Appendix for
"Distributional and Efficiency Impacts of Increased U.S. Gasoline Taxes"

A Data

Our automobile data set has two main components: (1) a random sample of U.S. household's complete automobile 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 U.S. Environmental Protection Agency and Department of Energy's (*EPA/DOE*) *fueleconomy.org* web site. We refined and augmented these data with additional information from a number of sources summarized in Table 1.

The next section discusses the specific data we use from each source in Table 1. Section 2 follows with a summary of how we merged the data into our final data set. We conclude in section 3 with a summary statistics from the final data set.

1 Data Sources

1.1 2001 National Household Travel Survey (NHTS)

Our household automobile choice data comes from the 2001 *National Household Travel Survey* (*NHTS*), the most recent and comprehensive survey of U.S. automobile demand. Sponsored by three agencies within the U.S. Department of Transportation (DOT) and conducted between March 2001 and May 2002, the survey collected automobile demand and socio-demographic data from a random sample of U.S. households. A random digit dialing protocol was initially used to screen and elicit household participants, and follow-up household and personal phone surveys as well as written diaries collected all relevant information. The survey response rates ranged from 41.2 percent at the household level to 32.2 percent at the personal (household members at least 18 years old) level. Although somewhat low, these response rates are not surprising given the survey's length and complexity, and the *NHTS* includes sampling weights that adjust for nonresponse bias. In total, responses from 26,038 households are included in the *NHTS*.

With help from DOT staff, we obtained the confidential version of the *NHTS* data files that contained the following information relevant to our analysis:

1) Household income
2) All automobile holdings by make, model, and year[1]
3) Vehicle Miles Traveled (VMT) for each automobile over the past 12 months
4) Household and individual level socio-demographic data (e.g., household size and composition, sex, education, employment status, etc.)
5) Geographic data (state, Metropolitan Statistical Area (MSA), and zip code)

Although the quality of the *NHTS* data was generally high, we found it to be deficient in a few important dimensions. About 14 percent of households (3,723 in total) did not supply complete income data. Among those who did, some older households reported incomes that were implausibly low in our judgment. To address these data deficiencies, we first imputed 1999 Census zip code level median household incomes adjusted to 2001 dollars using the U.S. CPI. We then adjusted the incomes of all households with one or more senior citizens (adults 65 and above) to be at least the 2001 average Social Security payment for senior citizens ($10,224 per senior citizen). In total, these later income adjustments affected 1,006 households in our sample.

Other limitations with the data forced us to drop observations from our analysis. The *NHTS* data files do not always contain sufficient information to identify all cars or the characteristics of cars households drive. Our treatment of these cars and households depended on whether the unidentified cars' VMTs were more than 1000 miles. If the unidentified car's VMT was above 1000 miles, the household was dropped from our analysis; otherwise, the household was retained and the unidentified car ignored. 2,542 households were dropped from our analysis as a result.

A related difficulty arose with households who held autos produced on or before 1983. As we discuss below, our automobile price and characteristics data did not cover these older

[1] The survey also collected detailed information on motorcycle and motor home holdings. Because these vehicles generally serve different household purposes than automobiles, we choose to ignore them in our analysis.

autos. Similar to unidentified autos, our treatment of these older cars and households depended on whether the unidentified cars' VMTs were more than 1000 miles. If the older car's VMT was above 1000 miles, the household was dropped from our analysis; otherwise, the household was retained and the older car ignored. 2,332 households were consequently dropped from our analysis.

Finally, VMT data was sometimes incomplete or implausible. The *NHTS* collected annual VMT information through a veriety of channels: 1) direct questioning (i.e., "what was the total VMT for this automobile in the past 12 months?"), 2) extrapolations based on changes in reported odometer readings over a two month period, and 3) extrapolations based on detailed one-day travel diaries. Based on household responses, the *NHTS* reports two VMT estimates for each automobile: *annmile* and *bestmile*. The former relies exclusively on the direct questioning approach to eliciting VMT and the latter uses regression techniques and arbitrary judgments to combine all three. Both variables have missing values, but *bestmile*, because it is based on more information, has fewer. Values for both variables range from 1 to 200,000, but our judgment was that estimates below 100 miles or above 60,000 miles were implausible, and therefore we recoded them as missing. In our analysis we use *annmile* as our VMT measure whenever available and *bestmile* otherwise. If both are missing, we dropped the corresponding household from our analysis. This protocol resulted in us losing an additional 719 households. We also recorded as missing all VMTs for a given household if its average VMT per adult was greater than 60,000 miles. This last step resulted in 16 additional households being dropped.

As a result of these cleaning procedures, 20,429 of the original 26,038 households remained in our estimation sample. Our estimation results are therefore based on 78.8 percent of the *NHTS* sample, a relatively large percentage in our view. To make our usable subsample from the *NHTS* broadly representative of the general population, we adjusted the sampling weights based on geographic and socio-demographic criteria accordingly.

1.2 NBER Tax Calculator

Because a significant portion of household income is subject to federal, state, and local taxation, we used the *NBER*'s publicly available software package *TAXSIM, version 5.1* to calculate each household's after-tax income. *TAXSIM* requires several pieces of information as input (e.g., tax year, state of residence, marital status, number of children, wages of the primary tax filer and his/her spouse, pensions, unemployment compensation), and not all of this information was available from the *NHTS*. We therefore made the following set of assumptions when calculation after tax income:

1) The tax year was taken as the year of the household interview (either 2001 or 2002).
2) Marital status was derived from the marital status of the main *NHTS* survey respondent. Our sense was the main *NHTS* survey respondent was the head of household in most cases, but we recognize that the respondent might be any adult 18 years or older in the household.
3) In households with more than one working adult, the income of each adult is frequently missing; only total household income is reported. In these cases, we assume that the tax filer and spouse's income are 60 and 40 percent of total household income, respectively.
4) If both tax filer and his/her spouse are 65 and above, their total income is treated as pensions.
5) If all adults in the household are unemployed but less than 65, their total income is treated as unemployment compensation.

1.3 Wards Automotive Yearbook

The 1983-2002 *Wards Automobile Yearbook* provided most of the car and truck characteristics used in our analysis. Characteristics obtained from *Wards* 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 time period. The data was scanned into electronic format and carefully checked for errors and inconsistencies. Some missing characteristics were imputed through regression analysis.

1.4 NADA Used Car Guide

The National Automobile Dealer's Association (*NADA*) publishes monthly the *NADA Used Car Guide*, a detailed summary of new and used car and truck prices. We obtained from *NADA* the April 2001 and 2002 editions 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. After deflating 2002 resale car and truck prices to 2001 dollars with the CPI, we differenced the 2001 and 2002 resale prices ($(P_j^{2001}$ and P_j^{2002}, respectively$)$) for car *j* to construct estimates of real depreciation D_j for a particular make, model, and year, i.e.,

$$D_j = P_j^{2001} - P_j^{2002} / (1 + CPI) .$$

Although we generally found estimates consistent with a 20 percent real depreciation rate and that varied in intuitive ways, careful inspection revealed that some missing and implausible estimates arose. In these cases, regression analysis was used to generate imputations.

1.5 EPA/DOE's Fueleconomy.org Web Site

The U.S. Environmental Protection Agency (*EPA*) and Department of Energy (*DOE*) jointly sponsor the web site fueleconomy.org which contains city and highway miles per gallon (MPG) data by make, model, and year for automobiles sold in the U.S. between 1985 to 2002. This data was helpful in checking for inconsistencies with the *Wards'* MPG data. The site also contains information on *EPA/DOE* car classification which was helpful for aggregating similar autos in our analysis.

1.6 Maintenance and Repair Costs

After numerous discussions with academic and government transportation researchers, we could not identify a comprehensive and up-to-date data set of average maintenance and repair (M&R) costs for new and used automobiles. The best data on M&R costs we could find came from *Edmunds.com* and *AAA*. For recent makes and models, the *Edmunds.com* web site reports ownership cost estimates (called the "True Cost to Own") for the initial five years of a car's use that contain separate M&R components. The maintenance component includes both scheduled (i.e., factory recommended items) and unscheduled (tires, brakes, battery, etc.) maintenance. Repair represents average repair costs not covered by the manufacturer's warranty. Both the repair and maintenance estimates assume 15,000 miles driven per year. Similarly, *AAA* annually reports per mile M&R costs (defined similar to *Edmunds*) for four representative new automobiles.

