

# **Assessing Consumer Valuation of Fuel Economy in Auto Markets**

by

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## **Abstract**

The need for and efficacy of CAFE standards for auto-makers depends largely on whether consumers properly value fuel efficiency in their vehicle purchases. In this paper we use data describing heterogeneous driving behavior and a hedonic model of new car prices to evaluate how well consumers value incremental changes in fuel economy in terms of avoided fuel costs. Results indicate car and SUV buyers mostly underpay for initial fuel economy investment while truck and van buyers dramatically overpay for fuel economy relative to avoided cost – implying that CAFE standards may be most necessary in car and SUV markets.

# **1. Introduction**

## *1.1 Motivation*

Growing concern over the environmental and geo-political consequences of the United States' use of petroleum has increased the nation's focus on the energy efficiency of transportation. In particular, because gasoline accounts for approximately 45% of US oil consumption (Energy Information Agency, 2009), promoting increased automobile fuel efficiency through legislation is considered by many to be "low hanging fruit" when it comes to emissions abatement and energy efficiency. Automobile efficiency legislation has found form in Corporate Average Fuel Economy (CAFE) standards for automobile manufacturers, set currently at 27.5 mpg for cars and 22.2 mpg for light trucks. The Energy Independence and Security Act of 2007 has made these standards even more strict by setting a target of 35 mpg for the combined fleet of cars and light trucks by 2020 (Sissine, 2007).

However, previous studies have found CAFE standards to be both a less robust and less cost-effective policy option than a carbon tax (Fischer, 2004). In theory, a tax will directly internalize the negative externalities associated with oil consumption across all energy-consuming sectors by increasing the cost of emitting carbon. This explicit price increase for consumers will increase demand for energy efficiency which, in turn, will spur innovation. CAFE standards, on the other hand, are a more indirect policy because they only require that producers maintain an average fleet fuel economy – consumers are not directly affected and could substitute away from expensive but fuel-efficient vehicles. Moreover, CAFE could also create a "rebound effect," which holds that, as automobile fuel efficiency increases, the cost to drive a mile declines. This provides an incentive to increase vehicle miles traveled (VMT) and undermines the intended purpose of the standard (Small and Van

Dender, 2006). A tax on emissions – and thus, driving – would create a direct incentive to *decrease* VMT.

Nonetheless, some studies may unfairly criticize CAFE standards because they typically assume that consumers rationally and correctly value fuel economy when making automobile purchase decisions (Gerard, 2003). If consumers undervalue fuel efficiency, auto firms receive incorrect willingness to pay (WTP) signals, indicating “that standards need to be tightened over time to ensure that emerging, cost-effective fuel-saving technologies are adopted” (Fischer, 2004; Greene, 1997).

Even if carbon externalities have been accounted for through a tax, CAFE standards may still be welfare improving if consumers are irrational (myopic) in their fuel economy decisions. Previous empirical work (Kahn, 1986; Kilian, 2006; Sallee and West, 2008) has tested for consumer myopia in valuing fuel economy by comparing changes in operating cost of used vehicles due to gas price fluctuation to changes in used vehicle prices. By viewing automobiles as assets that generate a “service flow” to consumers over the vehicle’s life, past models predict that “positive shocks to the price of gasoline should depress the price of an automobile proportionately to the change in expected lifetime operating expenses resulting from the increased cost of gasoline” (Kilian, 2006). Under this framework, vehicle prices have been found to vastly under-adjust to fuel price shocks. This is taken as indication that consumers are myopic in their vehicle purchase decisions.

Some empirical research has, however, concluded that consumers are not myopic, but that they fully internalize the value of fuel savings. For example, using an approach that compares the marginal cost of fuel efficiency to the discounted lifetime avoided cost

associated with an efficiency increase, Espey (2004) concludes that consumers correctly value or even overpay for fuel economy.

In this paper, we construct an alternative model using novel data to evaluate consumer rationality with respect to automobile fuel efficiency. While the models previous papers rely on assumptions about annual usage (Kahn 1986, and Sallee and West 2008 assume annual VMT to be 10,000 across all vehicles; Espey 2004 assumes 145,000 lifetime VMT), our model instead incorporates data to describe consumer behavior in this dimension. Utilizing this information about driving behavior, we allow for important consumer heterogeneity across driving behavior that we believe greatly improves upon previous models of vehicle consumer rationality.

## *1.2 Theoretical Background*

When purchasing an automobile, the consumer is faced with a cost minimization problem<sup>1</sup>. The rational consumer minimizes the total cost of the automobile as a function of the upfront automobile purchase price plus the present value lifetime operating costs of the vehicle:

$$C = P_V(F, X) + \sum_{t=0}^T P_{F,t} F M_t \delta_t \quad (1)$$

where C is the present value cost of owning and operating the vehicle;  $P_V$  is the price (\$) of the vehicle; E is fuel efficiency (mpg); F is  $1 / E$  or (gallons / mile), termed “fuel intensity”<sup>2</sup>; X is a vector of all other vehicle attributes;  $P_f$  is the expected fuel price (\$/gallon);  $M_t$  is the

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<sup>1</sup> Professor Richard Newell helped in defining this cost minimization problem.

<sup>2</sup> We formulate the problem in terms of changes in fuel intensity, rather than fuel efficiency, because fuel savings are proportional to intensity, not efficiency (which has fuel use in the denominator). Fuel savings are non-linear with respect to changes in MPG but are linear with respect to changes in GPM.

expected vehicle miles traveled (miles/year)<sup>3</sup>;  $T$  is the expected vehicle lifetime (years)<sup>4</sup>; and  $\delta_t$  is the discount factor for year  $t$ .

The first-order condition for cost-minimizing decisions is given by choosing vehicle fuel intensity ( $F$ ) such that

$$-\frac{dP_V}{dF} = \sum_{t=0}^T P_{F,t} M_t \delta_t \quad (2)$$

Rationality predicts that, all else equal, consumers choose fuel intensity such that the incremental price increase of a more fuel-efficient vehicle is equal to the incremental present value of expected cost savings from lower operating costs over the life of the vehicle. Thus, a cost-minimizing consumer should be willing to pay  $-dP_V/dF$  for a 1 gallon per mile (GPM) decrease in fuel intensity. For example, if  $r = 0.05$  and  $T = 14$ ,  $M = 10,000$  and  $P_f = \$1.25$ , for a .001 decrease in gallons per mile, (which is what a consumer would get from purchasing a vehicle that gets 31 instead of 30 miles per gallon) a consumer should be willing to pay as much as \$124. Given independent information on the variables in Equation (2), one can compare the left- and right-hand-side of the equation to ascertain the degree to which consumers do, in fact, minimize present value costs.

Our model tests for consumer rationality by estimating and then comparing each side of this cost minimization problem. The marginal cost of decreasing fuel intensity ( $-dP_V/dF$  in equation (2) above) can be estimated via a hedonic price function. Because of our allowance for heterogeneity,  $-dP_V/dF$  varies by vehicle type, and a different marginal cost

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<sup>3</sup> Note that one could alternatively structure the problem as one of utility maximization, treating the level of transportation services (miles traveled) as endogenous. This endogeneity (i.e. the rebound effect) is incorporated in an alternate specification of the model. See Appendix 1.

<sup>4</sup> Note that vehicle *lifetime* and not vehicle *ownership* is used here because we assume used car markets to be efficient. That is, although the typical consumer owns a vehicle for much shorter than its full lifetime, we assume that when the new car buyer sells the car in year  $k$ , he will recoup the net present value (discounted through  $T - k$  years) of the car in the used car market, including any value associated with its operating cost.

of efficiency is associated with each consumer type. Change in vehicle operating cost associated with decreasing fuel intensity (i.e. the right hand side of Equation (2) above) will vary across consumer according to the degree of heterogeneity in  $P_{F,t}$ ,  $M$ ,  $\delta$ , and  $T$ . These parameters are determined using data on fuel economy and consumer driving behavior together with assumptions about future gas price expectations and discount rates. On the margin, the rational consumer will equalize the *increased* automobile purchase price of a car with greater efficiency against the *decreased* operating costs incurred throughout the life of the car.

