Pricing Automobile Fuel Economy:  
A New Hedonic Approach

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Abstract

This paper proposes a new approach to analyzing how automobile fuel economy is valued in the market. A distinctive feature of our approach is the use of each vehicle’s miles traveled: a consumer’s marginal willingness to pay (MWTP) for fuel economy is inferred with her vehicle’s miles traveled. With the inferred MWTP, we apply the steps of the standard hedonic method backward and estimate each vehicle’s marginal and total price of fuel economy, and consumers’ discount rate for future fuel cost savings. We find that the standard hedonic method may not provide a stable and reasonable estimate of the value of fuel economy, likely due to the omitted variable bias from vehicle attributes such as safety features, interior equipment and reliability. Our method makes it possible to separate the portion of vehicle price that is attributable to fuel economy, and significantly alleviates the omitted variable bias. Applying the procedure to model year 2001 vehicles in the U.S. market, we estimate that consumers discount future fuel cost savings at the annual rate of 26-43%, that for the middle case of the discount rate of 34%, the price of a 0.1 gallon per 100 miles improvement in fuel efficiency is on average $75 (in 2000 U.S. dollars), and that for the same case, the average total price of fuel economy is $1,950. We also find that larger, less fuel efficient vehicles tend to have higher marginal and total prices of fuel economy.

Keywords: automobile fuel economy, willingness to pay, fuel economy price, hedonic approach
1 Introduction

A number of papers have used the hedonic method to estimate the relationship between vehicle price and attributes (e.g., Atkinson and Halvorsen, 1984; Ohta and Griliches, 1986; Dreyfus and Viscusi, 1995). Some of these studies include fuel economy as a regressor and analyze the marginal price of fuel economy, i.e., how changes in fuel economy affect vehicle prices, with other attributes held constant. In the standard hedonic approach, the marginal price of fuel economy, or equivalently consumers’ marginal willingness to pay (MWTP) for fuel economy is estimated in two steps. First, assuming a reasonable functional form, we regress vehicle price on various vehicle attributes (e.g., weight, horsepower and fuel economy) and obtain the hedonic price function that describes the relationship between vehicle price and attributes. Then, the marginal price of fuel economy is given as the partial derivative of the hedonic price function with respect to fuel economy.

A common problem many previous studies have encountered is that the marginal price of fuel economy (miles per gallon) is often estimated to be only insignificantly positive, or sometimes even negative (e.g., Knittel, 2011; Arguea and Hsiao, 1993; Goodman, 1983; Deaton and Muellbauer, 1980; Hogarty, 1975). This is counter-intuitive because other things equal, a vehicle with better fuel economy, which reduces the owner’s fuel cost spending, will be valued more highly and thus should be more expensive. Some studies (e.g. Matas and Raymond, 2009; Espey and Nair, 2005; Murray and Sarantis, 1999) have obtained a statistically significant and correct sign on fuel economy. However, the frequency of obtaining insignificant or wrongly signed estimates casts doubt on the robustness of the standard hedonic approach in analyzing the value of fuel economy.

Previous studies argue that unreasonable estimates result from multicollinearity and/or omitted variables. First, fuel economy is very highly correlated with some vehicle attributes, such as weight and horsepower. Thus, including fuel economy and these variables simultaneously on the of right-hand side of the hedonic price regression may result in multicollinearity and give unstable estimates on fuel economy. Second, there are many vehicle attributes that are difficult to observe and not well represented in the hedonic regression (e.g., interior quality, safety features, reliability). Though these attributes would be technologically independent of fuel economy, we will see in Section 2 that they are very likely correlated with fuel economy (and other included variables) through consumer preferences, thus causing omitted variable bias. The results in Section 2 imply that omitted variable bias is a more serious problem than multicollinearity.

This paper proposes an alternative approach to estimating how fuel economy is priced in the market and how consumers discount future fuel cost savings. A distinctive aspect of our approach is the use of each vehicle’s miles traveled, or how much the vehicle is driven. Based on an optimization problem for consumers’ vehicle purchase, we derive an equation relating vehicle miles traveled (VMT) and the marginal price of fuel economy. We use this equation and estimate each vehicle’s marginal price of fuel economy and the
discount rate for future fuel cost savings. An advantage of our approach is that it can significantly alleviate the omitted variable bias from the attributes unrelated with fuel economy, such as interior quality, safety features, and reliability. This is possible because the equation relating fuel economy and the marginal price of fuel economy is only slightly, if any, affected by the unrelated attributes.