Due to the limited scope of the *Edmunds.com* and *AAA* data, we were forced to make strong and somewhat arbitrary judgments about how M&R costs in general relate to our limited set of estimates. Both the *Edmunds'* and *AAA* data consistently suggested that per mile M&R costs were roughly proportional to per mile gasoline costs. In general, new autos had slightly lower M&R costs relative to their gas costs, while older pre-1995 autos had slightly higher costs. We therefore decided to set the per mile M&R costs to 90 percent of per mile gas costs for 2001-2002 autos, 95 percent for 1999-2000 autos, 100 percent for 1995-1998 autos, 105 percent for 1990-1994 autos, and 110 percent for pre-1990 autos.

1.7 ACCRA Regional Price Data

Our gas price and regional cost of living index (COLI) data came for the American Chamber of Commerce's 2000-2002 *ACCRA* data base. Every quarter, the American Chamber of Commerce publishes per-gallon gas prices and summary COLI indexes for over 300 Metropolitan Statistical Areas (MSAs) and rural communities. This geographic resolution permitted us to link fairly precise measures of gasoline prices and regional COLIs to each household in the *NHTS*. To account for the relatively small number of missing prices, regression techniques were again used.

1.8 NAIC & State Farm Insurance Data

We develop insurance cost estimates that vary by state, vehicle class and year based on published data from the National Association of Insurance Commissioners (*NAIC*) and unpublished data from the *State Farm* Insurance Company. *NAIC* publishes periodically state level average insurance expenditures and premiums for personal automobile insurance, and we use their 2001 published estimates. *State Farm* supplied us with unpublished adjustment factors that allowed us to scale these estimates upwards or downwards to account for differences in automotive class and age.

1.9 FHWA's Auto Registration Fees Data

The Federal Highway Administration (*FHWA*) periodically collects and publishes state level automotive registration fee data. We use their 2001 data that we accessed on June 1, 2004 from the web at http://www.fhwa.dot.gov/ohim/hwytaxes/2001/pt11.htm. Although useful in terms of identifying differences in registration fees across states, the data is limiting in the sense that it does not contain information on new and used car taxes or the costs of environmental emissions testing.

2 Merging the Alternative Data Sources into the Final Data Set

2.1 Merging the Car Characteristics & Constructing Aggregate Automobiles

As discussed above, our new and used car prices and characteristics come from three primary sources – *Wards*, *NADA*, and *EPA/DOE*. Merging these data sources together proved challenging because no common vehicle identification code was present in each data set and the levels of coverage and aggregation for each make, model, and year varied considerably across the data sets.[2] Moreover, the description of automobiles in the *NHTS* is highly aggregated – we only know the make, model, and year of a given automobile,[3] and nothing about its engine size (e.g., 4 or 6 cylinders), transmission (automatic or manual), or body shape (coupe, sedan, hatchback, or wagon). To address these data limitations, we separately collapsed the price and

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[2] An example about the nature of the problem we confronted may be instructive. Consider a 1995 Honda Civic. In one data set, this make, model, and year triplet might be reported as two separate vehicles – a 1995 Honda Civic Coupe and a 1995 Honda Civic Sedan. In another data set it might be reported as three vehicles – the 1995 Honda Civic CRX, the 1995 Honda Civic DX, and the 1995 Honda Civic S. In the third data set it may be reported as four vehicles - the 1995 Honda Civic CRX 2 Door, the 1995 Honda Civic CRX 4 Door, the 1995 Honda Civic DX manual, and the 1995 Honda Civic DX automatic. Notice that none of the car descriptions across the three data sets match perfectly. They not only differ in terms of their degrees of aggregation but also in terms of their coverage.

[3] In some cases the *NHTS* does not even report the specific model a household owns but rather a group of models that contains the specific model owned. In general the models fell within a common class (e.g., the Volkswagon Golf and Cabriolet). This data limitation required further aggregation across automobile models.

non-price characteristics for all vehicles with a common make, model, and year into a single vector of characteristics using an unweighted geometric mean formula before merging the alternative data sets. Once this initial aggregation was performed, merging the three data sets by common make, model, and year was feasible, although regression analysis was necessary to fill in a relatively small number of missing values. One limitation with the merge was that although *Wards* and *NADA* had coverage for the same years (1983-2002), the *EPA*/*DOE*'s coverage was only from 1985 to 2002. Since only the MPG and class variables from the *EPA*/*DOE* data set were used in our final analysis and the *Wards* data also contained MPG estimates, we relied exclusively on *Wards'* MPG data and assumed the car classes for particular makes and models in 1985 were the same in 1983 and 1984.

After the merge was completed, roughly 4,500 distinct make, model, and year combinations remained in our data set. Including such a relatively large number of choice alternatives in our econometric model was not feasible and thus additional aggregation was required. We therefore stratified cars into seven make categories (Ford, Chrysler Daimler, GM, Honda, Toyota, other East Asian, and European), ten class categories (non-luxury compact, non-luxury midsize, non-luxury fullsize, luxury compact, luxury midsize/fullsize, small truck, large truck, small SUV, large SUV/van, and minivan),[4] and five age categories ('01-02, '99-'00, '95-'98, '90-'94, and '83-'89). 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*.[5] This approach to aggregation resulted in a total of 284 composite cars being generated.[6]

[4] Compacts with manufacturer's suggested retail price (MSRP) greater than $31,000 (in $2001 $s) were treated as luxury automobiles. Similarly, midsize and fullsize autos with MSRPs greater than $35,000 were treated as luxury autos. Large trucks and SUVs were assumed to have curbside weights greater than 4,000 and 4,250 pounds, respectively.

[5] Using the simple frequency weights from the *NHTS* implied that most make, model, and year combinations did not enter into the aggregate autos. To avoid this we "smooth" the weights as follows. One-third of the weight for a particular make/model/year combination remained with the specific make/model/year, another third was allocated evenly across years where similar makes and models were produced, and the final third was distributed evenly across similar makes and classes within the particular year the car was produced. The sum of these "smoothed" weights is the weight used to construct aggregate cars.

[6] Note that 66 of the possible 350 make, class, and age strata had no cars or trucks in them and were not included in our analysis.

Table 1
Data Sources

Source	***Description***	***Main variables***
NHTS	Federal Highway Administration's (FHWA) 2001 *National Household Travel Survey,* confidential files	Demographic & geographic household characteristics, automobile characteristics (e.g., make, model, year, VMT)
NBER	*TAXSIM, version 5.1*	Federal tax, state tax, & FICA for every household in NHTS
Ward's	*Ward's 2000-2002 Automotive Yearbook*	Car characteristics (e.g., horsepower, length, weight, height, width, wheelbase) for 1979-2002 make/models
EPA/DOE	Department of Energy & Environmental Protection Agency's www.fueleconomy.org web site	EPA city & highway MPGs, car class, engine size (liters, cylinders) for 1985-2002 make/models (accessed on June 1, 2004)
NADA	2001 & 2002 *National Automobile Dealers' Association Used Car Guide*	Used car prices and Manufacture's suggested retail prices (MSRP) for all 1982-2002 make/models in April & December of 2001-2002
Edmunds.com and AAA	Edmunds "True Cost to Own" data accessed at http://www.edmunds.com, and AAA's "Your Driving Costs" annual publication, 1990-present	Maintenance & repair data (accessed at Edmunds.com on June 15, 2004)
ACCRA	American Chamber of Commerce Researchers Association's *Regional Cost of Living Index*	2001-2002 composite cost of living & gas price indexes by metropolitan statistical area (MSA)
NAIC	National Association of Insurance Commissioners' *2001 State Average Expenditures & Premiums for Personal Automobile Insurance*	2001 average state level insurance expenditures
State Farm	Personal communication with State Farm Insurance's national public relations office	Adjustment factors for vehicle class & year from State Farm
FHWA	Federal Highway Administration, Office of Highway Policy Information's web site, http://www.fhwa.dot.gov/policy/ohpi/	2001 State level auto registration fees (accessed on June 1, 2004)

B Demand Estimation

1 Estimation Algorithm

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 $f(\bar{\delta}, \Sigma_\delta \mid \mathbf{x})$. By decomposing the parameter space into disjoint sets and iteratively simulating each set conditionally on the others, the Gibbs sampler generates simulations from the unconditional posterior distribution after a sufficiently long burn-in.

