105)
p_{52} (α_{S2})	-0.011	-0.453	-0.013
	(0.049)	(0.380)	(0.080)
p_{41} (α^4_{CAR})	-0.240**	-0.374**	-0.399**
	(0.024)	(0.143)	(0.062)
p_{42} (α^4_{SUV})	-0.084**	-1.331	-0.662**
	(0.022)	(1.582)	(0.103)
q_1 (α_{q1})	-0.012**	-0.370E-03	-0.004**
	(0.003)	(0.002)	(0.001)
q_2 (α_{q2})	0.010**	-0.010**	-0.219E-36
	(0.001)	(0.002)	(0.936E-36)
y (β)	-1.408**	1.134**	-0.420**
	(0.086)	(0.134E-03)	(0.001)
k (β_1)	-0.671**	-0.456**	-0.405**
	(0.108)	(0.034)	(0.023)
Choice specific:			
constant 2 (α^2_0)	-1.403**		0.645**
	(0.278)		(0.035)
constant 3 (α^3_0)	4.219**		1.860 **
	(0.516)		(0.031)
constant 4 (α^4_0)	5.057**		2.063**
	(0.650)		(0.051)
constant 5 (α^5_0)	2.401**		2.320**
	(0.685)		(0.062)
constant 6 (α^6_0)	-2.045**		-0.948**
	(0.383)		(0.132)
Demand-Specific:			
constant 1 (α_{V1})		9.578**	0.302**
		(0.179)	(0.087)
constant 2 (α_{V2})		7.361**	0.805**
		(0.187)	(0.088)
constant 3 (α_{W1})		9.346*	2.580**
		(5.007)	(0.298)
constant 4 (α_{W2})		5.147**	5.114**
		(0.176)	(1.259)

(continued on the next page)

Table 7. Estimation Results (cont'd)

Famsize	0.332	0.072**	0.058**
	(0.542)	(0.002)	(0.001)
Earnr	0.270**	0.067**	0.032**
	(0.067)	(0.001)	(0.183E-03)
Kids	0.510	0.081**	-0.031**
	(0.527)	(0.002)	(0.001)
Drivers	0.190	0.060**	-0.041**
	(0.535)	(0.001)	(0.001)
Metro	-0.552**	-0.012**	0.012**
	(0.123)	(0.002)	(0.474E-03)
Pop4	-0.340**	-0.013**	0.012**
	(0.085)	(0.001)	(0.290E-03)
Urban	-0.441**	-0.058**	0.105**
	(0.161)	(0.002)	(0.001)
Age	0.046**	-0.007**	0.004**
	(0.003)	(0.290E-04)	(0.128E-04)
White	0.056	0.136**	0.097**
	(0.091)	(0.001)	(0.386E-03)
Male	0.057	0.109**	0.004**
	(0.085)	(0.001)	(0.240E-03)
Educ	0.020	0.058**	0.036**
	(0.072)	(0.001)	(0.263E-03)
Northwest	0.244	0.042**	0.046**
	(0.179)	(0.001)	(0.386E-03)
Midwest	0.401**	0.064**	0.059**
	(0.173)	(0.001)	(0.380E-03)
South	-0.726**	-0.150**	0.072**
	(0.121)	(0.001)	(0.374E-03)
λ_1	0.814**		0.138**
	(0.053)		(0.006)
λ_2	0.066**		0.103**
	(0.003)		(0.005)
Log Likelihood	-28917.8	-786857	-0.310E+07

* indicates 0.10 significance level, and ** indicates 0.05 significance level.