Our approach additionally estimates something previous studies have not estimated: the total price of fuel economy. This is the portion of each vehicle’s retail price attributable to fuel economy, or how much consumers pay in total for each vehicle’s fuel economy (consumers’ total willingness to pay for fuel economy). This price is not observed explicitly in the market, although it surely exists. The difference in the total price of fuel economy across vehicles mainly comes from the difference in the cost of achieving different combinations of fuel economy and other attributes that affect fuel economy, such as weight and horsepower.

Theoretically, the key feature of our approach is that we take the steps of the standard hedonic method backward. In the standard approach, using data on vehicle price and attributes, we first estimate the hedonic price function for automobiles by regressing vehicle price on various attributes. Then, the marginal price of an attribute is obtained as the first derivative of the estimated hedonic price function with respect to that attribute. In our approach, we first construct a proxy for each vehicle's marginal price of fuel economy by using data on gasoline prices and the vehicle’s estimated annual miles traveled. The logic behind this is as follows. With Rosen’s (1974) argument that at a point in the space of product attributes where a transaction occurs, the hedonic price function is tangent to the consumer’s bid function, each vehicle’s marginal price of fuel economy equals its buyer’s MWTP for fuel economy. In turn, his MWTP should equal the present value of expected fuel cost savings over the life of the vehicle due to a marginal fuel economy change. And the present-value expected fuel cost savings depend on gasoline prices and vehicle miles traveled (VMT). Therefore, we can obtain a proxy for each vehicle’s marginal price of fuel economy based on gasoline prices and its VMT. We thus observe a proxy for each vehicle’s marginal price of fuel economy, in addition to its attributes. Second, we recover the hedonic price function for fuel economy, the function relating the total price of fuel economy with vehicle attributes such as fuel economy and weight, as an envelope of different vehicles’ (proxied) marginal prices of fuel economy. Therefore, compared to the standard hedonic approach, we are essentially taking the procedure backward. From the estimated hedonic price function, we obtain an estimate of each vehicle’s marginal price of fuel economy (which would be more accurate than the proxy variable originally used).

We apply our approach to model year 2001 vehicles sold in the U.S. Information on vehicle attributes such as vehicle weight, horsepower and fuel economy is taken from the U.S. Environmental Protection Agency’s fuel economy test data. The National Household Travel Survey provides the make, model, year, and estimated VMT of each vehicle. We match these two data sets and take them to estimation.

Estimation results suggest that our approach works. We estimate that consumers discount future fuel
cost savings at the annual rate of 26-43%, much higher than usual rates of return on investment. As for the marginal price of fuel economy or MWTP for fuel economy, a fuel efficiency improvement of 0.1 gallon per 100 miles on average increases vehicle price by $74.7 in 2000 U.S. dollars (for the middle case of the discount rate of 34%). Larger vehicles tend to have higher marginal prices of fuel economy, basically because these vehicles are driven more miles, so buyers of these vehicles are more willing to pay for fuel economy. The average total price of fuel economy is $1,950 (for the case of the discount rate of 34%). Larger vehicles tend to have higher total prices of fuel economy as well, which implies that the cost spent for fuel economy is higher in these vehicles than in smaller vehicles. The estimated total prices of fuel economy suggest that for most vehicles around 5-10% of their retail price is attributable to fuel economy.

The paper is organized as follows. Section 2 applies the standard hedonic approach to our data and analyzes potential problems of the approach. Sections 3 and 4 discuss the theoretical background and framework of the new approach we propose. Section 5 describes the estimation procedure, and Section 6 explains the data sets used. Section 7 reports the results of our estimation. Section 8 checks the robustness of the results. Section 9 concludes.

