Distributional and Efficiency Impacts of Increased U.S. Gasoline Taxes

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We examine the impacts of increased U.S. gasoline taxes in a model that links the markets for new, used, and scrapped vehicles and recognizes the considerable heterogeneity among households and cars. Household choice parameters derive from an estimation procedure that integrates individual choices for car ownership and miles traveled. We find that each cent-per-gallon increase in the price of gasoline reduces the equilibrium gasoline consumption by about .2 percent. Taking account of revenue-recycling, the impact of a 25-cent gasoline tax increase on the average household is about $30 per year (2001 dollars). Distributional impacts depend importantly on how additional revenues from the tax increase are recycled. (*JEL* C50, H22, H23, L51, L62)

For several reasons, reducing automobile-based gasoline consumption is a major U.S. public policy issue. Gasoline use generates environmental externalities. In 2004, approximately 22 percent of U.S. emissions of carbon dioxide – the principal anthropogenically sourced "greenhouse gas" contributing to global climate change -- derived from gasoline use. Other environmental externalities from gasoline combustion include the impacts from emissions of several "local" air pollutants such as carbon monoxide, nitrogen oxides, and volatile organic compounds. Reduced gasoline use could lead to improved air quality and associated benefits to health.[1, 2] In addition, gasoline consumption accounts for 44 percent of the U.S. demand for crude oil, and the nation's dependence on crude oil makes the U.S. vulnerable to changes in world oil prices emanating from disruptions in the world oil market. Some analyses claim that this vulnerability is not accounted for in individual consumption decisions and thus represents another externality from gasoline consumption.[3] The various externalities provide a potential rationale for public policy oriented toward gasoline consumption.

Recently, analysts and policy makers have called for new or more stringent policies to curb gasoline consumption. The U.S. Senate recently passed a bill that would raise corporate average fuel economy (CAFE) standards for passenger vehicles for the first time since 1985. The standards would be increased from the current 27.5 miles per gallon to 35 miles per gallon by 2020. The 2005 Energy Bill includes tax credits for households purchasing relatively fuel-efficient vehicles such as hybrid cars. The California State Assembly recently enacted AB 1493, which mandates carbon dioxide emissions that would require significant improvements

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[1] Ian W. H. Parry and Kenneth A. Small (2005) and the National Research Council (2002) examine the various externalities from gasoline use and offer estimates of the overall marginal damages. The former study estimates the overall external cost from U.S. gasoline consumption (including effects relating to local pollution, climate change, congestion, and accidents) to be about 75 cents per gallon in year-2000 dollars. This suggests that U.S. taxes on gasoline are below the efficiency-maximizing level, since the federal tax plus average state tax totals 41 cents.

[2] The extent of the health improvement from improved air quality depends on both the reduction in gasoline use and possible changes in pollution per gallon of gasoline used. Air districts currently in compliance with air pollution regulations under the 1990 Clean Air Act amendments might well respond to reductions in gasoline use by relaxing "tailpipe" emissions requirements, that is, on the allowable emissions per unit of fuel combusted. This would offset the air-quality and health improvements from reduced gasoline consumption.

[3] See, for example, National Research Council (2002).

in automobile fuel economy. Other proposals include subsidies to retirements of older (gas-guzzling) vehicles and increments to the federal gasoline tax.[4]

This paper examines the gas tax option, employing an econometrically-based multi-market simulation model to evaluate the policy's efficiency and distributional implications. We investigate the impacts of increased U.S. gasoline taxes on fuel consumption, relating these impacts to changes in fleet composition (shifts to higher mileage automobiles) and vehicle miles traveled (VMT). We also evaluate the economy-wide costs of higher gasoline taxes, and explore how the costs are distributed across households that differ by income, region of residence, race, and other characteristics. We consider how the distribution of impacts depends on the ways revenues from the tax are returned to the private sector.

Some prior studies have examined the impact of gasoline taxes by estimating the demand for gasoline as a function of gasoline price and household income. For example, Jerry A. Hausman and Whitney K. Newey (1995) use household-level data on gasoline consumption to estimate deadweight loss from gasoline taxes, while Sarah E. West and Roberton C. Williams III (2004, 2005) use such data to assess the distributional impacts of gasoline taxes and the optimal gasoline tax.

Other studies infer the demand for gasoline from automobile choice and utilization models. For example, James Berkovec (1985), Fred L. Mannering and Clifford Winston (1985), Kenneth E. Train (1986), and West (2004) estimate the household's discrete automobile purchase decision and its continuous choice of VMT. Following Jeffrey A. Dubin and Daniel L. McFadden (1984), these authors account for the connections between these two choices, although the cross-equation restrictions implied by a unified structural model of behavior are not imposed.

A third set of studies focuses on supply-side phenomena – in particular, the impacts of policies on new-car production and the composition of the automobile fleet, and the associated effect on gasoline consumption. In contrast with the previously mentioned studies, this third set considers explicitly the imperfectly competitive nature of the new car market and the pricing behavior of new-car producers. For example, Steven T. Berry, James Levinsohn, and

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[4] The general public appears to be growing increasingly supportive of stronger measures to curb gasoline use. A February 2006 New York Times / CBS News Poll found that a majority of Americans would support a higher gasoline tax if it reduced global warming or made the U.S. less dependent on foreign oil.

Ariel Pakes (1995), Pinelopi K. Goldberg (1998) and David H. Austin and Terry M. Dinan (2005) develop models of new car market that combine supply decisions by imperfectly competitive producers with discrete demand choices by households. The latter two studies explore impacts of automobile policies on the new car market. Goldberg (1998) and Andrew M. Kleit (2004) analyze tighter CAFE standards; Austin and Dinan (2005) examine CAFE standards and a gasoline tax increase.

The present study differs from earlier work in several ways. First, in contrast with nearly all prior work,[5] this analysis considers supply and equilibrium not only in the new car market but in the used car and scrap markets as well. The wider scope helps provide a more complete picture of the impact of a gasoline tax. In addition, addressing the equilibrium in all three car markets enables us to capture important dynamic effects. Higher gasoline taxes are likely to cause an increase in the share of relatively fuel-efficient cars among new cars sold. The extent to which the fuel-efficiency of the *overall* (new and used car) fleet improves will depend on the rate at which the newer, more efficient cars replace older cars. This depends on the relative size of the stocks of new and used cars and the rate at which older cars are taken out of operation (scrapped). By considering the new, used, and scrapped car markets, the model is able to consider the dynamics of changes in fleet composition and related short- and long-run impacts on gasoline consumption. As in Goldberg (1995), Berry, Levinsohn, and Pakes (1995), Amil K. Petrin (2002), and Austin and Dinan (2005), we consider the imperfectly competitive nature of the new car market. However, in contrast with these studies, we connect this market to the used and scrap markets. This allows us to consider how policies affect the entire fleet of cars and associated demands for gasoline.

A second major difference from earlier work is the model's ability to capture distributional effects. The model considers over 20,000 households that differ in terms of income, family size, employment status (working or retired), region of residence, and ethnic background. This enables us to trace distributional impacts in several important dimensions. All household demands stem from a consistent, utility maximization framework, enabling us to measure distributional impacts in terms of theoretically sound welfare indexes. Prior studies have examined distributional effects by focusing on how gasoline expenditure shares differ

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[5] One exception is Berkovec (1985), who develops a model with interactions among these markets. His model assumes pure competition among auto producers, however.

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across income groups[6]. In contrast, the present model considers not only the expenditure-side impacts but also the ways that the government's disposition of gas tax revenue influences the distribution of policy impacts.

Finally, the model differs in its econometric approach to estimating consumer demand for automobiles, VMT, and gasoline. Berkovec (1986), Mannering and Winston (1986), Goldberg (1998), and West (2004) account for the connections between the automobile purchase and use (VMT) decisions by employing sequential, two-step estimators. Their approach accounts for correlations between the discrete and continuous choice margins but ignores the cross-equation restrictions implied by a unified behavior model. In contrast, we adopt a full-information, one-step structural approach that simultaneously estimates these choice dimensions within a utility-theoretic framework that permits us to recover sound welfare estimates. [7] In addition, we assume that all parameters entering preferences vary randomly across households. Random coefficients allow us to account for correlations in the unobservable factors influencing a household's discrete car choice and continuous VMT demand while simultaneously allowing for more plausible substitution patterns among automobiles (McFadden and Train, 2000; David S. Bunch *et al.*, 1996).

The rest of the paper is organized as follows. Section I describes the equilibrium simulation model. Section II outlines the model's data sources, with emphasis on the data employed to estimate household demands for vehicles and travel. Section III presents our approach for estimating households' automobile purchase and driving decisions. Section IV presents and interprets results from simulations of a range of gasoline tax policies. Section V offers conclusions.

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[6] See James M. Poterba (1989, 1991) for expenditure-based estimates of the incidence of gasoline taxes.
[7] A difficulty with welfare measurement from two-step estimators is that each step yields a different set of estimates for the same parameters. Each set may have different welfare implications for the same policy. One-step estimators generate a single set of parameter estimates and therefore avoid this difficulty. To our knowledge, the only other automobile study to incorporate a one-step procedure is that of Ye Feng, Don Fullerton, and Li Gan (2005).

Other studies have estimated the demand for automobiles separately from the demand for gasoline and VMT. Berry, Levinsohn, and Pakes (2004) and Petrin (2003) focus on the demand for automobiles; Hausman and Newey (1995), Richard L. Schmalensee and Thomas M. Stoker (1999), and West and Williams (2005) concentrate on the demand for gasoline. Austin and Dinan (2005) obtain demand functions for cars by calibrating the parameters of their simulation model to be consistent with internal estimates by General Motors.

I. Model Structure

A. Overview

The economic agents in the model are households, producers of new cars, used car suppliers, and scrap firms. The model considers the car-ownership and vehicle-miles-traveled (VMT) decisions of 20,429 households. The ownership and VMT decisions are made simultaneously in accordance with utility maximization.

The model distinguishes cars according to age, class, and manufacturer. Table 1 displays the different car categories, which imply 350 distinct cars of which 284 appear in our dataset and simulation.[8]

[Table 1 about here]

The used-car market equates the supply of used cars remaining after scrapping with the demand for ownership of those cars. Producers of new cars decide on new-car prices in accordance with Bertrand (price) competition. These producers consider households' demand functions in determining optimal pricing. Price-markups reflect the various price elasticities of demand for cars as well as the regulatory constraints posed by existing CAFE standards.

The model solves for a sequence of market equilibria at one-year intervals. Car vintages are updated each year, so that last year's new cars become one-year-old cars, last year's one-year-old cars become two-year-old cars, etc. Once a car is scrapped, it cannot re-enter the used car market. Characteristics of given models of new cars change through time, as described in Section IV. In particular, producers change the fuel-economy of new models in a manner consistent with profit-maximization.

B. Household Demands

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[8] The number of distinct cars increases over time as some unique new models become old and enter the used car fleet.

Households obtain utility from car ownership and use, as well as from consumption of other commodities. The utility from driving depends on characteristics of the automobile as well as VMT. Each household has exogenous income; most households also are endowed with cars. If a household has a car endowment, it chooses whether to hold or relinquish (sell or scrap) that car; if it relinquishes the car it also decides whether to purchase a different car (new or used). If a household does not have a car endowment, it chooses whether to purchase a car.

If household i owns car j, its utility can be expressed by:

(1) $$U_{ij} = U_{ij}(z_j, M_i, x_i)$$

where z_j is a vector of characteristics of car j, and M_i and x_i respectively refer to household i's vehicle miles traveled and its consumption of the outside (or Hicksian composite) good. The household's utility conditional on choosing car j can be expressed through the following indirect utility function:

(2) $$V_{ij} = V_{ij}' + \mu_i \varepsilon_{ij}$$

with

(3) $$V_{ij}' = V_{ij}'(y_i - r_{ij}, p_{ij}^M, p_{ix}, z_j, z_i, z_{ij})$$

where

y_i	=	income to household i
r_{ij}	=	rental price of car j to household i
p_{ij}^M	=	per-mile operating cost
p_{ix}	=	price of the outside good, x
z_i	=	vector of characteristics of household i
z_{ij}	=	vector of characteristics of household i, interacted with characteristics of car j

Household income y_i is devoted toward purchasing a car (or cars[9]), car operation, and the purchase of the outside good. We treat car purchases as rentals, so that payments are spread over many years. The household budget constraint can then be written as:

(4) $$y_i = r_{ij} + p_{ij}^M M_i + p_{ix} x_i$$

If a household owns a vehicle, the stream of rental income from that vehicle is included in its income. A household that chooses to retain its existing car effectively makes a rental payment equal to its implicit rental income from that car. Income also includes the household's share of profits to new car producers, government transfers, and capital gains or losses resulting from changes in automobile prices.[10] The government transfer component of income includes revenue from the gasoline tax and adjusts as policy changes.