By applying our model to data on actual vehicles, consumers grouped by each major vehicle type (cars, vans, SUVs, and pickup trucks) are assessed by how rationally they value fuel efficiency (See Figure 3). Our results indicate that, relative to the present value expected fuel savings, 19-27% of car-buyers overpay in initial investment in fuel economy; 94-97% of van-buyers, 12-18% of SUV-buyers, and 95-98% of pickup truck-buyers overpay for fuel economy relative to avoided lifetime fuel costs. Put differently, these are the percentages of consumers in each vehicle segment who pay more for an incremental fuel economy increase than we would expect it to be worth in fuel cost savings.

When considering each consumer's net overpayment (the difference between incremental willingness to pay for increased fuel economy and present value fuel savings), car buyers in our sample *underpay* by \$75.32 to \$114.91 per capita and SUV buyers in the sample *underpay* by \$95.15 to \$139.57 per capita (See Figure 6). Conversely, van buyers in the sample *overpay* by \$240.60 to \$285.14 per capita and pickup-truck buyers *overpay* by \$316.27 to \$361.93 per capita. By combining observations from all four vehicle segments in our sample, there is a *net underpayment* of \$4.93 per capita for the low-end discount rate and



a *net overpayment* of \$37.17 per capita for the high-end rate. While this combination of all vehicle segments suggests a small to negligible net overpayment, car and SUV buyers generally reap large benefits while van and pickup buyers incur large losses from their investments in fuel economy. That is, because overpayment depends so much on vehicle type – as seen by the wide range of fuel efficiency overpayment across vehicle type – the aggregate overpayment figures miss the more nuanced heterogeneous results of this paper.

The rest of this paper is organized as follows: Section 2 describes our three part estimation strategy; Section 3 describes the data used; Section 4 summarizes results; and Section 5 concludes and offers areas for further study.

## **2. Model**

A three-part model was used to assess consumer rationality in fuel efficiency purchase decisions. In the first step of the model, we use hedonic-regression analysis to estimate  $-dP_v/dF$ , or the marginal willingness to pay for decreased fuel intensity. In Part 2 of the model we utilize driving behavior data to estimate the effect that a marginal decrease in fuel intensity will have on the net present value of a vehicle's operating cost. In Part 3 of the model, we compare consumers' upfront investments in fuel economy at the margin (found in Part 1) to the present value savings in fuel cost that such investments would generate (found in Part 2). In particular, Part 3 focuses on how cross-sectional differences (in terms of vehicle segment and driving behavior) affect our assessment of a consumer's rationality as estimated in the model.

## 2.1 Hedonic Regression Analysis

The model's first component employs hedonic regression analysis using R.L. Polk & Company data on new vehicles from 1996 – 2002. Hedonic valuation, used in empirical work since the early 1960's (Griliches, 1961), is based on the assumption that automobile prices are “functions of the levels of various well-defined characteristics present in the automobiles” (Kahn, 1986). That is, hedonic regression analysis parses automobile price into the effects of automobile characteristics in order to isolate the effects of certain attributes on an implied price. These individual effects (termed the “hedonic prices”) signal consumers' marginal willingness to pay for each attribute. The hedonic regression specification is found below:

$$P_v = \beta_0 + (F * GenSegm)' \beta + DetailSegm' \phi + X' \gamma + Year' \lambda + Fid' \theta + \varepsilon \quad (3)$$

The hedonic regression used in our model regresses vehicle price ( $P_v$ ) on pertinent characteristics in order to isolate how much consumers pay on the margin for decreased fuel intensity ( $F$ ). To make the regression more robust, interaction terms are used to allow for heterogeneity across vehicle segments in the coefficient for GPM. Vehicle “general segment” dummies (cars, minivans, SUVs, and pickup trucks) are multiplied by each GPM rating so that the value of decreasing GPM on the margin can differ for each vehicle segment. This allowance for heterogeneity accounts for the fact that the value of increased fuel efficiency on the margin may be capitalized into vehicle price differently across different vehicle segments.

In addition to fuel intensity, price was regressed on a vector ( $X$ ) of other vehicle attributes: horsepower, vehicle weight, engine displacement, and airbags. Model year

dummies (Year), vehicle make dummies (Make), and vehicle “detail segment” dummies (DetailSegm)<sup>5</sup> are also included. Make dummies, in particular, help control for varying levels of market power possessed by different firms, which could affect the price they are able to charge.

## 2.2 Modeling Heterogeneity in Driving Behavior to Calculate Operating Cost

Part 2 of the empirical model calculates the right-hand side of Equation (2) –

$$\sum_{t=0}^T P_{F,t} M_t \delta$$

– which is the net present value of expected fuel costs associated with an incremental change in fuel intensity.

We find heterogeneity in vehicle miles traveled ( $M_t$ ) across auto consumers with different attributes to be a particularly important aspect of our model. While past empirical models (Kahn, 1986; Kilian, 2006; Sallee and West, 2008) assumed that all vehicles travel 10,000 miles in a year, the additional data allow our model to distinguish, for example, the VMT of a sole vehicle owned by a family of six with four children from that of a vehicle owned by a retired couple that also owns two other cars.

We use the 2001 National Household Transportation Survey for data on annual vehicle miles traveled of the consumer ( $M_t$ ), vehicle segment, and vehicle fuel economy. Along with these data on VMT, we use gas price data ( $P_{F,t}$  – varying by year and by state) and an assumption about vehicle lifetime (assumed to be 14 years<sup>6</sup>) to calculate a total lifetime vehicle fuel cost. Finally, we assume a range of discount rates (varying from 3% to

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<sup>5</sup> Detail-Segment dummies are more specific than the General-Segment dummies (used in the interaction terms) and include: subcompact car, compact car, midsize car, large car, luxury car, minivan, van, small SUV, mid SUV, large SUV, premium SUV, SUV pickup, small crossover, premium crossover, small pickup, large pickup.

<sup>6</sup> Although typical vehicle *ownership* may be closer to 5 years, vehicle *lifetime* (which is most relevant for our purposes if used car markets function well) is much longer.

7%) to arrive at the right-hand side of Equation (2) – i.e., present value change in vehicle operating costs from a marginal decrease in fuel intensity. We believe that 3% to 7% covers the relevant range of consumer discount rates, taking into account inflation. These assumptions about interest rate and time horizon have a significant effect on the *aggregate* results – though not necessarily on the more important *relative* results across vehicle segments (see Figures 3 and 5).

In keeping with previous literature on new vehicle demand (Bento, 2008; Berry, 1995; Goldberg, 1995; Li, Timmins, and von Haefen, 2008) we assume that gas prices ( $P_{F,t}$ ) follow a random walk. Given the linearity of our model, this implies that consumers take into account only current gasoline prices, which they assume will remain constant for the 14 year life of the vehicle. With these assumptions about gasoline prices and length of ownership, we arrive at the total lifetime operating cost savings that would be realized by decreasing fuel intensity by .001 GPM<sup>7</sup>.

As in the hedonic regression of new cars, we are interested in heterogeneity of effects across different segments of vehicles. For each vehicle “general-segment” we group the marginal operating cost savings together for comparison across segments.

In the primary specification of the model, we choose not to treat  $M_t$  as an endogenous function of  $F^8$ . Our primary reason for excluding this secondary effect is that the rebound effect has been determined empirically to be very small, and does not meaningfully change our results. Our results indicate that decreasing price per mile (gas price / MPG) by 1% will increase vehicle miles traveled by 1.67%, on average. This is even smaller than previous

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<sup>7</sup> Increasing fuel intensity by one gallon per mile amounts to an unrealistically large decrease in fuel efficiency. For example, increasing fuel intensity by 1GPM would decrease a vehicle’s efficiency from 30 MPG to .97, while a 0.001 increase in GPM would decrease efficiency to a more realistic 29 MPG.