We assume the following diffuse priors for $\bar{\delta}$ and Σ_δ:

$$\text{(1a)} \quad \begin{aligned} &\bar{\delta} \sim N(\delta^{FP}, \tau I_k) \\ &\Sigma_\delta \sim IW(k, I_k), \end{aligned}$$

where $N(\cdot)$ and $IW(\cdot)$ denote the multivariate normal and inverse Wishart distributions, respectively, δ^{FP} are the fixed parameter maximum likelihood estimates, τ is a scalar chosen such that $1/\tau$ approaches zero, k is the dimension of δ, and I_k is a k-dimensional identity matrix. These priors, in combination with our assumed data generating process, imply the following conditional posterior distributions for $\bar{\delta}$ and Σ_δ as well as the individual specific δ_i:

$$\text{(2a)} \quad \begin{aligned} f(\bar{\delta} \mid \delta_1, \ldots, \delta_N, \Sigma_\delta, \mathbf{x}_1, \ldots, \mathbf{x}_N) &\propto N(\bar{B}, \Sigma_\delta / N) \\ f(\Sigma_\delta \mid \delta_1, \ldots, \delta_N, \bar{\delta}, \mathbf{x}_1, \ldots, \mathbf{x}_N) &\propto IW\left[k + N, (kI_k + N\bar{S})/(k+N)\right] \\ f(\delta_i \mid \bar{\delta}, \Sigma_\delta, \mathbf{x}_i) &\propto L_i(\mathbf{x}_i \mid \delta_i) \times n(\delta_i \mid \bar{\delta}, \Sigma_\delta) \quad \forall i, \end{aligned}$$

where $L_i(\mathbf{x}_i \mid \delta_i)$ is the conditional likelihood function from equation (4.6) for individual i, $n(\cdot)$ is the normal density function, and

$$\begin{aligned} \bar{B} &= N^{-1} \sum_i \delta_i \\ \bar{S} &= N^{-1} \sum_i (\delta_i - \bar{\delta})^{\mathsf{T}} (\delta_i - \bar{\delta}). \end{aligned}$$

The Gibbs sampling algorithm proceeds by iteratively drawing from the conditional distributions in (2a), with each draw being made conditional on the remaining parameters' most recent draws. As Train (2003) describes, simulating from the multivariate normal and inverse Wishert distributions is relatively straightforward. However, simulating from δ_i's posterior distribution is more complex and requires an adaptive Metropolis-Hastings algorithm (Chib and Greenberg, 1995). Thus iteration *s* of the Gibbs sampler involves the following steps:

1) Simulate $\bar{\delta}^s$ from $N(\bar{B}^s, \Sigma_\delta^{s-1}/N)$, where $\bar{B}^s = N^{-1}\sum_i^N \delta_i^{s-1}$. To initialize the algorithm, set $\Sigma_\delta^0 = kI_k$ and $\delta_i^0 = \delta^{FP}$, $\forall i$.
2) Simulate Σ_δ^s from $IW\left[k+N, (kI_k + N\bar{S}^s)/(k+N)\right]$ where $\bar{S}^s = T^{-1}\sum_i (\delta_i^{s-1} - \bar{\delta}^s)^\mathsf{T}(\delta_i^{s-1} - \bar{\delta}^s)$.
3) Simulate δ_i^s for each observation using one iteration from the following Metropolis-Hastings algorithm:
   a. For each observation, simulate a candidate vector $\tilde{\delta}_i^s$ from $N(\delta_i^{s-1}, r^{s-1}\Sigma_\delta^s)$, where r^{s-1} is a constant. To initialize the sequence, set r^0=0.1.
   b. For each observation, construct the following statistic:
   $$\chi_i^s = \frac{L_i(\mathbf{x}_i \mid \tilde{\delta}_i^s)n(\tilde{\delta}_i^s \mid \bar{\delta}^s, \Sigma_\delta^s)}{L_i(\mathbf{x}_i \mid \delta_i^{s-1})n(\delta_i^{s-1} \mid \bar{\delta}^s, \Sigma_\delta^s)}.$$
   If $\chi_i^s \geq U_i^s$ where U_i^s is a uniform random draw, accept the candidate random parameters, i.e., $\delta_i^s = \tilde{\delta}_i^s$. Otherwise, set $\delta_i^s = \delta_i^{s-1}$.
   c. Gelman et al. (1995) argue that the Metropolis-Hastings algorithm for the normal distribution is most efficient if the acceptance rate of candidate parameters averages between 0.23 and 0.44. Therefore, we set r^s=(1.01)r^{s-1} if the sample's proportion of accepted candidate parameter values is less than 0.3. Otherwise, set r^s=(0.99)r^{s-1}.
4) Iterate.

After a sufficiently long burn-in, this algorithm generates random draws from the posterior distributions of δ_i, $\overline{\delta}$, and Σ_δ. In practice, the burn-in length necessary to achieve convergence (i.e., random draws from the posterior distributions) is difficult to ascertain. However, our experience has been that the Gibbs sampler algorithm is relatively fast even in our large choice set application, and thus the analyst can cheaply add burn-in iterations if convergence is in doubt. Finally, because the Gibbs sampler induces serial correlation in δ_i, $\overline{\delta}$, and Σ_δ, we only use each 10^{th} simulation after the burn-in to construct distributional summary statistics and welfare measures.

Due to 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, we stratified the sample into 12 different groups based on demographic characteristics and estimated separate models within each strata. The stratification criteria and resulting strata sizes are summarized in Table 1.

2 Empirical Results

All posterior mean and corresponding variance parameter estimates for the 12 different strata are summarized in Tables 2 through 5. These estimates were generated with a total of 40,000 iterations of our Gibbs sampler estimation algorithm where we treated the first 30,000 iterations as burn-in and used every 10^{th} iteration thereafter to construct the reported estimates.

Table 1a
Strata Definitions

Strata	*Initial Size*	*Description*
1	1167	1 male adult, no children, not retired
2	1609	1 female adult, no children, not retired
3	2096	1 adult, no children, retired
4	1450	2+ adults w/ average age ≤ 35, no children, not retired
5	1722	2+ adults w/ average age > 35 & ≤ 50, no children, not retired
6	1846	2+ adults w/ average age > 50, no children, not retired
7	1897	2+ adults w/ average age ≤ 67, no children, retired
8	1730	2+ adults w/ average age > 67, no children, retired
9	1777	1+ adults w/ youngest child < 3 years old
10	1562	1+ adults w/ youngest child 3-6 years old
11	1765	1+ adults w/ youngest child 7-11 years old
12	1808	1+ adults w/ youngest child 12-17 years old
Total	20429	

Adults are at least 18 years old. Unweighted geometric mean formula used to calculate average adult age. Retirement status is self-reported. Cleaned size results from dropping households that have more cars than adults + 1 or that can not afford cars they are observed to purchase.