The operating cost p_{ij}^M includes the fuel cost (including gasoline taxes) as well as maintenance and variable insurance costs. The rental price r_{ij} accounts for depreciation, registration fees, and fixed insurance costs. As indicated in expression (2) above, indirect utility includes the random component $\mu_i \varepsilon_{ij}$, where ε has a type I extreme-value distribution (following the econometric model) and μ is a scale parameter. We assume the household chooses the vehicle (or vehicles) yielding the highest conditional utility, given V' and the random error. The probability that a given car j maximizes utility for household i is:

(5) $$\exp\left(\frac{V_{ij}'}{\mu_i}\right) \Big/ \sum_k \exp\left(\frac{V_{ik}'}{\mu_i}\right)$$

The indirect utility function V_{ij} can be differentiated following Roy's identity to yield the optimal choice of miles traveled, M_{ij}, conditional on the purchase of car j. Aggregate automobile and VMT demand are the sum of these micro decisions. In specifying aggregate

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[9] In Section III we discuss how we allow for multiple car ownership.

[10] If a household is endowed with one vehicle of type j entering the period, its gain is computed as:

$$(r_j' - r_j) \cdot (1 - \theta_j) + \frac{1}{2}(r_j' - r_j)(\theta_j - \theta_j')$$

where r_j and r_j' respectively denote the rental price of car j in the reference and policy-change cases, and θ_j and θ_j' represent the probability of the car's being scrapped in the two cases. The first term represents the gain in the value of the car owned, while the second is an adjustment to the gain that accounts for the change in the probability that the car is scrapped.

demand for automobiles, we treat each individual in our sample as a representative of a subpopulation of like individuals and sum up the probabilities. Similarly for aggregate VMT demand, we sum up each individual's probability-weighted VMT demand for each car.

C. Supply of New Cars

Each of the seven producers in the model sets prices for its fleet of automobiles to maximize profits, given the prices set by its competitors and subject to fleet fuel economy constraints. Thus we assume Bertrand competition. Producers face less than perfectly elastic demands for their cars: that is, two new cars of the same class can sell at different prices if produced by different firms.

The producer problem accounts for the presence of CAFE standards. These standards require that each manufacturer's fleet-wide average fuel economy be above a certain level in each of two general categories of cars: "light trucks" and "passenger cars." The classes in the passenger car category are non-luxury compact, non-luxury midsize, non-luxury fullsize, luxury compact, and luxury midsize/fullsize. Those in the light truck category are small truck, large truck, small SUV, large SUV/van, and minivan.[11]

In the following, the subscript k refers to the cars made by a particular manufacturer. The boldface vector p includes prices of the cars made by all seven manufacturers.[12] T and C denote the sets of cars (for a given manufacturer) in the light truck and passenger car categories, respectively. $\bar{e}_T$ and $\bar{e}_C$ refer to the efficiency requirements for light trucks and passenger cars and e_k is the fuel economy of car k. A given producer chooses a vector of prices, p_k, and a vector of individual-model fuel economies, e_k, to maximize profit:

(6) $\quad \max_{\{p_k, e_k\}} \sum_k \left(p_k - c_k(e_k) \right) \cdot q_k(p, e)$

subject to:

$$\frac{\sum\limits_{k \in C} q_k}{\sum\limits_{k \in C} \dfrac{q_k}{e_k}} \geq \overline{e}_C \quad \text{and} \quad \frac{\sum\limits_{k \in T} q_k}{\sum\limits_{k \in T} \dfrac{q_k}{e_k}} \geq \overline{e}_T$$

where p_k and c_k refer to the purchase price and marginal cost, respectively, of a particular car and q_k is the demand as a function of all prices.[13] For any given model k, marginal cost is a function of e_k, the chosen level of fuel economy for that car. Each producer's solution to (6) determines the quantities of vehicles sold in each class. Producers can alter fuel economy and the mix of vehicles, but cannot introduce new vehicle classes, exit existing vehicle classes, or alter attributes like weight and horsepower that determine class.

The solution to (6) requires a demand function (which is given within the model by the sum of individual demands from (5)) and a cost function. To identify the cost function parameters, we employ data on automobile markups, prices, and quantities sold, along with our estimated household demand elasticities for different automobiles. The relationship between production cost and fuel economy is taken from engineering estimates of the incremental costs of fuel economy from the National Research Council (2002). These relationships pose the technological and cost constraints under which producers in the model choose optimal levels of fuel-economy. Details are provided in the appendix, available online at www.stanford.edu/~goulder.

We must solve the constrained optimization problem for all of the firms simultaneously since the residual demand curve faced by a given firm depends on the prices set by the others. The solution method is discussed in subsection E below.

D. Used Car and Scrap Markets

1. The Used Car Market

In the model, "used car" refers to all cars that are neither new nor scrapped. The available supply of used cars of a particular vintage (i.e., model year) is the total stock of that vintage operating in the previous year less those that are scrapped. The total supply of all used

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[13] Our treatment ignores some complexities of the CAFE regulations. The actual regulations allow for intertemporal banking and borrowing: the standard can be exceeded in one year if the firm overcomplies in another. In addition, some manufacturers can and do elect to pay a fine rather than meet the standards, and others are not in fact constrained by the standards. Work in progress (Mark R. Jacobsen, 2006) addresses these issues.

cars in the current period is the aggregate supply from the previous period net of scrappage, plus an increment to the supply representing the cars that were new in the previous period. Let ℓ refer to a given manufacturer and class of vehicle. For each manufacture-class category ℓ, the quantity of used cars evolves according to:

(7) $\qquad q^U_{\ell,t+1} = (1 - \theta_\ell)q^U_{\ell,t} + q^N_{\ell,t}$

where $q^U_{\ell,t}$ and $q^N_{\ell,t}$ refer to the quantity of used and new cars of the manufacturer-class combination ℓ available in year t, and θ_ℓ represents the average probability that used cars of type ℓ are scrapped. This scrap rate will depend on the car's expected resale value if kept in operation. We discuss the specification of θ_ℓ in the next section.

Each used car type, or age-manufacturer-class combination, has a different rental price. The model determines the set of rental prices that clears the used-car market, that is, that causes every car to be sold. Household demands for used cars come from household demands computed as in (5). Since the demand for a given used car will depend on the rental prices of all used cars (and on new car prices), all used car rental prices need to be solved simultaneously.

2. The Scrap Market

We assume that households will scrap a car when the scrap value exceeds the resale value. However, each car (age-manufacturer-class combination) in our model actually represents a group of cars of varying quality and value, some of which may fall under the cutoff for scrapping even if the average car in the group does not. To allow for scrapping of some cars of a given type, we assign a scrap probability to each car. The scrap decision depends on p_j, the purchase price or resale value of a used car. Today's purchase price is the discounted sum of future rental prices, adjusted for the possibility that a car will be scrapped (and earning no rental price) before reaching each progressively older age. The household has myopic expectations: it assumes that future rental values will be the same as the current-period rental values of older vintages of the same vehicle type. Changes in the gasoline tax affect

scrap decisions through their effects on purchase prices.[14] When this value changes as a result of a change in the gasoline tax, so does the probability of scrap.

In terms of the resale value for each used car, the scrap probability θ_j is modeled simply as:

(8) $\theta_j = b_j \cdot (p_j)^{\eta_j}$

where b_j is a scale parameter used for calibration and η_j is the elasticity controlling the change in scrap probability as the price of the car changes. Scrap rates increase with car age and are calibrated to 0.05, 0.06, 0.09, and 0.20 for the four categories of used cars. These values are derived from the distribution of car age in the data (see appendix for details).

E. Solution Method

To solve the model, we must obtain the full vector of new and used car rental prices for a particular year that satisfies the following conditions: (1) every available (not scrapped) used car has a buyer (or retainer) and (2) for every new car producer, the first-order conditions for constrained profit-maximization are satisfied.[15] Note that the second requirement is a function of all prices, not just new-car prices. We determine overall demands for a given car by aggregating across households their probability-weighted demands for that car.

The solution method embeds the used-car problem within the broader problem of solving for both used- and new-car prices. Specifically, we solve for the used-car prices that satisfy requirement (1), conditional on a set of posited prices for the new cars. We then adjust the new car prices in an attempt to meet condition (2), and solve again for used-car prices that

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[14] Here it is relevant that we are simulating a permanent and constant change to the gasoline tax. If the policy involved government committing to a path of varying gasoline taxes in the future, for example, a more complex modeling of expected future prices might be called for.

[15] Note that the calibration procedure is embedded in a baseline simulation, before the introduction of an increment to the gasoline tax. The values of calibrated parameters (determining new car supply and costs, and used car scrap rates) are then saved and introduced into the policy simulation, solved as described in this section.

meet requirement (1) conditional on the adjusted new-car prices. We repeat this procedure until conditions (1) and (2) are met within a desired level of accuracy.[16]

The government's revenue from gasoline taxes is returned to households according to the various "recycling" methods described in Section IV. Government revenues and transfers are mutually dependent: the level of transfers affects household demands and government revenues, while the level of revenues determines the transfer level consistent with the government's budget constraint. Thus, solving the model also requires that we determine the equilibrium level of government revenue and transfers. The overall solution is a set of prices for each car that simultaneously clears all markets, and an aggregate transfer level that equals the government's revenues from the gasoline tax. To solve the multidimensional system we use Broyden's method, a derivative-based quasi-Newton search algorithm.

II. Data

Our dataset has two main components: (1) a random sample of U.S. households' automobile ownership choices from the 2001 National Household Travel Survey (NHTS) and (2) new and used automobile price and non-price characteristics from *Wards Automotive Yearbook*, The National Automobile Dealer's Association (NADA) *Used Car Guide*, and the Department of Energy (DOE) fueleconomy.org website. By merging these two types of information, we obtain an unusually rich data set, one that allows us to consider household choices among a wide range of new and used cars and that permits us to distinguish households along many important dimensions. In the appendix, we offer details on how we merged the data sets and constructed needed variables.

A. The NHTS Sample

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[16] The oligopolistic structure of the new car market involves both multiple products and multiple producers. Under these conditions, theory leaves open the possibility of non-uniqueness. We have tested for non-uniqueness by randomizing starting values over a uniform distribution and in these experiments the model has always converged to one solution.

The 2001 NHTS consists of 26,038 households living in urban and rural areas of the United States. With the help of Department of Transportation staff, we obtained the confidential NHTS data files containing relevant data for our analysis. For each household we have information on income, automobile holdings (by make, model, and year), and vehicle miles traveled. In addition, we have data on the household's demographic characteristics (including household size, composition, gender, education, and employment status) and geographical identifiers (including the state, metropolitan statistical area, and zip code of residence).

After cleaning the data our final sample consists of 20,429 households from the original 26,038. Table 2 presents major demographic statistics of our final sample.

[Table 2 about here]

B. **The Automobile Sample**

The 1983- 2002 *Wards Automobile Yearbook* provided most of the car and truck characteristics used in our analysis. Automobile characteristics include horsepower, weight, length, height, width, wheelbase, and city and highway miles per gallon (MPG) by make, model, and year for all cars and trucks sold during this period. We obtained information on car and truck prices from the National Automobile Dealer's Association (*NADA*), which publishes this information in the monthly *NADA Used Car Guide*. We used price information from the April 2001 and 2002 editions of the *Car Guide*, which we obtained in electronic format. Each edition contained the manufacturer's suggested retail price and current resale price (a weighted average of recent transaction prices) for all new and used cars and trucks dating back to 1983. As indicated in the appendix, we calculated depreciation based on changes in prices for a given car over the 2001-2002 period.