<sup>8</sup> See Appendix 1 for a secondary specification that includes the rebound effect.

calculations, which estimate the short-run rebound effect to be 2.2% using data from 1997 to 2001 (Small and Van Dender, 2007). An advantage of this assumption is that we can treat driving behavior non-parametrically, using a specific value for every individual in the sample.<sup>9</sup> Not having to estimate a value for M and instead relying solely on the data provides further richness to our model of heterogeneity.

### *2.3 Comparison: Assessing Rationality*

In the preceding two parts of our model, we assess how consumers value a .001 decrease in fuel intensity in terms of vehicle price and then in terms of expected fuel savings. In Part 1 of the model, we calculate how much each segment of automobile consumers typically pays for fuel efficiency when purchasing a new car. In Part 2 we calculate the expected net present value of the savings gains due to decreasing fuel intensity. In Part 3 of the model, we compare the marginal cost increase to the marginal cost savings of fuel to assess rationality.

As described in Equation (2), the rational, cost-minimizing consumer chooses fuel intensity such that the incremental cost of a more fuel-efficient vehicle is equal to the incremental present value of expected cost savings from lower operating costs over the life of the vehicle. The rational consumer would correctly foresee his operating cost savings and would be willing to pay exactly that amount as an upfront investment in greater fuel economy.

As in Parts 1 and 2, in Part 3 we again focus on heterogeneity across vehicle segments. In Part 1, we calculate the difference between what each “general segment” of

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<sup>9</sup> If we included the rebound effect, we would need to predict each individual’s driving behavior given a change in F. This would require us to specify a parametric equation for M.

vehicle consumer pays for decreased fuel intensity and what each consumer expects to save in operating costs. The consumers who pay more than they expect to save in operating costs are considered to be acting irrationally under our model. That is, in Part 3 we rearrange Equation (2) to calculate

$$-\frac{dP_v}{dF} - \sum_{t=0}^T P_{F,t} M_t \delta_t = \textit{overpayment}$$

However, our model only accounts for irrationality in terms of the relatively narrow private costs that we consider. Although the model does not consider such costs, the consumers considered “irrational” under our model may simply be taking into account other external costs (e.g. environmental considerations) of their gasoline use, and therefore may not be acting irrationally at all. This is to say our model is narrow in its scope of costs, including only private costs.

### 3. Data

#### 3.1 Polk Dataset

To assess the value consumers place on fuel economy in vehicle purchases, we assemble data from the R.L. Polk and Co. Car Stock Guide of new cars from years 1996 – 2005<sup>10</sup>. These data provide the make and model of new cars and trucks from these years with their descriptive attributes (e.g. height, weight, horsepower, MPG<sup>11</sup>, MSRP, etc.), allowing us to observe the evolution of new car characteristics over this period. The Polk dataset contains a representative sample of 2,054 new vehicle make-model types. Throughout this

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<sup>10</sup> These were merged from separate Car Stock file and a Truck Stock File. MPG from fueleconomy.gov was appended by Shanjun Li.

<sup>11</sup> Overall MPG was calculated using the EPA’s weighted harmonic mean convention:  $MPG = 1/[(0.55 / \textit{City MPG}) + (0.45 / \textit{Highway MPG})]$

period, the sample indicates that there was no significant change in fuel economy of new registered vehicles, with both the mean (about 21 MPG each year) and median (20 MPG each year) staying relatively constant across all ten observed years. Real vehicle prices<sup>12</sup>, however, slightly depreciated across time. In 1996, mean vehicle price was \$29,552 and median price was \$24,916. In 2005, by contrast, the mean vehicle price was \$28,526 and the median price was \$24,335 (See Figure 1).

### *3.2 NHTS Dataset*

In Part 2 of the model, we use the National Household Transportation Survey (NHTS) to measure vehicle miles traveled (VMT) in 2001. This survey was conducted over the 14-month period from March 2001 to May 2002 and details the travel behavior and distinguishing characteristics of 70,000 American households. Of the 139,000 vehicles in the dataset, 52,000 had values for the variable “bestmile” – an NHTS “best guess” calculation of annual VMT based on a combination of odometer checks and survey questions (mean of 11,700, median of 9,400). The dataset contained 45,000 vehicles with values for “eiadmpg” – the EIA derived and adjusted (for actual “on road” and “in use” short fall) estimation of MPG (mean of 20.66, median of 19.92). The distribution of “bestmile” and “eiadmpg” differed when considering key vehicle segments: cars tended to have lower VMT and higher MPG (medians of 9,185 and 22.14, respectively) compared to vans (11,400 and 19.17), SUV’s (11,800 and 16.64), and pickup trucks (9,500 and 16.33).

In addition to VMT and MPG, the NHTS dataset contains other information used as additional explanatory variables in the rebound effect estimation (See Appendix 1).

Specifically, the NHTS contains information about the vehicle (e.g. engine characteristics,

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<sup>12</sup> Prices are deflated using 2001 dollars with the Personal Consumption Expenditure (PCE) Index for new autos.

vehicle age, and whether airbags were included), the vehicle-owning household (e.g. income, number of drivers, and number of small children), the household's location (e.g. state, population, and an urban/rural designation), and the household member who responded to the survey (e.g., age, sex, race, level of education).

Because the R.L. Polk and Co. data contain only data on new cars, our model assumes that all cars were bought new. To make this assumption more realistic, NHTS data were truncated to include only vehicle model-years within 5 years of the survey period (2001). That is, any vehicles with model-years prior to 1997 were not used in our model.

For fuel price data, the American Chamber of Commerce Research Association (ACCRA) cost of living index (COLI) was used. The ACCRA COLI collects and records quarterly prices of about sixty basic consumer goods, including gasoline. The fuel price data were collected from a number of cities in each of 49 states (excluding Hawaii) and British Columbia from 1990 - 2008. Quarterly fuel prices were averaged and cities' prices within each state were averaged to arrive at state-by-state, yearly gasoline price estimates. For the period in question (1997 - 2001), fuel prices increased only slightly from a \$1.23 median in 1997 to a \$1.40 median in 2001 (See Figure 2). Gasoline prices were matched to vehicles in the NHTS data based on the vehicle purchase year and state. For example, a vehicle owned in Alabama with model year 1999 would be matched to the Alabama's 1999 average gasoline price. As noted above, this match is based on the assumptions that (1) all NHTS cars were purchased new and that (2) consumers expect gasoline prices to follow a random walk based on the vehicle purchase year price of gasoline.

After accounting for VMT, fuel economy, gas price, and a five year or less vehicle age, 17,627 observations in the NHTS sample remain. Unlike the static assumptions made in



previous papers, VMT differs substantially across our sample, indicating that heterogeneity in VMT is a particularly important aspect of the model (See Figure 7).

## 4. Results

### 4.1 Hedonic Estimation Results

Our hedonic regression analysis estimates  $-dP_v/dF$  to be relatively large for vans and pickups compared to cars and SUVs (See Table 1: Regression 1, below). Specifically, van and pickup buyers have a highly significant marginal willingness to pay (WTP) of \$471.77 and \$553.76, respectively, for a .001 decrease in GPM (calculated by dividing their coefficients by 1,000). The incremental increase in price for cars and SUVs, on the other hand, was less significant and only \$73.02 and \$126.32, respectively.

After finding that the coefficients for cars and SUVs were not significantly different from each other, we re-ran the regression with cars and SUVs as a combined variable (Regression 2). These new results were significant, with an incremental price increase of \$468.15 and \$549.57 for vans and pickups, respectively, and a combined \$87.35 increase for cars and SUVs.

One possible explanation for this difference across segments could be that vans and pickups have less dense markets. That is, many consumers who purchase vans or pickup trucks need them for their specific practical benefits (e.g. for large families or truck beds) and therefore might be highly willing to pay for better fuel economy, but there might not exist more fuel efficient vehicles available in the van and pickup markets. On the other hand, people who buy SUVs may be doing so less out of necessity than out of preference, causing

SUVs to be much more substitutable with more fuel efficient cars (see Section 4.4 for further discussion).