Table 2a
Posterior Mean Parameter Estimates – Strata 1-6

Strata	*#1*		*#2*		*#3*		*#4*		*#5*		*#6*	
	Mean	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*
α parameter												
Age category #1 – 2001-02	1.95	0.11	1.99	0.05	1.98	0.08	2.34	0.05	2.25	0.06	2.35	0.05
Age category #2 – 1999-00	2.18	0.08	2.14	0.06	2.11	0.07	2.43	0.05	2.30	0.06	2.45	0.05
Age category #3 – 1995-98	2.39	0.07	2.29	0.08	2.28	0.08	2.51	0.04	2.30	0.04	2.51	0.04
Age category #4 – 1990-94	2.16	0.06	2.04	0.04	1.97	0.06	2.20	0.05	2.13	0.05	2.16	0.04
Age category #5 – 1983-89	1.66	0.04	1.37	0.10	1.46	0.05	1.41	0.07	1.54	0.09	1.52	0.07
Horsepower (HP) / weight	-0.08	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.02	0.00	0.00	0.00
(HP / weight)*(avg adult age)	-0.36	0.65	-7.58	0.52	-6.74	0.37	-5.56	0.77	-6.60	0.56	-4.62	0.46
# of females	-	-	-	-	-0.46	0.05	-0.09	0.11	-0.02	0.06	-0.31	0.09
# of workers	-	-	-	-	-	-	0.08	0.07	0.21	0.06	0.39	0.04
β parameter												
Compact	1.56	0.04	1.43	0.05	1.54	0.03	1.57	0.07	1.77	0.03	1.81	0.04
Luxury compact	2.74	0.16	2.43	0.09	3.37	0.10	2.32	0.13	2.93	0.07	2.07	0.04
Midsize	1.67	0.06	1.58	0.03	1.44	0.07	1.77	0.05	1.77	0.04	1.64	0.04
Fullsize	2.25	0.15	2.01	0.05	1.36	0.04	2.25	0.16	1.89	0.05	1.79	0.06
Luxury midsize/fullsize	2.79	0.11	2.71	0.13	1.53	0.05	2.81	0.17	2.12	0.06	1.74	0.06
Small SUV	2.18	0.06	2.59	0.07	2.37	0.06	1.94	0.10	1.86	0.05	1.89	0.05
Large SUV/van	1.99	0.07	2.19	0.07	2.13	0.09	1.89	0.06	1.78	0.08	1.56	0.04
Small truck	1.91	0.06	3.01	0.06	2.85	0.07	2.14	0.06	2.00	0.06	1.92	0.07
Large truck	1.35	0.04	2.98	0.10	1.75	0.07	1.72	0.08	1.52	0.03	1.51	0.04
Minivan	2.75	0.09	2.95	0.08	3.11	0.10	2.92	0.11	2.00	0.04	2.04	0.07
λ parameter												
Constant	-4.33	0.17	-3.54	0.04	-3.26	0.06	-3.23	0.04	-3.42	0.05	-3.58	0.04
τ parameter												
Luxury compact	-6.81	0.20	-4.80	0.11	-4.86	0.09	-7.32	0.17	-7.19	0.17	-5.40	0.14
Midsize	-3.84	0.18	-1.22	0.14	-0.72	0.08	-2.90	0.14	-2.65	0.10	-2.56	0.14
Fullsize	-2.54	0.15	-2.83	0.24	-1.29	0.11	-4.86	0.16	-4.07	0.10	-2.54	0.18
Luxury midsize/fullsize	-4.54	0.22	-3.79	0.19	-2.37	0.12	-5.90	0.17	-5.45	0.11	-3.44	0.19
Small SUV	-6.49	0.14	-4.91	0.19	-3.56	0.10	-5.09	0.23	-5.36	0.11	-5.95	0.08
Large SUV/van	-2.62	0.19	-4.81	0.17	-4.56	0.21	-3.93	0.24	-4.29	0.10	-3.49	0.11
Small truck	-4.59	0.16	-5.41	0.09	-4.64	0.08	-4.58	0.19	-4.74	0.13	-4.74	0.22
Large truck	-0.52	0.12	-2.90	0.13	-2.38	0.17	-2.01	0.10	-1.11	0.11	-0.41	0.11
Minivan	-6.89	0.16	-5.82	0.19	-6.29	0.18	-7.34	0.10	-7.02	0.12	-6.15	0.11
Ford	-4.92	0.13	-4.09	0.13	-3.89	0.10	-5.27	0.23	-4.93	0.27	-4.36	0.16
Chrysler	-6.70	0.23	-5.76	0.16	-6.02	0.29	-6.48	0.14	-6.22	0.23	-5.81	0.12
GM	-4.50	0.25	-2.62	0.08	-2.67	0.12	-4.52	0.18	-3.65	0.18	-3.17	0.14
Honda	-4.37	0.08	-3.99	0.12	-6.24	0.07	-4.76	0.20	-6.31	0.23	-6.25	0.09
Toyota	-6.04	0.17	-4.24	0.14	-5.20	0.10	-7.38	0.15	-7.39	0.11	-5.82	0.21
Other East Asian	-6.19	0.25	-5.21	0.10	-6.09	0.13	-5.72	0.24	-6.53	0.12	-7.24	0.12
European	-7.52	0.16	-7.03	0.17	-7.87	0.17	-7.91	0.24	-9.47	0.14	-8.48	0.23
Age category #1 – 2001-02**	-3.99	0.10	-1.31	0.06	-3.67	0.09	-2.99	0.13	-2.45	0.15	-3.02	0.11
Age category #2 – 1999-00**	-2.16	0.10	-0.99	0.07	-3.57	0.09	-1.88	0.10	-1.16	0.13	-2.56	0.11
Age category #3 – 1995-98**	-4.18	0.11	-3.48	0.08	-3.50	0.16	-4.83	0.14	-5.04	0.12	-4.24	0.10
Age category #4 – 1990-94**	-5.08	0.12	-4.61	0.18	-4.16	0.12	-3.87	0.11	-3.91	0.16	-5.03	0.11
Weight / 100**	-0.14	0.00	-0.16	0.01	-0.19	0.00	-0.15	0.00	-0.13	0.00	-0.15	0.00
Wheelbase / 100**	-5.14	0.16	-6.43	0.12	-5.23	0.26	-5.49	0.19	-5.76	0.16	-5.42	0.12
HP / weight**	-0.21	0.01	-0.16	0.01	-0.16	0.01	-0.19	0.01	-0.18	0.01	-0.20	0.01
ϕ parameter												
MSA < 250k	0.06	0.18	0.24	0.17	0.13	0.09	0.33	0.14	1.30	0.10	-0.19	0.09
MSA < 500k & ≥ 250k	1.98	0.20	2.45	0.17	2.29	0.09	2.42	0.10	1.81	0.09	1.86	0.12
MSA < 1m & ≥ 500k	0.70	0.12	1.41	0.09	0.46	0.08	1.67	0.11	2.46	0.12	1.26	0.14
MSA < 3m & ≥ 1m	2.36	0.15	1.40	0.13	0.90	0.13	2.04	0.23	2.63	0.18	2.38	0.10

MSA ≥ 3m	4.14	0.14	2.94	0.18	2.54	0.08	3.29	0.13	3.79	0.16	4.64	0.13
White respondent	2.85	0.13	1.64	0.08	1.88	0.11	0.82	0.11	0.58	0.08	4.25	0.18
HS diplomas per adult	6.35	0.17	3.09	0.14	0.74	0.08	5.08	0.21	6.21	0.16	5.92	0.11
4-yr college deg. per adult	-0.62	0.13	-0.40	0.11	-1.30	0.06	-0.36	0.17	-0.42	0.12	-0.04	0.07
Average adult age	2.35	0.24	4.51	0.08	4.39	0.18	-0.38	0.24	1.66	0.23	1.77	0.15
Other parameters												
μ^*	1.15	0.02	0.77	0.02	0.64	0.02	0.98	0.02	1.18	0.02	1.34	0.02
σ^*	-0.04	0.08	-0.27	0.09	-0.77	0.06	1.07	0.05	0.70	0.05	0.44	0.06

All estimates generated with 40,000 iterations of the Gibbs sampling algorithm. The first 30,000 iterations were discarded as burn-in, and every 10th iteration thereafter was used to construct the reported estimates.
** For the tau parameter, weight wheelbase, and hp / weight are restricted to be positive. Also, the age dummies are restricted to be positive and monotonically increasing in the newness of the car. That is, the age coefficient for a car produced between 1990 and 1994 is $\exp(\beta_{\text{age category \#4}})$, whereas the age coefficient for a car produced in 2000 or 2001 is $\exp(\beta_{\text{age category \#4}} + \beta_{\text{age category \#3}} + \beta_{\text{age category \#2}} + \beta_{\text{age category \#1}})$.