Combining information from the Wards and NADA data sets yielded a vector of prices and various automobile characteristics for roughly 4,500 automobiles distinguished by manufacturer, model, and year. We aggregated these data into the seven manufacturer categories, ten class categories, and five age categories in Table 1. We used a weighted

geometric mean formula to aggregate price and non-price characteristics within each make, class, and age category, where the weights were proportional to the holdings frequencies in the *NHTS*.

[Table 3 about here]

Table 3 displays statistics on miles per gallon, horsepower, and rental price from our data. The data show significant MPG differences across classes and age categories. A new compact, for example, is 1.48 times more efficient than a large SUV. The newest compacts yield 1.47 more miles per gallon than those in the oldest age category. In contrast, the newest midsize and large SUVs are less fuel-efficient than the older models. As for horsepower, most of the increases apply to compacts and full size cars. Average horsepower of compacts increased 60 percent, and average horsepower of full size cars rose 75 percent. Differences in rental price are most substantial for new cars, due to the particularly rapid depreciation of new luxury vehicles. Older cars have much lower rental prices, and these prices are more similar across classes.

C. Calculation of Rental Prices and Per-Mile Operating Costs

Two important variables we must construct from our data are the automobile rental prices and per-mile operating costs (the "price per mile" variable in Section I) for all 284 autos. The underlying inputs into these prices and costs differ by region as well as automobile type. For household i owning car j, the rental price is given by:

(9) $$r_{ij} = D_j + 0.85 I_{ij}^A + F_{ij} + R \cdot p_j$$

where

D_j	=	depreciation in the real value of car j
I_{ij}^A	=	household i's annual insurance costs for car j
F_{ij}	=	household i's automotive registration fees for car j
R	=	real interest rate

Thus, the one-year rental price of a car is the sum of depreciation, insurance, and registration costs, plus the forgone real return on the principal value of the car.[17] For the real interest rate, R, we use a value of 3.89 percent, the 2001 average daily real rate on 30-year T-bills. We include insurance costs in both the rental price (associated with the choice of car) and the per-mile operating cost (associated with VMT). Representatives from State Farm Insurance suggested to us that roughly 85 percent of auto insurance premiums are fixed and independent of VMT. Hence, 85 percent of insurance costs appear in the rental price formula, while the remainder is allocated to operating costs.

The rental prices are included in the household utility function relative to the price of the outside good (cost of living) faced by each household. We incorporate a cost of living index for 363 distinct regions that, together with differences in insurance and registration fees, reflects variation across households in the effective rental price of vehicles.[18]

The per-mile operating cost, p_{ij}^M, is expressed by:

$$(10) \qquad p_{ij}^M = \frac{p_i^{gas}}{MPG_j^*} + N_j + 0.15 I_{ij}^M$$

where

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\begin{array}{lll}
p_i^{gas} & = & \text{household } i\text{'s per gallon price of gasoline} \\
MPG_j & = & \text{miles per gallon for car } j \\
N_j & = & \text{per-mile maintenance and repair costs for car } j \\
I_{ij}^M & = & \text{household } i\text{'s per-mile insurance costs for car } j
\end{array}
$$

The price of gasoline (and therefore operating cost) varies among households based on differences across 363 distinct regions of residence. The average after tax gasoline price faced by households in 2001 ranged from \$1.19 (Albany, Georgia) to \$1.86 per gallon (San Francisco).

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[17] If the household has purchased the car using a loan, this term can be equivalently interpreted as the interest payment on that loan.

[18] Further details about the regional cost of living index are provided in the appendix; It varies by a factor of 1.77 across households.

III. Estimation of Household Ownership and Utilization Decisions

A. The Econometric Model

1. Challenges

Two overarching concerns influenced our approach to estimating household automobile demand. The first was our desire to integrate consistently the car ownership and utilization decisions. Such integration is crucial for generating consistent estimates of welfare costs from gasoline taxes. The second concern arose from an important feature of the data: households frequently own more than one car. In the 2001 *NHTS*, 41.5 percent of households own zero or one car, another 43.6 percent own two cars, and the remaining 14.9 percent own three or more autos. This implies that many households have a potentially enormous number of auto bundles from which to choose. If, for example, there are *J* different cars and trucks and we consider only bundles consisting of no more than two cars, there are $1+J+J(J+1)/2$ bundles that households can potentially choose. With our automobile data set consisting of 284 composite cars and trucks, there are 40,755 distinct bundles that households might choose (and this large number ignores all bundles with three or more autos).[19]

As discussed in the introduction, nearly all past efforts to integrate automobile ownership and utilization decisions have relied on reduced-form, sequentially-estimated models. Our structural approach estimates simultaneously the decisions on both margins. To account for different households owning different quantities of cars, we adopt a variation of Igal E. Hendel (1999) and Jean-Pierre H. Dube's (2004) repeated discrete-continuous framework. In the context of automobile choice, the framework assumes that a household's

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[19] Past transportation applications have addressed this dimensionality problem by randomly sampling from the full set of choice alternatives in estimation. As discussed in Train (1986), such an approach works only with restrictive fixed parameter logit and nested logit models. We cannot adopt this sampling approach in our model because, as described below, our model employs random coefficients to introduce correlations in the unobservables entering the discrete and continuous choice margins. Moreover, although the sampling approach solves the dimensionality problem in estimation, it does not solve the problem in a simulation model, where the full choice set would need to be employed to construct aggregate automobile demands.

ownership and utilization choices arise from separable choice occasions. On each choice occasion, the household makes a discrete choice of whether to own one of J automobiles. If an auto is chosen, the household conditionally decides how much to drive it during the year. To account for ownership of multiple automobiles, households have multiple choice occasions on which different automobile services may be demanded. Intuitively, different choice occasions in our framework correspond to different primary tasks or purposes for which households might demand automobile services (e.g., commuting to work, family travel, shopping excursions, or any combination thereof). We assume their number depends on the number of adults in a given household.[20]

Our approach to modeling automobile demand has advantages and drawbacks. Its main advantages are that it consistently links ownership and utilization decisions and reduces the dimension of the households' choice set on a given choice occasion to $J+1$ alternatives (J autos and the no auto alternative). The latter feature makes our approach econometrically tractable with our 284 composite auto data set. It also has the virtue of allowing for households to own several cars. A main drawback is that it does not allow for interaction effects among the fleet of autos held by households -- for example, a four-person household's utility from holding a second minivan being less than holding a single minivan. To account for such interactions, one would need to regard bundles of automobiles, rather than individual cars, as the objects of choice. However, as suggested above, such an approach would require *substantially* more aggregation of cars beyond what we have pursued.[21] This would rule out significant product differentiation and thus severely limit our ability to account for the imperfectly competitive nature of the automobile industry. In addition, it would compel us to put a limit of two on the number of cars owned by any household, which would eliminate from our sample those households likely to be most affected by changes in gasoline taxes.

2. Specifics

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[20] There is some evidence in the non-market valuation literature that the specification of the number of choice occasions, as long as it is larger than the chosen number of goods, does not have significant effects on estimated welfare measures (Roger H. von Haefen, D. Matthew Massey, and Wiktor L. Adamowicz, 2005). Moreover, we do not expect that it has much if any effect on the relative efficiency rankings of policies.

[21] Feng, Fullerton, and Gan's (2005) bundling approach aggregates all automobiles into one of two composites – cars and trucks.

Our repeated discrete-continuous model of automobile demand works as follows. Household i ($i = 1,…,N$) is assumed to have a fixed number of choice occasions, T_i. We let T_i equal the number of adults in each household plus one.[22] On choice occasion t, household i is assumed to have preferences for car j ($j=1,…,J$) that can be represented by the following conditional indirect utility function:

$$V_{itj} = V_{ij}^{'} + \mu_i \varepsilon_{ijt}$$

$$V_{ij}^{'} = \frac{-1}{\lambda_i}\exp\left(-\lambda_i\left(\frac{y_i/T_i - r_{ij}}{p_{ix}}\right)\right) - \frac{1}{\beta_{ij}}\exp\left(\alpha_{ij} + \beta_{ij}\frac{p_{ij}^M}{p_{ix}}\right) + \tau_{ij}$$

$$\alpha_{ij} = \tilde{\alpha}_i^{\mathsf{T}} z_{ij}^{\alpha}$$

(11)
$$\beta_{ij} = -\exp(\tilde{\beta}_i^{\mathsf{T}} z_{ij}^{\beta})$$

$$\lambda_i = \exp(\tilde{\lambda}_i^{\mathsf{T}} z_i^{\lambda})$$

$$\tau_{ij} = \tilde{\tau}_i^{\mathsf{T}} z_{ij}^{\tau}$$

$$\mu_i = \exp(\mu_i^*)$$

where $(y_i, r_{ij}, p_{ij}^M, p_{ix})$ are household i's income, rental price for the jth auto, utilization (or *VMT*) price for the jth car, and the Hicksian composite commodity price, respectively; $(z_{ij}^{\alpha}, z_{ij}^{\beta}, z_{ij}^{\tau})$ are alternative automobile characteristics (including make, age, and class dummies that control for unobserved attributes[23]) interacted with household demographics; z_i^{λ} contains just household characteristics; $(\tilde{\alpha}_i, \tilde{\beta}_i, \tilde{\lambda}_i, \tilde{\tau}_i, \mu_i^*)$ are parameters that vary randomly across households; and ε_{ijt} contains additional unobserved heterogeneity that varies randomly across households, automobiles, and choice occasions.[24] If the household instead decides not to rent a car (i.e., automobile 0), its conditional indirect utility function is:

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[22] The 2001 *NHTS* indicates that 11.1 percent of households have more automobiles than the number of adults. For the 1.84 percent of household with more autos than the number of adults plus one, we set the number of choice occasions equal to the number of held autos.

[23] Berry, Levinsohn, and Pakes (1995, 2004) use alternative specific constants for every automobile to control for unobserved characteristics. Given the highly nonlinear-in-parameters structure of our conditional indirect utility functions, we could not estimate a model with a full set of alternative specific constants and instead adopted a more parsimonious specification with make, age, and class dummies as in Goldberg (1995).

[24] The level of income in the budget constraint associated with each choice occasion is the household's income divided by the number of choice occasions. This assures that overall spending is consistent with the household's total income.

$$(12) \quad V_{it0} = \frac{-1}{\lambda_i} \exp\left(-\lambda_i \left(\frac{y_i / T_i}{p_{ix}}\right)\right) + \phi_i^\mathsf{T} z_i^\phi + \mu_i \varepsilon_{i0t}$$

where z_i^ϕ and ϕ_i are individual characteristics and parameters, respectively. The rational household is assumed to choose the alternative that maximizes its utility on each choice occasion. Assuming each ε_{ijt} ($j = 0,...,J$) can be treated as independent draws from the normalized type I extreme value distribution, the probability that individual i chooses alternative j on choice occasion t condition on the model's structural parameters is:

$$(13) \quad \Pr_{it}(j) = \frac{\exp(V_{ij}^{'} / \mu_i)}{\sum_k \exp(V_{ik}^{'} / \mu_i)}.$$

Assuming the household chooses automobile j, Roy's identity implies that the household's conditional *VMT* demand is:

$$(14) \quad M_{itj} = \exp\left(\alpha_{ij} + \beta_{ij}\left(\frac{p_{ij}^M}{p_{ix}}\right) + \lambda_i\left(\frac{y_i / T_i - r_{ij}}{p_{ix}}\right)\right).$$

We assume the analyst imperfectly observes M_{itj} due to measurement error in our data.[25],[26] The analyst observes $\widetilde{M}_{itj} = M_{itj} + \eta_{itj}$, where η_{itj} is an independent draw from the normal distribution with mean zero and standard deviation $\sigma_i = \exp(\sigma_i^*)$.[27] The likelihood of observing $\widetilde{M}_{itj}$ conditional on the model parameters is:

$$(15) \quad l(\widetilde{M}_{itj} \mid j \text{ chosen}, j \neq 0) = \frac{1}{(2\pi)^{1/2}\sigma_i} \exp\left(-\frac{1}{2}\left(\frac{\widetilde{M}_{itj} - M_{itj}}{\sigma_i}\right)^2\right).$$

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[25] Because the 2001 *NHTS* survey elicited VMT in part by asking respondents to recall their past driving behavior, we believe it is appropriate to account explicitly for measurement error in reported VMT.