After considering significance and an economic explanation, the regression with the combined car and SUV variable (Regression 2) was chosen for the model.

**Table 1: Regress Vehicle Price on Fuel Intensity (GPM)**

Variable	Regression 1			Regression 2		
	Coefficient	Std. Err.	t-stat.	Coefficient.	Std Err	t-stat
cars*GPM	-73022.64	43490.42	-1.68			
vans*GPM	-471770.3	103601.6	-4.55	-468153	103508.6	-4.52
SUVs*GPM	-126319.9	60676.48	-2.08			
pickups*GPM	-553761.6	95299.28	-5.81	-549569	95167.13	-5.77
(cars+SUVs)*GPM				-87349.1	40142.99	-2.18
Hp	28.78605	6.204614	4.64	29.90907	6.064106	4.93
Wt	7.693808	0.521927	14.74	7.609789	0.5125924	14.85
Displacement	3986.338	408.7145	9.75	3954.065	406.9469	9.72
Airbags	130.4298	447.148	0.29	138.2672	447.0245	0.31
DetailSegment Dummies						
Year Dummies						
Manufacturer Dummies						
_cons	-9576.885	3910.963	2.45	-11244.6	3391.639	-3.32
Number of obs	2048			2048		
F( 54, 1993)	216.4			220.5		
Prob > F	0			0		
R-squared	0.8543			0.8542		
Adj R-squared	0.8503			0.8504		
Root MSE	5697.1			5696.8		

#### 4.2 Expected Operating Cost Results

Part 2 of the model calculates expected savings associated with a .001 decrease in fuel intensity across vehicle types. For each vehicle segment, a decrease in fuel intensity yields present value savings in fuel costs with a similarly shaped distribution, and the 3% low-end and 7% high-end discount rates have relatively small effects on each distribution (See Figure 3). Across vehicle segments, a decrease in GPM by .001 for the low-end discount rate will create a median savings of \$167.42 for cars in our sample, which is substantially lower than for vans (\$194.67), SUVs (\$197.78), and pickups (\$193.97). As previously mentioned, the fact that cars buyers tend to drive fewer miles annually than buyers of other vehicles could in part explain why car savings are relatively lower.

#### 4.3 Assessing “Rationality”

Combining WTP with fuel savings yields results that vary by vehicle type. By subtracting expected fuel savings from WTP, we are able to determine how much each consumer overpays in their investment in fuel economy relative to avoided lifetime fuel costs. The results indicate that only 19-27% of car-buyers and 12-18% of SUV-buyers overpay, while as high as 94-97% of van-buyers and 95-98% of truck buyers overpay (based on the 3% and 7% discount rates, respectively). When considering the sample’s aggregate net investment in fuel economy (the difference between total dollars underpaid and total dollars overpaid), the car buyers in our analysis *underpay* by \$75.32 to \$114.91 per capita and SUV buyers *underpay* by \$95.15 to \$139.57 per capita. Conversely, van buyers *overpay* by \$240.60 to \$285.14 and pickup-truck buyers *overpay* by \$316.27 to \$361.93 (See Figure 6).

Combining observations from all four vehicle segment, there is a net underpayment of \$4.93 per capita for the low-end discount rate and a net overpayment of \$37.17 per capita for the high-end rate<sup>13</sup>. While this combination of all vehicle segments suggests a small to negligible net overpayment, car and SUV buyers generally reap large benefits while van and pickup buyers incur large losses from their investments in fuel economy. Aggregating the results by summing across all vehicle segments misses the more nuanced result that “rationality” depends greatly on the type of vehicle purchased and driven by the consumer.

The results of this paper contrast with the results of many previous papers that have concluded that consumers dramatically underpay for fuel economy. To more directly compare the specifications of this paper to those of previous papers, we also estimate our model with the specifications used by Kahn (1986) and Sallee and West (2008). That is, instead of relying on data about driving behavior, we assume a constant 10,000 VMT for all drivers and a 5% discount rate. Additionally, we assume a vehicle life of 10 years rather than 14 years used in our model. These specifications result in qualitatively similar, but much more extreme results (See Figure 4)<sup>14</sup>: 18% of both car and SUV buyers and 100% of both van and pickup truck buyers overpay for an initial investment in fuel efficiency. In terms of net overpayment, car and SUV buyers in the sample only *underpay* by \$16.22 and \$17.19 per capita, while van and pickup buyers in the sample *overpay* by as much as \$365.27 and \$446.28 per capita, respectively (See Figure 6). This sums to a much larger net loss equal to \$106.53 per capita *overpaid* for investments in fuel economy.

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<sup>13</sup> By applying a sensitivity test, it appears that the time horizon assumption has a much larger effect on the results than our discount rate assumption (See Figure 5).

<sup>14</sup> Note that this does not represent the model used by these previous papers, but only their parameter specifications.

#### *4.4 Discussion*

According to our results, few consumers are “rational”, as narrowly defined in our model. As mentioned above, vans and pickups consumers’ “irrationality” in overpaying for fuel economy may be a reaction to a less dense market. Vans and pickups are notoriously fuel-inefficient; however, their inefficiency is, in part, the result of a tradeoff between a practical benefit (e.g. size of the truck bed or multiple rows of seating) and fuel efficiency. Because consumers make choices among vehicles as bundles of fixed attributes, especially in the case of trucks and vans, they cannot increase one attribute (e.g. efficiency) without dismissing another (e.g. truck bed space). So, while the regression analysis indicates that these consumers are willing to pay a large amount to marginally decrease the fuel intensity of their inefficient vehicles, perhaps these customers are unable to find more fuel-efficient vehicles without sacrificing other more important vehicle requirements. This raises an interesting question that is beyond the scope of our analysis: unless it is technologically infeasible, why don’t van and pickup producers introduce more fuel efficient vehicles to capture the profits suggested by these hedonic prices?

In the market for cars and SUVs, the tradeoff between practical benefits and fuel efficiency is less pronounced. People who buy SUVs may be doing so less out of necessity than out of preference.<sup>15</sup> Both SUV and car buyers’ willingness to pay for fuel economy is quite low compared to van and truck buyers, and SUV buyers’ willingness to pay is not statistically different from that of cars. This may be due to the fact that consumers view SUVs as substitutable with more fuel efficient cars. Among potential car or SUV buyers,

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<sup>15</sup> For example, van owners may have little choice given their family size, and truck owners may need the functionality for work purposes. SUVs are fundamentally more similar to cars, but generally have worse fuel economy. Those who choose to buy an SUV instead of a car appear much more likely to be concerned with (or at least aware of) the operating cost implications of fuel efficiency. This is consistent with the fact that they are the most likely to underpay for fuel efficiency.

those who strongly value fuel economy will simply buy a car because they are not losing any practical benefits from buying an SUV. This substitutability decreases the observed fuel economy WTP of SUV buyers.

The similarity between the marginal prices of fuel economy in cars and SUVs may also be due in part to the fact that SUVs are often built on car chassis. This similarity in design may make the relationship between technology (including efficiency) and cost for car manufacturers similar across cars and SUVs. Supporting this explanation, the fuel intensity coefficient for SUV buyers is not statistically different from that of cars. Additionally, we suspect that car-buyers may have relatively low WTP because cars generally have fewer annual vehicle miles travelled. Thus, a car buyer's gains from decreases in fuel intensity will be relatively lower than that of a pickup truck, for example, that drives many more miles per year.