Table 8. Elasticities of Discrete Choices for each Variable

	Bundle					
Variable	1 (Car)	2 (SUV)	3 (C,C)	4 (C,S)	5 (S,S)	6 (none)
Sequential: [a]						
p	0.015	-0.106	0.006	-0.177E-03	0.034	--
q	-0.207	3.618	-0.116	-0.033	-6.077	--
q_{car}	1.530	-6.318	0.139	0.127	-3.470	--
q_{suv}	-1.737	9.937	-0.255	-0.160	-2.603	--
y	-0.106	0.591	-0.042	-0.006	-0.011	-0.006
k	0.086	-0.427	0.061	0.008	-0.303	--
k_{car}	-0.008	0.127	0.056	-0.944	4.336	--
k_{suv}	0.110	-0.413	0.134	-1.099	4.703	--
Simultaneous: [b]						
p	0.009	-0.073	0.695	-0.793	0.020	--
q	0.025	0.193	0.066	0.283	-0.001	--
q_{car}	0.177	-0.966	0.151	0.352	-0.147	--
q_{suv}	-0.153	1.159	-0.085	-0.069	0.146	--
y	0.341	-1.203	-0.818	0.634	0.010	-0.074
k	-0.321	0.390	1.655	-6.319	-0.377	--
k_{car}	-1.229	7.315	-13.021	7.345	1.263	--
k_{suv}	0.908	-6.925	14.676	-13.665	-1.640	--

[a] Calculation based on estimates in column 1 of Table 7.

[b] Calculation based on estimates in column 3 of Table 7.

Table 9. Short-Run Elasticities of Continuous Demands

Variable	Bundle 1 (Car)	2(SUV)	3 (C,C)	4 (C,S)	5 (S,S)	Total Emissions [c]
Sequential: [a]						
p	-0.026	-0.066	-0.038	-0.117	-0.098	-0.211
q	0.012	0.013	0.306	0.360	0.362	0.631
q_{car}	0.012	--	0.306	0.012	--	0.368
q_{suv}	--	0.013	--	0.349	0.362	0.263
y	-2.581	-2.788	-4.024	-3.836	-3.885	-11.472
k	-1.570	-1.840	-3.113	-3.434	-3.695	-8.746
Simultaneous: [b]						
p	-0.024	-0.037	-0.026	-0.070	-0.038	-0.136
q	0.122	0.141	0.120	0.123	0.141	0.434
q_{car}	0.122	--	0.120	0.123	--	0.293
q_{suv}	--	0.141	--	7.933E-36	0.141	0.141
y	0.956	1.032	1.490	1.420	1.438	4.246
k	-1.397	-1.637	-2.770	-3.056	-3.288	-7.783

Each entry is the elasticity of *VMT* or *Wear*, in the first or second vehicle, with respect to each variable.

[a] Calculation based on estimates in column 2 of Table 7.

[b] Calculation based on estimates in column 3 of Table 7.

[c] The last column is the percent change in total emissions, $E = \sum \text{EPM} \times \text{miles}$, adding over all vehicles in all bundles, for a one percent change in each variable.

Market Mechanisms and Incentives: Applications to Environmental Policy

October 17, 2006

Discussant: Ed Coe

Session III: Mobile Sources

Tradable Fuel Economy Credits: Competition and Oligopoly

Given that there is some increased interest in examining options for reducing GHGs from the transportation sector, this study comes at an opportune time. Also, since many groups are examining many different options, it is useful to have a model that can examine a number of different options.

While there are a number of models that exist that can estimate the impacts of changes in CAFÉ standards, the particular strength of this model is its ability to estimate the impacts on particular auto manufacturers. Since this model also examines different platforms, it should be possible to examine impacts if the passenger car CAFÉ standards were set in a fashion similar to the light-duty truck reformed CAFÉ standards, which are based on six platforms. Also, given that some auto manufacturers are exploring the possibility of merging or developing partnerships, this model might be able to assess, to some extent, the impacts of the combined entity.

It is very useful, from a policy perspective, that this model can examine the impacts assuming perfect competition, and oligopolistic approaches. It's useful to note from a policy perspective, that a significant portion of the total savings available is from class averaging within firms – it is important to note this, if one assumes that there might be non-competitive behavior regarding credits.

DOE's NEMS considers a technology to be cost-effective if the technology pays back in three years at a 15% discount rate. It would be interesting to apply those assumptions here and see what kind of impacts they might have on the results.