[26] Our assumption that some disturbances capture preference heterogeneity while others pick up measurement error makes our model conceptually similar to the Gary Burtless and Jerry A. Hausman (1978) two-error discrete-continuous model that is frequently used in nonlinear budget constraint applications.

[27] Following Dubin and McFadden (1984), past automobile applications assume some degree of correlation between η_{itj} and the type I extreme value errors in the discrete choice model. Similar to King (1980), we instead assume that these disturbances are independent and introduce correlations between the discrete and continuous choices through random parameters as described below.

Given our assumed structure, the full likelihood of household i's automobile demand conditional on $\delta = (\tilde{\alpha}_i, \tilde{\beta}_i, \tilde{\lambda}_i, \tilde{\tau}_i, \phi_i, \mu_i^*, \sigma_i^*)$ is then:

$$(16) \qquad L_i = \prod_{t=1}^{T_i} \left[\prod_{j=0}^{J} \Pr_{it}(j)^{1_{itj}} \prod_{j=1}^{J} l(\widetilde{M}_{itj} \mid j \text{ chosen})^{1_{itj}} \right]$$

where 1_{itj} is an indicator function equal to one if car j is chosen on individual i's tth choice occasion and zero otherwise.

B. Estimation Strategy

Past econometric efforts to model vehicle ownership and derived VMT demand decisions have used variations of Dubin and McFadden's (1984) sequential estimation strategy that accounts for the induced selectivity bias in derived VMT demand with a Heckman-like (1979) correction factor. We employ a full-information estimation approach that accounts for correlations in the unobserved determinants of choice across discrete and continuous dimensions through random parameters (McFadden and Train, 2000). Intuitively, random parameters allow unobserved variations in taste to influence automobile ownership decisions and VMT demand decisions. We allow all parameters, $\delta = (\tilde{\alpha}_i, \tilde{\beta}_i, \tilde{\lambda}_i, \tilde{\tau}_i, \phi_i, \mu_i^*, \sigma_i^*)$, to be distributed multivariate normal with mean $\overline{\delta}$ and variance-covariance matrix Σ_δ. This approach is more general than earlier random coefficient discrete-continuous applications (e.g., Mervyn King, 1980; Feng, Fullerton, and Gan, 2005) that include only one random parameter. The more general specification offers a far richer degree of unobserved preference heterogeneity to influence household's ownership and use decisions than previous applications.[28]

Given the nonlinear nature of our likelihood function, the large number of households and sites in our data set, and the potentially large number of parameters on which we wish to draw inference, classical estimation procedures such as maximum simulated likelihood (Christian Gourieroux and A. Monfort, 1996) would be exceptionally difficult, if not impossible, to implement. In light of these computational constraints, we adopt a Bayesian

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[28] For example, under our random coefficients specification a household that is relatively insensitive to utilization costs and horsepower when purchasing a car will likewise be relatively insensitive to these factors when driving it.

statistical perspective and employ a variation of Greg M. Allenby and Peter J. Lenk's (1994) Gibbs sampler estimation procedure that is less burdensome to implement in our application.[29]

The Bayesian framework assumes that the analyst has initial beliefs about the unknown parameters $(\bar{\delta}, \Sigma_\delta)$ that can be summarized by a prior probability distribution, $f(\bar{\delta}, \Sigma_\delta)$. When the analyst observes a set of choices $\mathbf{x}$, she combines this choice information with the assumed data generating process to form the likelihood of $\mathbf{x}$ conditional on alternative values of $(\bar{\delta}, \Sigma_\delta)$, $L(\mathbf{x} | \bar{\delta}, \Sigma_\delta)$. The analyst then updates her prior beliefs about the distribution of $(\bar{\delta}, \Sigma_\delta)$ to form a posterior distribution for $(\bar{\delta}, \Sigma_\delta)$ conditional on the data, $f(\bar{\delta}, \Sigma_\delta | \mathbf{x})$. By Bayes' rule, $f(\bar{\delta}, \Sigma_\delta | \mathbf{x})$ is proportional to the product of the prior distribution and likelihood, i.e., $f(\bar{\delta}, \Sigma_\delta | \mathbf{x}) = f(\bar{\delta}, \Sigma_\delta)L(\mathbf{x} | \bar{\delta}, \Sigma_\delta)/C$ where C is a constant. In general, $f(\bar{\delta}, \Sigma_\delta | \mathbf{x})$ will not have an analytical solution, and thus deriving inference about the moments and other relevant properties of $(\bar{\delta}, \Sigma_\delta)$ conditional on the data is difficult. However, Bayesian econometricians have developed a number of Markov Chain Monte Carlo (MCMC) procedures to simulate random samples from $f(\bar{\delta}, \Sigma_\delta | \mathbf{x})$ and in the process draw inference about the posterior distribution of $(\bar{\delta}, \Sigma_\delta)$.

Following Allenby and Lenk (1994), we specify diffuse priors for $(\bar{\delta}, \Sigma_\delta)$ and use a Gibbs sampler with an adaptive Metropolis-Hastings component to simulate from $f(\bar{\delta}, \Sigma_\delta | \mathbf{x})$. By decomposing the parameter space into disjoint sets and iteratively simulating from each set conditionally on the others, the Gibbs sampler generates simulations from the unconditional posterior distribution after a sufficiently long burn-in. The implementation details of the algorithm are described in the appendix.

One further dimension of our estimation approach is worth noting. Because of the large number of households in our data set ($N = 20,429$) and our desire to account for differences in automobile demand across different household types (e.g., single males, two-adult households with and without children, retired couples), we stratified the sample into 12 groups based on

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[29] Although the Bayesian paradigm implies a very different interpretation for the estimated parameters relative to classical approaches, the Bernstein-von Mises theorem suggests that the posterior mean of Bayesian parameter estimates, interpreted within the classical framework, are asymptotically equivalent to their classical maximum likelihood counterparts. Following Train (2003), we interpret this result as suggesting that both approaches should generate qualitatively similar inference, and thus the analyst's choice of which to use in practice can be driven by computational convenience.

demographic characteristics and estimated separate models within each strata. In addition to decomposing a computationally burdensome estimation problem on a large data set into a series of more manageable estimation problems on smaller data sets, stratification allows us to better account for observable and unobservable differences among households.

C. Empirical Results

For all 12 strata, we obtain precisely estimated posterior mean values for $(\bar{\delta}, \Sigma_\delta)$.[30] Many of the parameters that are common across the 12 strata vary in magnitude considerably, suggesting that there is significant preference heterogeneity across the different subpopulations. We also find that the diagonal elements of Σ_δ are generally large, suggesting considerable preference heterogeneity within each stratum as well. The latter preference heterogeneity and the highly nonlinear structure of our preference function mean that the estimated parameters do not have a simple economic interpretation. Thus instead of focusing on the estimated parameters, we examine the various elasticities that they imply. We display these elasticities in Table 4, broken down by household and automobile types. Our cross-section estimation implies that these should be interpreted as long-run elasticities.

[Table 4 about here]

The first column of Table 4 reports the elasticity of gasoline use with respect to gasoline price. In the "All" and "By Household" panels, the elasticities allow for responses in both VMT and car choice (and associated fuel economy). In the "By Auto" panel, the elasticities are conditional on car choice. Across all households and cars, we obtain a mean estimate of -0.35. The estimated elasticities are larger for families with children and owners of trucks and SUVs. D. J. Graham and Stephen Glaister's (2002) survey of past studies indicates long-run elasticities in the U.S. ranging from -0.23 to -0.80. Kenneth A. Small and Kurt Van Dender's (2007) more recent state-level analysis produces a central estimate of -0.33.

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[30] Parameter estimates for each of the 12 strata are reported in the appendix.

The second column of the table shows the elasticity of gasoline use with respect to income. On average, we find estimates of around 0.76. The elasticity is highest for families with children and owners of new vehicles. Graham and Glaister report long-run estimates in the range of 1.1 to 1.3.[31]

The third column reports car ownership elasticities with respect to the own rental price. For new cars, rental price elasticities should track purchase price elasticities if rental and purchase prices vary proportionally. Our results imply mean rental price elasticities of -0.88 for all vehicles and -1.97 for new vehicles only. Luxury cars, large SUVs, and large trucks, which have the highest rental prices, have the highest rental price elasticities among automobile classes.

Our estimated elasticities with respect to rental prices are smaller in absolute magnitude than those found in some studies, such as Berry, Levinsohn, and Pakes (1995), which obtained elasticities ranging from -3 to -4.5. A plausible explanation is that the objects of choice in our study are not individual make-models but automobile composites (i.e., make-model combinations aggregated by age, class, and make). This aggregation implies that we have only 59 new cars in our data set, not the 200-300 cars typically found in other applications. By collapsing make-models into composite cars, we reduce the number of channels for substitution.

Much of the work estimating these elasticities has focused exclusively on new vehicles (e.g., Berry, Levinsohn and Pakes, 1995, and Petrin, 2002). These studies have generally employed multiple years of automobile sales data and controlled for the potential endogenity of price arising from unobserved car characteristics.[32] In contrast, we have a single household-level cross section and control for unobserved product characteristics through class, make, and age dummies that vary across household types.

A close comparison with data types and results from other studies suggests that our smaller elasticities might also reflect limitations from cross-sectional data and are not likely due to a failure to adequately control for unobserved car characteristics. Our elasticities are

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[31] Although our estimated income elasticities are lower than in much of the previous literature, we note that our stratification of the sample allows parameters controlling income effects to vary among types of households, which may yield a more accurate estimation of income effects than in prior (mainly time-series) work.

[32] For example, Berry, Levinsohn, and Pakes (1995) employ 20 years of market-level data for new make-model combinations, and use alternative specific constants and instrumental variables to identify price effects.

similar in magnitude to those reported in Berry, Levinsohn, and Pakes (2004) and Train and Winston (2007), studies that employ household-level cross sectional data and control for price endogeneity with alternative specific constants and instrumental variables.[33] In addition, Goldberg (1995), using five years of household-level data and an identification strategy comparable to ours, finds elasticities for make-models that are similar in magnitude to Berry, Levinsohn, and Pakes' (1995). [34] Combined, these results suggest that our estimates control sufficiently for endogeneity of price but may reflect limitations from the cross-section of data used.

The final column of the table reports long-run VMT elasticities with respect to operating costs. Across all households and cars, the average elasticity is -0.74. This elasticity is lower for new cars than for older vehicles. Older cars are disproportionately owned by lower income households, who exhibit higher VMT elasticities. Because gasoline makes up slightly less than half of per mile operating costs, our average estimate implies an average VMT elasticity with respect to the price of gasoline of -0.34. In their survey, Graham and Glaister report that from prior studies the average estimate for this long-run elasticity is -0.30, while Small and van Dender report an estimate closer to -0.1. Both sets of authors note that existing estimates are quite sensitive to the data and modeling assumptions employed, and thus the caveats mentioned earlier concerning the limitations of cross-sectional data may apply here as well. Past applications that (like ours) use disaggregate household data to control for endogenous vehicle choice tend to find larger elasticities than aggregate time series or panel data studies that combine household and commercial demand for highway VMT (Mannering, 1986).

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[33] Train and Winston use a cross-section of household level data involving 200 new cars and find average elasticities for new cars ranging from -1.7 to -3.2.

[34] We explored the sensitivity of estimates to several alternative specifications and estimation strategies. In particular, we experimented with allowing the income coefficient to vary across car classes and age groups, and restricting a subset of parameters to be fixed across the sample. None of these alternatives generated elasticities significantly different from those in Table 4.1.