But it is also possible that underpayment for fuel economy in cars also has roots in behavioral economics. In markets where consumers pay less than the economically efficient price for fuel economy (as in the market for cars and SUVs) Green, et al. (2009) explains that a consumer's low willingness to pay is the result of risk aversion and uncertainty. Indeed, uncertainties abound in the cost minimization problem faced by auto consumers in Equation (2) – consumers are uncertain about actual fuel efficiency (e.g. despite labeling, consumers are likely still uncertain about actual on-road fuel economy), fuel prices, vehicles miles per year, vehicle lifetime, and discount rates. Faced with such levels of uncertainty, the risk-averse consumer will not be willing to make a large investment in a marginal increase in fuel efficiency. This risk aversion in the face of uncertainty is evidenced in the rationality

assessment for car and SUV buyers, which indicates that these buyers undervalue marginal increases in fuel efficiency relative to expected fuel cost decreases.

## **5. Policy Implications and Conclusion**

In contrast to previous studies, this research uses heterogeneity in driving behavior to determine how well consumers value fuel efficiency in terms of avoided fuel cost. Due to this allowance for heterogeneity, this study has determined that consumers of different vehicle segments value fuel efficiency differently relative to expected future fuel costs. We postulate that these differences could be due to differences in market density (causing truck and van buyers to overpay for fuel economy) and risk aversion under uncertainty (causing car and SUV buyers to underpay for fuel economy). However, the primary results of this paper are that consumers value fuel efficiency and future fuel savings differently depending on their vehicle type. Whatever their underlying causes, these differences have larger implications for the auto market and for public policy.

When a consumer makes a choice about fuel economy in a vehicle purchase, the hedonic price implied by the vehicle's cost sends a willingness to pay for fuel economy signal to the vehicle manufacturer. While the consumer can make choices among the available options of fuel economy, it is only the manufacturer who knows and decides on the fundamental relationship between efficiency technologies and cost in a line of vehicles. That is, the problem is that the auto manufacturer uses willingness to pay signals from consumers to act as their agent in determining in which form (e.g., fuel efficiency, horse power, comfort, etc.) to apply technology. "If the manufacturer believes that increasing fuel economy is not a bet that the consumer is willing to take, the [fuel efficiency] technologies will not be applied

or will be applied for other purposes for which manufacturers are willing to pay, such as increasing horsepower or weight” (Greene, 2009).

A primary argument in favor of CAFE standards is that consumers systematically undervalue fuel efficiency in automobiles. Undervaluing fuel efficiency sends low WTP signals to automakers, which subsequently do not adopt fuel savings technology in automobiles. CAFE standards help to correct this market failure by mandating that auto manufacturers increase fleet fuel economy, compensating for the fact that consumers, for a number of reasons, send insufficient WTP signals to manufacturers.

Due to the allowance for heterogeneity across vehicles segments (in terms of hedonic prices for fuel economy and avoided fuel costs), our analysis is able to both confirm *and* reject the preceding argument based on the vehicle segment in question. In the market for pickup trucks and vans, our results imply that CAFE standards may not be necessary, as the marginal cost for decreased fuel intensity (increased fuel efficiency) outweighs avoided fuel costs. Results indicate that although consumers of trucks and vans may prefer to purchase greater fuel economy, there are not more fuel-efficient options that meet these consumers’ functional requirements (e.g. additional rows of seating or a large truck bed). In these markets, CAFE standards may not be necessary. Given the high WTP signals sent by consumers, manufacturers should not need further incentive to implement fuel saving technologies in vans and trucks. This, of course, begs the question of why truck and van manufacturers have not focused on fuel economy. We suspect that these manufacturers focus their resources on functional requirements rather than fuel economy because of high technological and cost barriers preventing further increases in fuel economy.



In the market for cars and SUVs, by contrast, consumers underpay for marginal increases in fuel efficiency relative to avoided fuel costs. Because this sends a low WTP signal to auto manufacturers, CAFE standards may still be necessary in these markets. Auto manufacturers surely see that, even in the presence of a carbon tax, consumers are not willing to take the bet of paying more money for increased fuel economy. Thus without efficiency standards, auto manufacturers will not provide a fleet of cars and SUVs with high enough fuel economy to be economically or socially optimal.

The focus of this paper has been to use data and assumptions on vehicle miles traveled, vehicle prices, gas price expectations, time horizons, and discount rates to assess consumer rationality in purchase decisions. However, this is by no means exhaustive, and alternative perspectives are possible. For example, if consumers are assumed to be rational and assumptions about gas price expectations are used, what must be the implied discount rates? Or, if consumers are again assumed to be rational and assumptions about discount rates are made, what are consumers' implied expectations about gas prices? Both of these specifications would allow for slightly different perspectives on the same question we ask in this paper: how correctly do consumers value fuel economy in automobiles?