Other thoughts
Price set by EIA's reference case of $1.51/gallon, and "high B" forecast of $1.84/gallon
Miles driven is fixed for each vehicle class (no rebound?)
No diesel or hybrid technology
No alternative fuel – E85 vehicles?
After the fact FFV credits?

Environmental Marketing of Passenger Vehicles: Strategies and Impacts

It's no secret to anyone that the effectiveness of eco-communications or labeling programs is very difficult to quantify. I think that this study makes a good attempt at attempting to quantify the effectiveness of these types of programs, and at the very least, does show trends.

From a policy and program perspective, the quantification of these types of programs would go a long way in assisting states meeting their State Implementation Plans (SIPs). However, it's not clear to me that such a rigorous model could be developed in the near future, but I'm willing to be convinced otherwise [real reductions, verifiable, enforceable].

I noticed that the methodology is done in a two step process, a person picks the class of vehicle to purchase, then considers information within a class. But, a Maritz study, which is a Car Buyer Market Research firm, recently conducted a study of new car buyers and found that about 1/3 of all new car buyers look across classes. Is it possible to model that behavior?

EPA has developed the Green Vehicle Guide, which is on the Web. Those cars that meet certain air pollution and greenhouse gas emissions criteria get a special designation of SmartWay. It would be interesting to see a pilot program in which a state uses these designations and examine whether the SmartWay label has an effect on consumer choice.

I think that using Auto Dealers as a surrogate for Auto Producers might represent a weakness in the model, since auto dealers cannot develop new product lines, but might be useful from the perspective that they have some control over their inventory.

Would be interesting to see how people would react to today, given a greater awareness or sensitivity to gas prices.

<u>Vehicle Choices: Miles Driven, and Pollution Policies</u>

From a policy perspective, it is important to have a model that can estimate the effectiveness of policies or measures applied to the light-duty mobile sector for reducing criteria pollutant. Again, as in the last study, such a model that can estimate benefits within a certain band of uncertainty, can be useful in the State Implementation Plans context, to the extent that reductions are real, verifiable, and enforceable.

As you mentioned, the particular strength of this model, is its ability to capture the simultaneity of certain decisions and yield a single set of parameters.

You conclude that a higher price for gasoline would tend to shift households out of the Car-SUV pair and into the bundle with two cars. You also conclude that miles driven would be reduced. However, given that the SUV has been replaced by a car, and the cost of driving for that household has been reduced, is it possible that household might be induced to drive a little more?

Why use mpg as a variable instead of gallons-per-100 miles or other fuel consumption metric? mpg vs fuel consumed is non-linear while gallons-per-100 miles vs fuel consumed is a linear relationship.

[i.e. going from 10 to 12 mpg is a much larger fuel savings than going from 30 to 32 mpg, whereas going from 5 to 4 gallons per 100 miles saves the exact same amount of fuel as from 11 to 10 gallons per 100 miles]

Workshop on
Market Mechanisms and Incentives: Applications to Environmental Policy
October 17th and 18th, 2003
Resources for the Future

Mobile Source Session: Discussion

Winston Harrington

The three papers presented in the mobile source session were all high quality papers. Each asked a different question, but all were related. One was concerned with modeling vehicle supply, another with vehicle demand, and the third with whether and how vehicle demand might be shaped by public relations campaigns appealing to altruistic motives.

1. Rubin, Jonathan, Paul Leiby and David Greene, "Tradable Fuel Economy Credits: Competition and Oligopoly"

This is a very nice paper I think, and it generates some interesting results. It's not a welfare analysis and it doesn't compare CAFE to other potential fuel saving policies, but a cost-effectiveness paper focused on CAFE policy design. The authors have built an interesting model of vehicle supply that is both manufacturer and vehicle class-specific. Vehicle Classes are limited to cars and trucks, but that is enough for their purposes. The model allows them to compare the perfectly competitive solution to the Nash-Cournot and Stackelberg oligopoly models. They use the NAS cost assumptions for fuel-saving technologies. The purpose of the paper is to determine the potential cost savings available from various kinds of CAFE credit trading and the extent to which those savings are compromised by imperfect competition. The most important conclusions of the exercise is that (i) one can get most of the benefits of CAFE trading simply by pooling the car and light truck categories, without having trading across manufacturers, and (ii) the cost savings are not much affected by oligopoly.