IV. Simulation Results

A. Assumptions Underlying the Simulation Dynamics

The simulation model generates a time path of economic outcomes over 10 years at one-year intervals. As mentioned, the model solves in each period for the market-clearing new and used car prices. We assume that household incomes grow at an annual rate of one percent. In all simulations, the pre-tax price of gasoline is $1.04 and is taken as exogenous and unchanging over time.[35]

B. Baseline Simulation

The baseline simulation offers a reference scenario with which we compare the outcomes from various gasoline tax policies. Consistent with historical trends, we assume in this simulation that automobile horsepower and weight increase at an annual rate of five percent. In our central case we calibrate the baseline fuel economy technology to the "Path 1" assumptions of the National Research Council (2002) regarding improvements in fuel economy: over a 10-year period, such improvements range from 11 percent for compacts to 20 percent for large SUVs. As part of a sensitivity analysis below, we adopt in the baseline the more optimistic NAS "Path 3" assumptions regarding growth in baseline fuel economy technology. In our policy simulations, producers adjust fuel economy away from these baseline technologies following equation (6) above.

Table 5 displays the equilibrium quantities of new and used cars under the baseline simulation. Our reference case overpredicts the size of the vehicle fleet by about 8 percent, ranging from 5 percent for midsize cars to 14 percent for small trucks.

[Table 5 about here]

C. Impacts of Gasoline Tax Increases under Alternative Recycling Methods

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[35] Pre-existing federal taxes are $0.185 and average state taxes are $0.225.

Here we present results from simulations of permanent increases in gasoline taxes. We start by focusing on the impacts of a tax increase of 25 cents per gallon (other tax increases are considered below) under the following alternative ways of recycling the additional revenues from the tax increase:

-- *"flat" recycling:* revenues are returned in equal amounts to every household

-- *"income-based" recycling:* revenues are allocated to households according to each household's share of aggregate income

-- *"vmt-based" recycling:* revenues are allocated lump-sum according to each household's share of aggregate vehicle miles traveled in the baseline

Recycling could be accomplished by the government's mailing rebate checks to households on an annual basis. The shares of total revenues going to different households depend on baseline values and thus do not depend on behavioral responses to the gasoline tax.

1. Aggregate Impacts

Gasoline Consumption

[Table 6 about here]

Table 6 presents the impacts of this policy on gasoline consumption. In the short run (year 1), the percentage reduction is about 5.1 percent under flat and income-based recycling, and about 4.5 percent under VMT-based recycling. Compared with other recycling methods, VMT-based recycling gives a larger share of gasoline tax revenue to car owners, who tend to have larger income elasticities of gasoline use. As a result, there is a larger offsetting income effect on gasoline use under VMT-based recycling than under other recycling methods, and the overall reduction in gasoline consumption is smaller.

The percentage change in gasoline use is approximately equal to the percentage change in miles traveled (VMT) minus the percentage improvement in fuel economy (miles per gallon).

The table shows the contributions of these two components. Most of the reduction in gasoline use comes from the reduction in VMT: the improvements in fleetwide fuel economy are fairly small.[36]

In the short run, the major channel for improved aggregate fuel economy is an increase in the scrapping rate for vehicles with unusually low fuel economy. The augmented gasoline tax raises per-mile operating costs, which makes vehicles with low fuel economy relatively less desirable, causing their demand and prices to fall and their scrap rates to rise. In the first year of the policy, an additional 160,000 used large trucks and large SUVs are scrapped. Over the longer term, average fuel economy is influenced by changes in fleet-composition attributable to increased relative sales of new cars that are more fuel-efficient, and by price-induced increases in fuel economy of given models. The percent increase in fuel economy is larger in the long run, although fuel economy improvements still account for a small share of the overall reduction in gasoline consumption.

[Table 7 about here]

Table 7 summarizes the changes in fleet composition. On impact, the higher gasoline tax occasions a shift away from cars (more cars are scrapped) and, among cars that remain in operation, a shift toward used cars (which, as reflected in Table 3, are on average more fuel-efficient). In the long run, the percentage reduction in new cars is smaller. This is the case because new cars become increasingly efficient relative to older cars as time passes, and the gasoline tax increase gives greater importance to fuel-economy.[37]

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[36] In our simulations, the fraction of the response coming from fleet fuel economy improvements (as compared to reduced VMT) is much smaller than in Austin and Dinan (2005) and Small and Van Dender (2007), who find that over half of the response comes from fuel economy rather than VMT. The fuel economy response can be divided into (i) changes in fleet composition and (ii) improvements in the fuel economy of particular models. Our results differ from the Austin and Dinan's mainly because of differences in the magnitude of the second factor. Austin and Dinan calibrate the potential for technological improvements based on the cost estimates in NRC 2002. In contrast, we calibrate parameters determining the marginal costs of engineering improvements in a way that reconciles observed automobile choices with the assumptions of profit maximization and utility maximization. This yields marginal costs of improving fuel economy that are larger than the marginal costs implied by the NRC study.

[37] This increasing relative efficiency of new cars applies both under the baseline price path and under the policy change. The baseline path is based on the National Research Council's (2002) "Path 1" assumptions on new car fuel economy.

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Several prior studies[38] suggest that the overall reduction in gasoline consumption should be larger in the long run than in the short run, since the fleet-composition (fuel economy) channel requires considerable time to take effect. In fact our simulations indicate that, in percentage terms, the long-run reduction is smaller than the short-run reduction. This occurs because VMT per household falls by a smaller percentage in the long run than in the short run (see Table 6). This in turn stems from the fact that although in the long run there is a larger percentage reduction in the number of cars owned by the average household, there is a smaller percentage reduction in miles traveled per car.[39]

Table 6 shows that the 25 cent-per-gallon increase in the gasoline price leads to a reduction of 4 ½ to 5 percent in the *equilibrium* demand for gasoline in the long run, or about a .2 percent reduction for each penny increase in the gasoline price. It is difficult to compare this result with other studies, since other studies do not consider market equilibrium for both new and used cars, and do not consider time explicitly. However, it may be noted that Austin and Dinan (2005) report that a 30 cent per gallon increase in the gasoline tax would reduce gasoline consumption (by new cars) by 10 percent (cumulatively) over a 14-year period, or .3 percent reduction (cumulatively) for each penny increase.

Efficiency Costs

[Table 8 about here]

Table 8 displays the efficiency cost of gasoline tax increases of 10, 25, and 75 cents per gallon. This cost is the weighted sum of the negative of each household's equivalent variation, where a household's weight is proportional to its share of the total population. Here "cost" should be interpreted as a gross measure, since it does not net out the environmental or national security benefits stemming from the policy change.

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[38] Examples are Jean Agras and Duane Chapman (1999), Glaister and Graham (2002), and Olof Johansson and Lee Schipper (1997).

[39] In the long run, the cost of gasoline represents a smaller fraction of per-mile operating cost, a reflection of improvements in fleet fuel economy.

Under flat recycling, the (gross) cost per dollar raised is $.16, $.18, and $.24, for gasoline tax increases of 10, 25, and 75 cents per gallon, respectively. The costs under the alternative recycling cases are not much different from those in the flat recycling case: the nature of recycling, though very important distributionally (as indicated below), does not much affect the aggregate costs. This result requires careful interpretation. Another choice in the recycling decision is whether to return revenues in lump-sum form or instead by way of cuts in the marginal rates of prior taxes such as income or sales taxes. Prior

receive a share of the tax revenues that is considerably larger than their share of gasoline tax payments. While policy discussions often refer to the potential regressivity of a gasoline tax, these simulations indicate that flat recycling more than fully offsets this potential regressivity.[43]

Under income-based recycling the pattern of impacts is U-shaped. In this case the middle-income households experience the largest welfare loss. As indicated in Table 9, for these households the ratio of miles driven (or gasoline taxes paid) to income is highest; hence recycling based on income benefits these households less than other households. Only the very rich experience welfare gains under income-based recycling; these households have the lowest ratio of miles traveled (or gasoline tax paid) to income.

[Table 9 about here]

VMT-based recycling implies a fairly flat pattern of impacts across the income distribution, although the welfare losses are greater for higher-income households. In comparison with lower-income households, rich households drive more luxury cars, which are relatively less fuel-efficient. As a result, the ratio of gasoline taxes paid to VMT is especially large for richer households, and these households benefit least from VMT-based recycling.

[Table 10 about here]

Table 10 decomposes the welfare impacts into the various contributing factors: the change in gasoline price, the transfer (rebate) of gasoline tax revenue, the net capital gain or loss associated with policy-induced changes in car prices, and changes in profit to new-car producers. We have assumed that households own shares of new-car profits in proportion to their share of benchmark aggregate income. The table makes clear that changes in the gasoline price and the transfer are by far the most important sources of the household welfare impact. It also confirms that, depending on the type of recycling involved, the transfer may or may not offset the gasoline price impact to a particular household.

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[43] West and Williams' (2004) econometric study also finds that a gasoline tax with flat (or lump-sum) recycling is regressive.

Effects along Other Demographic Dimensions

[Figure 2 about here]

Figures 2a and 2b show VMT and policy impacts by race and income.   The figures reveal two main results. First, income seems to be a more important determinant of welfare impact than race: there is greater variation in welfare impacts across income groups than across racial categories. This reflects the fact that much of the welfare impact is determined by VMT, and the differences in VMT across income groups are much larger than the VMT differences across racial groups, after controlling for income (Figure 2a). Second, low-income African-American households enjoy the largest gains from flat recycling, while high-income African-Americans experience the smallest losses. This is in keeping with the relatively small differences in VMT between low-income and higher-income African-American households.[44]

[Figure 3 about here]

Figures 3a and 3b display differences in welfare impacts across states.[45]   The top map displays average VMT per household from the data. The bottom map exhibits the differences in average household welfare impact. The top and bottom maps are nearly identical, indicating that benchmark VMT is a strong predictor of the welfare impact. Benchmark VMT seems to be strongly correlated with population density. Several relatively densely populated states – New York, Pennsylvania, New Jersey, and Florida – experience the smallest average welfare

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[44] Although not displayed, the same pattern emerges under other forms of recycling: differences in income account for more of the variation of welfare impacts than racial differences do, and the variation in impacts between high-income and low-income African-American households is relatively small compared to the variation for other households.

[45] To generate the results in these figures, we first regressed the household welfare impacts (EVs) from the simulation on household characteristics and on the predicted baseline VMT and predicted baseline VMT squared. Next we used the coefficients from the regression, the same set of household characteristics, and household baseline VMT from the data (as opposed to predicted VMT) to get a new fitted value of EV for each household. We then aggregated this information by state.

impact, while many of the relatively sparsely populated states – Montana, Idaho, Utah, Oklahoma, Texas, Alabama, Georgia, and South Carolina – suffer the largest adverse impacts. However, population density does not perfectly correlate with benchmark VMT or the magnitude of the impact: some sparsely populated states – Wyoming and Nevada – nevertheless have low benchmark VMT and relatively small welfare impacts.

[Table 11 about here]

Table 11 shows how impacts differ depending on the employment status of the household. Retirees fare better than younger individuals, as they tend to drive less. Households with no children also do better, for the same reason.

D. Sensitivity Analysis

Here we consider the sensitivity of results to parameters affecting changes in fuel economy and scrapping. We also explore the extent to which responses to gasoline tax increases depend on the existence of the CAFE standard. Finally, we consider the welfare effects when revenue from the tax is not returned to households in any form (or used in any productive manner).

The impacts of gasoline tax increases could well be affected by the rate of technology change in automobiles over the next decade. One aspect of faster technological improvement would be speedier growth in the fuel economy of given car models in successive years.[46] To explore this possibility, we created an additional scenario allowing for easier improvements in fuel economy. Here we adopt the "Path 3" baseline assumptions from the National Research

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[46] Growth in fleetwide fuel economy has been promoted by the increased production and sale of hybrid vehicles. In our model, hybrid vehicles are merged with conventional cars within given manufacturer-class combinations (e.g., Toyota compacts). We are considering splitting out hybrids in future work. To estimate demands for hybrids, we may need to supplement our revealed-preference data with stated-preference information, since hybrids were introduced in the automobile fleet in 2001, the year corresponding to our benchmark data. Today they represent about four percent of the compact car fleet.