Figure 1

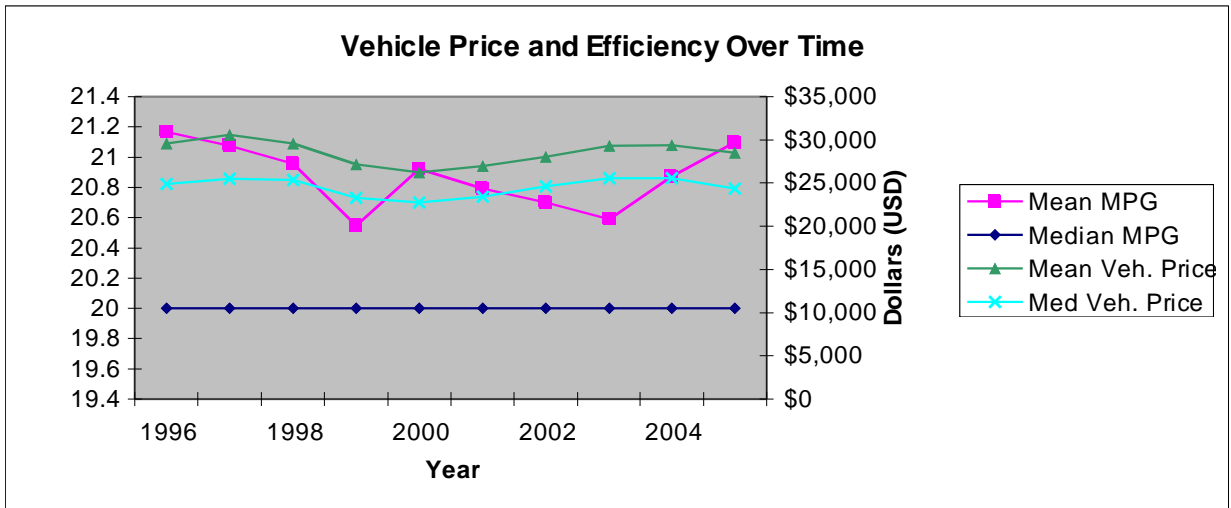


Figure 2

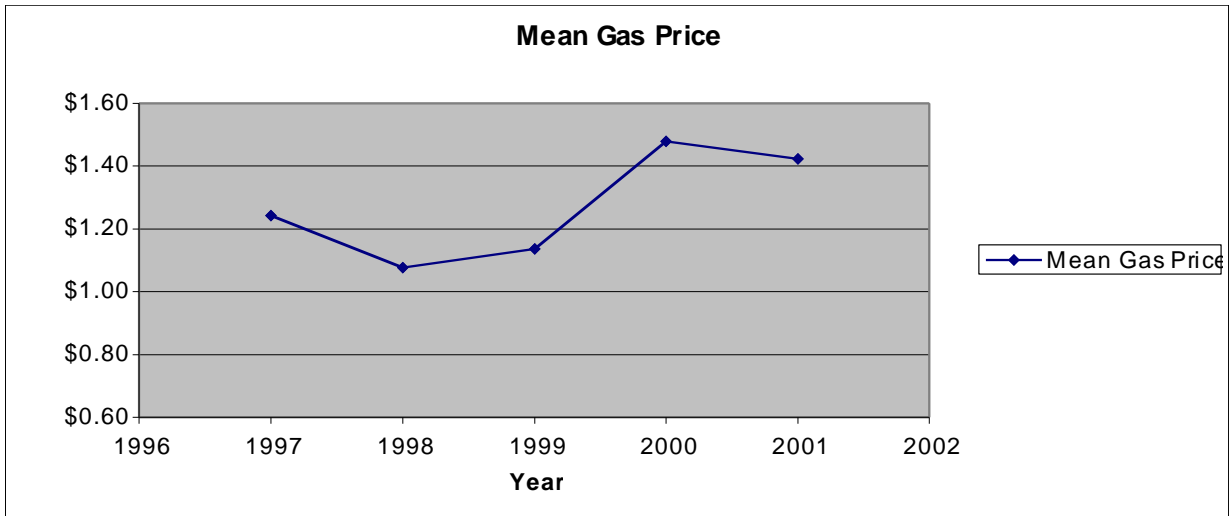
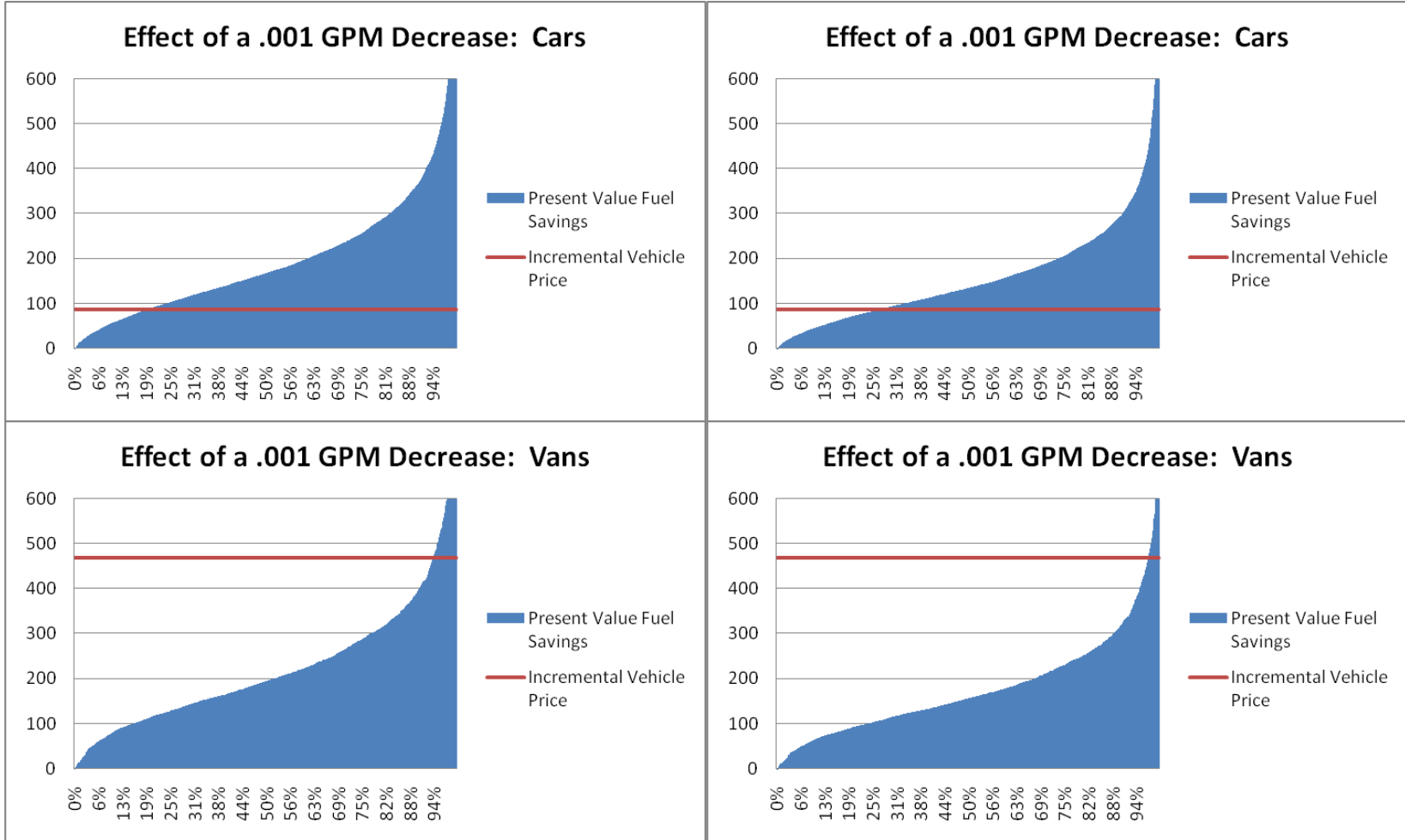


Figure 3:

**3% Discount Rate**

**7% Discount Rate**



**3% Discount Rate**

**7% Discount Rate**

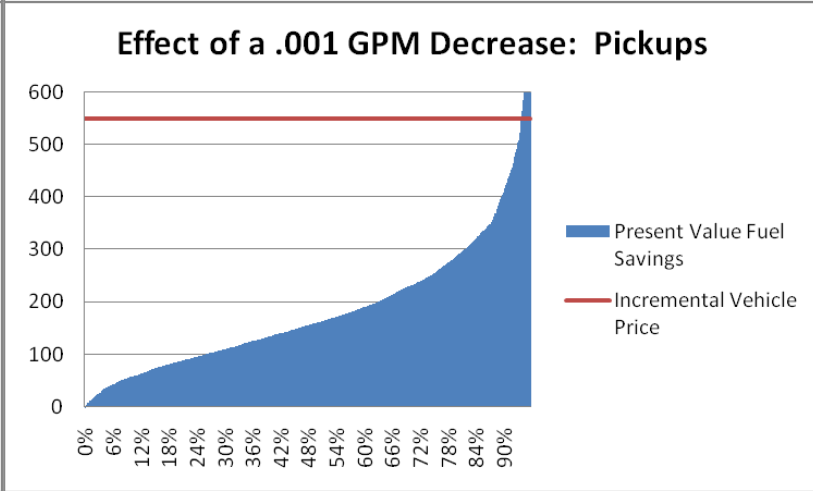
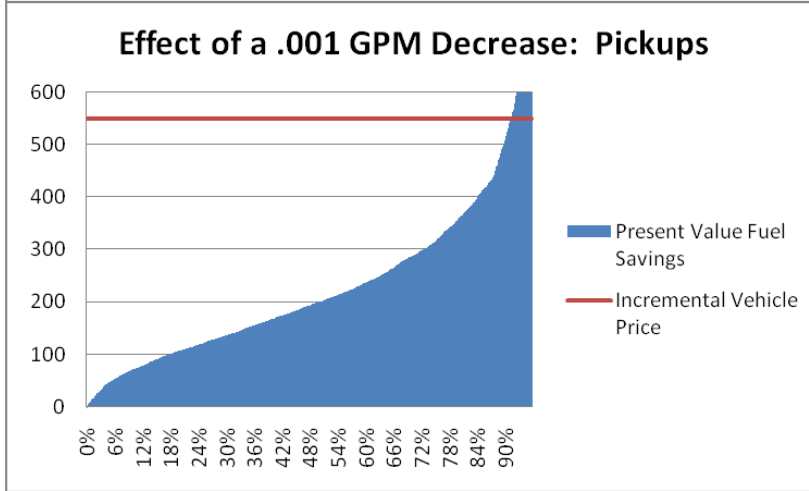
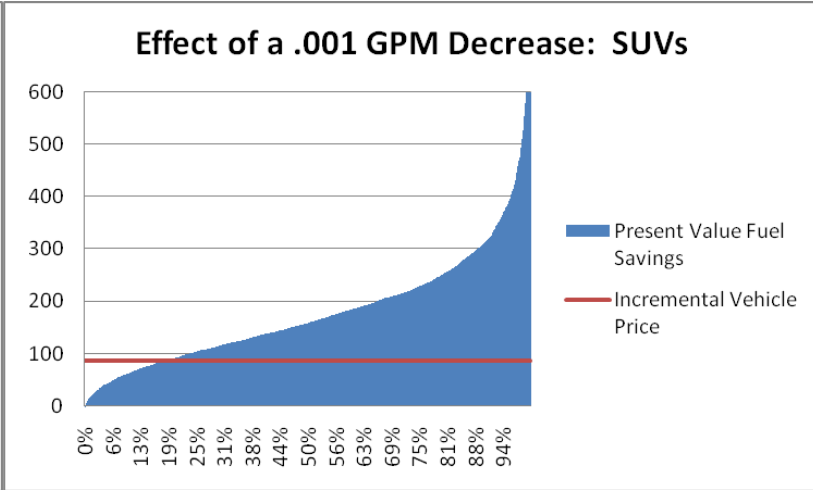
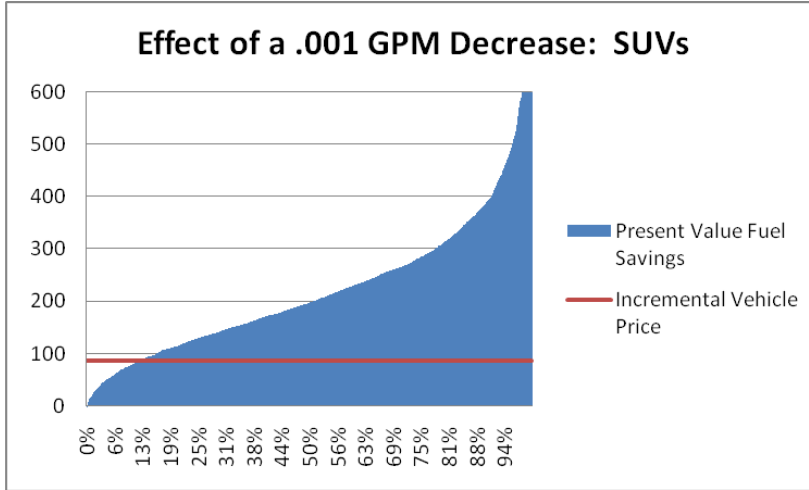