There were three further aspects of the results that caught my eye. First, in the perfectly competitive case, fully tradable CAFE can achieve cost savings that exceed 100%. That is, fully tradable CAFE can actually reduce costs. The authors observe this, but don't really offer an explanation. Considering that each CAFE technology has positive costs (i.e. no assumptions here of Porteresque efficiency gains from forcing manufacturers to look where they haven't before), this outcome deserves some discussion. One possibility that occurred to me concerns the baseline. The policies they examine are a 30 and 40 percent improvement in CAFE over the current US policy. Of course, the current policy has well-known inefficiencies, so perhaps the costs of more stringent CAFE standards are more than offset by the removal of the inefficiencies of the current CAFE policy.

Second, the authors' estimates of the distributional effects of tradable CAFE are striking and, it seems to me, counter to the conventional wisdom. I don't really understand how US manufacturers, like Ford and GM are not hurt, especially by the pooling of the car and truck categories. Ford's fleet mix is heavily weighted toward truck, so if permit allocations are based on the status-quo fleet, then Ford, with its vehicle fleet heavily weighted toward trucks, would seem to be at a disadvantage. It would be useful for the authors to provide a little intuition of how this could be

Third, the paper makes the point that if the cost of the technology is low, then there is little value to a marketable permit system, because the constraint is barely binding. If the cost is high, then there is little value to a permit market because no manufacturers will have "surplus" permits and there are few gains from trade. This conclusion, I think, is driven by the NAS cost estimates, which do not vary much across categories. Without cost heterogeneity, it is of course true that gains from trade are minimal. But I still think they are selling markets short, because without a mechanism you won't know what the costs are. One of the unsung advantages of markets is that they are effective devices for cost revelation.

2. Ye Feng, Don Fullerton and Li Gan, Vehicle Choices, Miles Driven and Pollution Policies."

This paper tackles a really important methodological problem involving discrete-continuous models of vehicles and use. These models were pioneered by Dubin and McFadden in the study of household appliance demand, and have been used by many authors to study the demand for motor vehicles. These models posit a utility function that yields a demand function for vehicles, and conditional on vehicles owned, a demand function for VMT. These two demand functions have many parameters in common, but in empirical work it has been the usual practice to estimate them not as a system but sequentially, a procedure that provides two distinct estimates of parameters that should be equal. This can be okay if you are simply trying to predict VMT at the household level, and these models do a pretty good job of that. But for other tasks, having what amounts to an *ad hoc* procedure can lead to problems. For example, if you are trying to estimate welfare, these models can lead to nonsensical results.

The reason researchers have not estimated a system of equations is that it has proved to be very difficult to do. Households have a huge number of possible choices for vehicle ownership combinations, and this variety presents real difficulties in estimation. Feng et al. make some innovations and simplications that make the estimation manageable. First, they classify vehicles into only two types: cars and trucks. In addition, Second, they make age a continuous variable, which is distinct from the usual practice of having distinct variables for each vintage. In effect age is turned into a variable that measures the value of the vehicle stock. Third, they limit themselves to only households containing two vehicle or fewer.

With these simplifications they are able to estimate a simultaneous system of equations, and they nicely contrast these results to the results of a sequential model in a table. They show first, how different the two estimates of the same parameter can be in the sequential model, and second, how the simultaneous model results are different from either.