Council (2002) study. This scenario's lower costs of fuel-economy improvements imply larger improvements over time in the baseline.[47]

[Table 12 about here]

Table 12 shows the different implications of the two technology paths. In contrast with the central case, in which baseline model fuel economy improves between 11 percent (compacts) and 20 percent (large SUVs), under this alternative scenario the baseline improvements are more than twice as large (see note 2 to the table). In the baseline, by year 10 average household gasoline consumption is 751.6 gallons in the fast technology improvement case. This is about 9 percent lower than in the central case baseline. Fuel economy (miles per gallon) is about 15 percent higher in the fast-improvement case. Average VMT is also higher (by 5 percent), reflecting the lower per-mile cost of driving associated with higher fuel economy.

In the case with lower cost fuel economy improvements, the gasoline tax increase induces a smaller long-run percentage reduction in consumption than it does in the central case. This is because gasoline occupies a smaller share of the household budget in the baseline in this alternative scenario, implying a smaller income effect from the tax increase. The average long-run welfare impact (EV) is 22 percent smaller under the fast technology growth scenario, which is also consistent with gasoline's smaller budget share. Thus, the baseline time-profile of fuel economy significantly influences the welfare consequences of a gasoline tax. However, the differences across the two scenarios in baseline welfare are greater than the welfare impact within either of the two scenarios of introducing a 25 cent gasoline tax increase.

The third main row heading in the table reports results from a simulation in which we double the scrap elasticity η_j to -6.0 from its central value of -3.0. With this change, the gasoline tax causes a somewhat larger reduction in gasoline use in the short run, reflecting a higher scrapping rate: with the higher scrap elasticity, the policy change causes 22 percent more cars to be scrapped compared with the policy under the central case. While the higher

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[47] The NRC study interprets the scenario involving faster fuel economy growth as due to technological advances that reduce producers' costs of supplying more fuel-efficient cars. Our simulations also express such a scenario. However, it should be noted that changes in the baseline time-profile of fuel economy could also reflect changes in household preferences. Our model cannot capture such demand-side changes, since we assume a stable utility function in our econometric estimation.

scrap elasticity implies a larger policy impact on gasoline consumption in the short run, it has little influence on the policy impact in later years.

The fourth panel of Table 12 displays results in an alternative case where (counter to fact) there is no binding CAFE standard – neither on small cars nor on trucks. In the absence of this standard, the increase in gasoline taxes yields a significantly larger short- and long-run improvement in fuel economy compared with the case of a pre-existing binding CAFE standard. Correspondingly, there is a larger reduction in gasoline consumption. After 10 years, gasoline consumption is reduced by about 6.2 percent, as compared with 5.0 percent in the central case. When firms are not constrained by the CAFE standard, producers have greater incentives to change the composition of their car or truck fleets to meet the increased consumer demands for fuel economy that stem from higher fuel costs. In contrast, when firms are constrained by the CAFE standard, the increase in the gasoline tax leads to smaller changes in the composition and average fuel economy of their fleets of cars and trucks. The composition of a producer's car or truck fleet is largely determined by the CAFE standard. In the presence of the CAFE standard, an increase in the gasoline tax affects a car producer's fleet composition mainly by altering the relative sales of cars versus trucks.

The final panel models the scenario where gasoline tax revenues are not returned to households in any form. The welfare costs rise from $30 to $218 per household since the tax revenue is now lost in addition to the distortion. Gasoline consumption and VMT fall more than in the central case due to the larger income effects. Finally, as opposed to the case with "flat" revenue recycling, this policy is regressive over most of the income distribution.

V. Conclusions

This paper has examined the impacts of gasoline tax increases with a model that considers jointly supply- and demand-side responses to policy changes. The model links the markets for new, used, and scrapped vehicles, and accounts for the imperfectly competitive nature of the automobile industry. Linking the three markets enables us to account for the penetration of the car fleet by new cars and thereby assess how the impacts of policy interventions evolve through time. We also address the considerable range of car choices in a

high-dimensional discrete-continuous choice model. Parameters for the household demand side of the model stem from a one-step estimation procedure that integrates individual choices for car ownership and miles traveled, thereby yielding consistent welfare measures. Finally, we allow for the considerable heterogeneity among car owners, which enables us to explore the distributional impacts of policy changes along many important dimensions.

We find that each cent-per-gallon increase in the price of gasoline reduces the equilibrium gasoline consumption by about .2 percent. The reduction in demand mainly reflects reduced miles traveled by car owners; shifts in demand from low to high miles-per-gallon vehicles appear much less important.   Under a 25-cent gasoline tax increase the size of the vehicle fleet falls about .5 percent. The impacts on new and used car ownership differ substantially over time. In the first year of the policy, the reduction in vehicle ownership comes largely by way of a decline in new car purchases. However, ratio of fuel economy of new to old vehicles increases over time, and the increased gasoline tax gives greater importance to fuel economy. As a result, the decline in new-car ownership is attenuated over time, and by year 10 the reduction in car ownership applies nearly uniformly to new and used vehicles.

The gasoline tax's marginal excess burden (excluding external benefits) per dollar of revenue raised ranges from about $.15 for a 10-cent tax-increase to $.25 for a 75-cent increase. This efficiency cost is considerably lower than the estimates of the marginal external benefits from higher gasoline taxes,[48] suggesting that increases in the gasoline tax would be efficiency-improving. Taking account of revenue-recycling (and disregarding external benefits), the impact of a 25-cent gasoline tax increase on the average household is about $30 per year (2001 dollars).

The distributional impacts of the gasoline tax differ dramatically under the three revenue-recycling approaches we considered. Under flat recycling, the average household in each of the bottom four income deciles experiences a welfare gain from a gasoline tax increase. The gain to the average household in the lowest income decile would be equivalent to about $125. This suggests that a single-rebate-check approach to recycling would more than eliminate (for the average household within a given income group) the potential regressivity of a gasoline tax increase. On the other hand, if revenues are recycled in proportion to income,

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[48] See, for example, Parry and Small (2005).

35

only very poor households (those in the lowest decile) and very rich households (those in the highest) stand to gain. The different impacts of the various recycling methods largely reflect differences across the income distribution in car use (VMT). However, household income does not perfectly correlate with VMT and other important determinants of the welfare impacts: controlling for income, we find significant differences in impacts across racial categories and regions of residence.

The framework presented here has considerable potential to address other automobile-related policies, including tightening of CAFE standards and subsidies to retirements of low-mileage (or high-polluting) automobiles. We plan to investigate these policies in future work, examining impacts not only on gasoline consumption but on automobile-generated pollution as well.

Two limitations in our model deserve mention. First, although the model allows the fuel-economy of new cars to respond endogenously to gasoline tax changes, it does not distinguish the demands for some of the most fuel-efficient cars – namely, hybrids – from the demands for conventional-fuel cars in the same vehicle class. Only recently have sales of hybrids become significant, and thus the data for isolating demands for such cars are quite limited. Nonetheless, in future work we hope to develop surveys that will enable us to consider specifically the demands for hybrid vehicles. In addition, the model abstracts from transactions costs (e.g., time costs, information-gathering costs, and transactions-related taxes) associated with the purchase or sale of new or used cars. These costs cause households to change their car holdings less frequently than they otherwise would. Although data limitations currently make it impossible to assess such costs in a rigorous manner, we believe it would be useful in the future to incorporate alternative assumptions about such costs within the estimation effort and to judge the implications of such costs for policy outcomes.

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Table 1: Included Car Types

Classes	Age categories	Manufacturers
Compact	New cars	Ford
Luxury compact	1-2 years old	Chrysler
Midsize	3-6 years old	General Motors
Fullsize	7-11 years old	Honda
Luxury mid/fullsize	12-18 years old	Toyota
Small SUV		Other Asian
Large SUV		European
Small truck		
Large truck		
Minivan		

Table 2:
Sample Demographic Statistics from the 2001 NHTS – 20,429 Observations

Variable	mean (std. dev.)
Household size	2.490 (1.34)
# of adults ! 18 years old	1.861 (0.69)
# of adults ! 65 years old	0.380 (0.67)
# of children 2 years old	0.096 (0.32)
# of children 3-6 years old	0.136 (0.41)
# of children 7-11 years old	0.185 (0.49)
# of children 12-17 years old	0.211 (0.54)
# of workers	1.272 (0.95)
# of females	1.033 (0.52)
Average age among adults (! 18)	49.56 (16.8)
Household income (2001 $s)	56,621 (43,276)

Household breakdown:	percentage
1 male adult, no children, not retired	5.71
1 female adult, no children, not retired	7.88
1 adult, no children, retired	10.3
2+ adults w/ average age 35, no children, not retired	7.10
2+ adults w/ average age > 35 & 50, no children, not retired	8.43
2+ adults w/ average age > 50, no children, not retired	9.04
2+ adults w/ average age 67, no children, retired	9.29
2+ adults w/ average age > 67, no children, retired	8.47
1+ adults w/ youngest child < 3 years old	8.69
1+ adults w/ youngest child 3-6 years old	7.65
1+ adults w/ youngest child 7-11 years old	8.64
1+ adults w/ youngest child 12-17 years old	8.85
White household respondent[1]	85.6
Black household respondent	7.62
Hispanic household respondent	6.25
Asian household respondent	2.17
Adults with high school diplomas	89.4
Adults with 4-year college degrees	30.5
Resident of MSA < 250k	7.62
Resident of MSA 250-500k	8.22
Resident of MSA 500k-1m	8.30
Resident of MSA 1-3m	22.2
Resident of MSA > 3m	32.5
Non-resident of MSA	21.1
Household income $25,000	22.8
Household income $50,000 & >$25,000	33.3
Household income $75,000 & >$50,000	19.8
Household income >$75,000	24.1

[1] The white, black, Hispanic, and Asian percentages sum to more than 100 percent because some respondents have multi-cultural backgrounds.

Table 3: Automobile Characteristics[1]