Figure 4: Other Papers' Assumptions

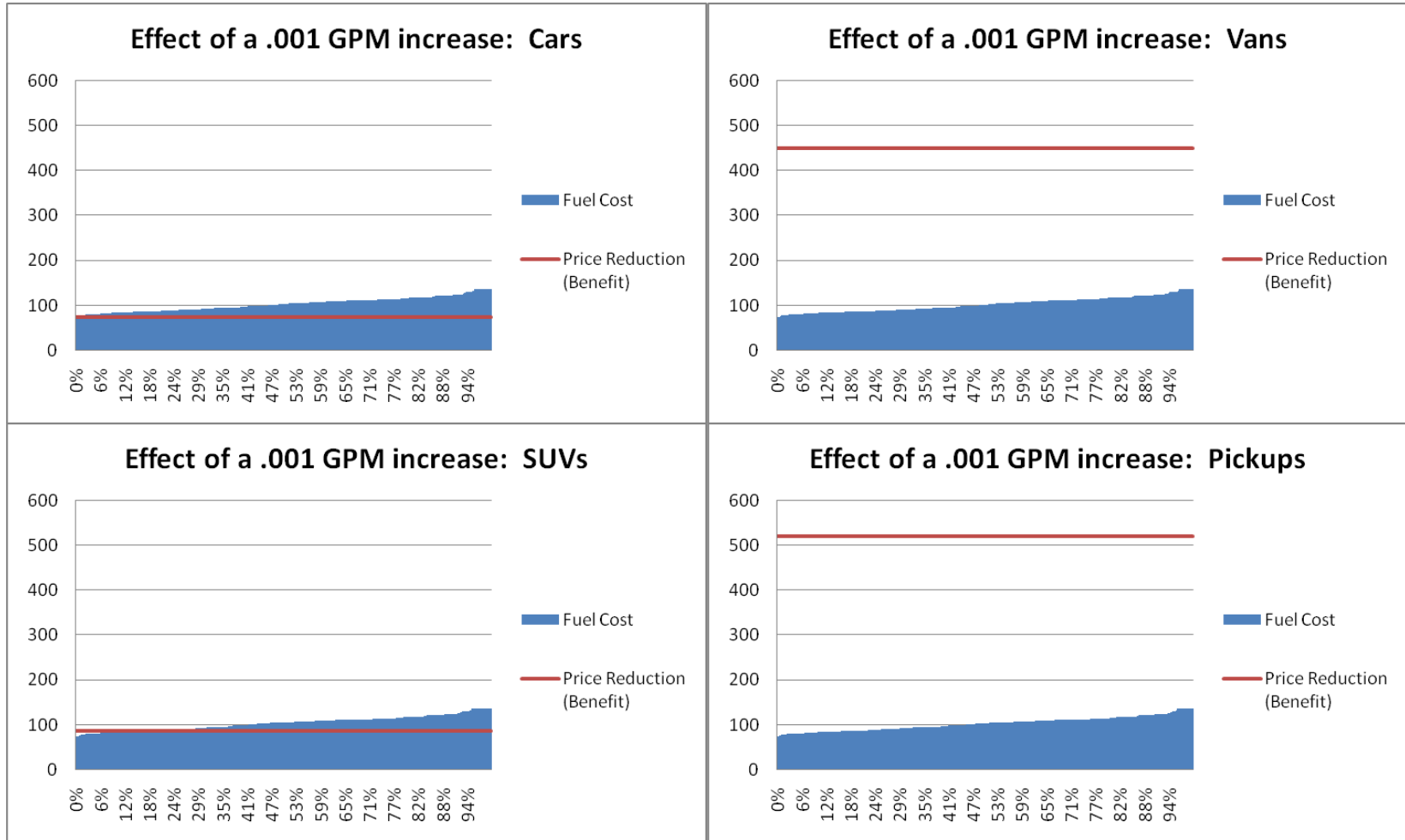


Figure 5  
SENSITIVITY TEST

Discount Rate	Time Horizon (years)			
	5	8	11	14
0.03	122.96	76.50	33.98	-4.93
	68%	50%	41%	37%
0.04	124.57	80.72	41.73	7.08
	69%	51%	43%	38%
0.05	126.12	84.70	48.93	18.02
	70%	52%	44%	39%
0.06	127.62	88.48	55.61	28.02
	70%	53%	45%	40%
0.07	129.06	92.05	61.83	37.17
	71%	55%	46%	42%