Table 3a
Posterior Mean Parameter Estimates – Strata 7-12

Strata	***#7***		***#8***		***#9***		***#10***		***#11***		***#12***	
	Mean	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*
α parameter												
Age category #1 – 2001-02	2.17	0.06	2.32	0.07	1.81	0.07	1.68	0.06	1.44	0.07	1.35	0.18
Age category #2 – 1999-00	2.17	0.06	2.36	0.05	1.90	0.07	1.83	0.12	1.56	0.07	1.40	0.18
Age category #3 – 1995-98	2.24	0.06	2.45	0.05	2.00	0.05	2.00	0.11	1.72	0.05	1.49	0.16
Age category #4 – 1990-94	1.89	0.06	2.11	0.04	1.69	0.05	1.72	0.10	1.48	0.05	1.27	0.16
Age category #5 – 1983-89	1.23	0.07	1.45	0.05	0.94	0.09	1.15	0.11	0.93	0.05	0.79	0.15
Horsepower (HP) / weight	0.02	0.01	0.01	0.01	-0.01	0.00	0.01	0.00	0.02	0.00	0.02	0.01
(HP / weight)*(avg adult age)	-3.67	0.69	-4.93	0.98	-0.89	0.55	-8.58	0.53	-4.43	0.60	-2.32	0.47
# of females	-0.09	0.07	-0.29	0.08	0.34	0.08	0.26	0.19	0.19	0.10	-0.01	0.05
# of workers	-	-	-	-	0.68	0.05	0.44	0.08	0.64	0.09	0.56	0.11
# of kids ≤ 17	-	-	-	-	0.46	0.06	-0.06	0.07	0.60	0.09	0.48	0.12
# of kids ≤ 11	-	-	-	-	0.09	0.07	0.56	0.09	-0.24	0.08	-	-
# of kids ≤ 6	-	-	-	-	-0.26	0.07	-0.42	0.16	-	-	-	-
# of kids ≤ 2	-	-	-	-	-0.31	0.08	-	-	-	-	-	-
β parameter												
Compact	2.01	0.04	1.92	0.06	1.82	0.03	1.86	0.03	1.99	0.03	1.89	0.04
Luxury compact	2.47	0.07	2.48	0.09	2.88	0.07	2.82	0.08	3.19	0.09	2.99	0.07
Midsize	1.89	0.06	1.45	0.05	1.91	0.04	1.98	0.05	2.05	0.05	1.98	0.05
Fullsize	1.85	0.04	1.36	0.04	2.06	0.11	2.17	0.05	2.25	0.08	2.05	0.06
Luxury midsize/fullsize	2.00	0.06	1.33	0.03	2.71	0.07	2.74	0.14	2.77	0.11	2.56	0.06
Small SUV	2.07	0.08	2.50	0.09	1.93	0.04	2.17	0.06	2.33	0.05	2.02	0.04
Large SUV/van	1.73	0.04	1.98	0.06	1.70	0.04	1.70	0.06	1.68	0.05	1.60	0.04
Small truck	2.18	0.03	2.50	0.09	2.41	0.05	2.30	0.05	2.30	0.05	2.34	0.06
Large truck	1.64	0.03	1.71	0.07	1.70	0.05	1.65	0.05	1.65	0.05	1.66	0.06
Minivan	2.03	0.05	1.84	0.08	1.79	0.05	1.85	0.04	1.87	0.03	1.85	0.08
λ parameter												
Constant	-3.31	0.05	-3.66	0.13	-3.13	0.06	-3.02	0.06	-3.26	0.04	-3.24	0.04
τ parameter												
Luxury compact	-3.98	0.20	-7.31	0.11	-5.23	0.20	-5.94	0.18	-4.24	0.29	-3.65	0.16
Midsize	-0.93	0.15	-1.51	0.14	-1.61	0.13	-1.87	0.11	-2.01	0.14	-1.97	0.14
Fullsize	-0.84	0.11	0.07	0.16	-2.73	0.12	-2.41	0.09	-2.65	0.17	-2.39	0.12
Luxury midsize/fullsize	-1.67	0.12	-3.05	0.28	-4.08	0.29	-3.53	0.18	-4.13	0.32	-3.28	0.10
Small SUV	-4.78	0.07	-7.18	0.29	-4.65	0.25	-3.06	0.14	-3.22	0.17	-3.02	0.10
Large SUV/van	-2.85	0.12	-4.06	0.08	-1.70	0.16	-1.83	0.19	-1.81	0.16	-2.16	0.11
Small truck	-2.82	0.11	-4.71	0.14	-3.21	0.30	-2.72	0.08	-3.37	0.25	-2.93	0.15
Large truck	-0.26	0.07	-1.93	0.11	-1.45	0.14	-1.02	0.10	-1.40	0.08	-0.83	0.12
Minivan	-3.26	0.11	-5.38	0.10	-2.01	0.21	-1.61	0.09	-1.66	0.10	-2.91	0.11
Ford	-1.96	0.19	-3.95	0.12	-2.93	0.18	-3.36	0.10	-2.77	0.16	-1.28	0.13
Chrysler	-4.03	0.12	-6.33	0.20	-3.67	0.16	-4.03	0.08	-3.46	0.11	-2.37	0.12
GM	-0.72	0.12	-1.82	0.11	-2.46	0.15	-2.88	0.10	-2.55	0.11	-0.94	0.17
Honda	-3.71	0.15	-6.90	0.16	-3.80	0.15	-4.90	0.12	-4.57	0.21	-2.93	0.18
Toyota	-3.94	0.11	-7.49	0.25	-4.94	0.13	-5.44	0.12	-4.99	0.10	-3.03	0.15
Other East Asian	-4.85	0.15	-7.68	0.21	-4.10	0.13	-4.97	0.18	-4.69	0.14	-3.04	0.17
European	-5.39	0.16	-8.21	0.07	-6.51	0.20	-6.75	0.15	-6.40	0.43	-5.79	0.18
Age category #1 – 2001-02**	-2.02	0.10	-2.90	0.16	-1.63	0.07	-2.51	0.14	-1.97	0.07	-1.94	0.19
Age category #2 – 1999-00**	-1.69	0.15	-2.31	0.13	-2.56	0.14	-1.39	0.10	-2.03	0.13	-1.46	0.15
Age category #3 – 1995-98**	-2.40	0.15	-3.23	0.08	-2.50	0.10	-3.04	0.09	-2.16	0.14	-2.71	0.09
Age category #4 – 1990-94**	-1.61	0.08	-3.47	0.10	-2.89	0.06	-3.14	0.10	-1.92	0.12	-3.56	0.11
Weight / 100**	-0.08	0.00	-0.12	0.00	-0.08	0.00	-0.08	0.00	-0.08	0.00	-0.09	0.00
Wheelbase / 100**	-3.01	0.06	-4.50	0.13	-3.68	0.15	-3.64	0.10	-3.45	0.08	-3.47	0.14
HP / weight**	-0.16	0.00	-0.28	0.01	-0.20	0.01	-0.15	0.01	-0.18	0.01	-0.17	0.01
ϕ parameter												

MSA < 250k	-0.45	0.11	-0.51	0.09	0.94	0.12	1.36	0.15	1.12	0.11	1.09	0.23
MSA < 500k & ≥ 250k	1.29	0.10	2.45	0.08	1.25	0.07	1.26	0.28	1.11	0.29	0.51	0.24
MSA < 1m & ≥ 500k	0.44	0.10	0.48	0.17	1.20	0.13	1.74	0.13	1.69	0.09	1.77	0.23
MSA < 3m & ≥ 1m	1.72	0.06	0.98	0.10	1.62	0.08	2.37	0.13	2.12	0.13	1.77	0.09
MSA ≥ 3m	2.28	0.07	1.61	0.06	2.72	0.08	2.81	0.11	3.03	0.08	2.48	0.13
White respondent	3.08	0.14	3.52	0.07	1.58	0.13	1.81	0.07	1.41	0.08	1.53	0.15
HS diplomas per adult	3.15	0.12	2.95	0.22	3.67	0.18	2.04	0.09	2.60	0.15	4.09	0.15
4-yr college deg. per adult	-1.59	0.17	-0.80	0.09	-0.86	0.16	-0.86	0.16	0.04	0.08	-1.10	0.10
Average adult age	5.80	0.31	5.73	0.43	4.98	0.37	3.97	0.26	3.44	0.19	3.60	0.16
Other parameters												
μ^*	0.85	0.02	1.05	0.02	0.82	0.03	0.74	0.02	0.81	0.04	0.80	0.03
σ^*	0.41	0.05	-0.25	0.07	0.81	0.07	0.84	0.04	0.77	0.05	1.06	0.06

All estimates generated with 40,000 iterations of the Gibbs sampling algorithm. The first 30,000 iterations were discarded as burn-in, and every 10th iteration thereafter was used to construct the reported estimates.