Of course, with the simplifications of the specification there will be costs. The aggregation to two vehicles ignores the role of particular vehicle characteristics in explaining consumer buying behavior, except insofar as they are captured in the car/truck difference. But cars (or trucks) differ greatly in acceleration, number of passengers, towing capacity, interior volume and other features. There is risk here of omitted variable bias. In two-vehicle households the difficulty becomes even more complex, since households looking for a particular feature may only require it in one of their vehicles. The authors defend this assumption by observing that these characteristics do not affect emissions, which is true as far as emissions of conventional pollutants are concerned, but not green house gases.

In addition, the restriction to households with two vehicles or less omits 18% of US households and 33% of all vehicles, which could account for a large share of VMT. In response to this comment at the workshop, it was claimed that the model with three households is just too complex to estimate. It was unclear to me whether this was due to a lack of computing power or something else. In addition, Don speculated that the VMT in the third (or greater) vehicle in the household would be much less than the two primary vehicles, but in fact the data from the 2000 Nationwide Household Travel Survey suggest that the falloff in mileage for the third car is surprisingly small. Perhaps this shouldn't be too surprising, since most of the households owning more than two vehicles also have more than two licensed drivers. What the data suggest is that households respond to the low marginal cost of vehicle operation, and once a vehicle is in the household, it is driven.

If I were to make any suggestions for the authors it would be to revisit the two-vehicle limitation and if possible, extend to allow for three vehicle households. Beyond this, one interesting comparison would be for the authors to estimate the welfare effect of vehicle fuel price, and compare to the welfare change estimated from the sequential model. If their experience is like ours, they will find that the welfare estimates made using the coefficients from the discrete part of the sequential model will be nonsensical.

3. Mario Teisl, Jonathan Rubin, and Caroline Noblet, Do Eco-Communication Strategies Reduce Energy Use and Emissions from Light Duty Vehicles?

This is a very well-conceived project, an experiment to estimate the effectiveness of providing consumers with information about the emission characteristics of new vehicles in pro-bono radio spots. The campaign itself consisted of two parts: a series of radio spots and other PR designed to raise consciousness. One of its striking features is the cooperative venture combining the efforts of state government, automobile dealerships, and environmentalists. As far as I am aware, you rarely see this kind of cooperation in an experiment. Usually the parties want something—PR, action, etc.—that makes it difficult to adhere to a proper experimental design.

The design here is classic. You have a localized treatment area and a control area consisting of the rest of the state. Two surveys conducted before and after a campaign to encourage purchase of environmentally benign vehicles allow the researchers to isolate the effects of the treatment from other influences on vehicle purchase decisions.

A few comments on the paper and the results, as opposed to the experimental design.

1. The paper itself shows signs of being an early draft, and I'm sure with more editing it will improve substantially. For example, the authors don't tell usmuch at all about the statistical approach. At the workshop Jonathan indicated that ordered logit was the statistical model used to analyze the attitudinal questions, but "logit" appears nowhere in the paper. There was also nothing in this draft about the bottom line—the effect on vehicle purchase decisions, and apparently there won't be. In his presentation I believe Jonathan said those results are in a separate paper. To me, it's a little disappointing to separate the results like that, and it belies the title of this paper.

2. The finding that the car dealerships were did not participate in the campaign in spite of the support given to it by their own trade association was surprising but not unprecedented. Karen Palmer has told me of other cases involving battery recycling where the efforts of the national trade association were ignored by the local members. It is a bit depressing; if contacting their trade association doesn't work, then how would it be possible to engage the dealerships?

3. Another outcome of interest was the change in the attitude variables as a result of the campaign. In particular, the variables CONC and AQUAL measured the respondents level of concern and his assessment of current air quality, respectively. Not surprisingly, the level of concern about air quality increased. But I *was* a little surprised that the campaign adversely affected respondents' assessment of current air quality. Large reductions in concentrations of fine particulates and ozone in the last 15 years or so have been one of the signal accomplishments of environmental regulation in the US. Now the question asked was whether air quality was good or bad, which is a bit different from whether it has improved or not. Nonetheless it seems to me that respondents are not getting the full picture of air quality in Maine. Perhaps it is too much to ask that respondents get a more nuanced picture of air quality in a survey such as this.