Characteristic	Compact	Luxury Compact	Midsize	Fullsize	Luxury Mid/Full	Small SUV	Large SUV / Van	Small Truck	Large Truck	Minivan	Total
Miles Per Gallon[2]											
All Car Ages:	29.73	24.18	27.16	25.57	23.65	23.75	20.04	23.60	19.82	23.45	24.39
	(27.8, 35.6)	(22.2, 26.9)	(24.2, 31.0)	(22.6, 30.5)	(21.3, 25.0)	(17.8, 27.0)	(16.6, 26.8)	(19.1, 27.7)	(16.8, 23.5)	(19.2, 27.2)	(16.6, 35.6)
Model Years:											
2001-2002	30.29	24.47	26.90	25.61	23.70	24.17	19.08	22.62	19.65	23.25	24.15
	(28.0, 32.8)	(22.9, 26.9)	(24.2, 30.5)	(23.0, 28.0)	(23.0, 24.2)	(21.9, 26.4)	(17.2, 22.5)	(19.2, 25.9)	(16.8, 23.5)	(20.6, 25.0)	(16.8, 32.8)
1999-2000	30.32	24.45	27.29	25.79	23.86	23.80	18.21	23.29	20.34	22.99	24.18
	(28.1, 35.6)	(23.1, 26.8)	(25.1, 29.7)	(22.6, 28.0)	(23.0, 24.4)	(19.8, 27.0)	(16.7, 19.6)	(19.1, 26.3)	(18.8, 23.4)	(19.2, 24.6)	(16.7, 35.6)
1995-1998	30.02	24.24	27.50	25.51	24.29	23.44	19.60	23.30	18.67	23.65	24.44
	(28.4, 32.1)	(22.3, 26.4)	(25.4, 29.8)	(23.0, 27.8)	(23.3, 25.0)	(19.6, 26.3)	(16.6, 23.7)	(19.6, 26.0)	(17.7, 19.4)	(21.3, 27.2)	(16.6, 32.1)
1990-1994	29.21	23.81	26.74	25.37	22.91	22.67	20.90	23.10	18.56	23.57	24.08
	(27.8, 30.4)	(22.2, 26.3)	(25.2, 30.0)	(23.5, 28.8)	(21.3, 24.0)	(17.8, 24.9)	(17.2, 26.0)	(20.5, 24.4)	(17.6, 20.0)	(22.2, 26.0)	(17.2, 30.4)
1983-1989	28.82	23.94	27.38	25.56	23.23	24.84	22.88	25.70	21.76	23.97	25.14
	(28.2, 29.4)	(22.6, 26.1)	(24.3, 31.0)	(23.8, 30.5)	(22.1, 24.3)	(23.3, 26.3)	(18.1, 26.8)	(23.7, 27.7)	(20.0, 23.3)	(21.1, 26.7)	(18.1, 31.0)
Horsepower/100											
All Car Ages:	1.286	2.275	1.530	1.726	2.177	1.531	1.909	1.386	2.011	1.575	1.719
	(0.88, 1.78)	(1.56, 3.63)	(0.98, 1.96)	(0.86, 2.21)	(1.42, 2.81)	(1.02, 1.95)	(0.88, 2.59)	(0.94, 1.72)	(1.30, 2.79)	(0.99, 2.18)	(0.86, 3.63)
Model Years:											
2001-2002	1.526	2.621	1.787	2.123	2.463	1.763	2.391	1.650	2.377	1.833	2.036
	(1.34, 1.78)	(1.64, 3.63)	(1.65, 1.96)	(1.97, 2.21)	(2.13, 2.81)	(1.65, 1.95)	(2.15, 2.59)	(1.52, 1.72)	(2.20, 2.79)	(1.40, 2.18)	(1.34, 3.63)
1999-2000	1.454	2.488	1.682	1.917	2.376	1.648	2.271	1.556	2.323	1.765	1.932
	(1.23, 1.68)	(1.70, 3.45)	(1.58, 1.80)	(1.50, 2.07)	(2.10)	(1.45, 1.88)	(2.12, 2.52)	(1.34, 1.69)	(2.15, 2.63)	(1.40, 2.10)	(1.23, 3.45)
1995-1998	1.342	2.414	1.597	1.835	2.237	1.554	2.024	1.430	1.992	1.513	1.773
	(1.09, 1.47)	(1.75, 3.38)	(1.47, 1.72)	(1.41, 2.07)	(2.01, 2.53)	(1.35, 1.83)	(1.86, 2.17)	(1.22, 1.59)	(1.88, 2.06)	(1.09, 1.77)	(1.09, 3.38)
1990-1994	1.152	2.075	1.418	1.469	1.952	1.467	1.476	1.257	1.698	1.378	1.516
	(1.05, 1.24)	(1.60, 2.54)	(1.28, 1.54)	(0.90, 1.74)	(1.83, 2.11)	(1.29, 1.59)	(0.90, 1.77)	(1.07, 1.46)	(1.55, 1.78)	(1.09, 1.51)	(0.90, 2.54)
1983-1989	0.955	1.777	1.166	1.212	1.637	1.164	1.244	1.038	1.435	1.272	1.270
	(0.88, 1.03)	(1.56, 2.15)	(0.98, 1.41)	(0.86, 1.36)	(1.42, 2.01)	(1.02, 1.27)	(0.88, 1.46)	(0.94, 1.12)	(1.30, 1.50)	(0.99, 1.51)	(0.86, 2.15)
Rental Price/1000											
All Car Ages:	2.570	5.959	2.749	3.029	5.680	3.141	4.289	2.654	3.478	3.336	3.681
	(0.38, 6.84)	(0.55, 26.6)	(0.38, 8.55)	(0.39, 8.67)	(0.45, 21.4)	(0.42, 7.81)	(0.43, 14.4)	(0.37, 6.88)	(0.46, 8.31)	(0.26, 8.32)	(0.26, 26.6)
Model Years:											
2001-2002	5.798	15.94	6.528	7.463	14.45	6.823	10.27	5.686	7.022	7.270	8.792
	(5.14, 6.84)	(7.23, 26.6)	(5.65, 8.55)	(6.84, 8.67)	(11.8, 21.4)	(6.12, 7.81)	(7.92, 14.4)	(4.78, 6.88)	(5.83, 8.31)	(6.21, 8.32)	(4.78, 26.6)
1999-2000	3.258	6.819	3.274	3.628	5.712	3.724	4.566	3.455	4.089	3.888	4.237
	(2.14, 4.24)	(3.74, 12.6)	(2.10, 4.72)	(3.13, 4.52)	(3.99, 8.69)	(3.11, 4.35)	(2.20, 7.69)	(2.91, 4.02)	(3.75, 4.59)	(2.95, 5.24)	(2.10, 12.6)
1995-1998	2.320	4.506	2.420	2.521	3.823	2.884	3.638	2.548	3.149	2.844	3.051
	(1.62, 3.27)	(2.59, 5.72)	(1.68, 3.18)	(2.06, 3.17)	(2.54, 5.61)	(2.20, 3.58)	(2.53, 5.66)	(2.08, 3.12)	(2.85, 3.63)	(1.94, 3.68)	(1.62, 5.72)
1990-1994	0.972	1.679	1.015	1.019	1.317	1.259	1.253	1.092	1.183	1.081	1.186
	(0.72, 1.29)	(1.11, 2.34)	(0.73, 1.33)	(0.75, 1.26)	(0.86, 1.79)	(0.98, 1.74)	(0.69, 2.04)	(0.87, 1.34)	(0.97, 1.39)	(0.74, 1.51)	(0.69, 2.34)
1983-1989	0.503	0.850	0.509	0.491	0.714	0.589	0.676	0.489	0.561	0.454	0.585
	(0.38, 0.67)	(0.55, 1.31)	(0.38, 0.67)	(0.39, 0.64)	(0.45, 1.21)	(0.42, 0.82)	(0.43, 1.31)	(0.37, 0.64)	(0.46, 0.69)	(0.26, 0.73)	(0.26, 1.31)

[1] Minimums and maximums reported in parentheses.
[2] Weighted harmonic mean of EPA test miles per gallon estimates.

Table 4: Posterior Mean Long Run Elasticity Estimates

	Elasticity of gasoline use wrt price[1]	Elasticity of gasoline use wrt income[1]	Car ownership elasticity wrt rental price	VMT elasticity wrt operating cost[1]
All	-0.35	0.76	-0.82	-0.74
By Household				
Retired	-0.32	0.61	-0.93	-0.69
Not retired, no children	-0.32	0.68	-0.72	-0.69
Not retired, with children	-0.39	0.96	-0.85	-0.83
By Auto				
By Class				
All Cars				
Compact	-0.27	0.83	-0.65	-0.59
Luxury compact	-0.30	0.78	-1.25	-0.64
Midsize	-0.28	0.74	-0.67	-0.60
Fullsize	-0.29	0.75	-0.73	-0.63
Luxury midsize/fullsize	-0.30	0.79	-1.25	-0.63
Small SUV	-0.29	0.93	-0.73	-0.63
Large SUV/van	-0.32	0.88	-0.98	-0.69
Small truck	-0.34	0.78	-0.62	-0.72
Large truck	-0.31	0.79	-0.85	-0.66
Minivan	-0.31	0.85	-0.77	-0.65
New Cars				
Compact	-0.28	1.14	-1.44	-0.60
Luxury compact	-0.27	0.76	-3.14	-0.46
Midsize	-0.29	0.95	-1.58	-0.60
Fullsize	-0.29	1.04	-1.77	-0.61
Luxury midsize/fullsize	-0.28	0.83	-3.04	-0.47
Small SUV	-0.26	1.86	-1.58	-0.55
Large SUV/van	-0.34	1.06	-2.30	-0.69
Small truck	-0.37	0.91	-1.32	-0.75
Large truck	-0.32	1.05	-1.69	-0.65
Minivan	-0.31	0.98	-1.67	-0.63
By Age				
New cars	-0.30	1.10	-1.97	-0.63
1-2 year old cars	-0.29	0.79	-1.01	-0.63
3-6 year old cars	-0.27	0.76	-0.73	-0.59
7-11 year old cars	-0.30	0.75	-0.28	-0.65
12-18 year old cars	-0.31	0.83	-0.13	-0.68

[1] Elasticities in the *By Auto* panel are conditional on car choice.

Table 5: Baseline Fleet Composition

Class	Year 1			Year 10		
	New	Used	All cars in operation	New	Used	All cars in operation
Compact	4.98	44.68	49.66	5.27	49.52	54.79
Lux compact	0.22	4.44	4.66	0.26	2.79	3.05
Midsize	2.63	27.58	30.21	2.82	27.30	30.12
Fullsize	1.32	16.32	17.64	1.49	14.64	16.13
Lux mid/full	0.32	8.30	8.62	0.39	4.67	5.06
Small SUV	1.32	10.65	11.97	1.41	12.99	14.40
Large SUV	1.10	15.93	17.02	1.30	12.92	14.23
Small truck	1.27	10.26	11.54	1.35	12.25	13.60
Large truck	2.17	19.83	22.00	2.42	22.16	24.58
Minivan	1.32	12.74	14.06	1.45	13.62	15.07
Total	16.65	170.73	187.39	18.15	172.87	191.03

Units are millions of privately owned cars in operation.

Table 6: Change in Gasoline Use with 25 Cent Tax Increase

Recycling Method	Flat		Income-based		VMT-based	
	Year 1	Year 10	Year 1	Year 10	Year 1	Year 10
Baseline gasoline use per household (gallons)	775.18	828.89	775.18	828.89	775.18	828.89
% change in gasoline use	-5.09%	-4.99%	-5.06%	-5.07%	-4.51%	-4.40%
% change in VMT	-5.01%	-4.84%	-4.98%	-4.93%	-4.43%	-4.21%
% change in VMT per car	-4.62%	-4.37%	-4.56%	-4.38%	-4.01%	-3.69%
% change in cars in operation	-0.41%	-0.49%	-0.44%	-0.57%	-0.44%	-0.54%
% change in overall MPG	0.08%	0.16%	0.08%	0.15%	0.09%	0.20%

Table 7: Fleet Size and Composition

| | Baseline[1] | | 25-cent gasoline tax increase[2] | | | | | |
| | | | Flat recycling | | Income-based recycling | | VMT-based recycling | |
	Year 1	Year 10	Year 1	Year 10	Year 1	Year 10	Year 1	Year 10
Cars in operation:								
All	188.3	191.0	-0.41%	-0.49%	-0.44%	-0.57%	-0.44%	-0.54%
New	16.7	18.2	-1.00%	-0.08%	-1.12%	-0.38%	-0.93%	-0.07%
Used	171.6	172.8	-0.35%	-0.53%	-0.37%	-0.59%	-0.39%	-0.59%
Low MPG	75.9	78.9	-0.47%	-0.81%	-0.50%	-0.82%	-0.49%	-0.77%
High MPG	112.4	112.1	-0.37%	-0.26%	-0.40%	-0.39%	-0.40%	-0.38%

[1]Millions of cars.

[2]Percent change relative to the baseline.

Table 8: Revenue and Costs from 25 Cent Increase in Gasoline Tax (Results for Year 1)

Revenue recycling	Flat			Income-based			VMT-based		
Tax increase (cents)	10	25	75	10	25	75	10	25	75
Net tax revenue ($billion)	7.43	17.96	48.46	7.43	17.97	48.43	7.52	18.29	49.91
Efficiency cost*									
Total ($billion)	1.23	3.24	11.43	1.25	3.28	11.72	1.11	2.89	10.38
Per dollar of additional revenue	0.165	0.180	0.236	0.168	0.183	0.242	0.147	0.158	0.208
Per avoided gallon of gasoline consumed ($)	0.71	0.76	0.96	0.73	0.78	0.98	0.72	0.77	0.97

*Negative of the weighted sum of equivalent variations of each household.