** For the tau parameter, weight wheelbase, and hp / weight are restricted to be positive. Also, the age dummies are restricted to be positive and monotonically increasing in the newness of the car. That is, the age coefficient for a car produced between 1990 and 1994 is $\exp(\beta_{\text{age category \#4}})$, whereas the age coefficient for a car produced in 2000 or 2001 is $\exp(\beta_{\text{age category \#4}} + \beta_{\text{age category \#3}} + \beta_{\text{age category \#2}} + \beta_{\text{age category \#1}})$.

Table 4a
Posterior Variance Parameter Estimates – Strata 1-6

Strata	#1		#2		#3		#4		#5		#6	
	Mean	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*
α parameter												
Age category #1 – 2001-02	1.44	0.13	0.94	0.08	1.05	0.11	0.79	0.08	0.90	0.11	0.86	0.06
Age category #2 – 1999-00	1.22	0.11	0.87	0.13	0.95	0.10	0.71	0.09	0.71	0.10	0.76	0.05
Age category #3 – 1995-98	0.96	0.08	0.80	0.10	0.87	0.07	0.62	0.06	0.75	0.09	0.73	0.05
Age category #4 – 1990-94	0.94	0.07	0.75	0.09	0.88	0.06	0.64	0.07	0.71	0.08	0.71	0.05
Age category #5 – 1983-89	0.98	0.09	0.99	0.08	1.07	0.11	0.94	0.11	0.79	0.09	1.00	0.11
Horsepower (HP) / weight	0.07	0.01	0.04	0.00	0.06	0.01	0.09	0.01	0.06	0.01	0.05	0.01
(HP / weight)*(avg adult age)	11.64	1.42	8.66	1.57	6.96	0.55	16.12	1.52	12.83	1.08	10.92	0.95
# of females	-	-	-	-	0.43	0.03	0.83	0.10	1.02	0.10	1.10	0.11
# of workers	-	-	-	-	-	-	0.78	0.12	0.57	0.07	0.56	0.05
β parameter												
Compact	0.74	0.08	0.53	0.04	0.75	0.07	0.60	0.05	0.55	0.03	0.67	0.04
Luxury compact	2.37	0.20	1.50	0.14	1.97	0.21	1.43	0.14	1.56	0.10	0.97	0.08
Midsize	0.75	0.07	0.64	0.06	0.62	0.05	0.69	0.06	0.61	0.06	0.64	0.04
Fullsize	1.13	0.12	0.92	0.10	0.62	0.04	0.89	0.13	0.60	0.06	0.71	0.06
Luxury midsize/fullsize	1.66	0.19	1.22	0.12	1.04	0.06	1.38	0.22	0.91	0.09	0.83	0.06
Small SUV	1.38	0.13	1.42	0.17	1.38	0.11	0.75	0.12	0.72	0.05	0.94	0.05
Large SUV/van	0.97	0.07	1.22	0.12	1.33	0.11	0.65	0.06	0.60	0.10	0.61	0.05
Small truck	0.92	0.10	1.45	0.12	1.48	0.16	0.71	0.06	0.66	0.08	0.66	0.05
Large truck	0.85	0.10	1.55	0.12	0.84	0.12	0.65	0.07	0.49	0.05	0.56	0.04
Minivan	1.75	0.14	1.49	0.13	2.40	0.22	1.18	0.11	0.75	0.06	0.90	0.07
λ parameter												
Constant	1.27	0.19	0.77	0.09	1.06	0.09	0.70	0.09	0.59	0.05	0.52	0.05
τ parameter												
Luxury compact	7.80	0.94	3.22	0.50	2.76	0.26	3.92	0.65	13.58	1.16	4.10	0.51
Midsize	12.37	1.48	3.85	0.41	4.69	0.57	4.62	0.48	6.21	0.50	8.87	0.97
Fullsize	4.17	0.60	6.18	0.86	5.18	0.39	3.88	0.53	5.85	0.47	6.96	0.74
Luxury midsize/fullsize	2.11	0.32	4.36	0.74	3.20	0.23	2.02	0.31	3.78	0.30	5.36	1.03
Small SUV	5.67	0.54	7.85	1.02	1.48	0.15	11.00	0.98	6.00	0.59	3.25	0.41
Large SUV/van	3.92	0.77	4.62	0.49	3.41	0.24	3.90	0.41	7.20	0.60	5.78	0.48
Small truck	9.77	1.69	4.65	0.38	3.64	0.51	5.40	1.11	6.15	1.22	7.56	0.79
Large truck	4.93	0.47	2.73	0.29	1.88	0.21	2.54	0.34	2.81	0.30	3.10	0.21
Minivan	3.47	0.34	3.53	0.30	3.13	0.39	3.82	0.54	5.06	0.54	3.16	0.44
Ford	5.36	0.60	6.48	0.58	4.84	0.51	7.39	0.62	15.27	1.91	17.69	1.76
Chrysler	9.50	1.01	7.22	0.77	5.83	0.99	4.55	0.63	9.73	0.78	8.02	0.83
GM	27.23	2.83	4.57	0.54	5.82	0.58	10.15	1.34	10.72	1.20	14.73	1.75
Honda	2.13	0.38	2.10	0.23	2.50	0.35	3.26	0.41	5.33	0.98	5.78	0.49
Toyota	9.23	1.33	3.96	0.36	2.96	0.38	8.78	0.89	5.51	0.54	6.04	0.77
Other East Asian	10.74	0.97	6.07	0.53	2.53	0.17	5.01	1.16	8.19	1.11	11.17	1.23
European	4.16	0.55	3.18	0.41	3.34	0.59	7.91	0.64	8.21	1.12	7.56	0.67
Age category #1 – 2001-02**	1.99	0.21	1.23	0.10	2.08	0.25	2.84	0.36	2.30	0.19	2.60	0.24
Age category #2 – 1999-00**	1.85	0.30	1.18	0.11	2.62	0.30	2.73	0.39	1.82	0.18	3.42	0.26
Age category #3 – 1995-98**	2.61	0.23	2.18	0.27	2.88	0.30	2.95	0.33	3.03	0.55	2.06	0.23
Age category #4 – 1990-94**	4.27	0.41	2.02	0.19	2.61	0.24	3.01	0.31	3.00	0.27	4.07	0.60
Weight / 100**	0.14	0.01	0.08	0.01	0.09	0.02	0.11	0.01	0.07	0.01	0.12	0.02
Wheelbase / 100**	3.83	0.52	2.54	0.50	2.29	0.39	3.67	0.49	2.44	0.28	2.92	0.24
HP / weight**	0.13	0.02	0.11	0.02	0.10	0.01	0.10	0.02	0.13	0.02	0.15	0.01
ϕ parameter												
MSA < 250k	2.01	0.27	4.37	0.43	2.22	0.20	2.95	0.33	3.90	0.33	2.29	0.23
MSA < 500k & ≥ 250k	4.03	0.39	2.33	0.56	3.48	0.48	3.69	0.36	2.00	0.31	2.42	0.23
MSA < 1m & ≥ 500k	3.82	0.35	2.58	0.32	2.16	0.42	2.24	0.49	3.79	0.52	5.18	0.60
MSA < 3m & ≥ 1m	3.52	0.64	1.84	0.24	1.89	0.27	4.76	0.49	2.50	0.47	2.30	0.26

MSA ≥ 3m	4.13	0.38	3.66	0.47	2.20	0.22	2.06	0.19	3.55	0.42	3.82	0.67
White respondent	4.73	0.90	2.26	0.41	3.52	0.45	1.80	0.38	2.39	0.21	2.93	0.39
HS diplomas per adult	4.65	1.09	2.72	0.21	2.09	0.18	3.58	0.69	4.19	0.46	3.38	0.34
4-yr college deg. per adult	2.61	0.43	2.19	0.33	1.89	0.17	2.00	0.31	3.55	0.36	3.41	0.43
Average adult age	10.55	1.07	2.76	0.36	4.75	0.82	6.52	1.66	3.52	0.36	4.30	0.48
Other parameters												
μ^*	0.23	0.02	0.19	0.01	0.17	0.01	0.19	0.01	0.17	0.01	0.16	0.01
σ^*	1.59	0.14	1.27	0.10	1.10	0.08	0.78	0.05	1.00	0.06	1.12	0.06

All estimates generated with 40,000 iterations of the Gibbs sampling algorithm. The first 30,000 iterations were discarded as burn-in, and every 10th iteration thereafter was used to construct the reported estimates.