Net Overpaid Per Capita (\$)  
% of Consumers that Overpay

Figure 6

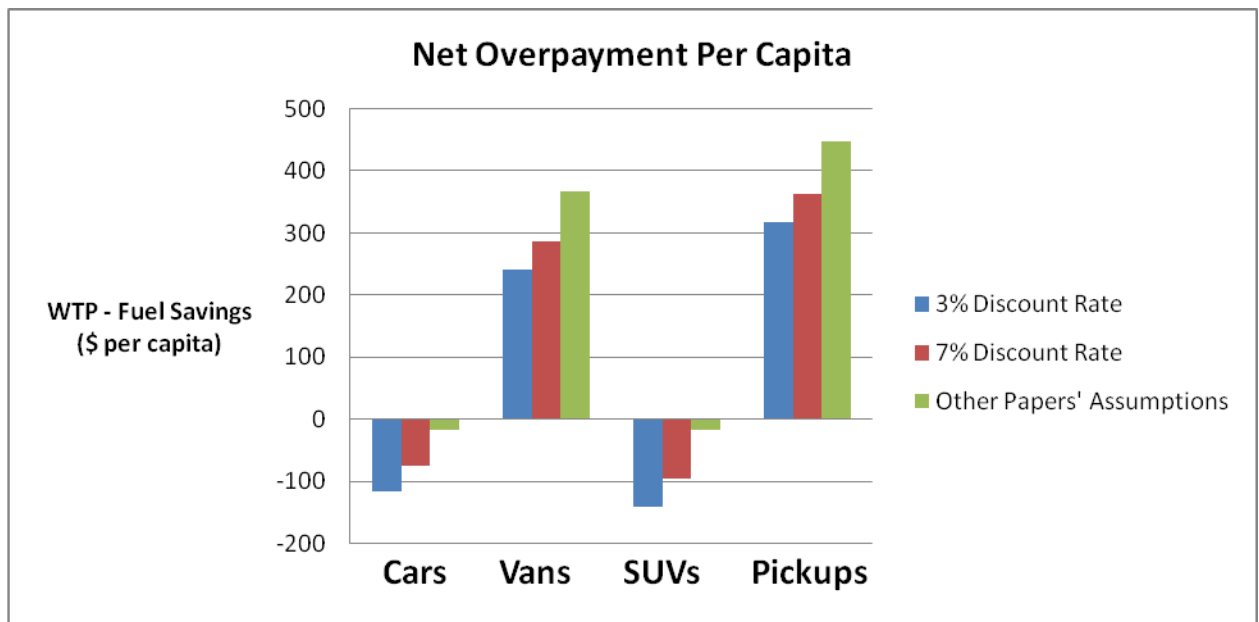
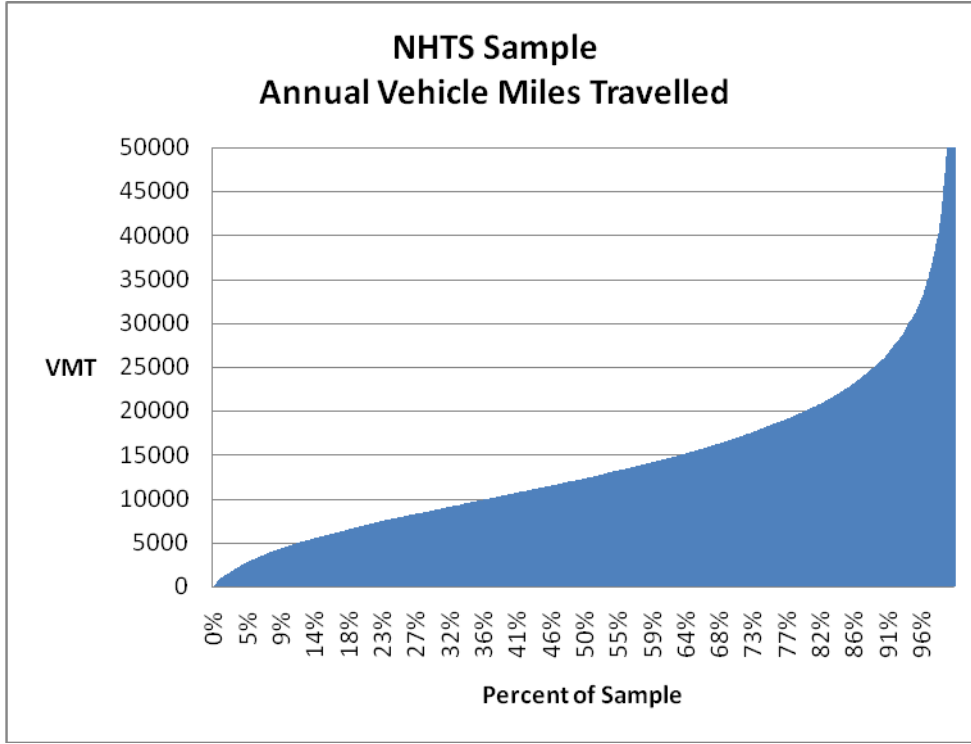


Figure 7



## **Appendix 1: Secondary Specification — Incorporating the Rebound Effect**

As mentioned, rather than taken as exogenously, annual vehicles miles ( $M_t$ ) could be treated as an endogenous variable (i.e. as a function of fuel intensity). That is, as automobile fuel intensity decreases, the cost to drive a mile declines, thereby providing an incentive to increase vehicle miles traveled (Small and Van Dender, 2007). This secondary effect of changing VMT in response to changes in fuel intensity is called the rebound effect. This alternative specification of Part 2 of our model allows for this rebound effect.

In this specification, we use regression analysis to determine how VMT is affected by vehicle type and household characteristics (city population, access to railroad, family size, number of vehicles in the family, income, location, etc.)<sup>16</sup>. Most importantly, we wish to see the effect on VMT of decreasing fuel intensity. In essence, we are using actual driving behavior to measure the rebound effect (described in many previous studies) of marginally decreasing fuel intensity.

In keeping with past studies on the rebound effect (Small and Van Dender, 2007), a log-log approach is used:

$$\ln(M_t) = \beta_0 + \ln(P_m)\beta + X'\phi + Y'\gamma + \varepsilon$$

Where  $P_m$  is the expected cost of fuel per vehicle mile traveled (Fuel Price / MPG);  $X$  is a vector of household characteristics (household size, number of drivers, race, income, education, home ownership status, number of vehicles in the household, number of workers

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<sup>16</sup> NHTS consisted of several smaller datasets that separately described vehicles and households. Considering that multiple vehicles could link to one household, regressing on households would require summary variables to describe each household's vehicle fleet. We believed that creating summary variables would be subjective and lead to substantial error for key variables (i.e. MPG and vehicle type). For this reason, we decided that regressing on vehicles was ideal despite the fact that some vehicles would share the same household data.



in the household, household “lifecycle”, and number of bicycles in the household); and  $Y$  is a vector of location characteristics (state, population, access to railways, and urban / rural indicators) – See Table 2 for complete regression results.

For each vehicle data point, the regression analysis of driving behavior implies a higher VMT with a marginal decrease in fuel intensity. That is, because demand for VMT is downward sloping, as the price of VMT ( $P_m$ ) decreases, demand for VMT increases. The elasticity of  $M_t$  with respect to  $P_m$  (or  $\varepsilon_{M, P_m}$ ) is typically defined as the rebound effect. We calculate the rebound effect to be -1.67%. That is, for a 1% decrease in  $P_m$ , we expect consumers to increase VMT by 1.67%.

Using this elasticity, the new, endogenously determined  $M_t(F, X)$  could be used in the calculation of the present discounted value of the change in operating cost. The VMT increase, when multiplied by a fuel price, yields the change in yearly expected operating cost resulting from marginally changing fuel intensity. This change in operating costs is a function of the direct GPM effect (which decreases operating cost) and the indirect rebound effect (which increases operating cost). However, this rebound effect is small enough that it can be safely ignored in the calculations of rationality.

**Table 2: Regress ln(VMT) on ln(Pm)**

Variable	Coefficient	Std. Err.	t-stat.
lnPm	-1.676596	0.0284019	-59.03
MSA Population	4.06E-09	2.25E-09	1.8
Acces to rails (dummy)	0.0423202	0.030118	1.41
Number of HH drivers	-0.0244999	0.0153651	-1.59
Income	0.0229817	0.0015997	14.37
HH Size	0.0126312	0.0098841	1.28
Number HH Vehicles	-0.0409693	0.006837	-5.99
Number HH Workers	0.0745256	0.0105706	7.05
Number HH bikes	0.0026823	0.004877	0.55
Veh. Type: Car	4.472108	0.5436263	8.23
Veh. Type: Van	4.924475	0.5441248	9.05
Veh. Type: SUV	5.201611	0.5442109	9.56
Veh. Type: Pickup Truck	5.069017	0.5441762	9.32
Veh. Type: Other Truck	4.427175	0.7684854	5.76
Veh. Type: RV (dropped)			
Veh. Type: Motorcycle	1.457992	0.5451018	2.67
Veh. Type: Other (dropped)			
State Dummies			
Urban / Rural Dummies			
HH Lifecycle Dummies			
Education Dummies			
cons	-1.029275	0.7403818	-1.39
Number of obs	16851		
F( 82, 16768)	81.52		
Prob > F	0		
R-squared	0.285		
Adj R-squared	0.2815		
Root MSE	0.76611		

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