Table 9: Consumption, Mileage, and Car-Ownership Patterns of Household Income Groups*

Income Decile	Gasoline Consumption Avg. Level (gallons)	Gasoline Consumption Share of Total	Miles Traveled Avg. Level (000's)	Miles Traveled Share of Total	Avg. Fuel-Economy of Owned Vehicles**	Share of Economy's Light Trucks and SUVs
1	157.3	0.02	4.03	0.02	25.61	0.02
2	315.7	0.04	7.97	0.04	25.25	0.04
3	473.6	0.06	11.69	0.06	24.68	0.05
4	588.3	0.08	14.33	0.08	24.35	0.08
5	724.0	0.09	17.65	0.09	24.38	0.09
6	823.7	0.11	19.76	0.11	23.98	0.11
7	922.0	0.12	22.35	0.12	24.25	0.13
8	1060.8	0.14	25.46	0.14	24.00	0.15
9	1227.1	0.16	29.55	0.16	24.08	0.17
10	1459.8	0.19	35.28	0.19	24.17	0.17

* Predicted values from simulation model
** VMT-weighted

Table 10: Decomposition of Welfare Impacts of 25 Cent Gasoline Tax Increase (Results for Year 1)

	Gasoline price	Transfer	Car prices	Producer profits	EV	EV as a percent of income
Flat Recycling						
Income						
<25	-84.36	157.58	2.62	-3.12	74.96	0.45%
25-50	-196.36	160.22	-0.43	-7.19	-51.87	-0.14%
50-75	-284.09	158.88	-3.16	-11.88	-154.50	-0.24%
>75	-334.45	160.29	-4.62	-19.11	-213.94	-0.21%
All	-176.02	159.04	0.04	-7.22	-29.73	-0.08%
Income-based Recycling						
Income						
<25	-83.90	68.33	2.90	-3.42	-13.75	-0.08%
25-50	-196.40	157.21	-0.40	-7.86	-55.45	-0.15%
50-75	-284.65	259.81	-3.40	-13.00	-55.33	-0.09%
>75	-336.04	417.87	-5.07	-20.90	39.99	0.04%
All	-176.06	157.83	0.10	-7.90	-31.48	-0.08%
VMT-based Recycling						
Income						
<25	-84.26	79.40	2.86	-2.80	-2.01	-0.01%
25-50	-197.37	181.56	-0.38	-6.44	-30.56	-0.08%
50-75	-285.89	261.01	-3.31	-10.64	-52.80	-0.08%
>75	-340.00	307.48	-4.92	-17.12	-69.87	-0.07%
All	-177.08	162.93	0.11	-6.46	-25.70	-0.07%

Welfare effects are expressed in price-adjusted 2001 dollars.

Table 11: Welfare Impact of 25 Cent Gasoline Tax Increase on Selected Household Groups

Recycling	Year 1			Year 10		
	Flat	Income-based	VMT-based	Flat	Income-based	VMT-based
All	-29.73	-31.48	-25.70	-31.02	-32.64	-25.55
Retired	46.81	8.65	-15.02	52.78	11.98	-12.69
Not retired, no children	-26.27	-33.02	-21.55	-21.52	-28.77	-15.16
Not retired, with children	-88.01	-58.40	-37.81	-101.03	-68.64	-45.98

Welfare effects are expressed in price-adjusted 2001 dollars.

Table 12: Impacts of Gasoline Taxes under Alternative Parameter Assumptions

	Year 1		Year 10	
		25 cent tax		25 cent tax
	Baseline	increase[1]	Baseline	increase[1]
Central Case				
Gasoline consumption (gallons/household)	775.18	-5.09%	828.89	-4.99%
Aggregate VMT (000's miles/household)	18.80	-5.01%	21.23	-4.84%
Avg. MPG (miles weighted)	24.26	0.082%	25.62	0.155%
Avg. EV (price-adjusted dollars)	-	-30.13	-	-31.28
Faster Fuel-Economy Improvements[2]				
Gasoline consumption	773.66	-5.07%	751.56	-4.48%
Aggregate VMT	18.83	-4.99%	22.25	-4.23%
Avg. MPG	24.34	0.080%	29.60	0.263%
Avg. EV	-	-29.67	-	-24.23
High Scrap Elasticity				
Gasoline consumption	775.18	-5.16%	828.89	-5.00%
Aggregate VMT	18.80	-5.08%	21.23	-4.86%
Avg. MPG	24.26	0.088%	25.62	0.154%
Avg. EV	-	-29.75	-	-30.93
No CAFE Standard				
Gasoline consumption	775.18	-5.25%	828.89	-6.21%
Aggregate VMT	18.80	-4.93%	21.23	-4.90%
Avg. MPG	24.26	0.339%	25.62	1.401%
Avg. EV	-	-29.28	-	-30.11
Gasoline Tax Revenue Not Recycled[3]				
Gasoline consumption	775.18	-5.49%	828.89	-5.62%
Aggregate VMT	18.80	-5.41%	21.23	-5.50%
Avg. MPG	24.26	0.084%	25.62	0.122%
Avg. EV	-	-218.07	-	-231.32

[1]Percent change relative to the baseline under the same parameter assumptions.

[2]Percent increases in fuel economy over 10 years are:
 Compact 41, Lux compact 41, Midsize 52, Fullsize 58, Lux mid/full 55,
 Small SUV 54, Large SUV 65, Small truck 58, Large truck 59, Minivan 59

[3]More precisely, assume revenue is neither recycled to households nor used in any productive way.

Welfare Impacts[1] across Household Income Groups
Under Alternative Revenue-Recycling Methods
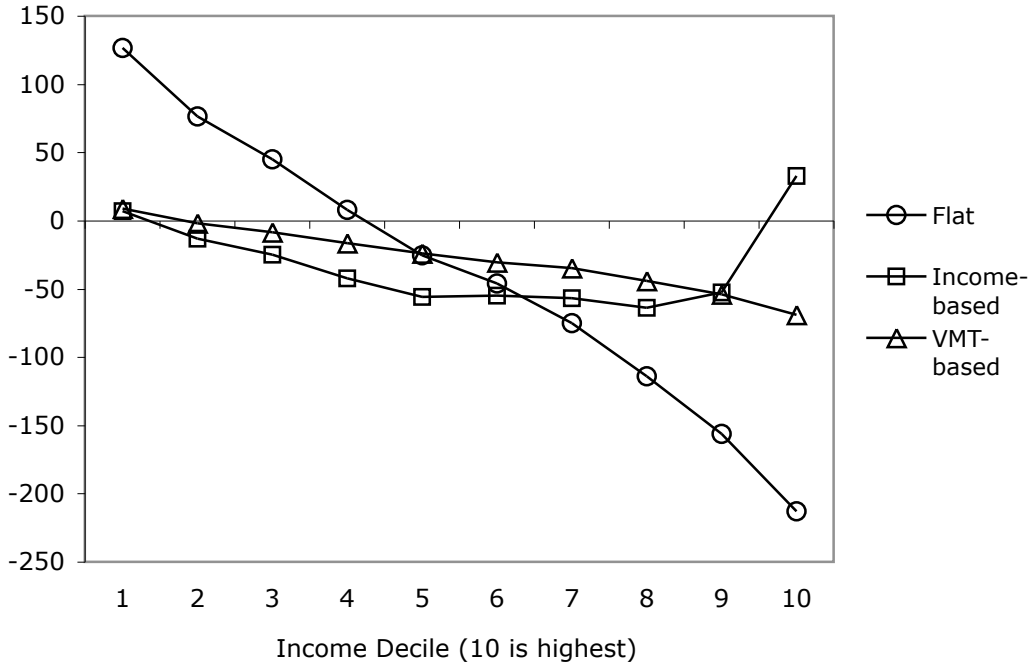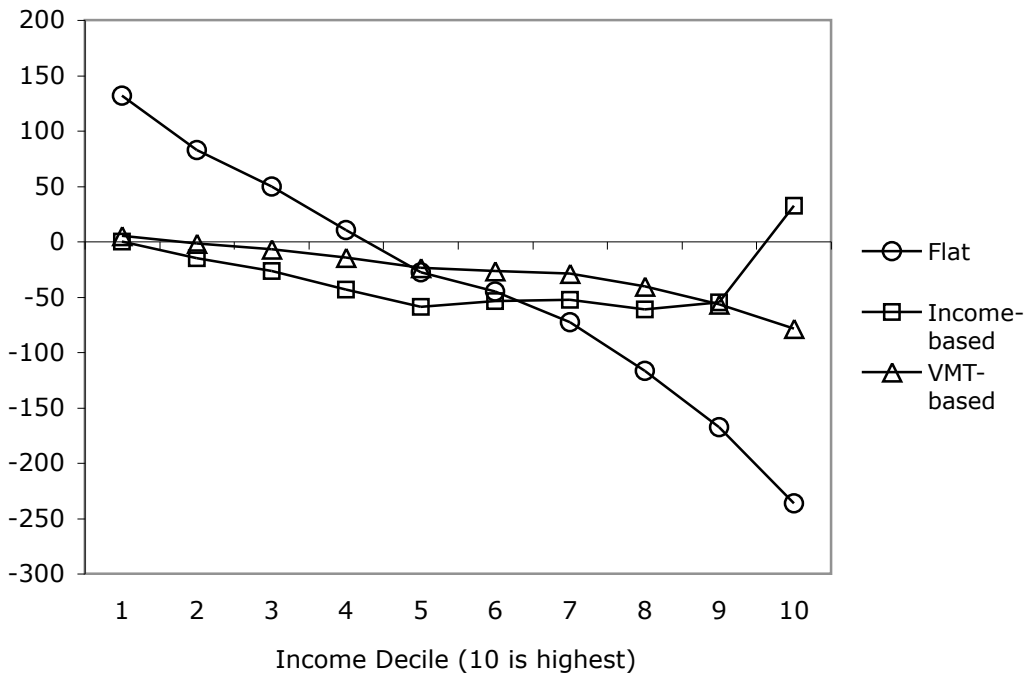
Figure 1a: Year 1, 25 Cent Tax

Income Decile (10 is highest)

Figure 1b: Year 10, 25 Cent Tax

Income Decile (10 is highest)

[1]Welfare impacts are in average price-adjusted 2001 dollars per household.

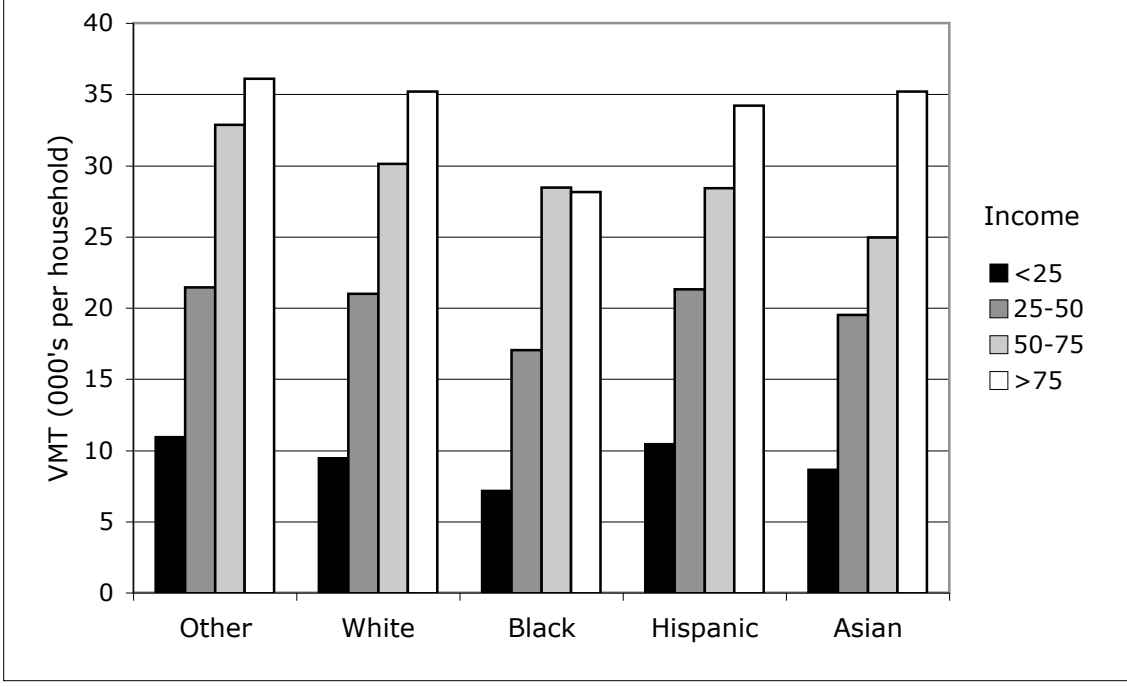Figure 2a: Base VMT by Race and Income

Figure 2b: Household EV by Race and Income –
25 Cent Gas Tax Increase with Flat Recycling