** For the tau parameter, weight wheelbase, and hp / weight are restricted to be positive. Also, the age dummies are restricted to be positive and monotonically increasing in the newness of the car. That is, the age coefficient for a car produced between 1990 and 1994 is $\exp(\beta_{\text{age category \#4}})$, whereas the age coefficient for a car produced in 2000 or 2001 is $\exp(\beta_{\text{age category \#4}} + \beta_{\text{age category \#3}} + \beta_{\text{age category \#2}} + \beta_{\text{age category \#1}})$.

Table 5a
Posterior Variance Parameter Estimates – Strata 7-12

Strata	***#7***		***#8***		***#9***		***#10***		***#11***		***#12***	
	Mean	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*	*Mean*	*St.Er.*
α **parameter**												
Age category #1 – 2001-02	0.86	0.07	1.06	0.13	0.85	0.09	0.93	0.13	0.82	0.09	0.86	0.12
Age category #2 – 1999-00	0.79	0.08	0.79	0.07	0.64	0.06	0.74	0.07	0.78	0.06	0.73	0.09
Age category #3 – 1995-98	0.63	0.06	0.71	0.07	0.60	0.05	0.60	0.04	0.66	0.05	0.61	0.05
Age category #4 – 1990-94	0.71	0.06	0.74	0.07	0.69	0.07	0.57	0.04	0.73	0.06	0.67	0.06
Age category #5 – 1983-89	0.79	0.07	0.89	0.07	0.87	0.09	0.81	0.08	0.85	0.07	0.80	0.11
Horsepower (HP) / weight	0.05	0.01	0.08	0.01	0.05	0.01	0.07	0.01	0.08	0.01	0.05	0.01
(HP / weight)*(avg adult age)	7.48	0.66	12.08	1.12	19.35	3.29	15.26	1.49	8.58	0.96	9.10	1.05
# of females	0.87	0.06	1.73	0.19	1.81	0.23	1.45	0.14	1.24	0.14	1.08	0.17
# of workers	-	-	-	-	0.81	0.07	1.07	0.12	1.01	0.12	0.78	0.09
# of kids ≤ 17	-	-	-	-	1.40	0.21	0.93	0.08	1.26	0.12	1.56	0.21
# of kids ≤ 11	-	-	-	-	1.66	0.19	1.25	0.20	1.31	0.14	-	-
# of kids ≤ 6	-	-	-	-	1.63	0.16	1.39	0.25	-	-	-	-
# of kids ≤ 2	-	-	-	-	1.86	0.24	-	-	-	-	-	-
β **parameter**												
Compact	0.60	0.04	0.64	0.08	0.48	0.04	0.54	0.05	0.46	0.03	0.49	0.04
Luxury compact	0.94	0.07	1.39	0.20	1.18	0.15	1.48	0.11	1.51	0.19	1.52	0.12
Midsize	0.62	0.04	0.67	0.05	0.54	0.05	0.60	0.05	0.61	0.04	0.49	0.05
Fullsize	0.50	0.06	0.56	0.03	0.70	0.10	0.72	0.07	0.73	0.05	0.55	0.05
Luxury midsize/fullsize	0.68	0.07	0.71	0.04	1.21	0.09	1.26	0.11	1.21	0.25	0.94	0.08
Small SUV	0.84	0.09	1.38	0.13	0.70	0.05	0.79	0.09	0.81	0.06	0.70	0.06
Large SUV/van	0.52	0.04	0.89	0.06	0.52	0.04	0.53	0.05	0.44	0.04	0.50	0.04
Small truck	0.70	0.05	1.03	0.11	0.81	0.05	0.72	0.07	0.74	0.07	0.72	0.08
Large truck	0.50	0.03	0.62	0.05	0.56	0.04	0.53	0.05	0.47	0.05	0.42	0.03
Minivan	0.65	0.05	1.12	0.09	0.53	0.03	0.57	0.06	0.52	0.06	0.55	0.05
λ **parameter**												
Constant	0.63	0.04	0.88	0.12	0.50	0.04	0.51	0.04	0.52	0.04	0.54	0.04
τ **parameter**												
Luxury compact	5.41	0.69	3.68	0.74	3.63	0.39	5.83	1.04	3.00	0.51	2.37	0.41
Midsize	3.09	0.35	9.21	1.52	2.92	0.30	2.48	0.27	2.57	0.42	3.38	0.84
Fullsize	3.90	0.49	3.53	0.29	2.34	0.32	4.20	0.42	3.65	0.34	3.26	0.30
Luxury midsize/fullsize	1.76	0.21	5.27	0.92	1.91	0.25	3.49	0.88	4.26	0.87	4.19	0.62
Small SUV	3.13	0.29	4.46	0.68	7.85	1.05	3.30	0.23	2.55	0.43	3.70	0.48
Large SUV/van	5.48	0.54	3.40	0.37	3.74	0.41	4.04	0.57	4.20	0.64	3.82	0.79
Small truck	5.10	0.60	7.55	0.67	3.15	0.44	1.89	0.17	2.79	0.35	3.38	0.36
Large truck	1.78	0.27	3.61	0.34	2.34	0.19	2.35	0.44	2.58	0.22	2.53	0.32
Minivan	3.51	0.50	5.87	1.05	2.98	0.32	2.75	0.57	3.36	0.39	3.72	0.39
Ford	8.88	1.08	9.72	0.85	7.04	0.85	3.36	0.43	6.88	0.59	10.04	1.39
Chrysler	7.01	0.50	6.97	1.20	2.97	0.53	3.65	0.36	5.47	0.97	5.77	0.67
GM	8.72	0.93	6.90	0.55	4.67	0.36	2.38	0.22	6.21	0.68	8.90	0.97
Honda	4.27	0.32	2.50	0.27	4.44	0.53	4.60	0.50	2.77	0.25	2.34	0.49
Toyota	5.15	0.50	10.60	1.92	4.56	0.66	5.22	0.47	2.95	0.32	2.54	0.23
Other East Asian	4.67	0.46	2.10	0.21	2.58	0.45	6.96	0.85	3.04	0.34	3.10	0.37
European	2.96	0.52	2.20	0.54	3.83	0.40	4.76	0.68	3.81	0.66	9.88	1.45
Age category #1 – 2001-02**	1.66	0.12	2.49	0.29	1.45	0.19	1.95	0.19	1.51	0.11	2.26	0.29
Age category #2 – 1999-00**	1.76	0.24	1.71	0.19	3.14	0.28	1.37	0.13	1.81	0.16	1.78	0.24
Age category #3 – 1995-98**	1.71	0.22	2.66	0.39	1.71	0.17	2.02	0.20	1.48	0.14	1.31	0.23
Age category #4 – 1990-94**	1.40	0.20	3.24	0.28	1.84	0.17	1.78	0.22	1.51	0.12	2.46	0.38
Weight / 100**	0.05	0.01	0.07	0.01	0.04	0.00	0.05	0.00	0.04	0.00	0.06	0.01
Wheelbase / 100**	1.74	0.13	2.45	0.26	2.00	0.28	2.40	0.32	1.60	0.23	1.79	0.26
HP / weight**	0.10	0.01	0.11	0.01	0.10	0.01	0.09	0.01	0.09	0.01	0.09	0.02
ϕ **parameter**												

MSA < 250k	2.86	0.48	2.98	0.20	2.43	0.21	2.67	0.18	2.13	0.31	3.11	0.29
MSA < 500k & ≥ 250k	1.67	0.19	1.85	0.19	2.28	0.27	2.70	0.67	2.56	0.30	4.34	1.15
MSA < 1m & ≥ 500k	2.30	0.48	2.66	0.27	2.76	0.28	2.33	0.22	1.63	0.17	2.15	0.26
MSA < 3m & ≥ 1m	1.91	0.18	1.92	0.17	1.72	0.26	1.52	0.31	1.81	0.21	2.18	0.24
MSA ≥ 3m	2.19	0.25	2.18	0.28	1.85	0.18	1.94	0.17	1.81	0.21	1.84	0.21
White respondent	6.90	0.89	1.91	0.21	2.47	0.34	1.78	0.21	3.86	0.38	2.99	0.47
HS diplomas per adult	3.08	0.32	3.69	0.42	5.97	0.63	2.55	0.28	2.61	0.24	4.88	0.55
4-yr college deg. per adult	2.01	0.17	1.91	0.42	1.62	0.11	1.78	0.22	1.61	0.23	2.76	0.28
Average adult age	8.46	0.97	4.36	0.44	3.67	0.61	3.23	0.70	2.41	0.24	3.62	0.39
Other parameters												
μ^*	0.15	0.01	0.14	0.01	0.18	0.01	0.18	0.01	0.18	0.01	0.21	0.02
σ^*	0.92	0.09	1.16	0.07	0.96	0.06	0.91	0.05	0.91	0.08	0.79	0.05

All estimates generated with 40,000 iterations of the Gibbs sampling algorithm. The first 30,000 iterations were discarded as burn-in, and every 10th iteration thereafter was used to construct the reported estimates.

** For the tau parameter, weight wheelbase, and hp / weight are restricted to be positive. Also, the age dummies are restricted to be positive and monotonically increasing in the newness of the car. That is, the age coefficient for a car produced between 1990 and 1994 is $\exp(\beta_{\text{age category \#4}})$, whereas the age coefficient for a car produced in 2000 or 2001 is $\exp(\beta_{\text{age category \#4}} + \beta_{\text{age category \#3}} + \beta_{\text{age category \#2}} + \beta_{\text{age category \#1}})$.

C Calibration of the Simulation Model

The individual household utility functions (and the associated system of automobile and VMT demands) are characterized entirely using the parameter estimates described in section 4 of the main text. As in the estimation, the demand for any particular vehicle is then a function of the rental prices of all other vehicles. The simulation model, however, also generates a supply function for both new and used cars that needs to be calibrated separately. The following two subsections describe the calibration method for the new and used car supply functions, respectively. This calibration procedure is run in a baseline simulation, before the introduction of an increment to the gasoline tax. The values of parameters that need to be calibrated are saved and introduced into the policy simulation.

1 Calibration of new car supply

The producer problem described in section 2-c of the main text requires demand and cost functions. The demand functions comes from household choices according to the parameters estimated in section 4 of the main text. The cost functions, $c_k(e_k)$, will represent marginal costs faced by each producer for each class of vehicle as a function of fuel economy. The calibration of cost functions proceeds in two steps:

First we calibrate the costs of baseline models (that is, new car models with fuel economy as observed in the baseline data) using the dealer markups available on www.edmunds.com[7] and the estimated ratio of dealer and manufacturer markups from Bresnahan (1986). This provides the following estimated total markup by class and manufacturer:

[7] www.edmunds.com provides the invoice prices and suggested retail prices for automobiles by make and model. We use data for 2001 (corresponding to our household sample period).

Table C-1: Markups by Manufacturer and Class

Class:	Ford	Chrysler	GM	Honda	Toyota	Other Asian	European
Compact	15	14	22	28	22	23	23
Lux compact		18	22	27	41	25	27
Midsize	19	21	24	34	33	16	26
Fullsize	16	20	26		38		
Lux mid/full	19	20	24	38	46		20
Small SUV	19	16	24	24	25	18	
Large SUV	37	27	41	33	43	23	29
Small truck	19	27	28		29	21	
Large truck	36	39	41		30		
Minivan	22	23	41	34	32	21	22

The baseline costs above can be expected to change as firms make different fuel economy choices. The second part of the calibration is then to specify the functions relating the changes in production cost to changes in fuel economy. The National Research Council (2002) develops estimates of the marginal cost of improvements in fuel economy based on a set of engineering studies. These cost functions can be approximated closely by quadratic functions fit to the points in the NRC study. We therefore choose to employ quadratic functions to specify $c_k(e_k)$, and calibrate the second derivatives of our cost functions to match the curvature of the fitted functions from the NRC study. The first derivatives of $c_k(e_k)$ at the baseline fuel economy level, on the other hand, can be determined endogenously in the baseline model: The first order conditions for profit maximization involve the derivative of demands with respect to fuel economy coming from our demand system and imply the derivative of cost with respect to fuel economy.

Specifically, the second derivatives of the cost functions are set exogenously to (costs expressed in 2001 dollars and fuel economy in miles per gallon):

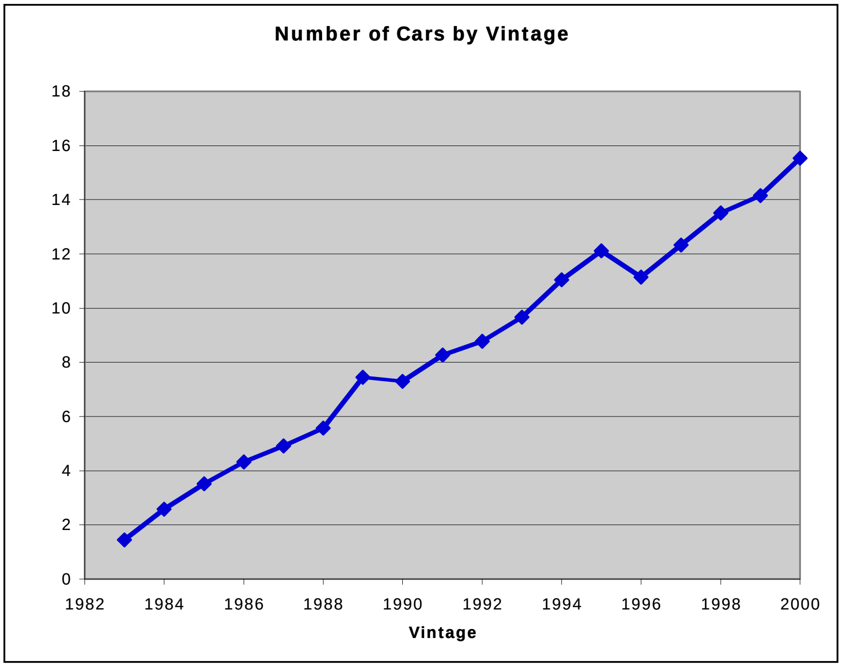
Table C-2: Cost Function Parameters by Class

Class:	$\frac{\partial^2 c_k}{\partial e_k^{\,2}}$
Compact	9.2
Lux compact	12.5
Midsize	12.3
Fullsize	12.5
Lux mid/full	11.2
Small SUV	11.2
Large SUV	16.6
Small truck	14.1
Large truck	16.2
Minivan	10.5

2 Calibration of used car supply (the scrap market)

The total quantity of used cars supplied of a given make, age, and class depends on how many are scrapped. The function controlling scrap is given in section 2-d-ii of the paper and requires both a calibration constant determining scrap level in the baseline case and an elasticity controlling how rapidly the quantity of scrapped vehicles changes. The maximum possible supply of a particular used vehicle is determined by how many were available in the market in the previous time period.

We use the parameter b_j to calibrate the probability a vehicle is scrapped in the benchmark. The calibration is based on the roughly linear trend of vehicle choice that can be observed in the data. The figure below shows the number of used cars of each vintage in our NHTS dataset:



We take the quantity of vehicles scrapped of each vintage in each year to be constant (as suggested by the figure), implying that the scrap rate for a vehicle of a given age is simply:

$$\theta_{age} = \frac{1}{20 - age} \quad \text{(for } age \text{ between 1 and 19)}$$

Note that this function implies the scrap rate for cars beginning their 19th year is 100%, meaning none enter the used car market in our simulations. Combining the scrap probabilities given by θ_{age} above into groups based on the age categories in the simulation yields benchmark (exogenous) scrap probabilities as follows:

Table C-3: Calibrated Scrap Rate by Age Category

Age (in years):	Scrap probability:
1-2	0.05
3-6	0.06
7-11	0.09
12-18	0.20

The parameter b_j is adjusted endogenously in the baseline simulation to reproduce these scrap rates.

After establishing the benchmark progression of scrap rates according to the above expression, we also calibrate the response of the scrap market to changes in vehicle values: The parameter controlling this response is the elasticity η_j. We take the aggregate results from Alberini et al. (1998) who find that a $1000 bounty (equivalent to 67% of the average vehicle value) causes a 193% increase in the number of vehicles scrapped. This implies an elasticity of 2.9. We adopt the round figure of 3 for our central case and double the value to 6 in our sensitivity analysis.

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