2 Applying the Standard Hedonic Approach to Our Data

To see if the standard hedonic approach works, we run a simple hedonic regression using the data from model year (MY) 2001 vehicles sold in the U.S. (We later apply our new approach to MY 2001 as well.) We estimate a hedonic price function by regressing the retail price ($H_i$) of each vehicle on its attributes including fuel economy. The function is estimated with the log-log form:

$$\ln(H_i) = \beta_1 + \beta_2 \ln(e_i) + \beta_3 \ln(w_i) + \beta_4 \ln(a_i) + \delta \cdot (\text{other controls}) + \varepsilon_i,$$  \hspace{1cm} (1)

where the subscript $i$ indicates vehicle trim $i$, $e_i$ is fuel economy (measured in gallons per 100 miles), $w_i$ is vehicle weight and $a_i$ is acceleration capacity (horsepower divided by weight). Some other controls are included as discussed below.

Vehicle price (manufacturer’s suggested retail price) data is taken from WARDs Automotive Yearbook. Vehicle attributes data is from the Environmental Protection Agency’s “fuel economy test car list data.” We use gasoline-engine vehicles only, so diesel-engine or hybrid-engine vehicles are excluded from the sample. The unit of analysis is at the vehicle trim level (1177 observations).\(^1\) Table 1 gives summary statistics. Section 6 explains more about the data sources.

Table 2 reports estimation results. Columns (1) and (2) are estimated with ordinary least squares (OLS), and columns (3) and (4) are with weighted least squares (WLS), where weights are given by the sales volume

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\(^1\)A trim is a subcategory of a model. For example, Toyota Camry CE is one of the trims under the model Toyota Camry.
Table 1: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retail price ($H)</td>
<td>26,555</td>
<td>12,797</td>
<td>9,045</td>
<td>129,595</td>
</tr>
<tr>
<td>Fuel economy (gallons/100 miles) (e)</td>
<td>5.24</td>
<td>1.04</td>
<td>2.56</td>
<td>8.16</td>
</tr>
<tr>
<td>Weight (lb) (w)</td>
<td>4,156</td>
<td>783</td>
<td>2,250</td>
<td>6,000</td>
</tr>
<tr>
<td>Horsepower/Weight (hp/lb) (a)</td>
<td>0.049</td>
<td>0.011</td>
<td>0.031</td>
<td>0.120</td>
</tr>
<tr>
<td>Light duty trucks (LDT)</td>
<td>0.625</td>
<td>0.484</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Manual transmission (MT)</td>
<td>0.449</td>
<td>0.498</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>All wheel drive (AWD)</td>
<td>0.286</td>
<td>0.452</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Rear wheel drive (RWD)</td>
<td>0.409</td>
<td>0.492</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

The number of observations is 1177.

of each trim. Dummy variables are included to control for the vehicle’s drive system (FWD/RWD/AWD),\textsuperscript{2} transmission type (AT/MT),\textsuperscript{3} and light duty truck status (LDT).\textsuperscript{4} Columns (2) and (4) additionally include a dummy variable for luxury vehicles (Luxury) and another variable (ABS/TC) that controls for the level of safety features.\textsuperscript{5}

Most regressors have significant coefficients with a reasonable sign in all columns. The results suggest that other things equal, increasing weight (w) or acceleration capacity (a) raises vehicle price. Additionally, other things equal, light duty trucks and manual transmission trims are less expensive, while all or rear wheel-drive, the luxury status, and safety features represented by the anti-lock brake system and traction control increase vehicle price. These results are consistent across all columns (and with most previous studies).

The coefficient on fuel economy (fuel consumption) e is of our primary interest. We expect its coefficient, or the elasticity of retail price with respect to fuel consumption, to be negative, as consumers are less willing to pay for a less fuel efficient vehicle (with a larger e), everything else equal. Comparing columns (1)-(4), we discuss two findings regarding the estimated coefficient of ln(e).

First, while the estimate has a reasonable negative sign in columns (1), (3) and (4), it is positive and significantly so at the 5% level in column (2). That is, only OLS with Luxury and ABS/TC gives a counter-intuitive sign for the coefficient of fuel consumption. The unreasonable sign in column (2) may be a result of using OLS. With OLS, trims with relatively small sales, which are more likely to be outliers in the sample, have a larger impact on the estimates than with sales-weighted least squares. They may be the main force

\textsuperscript{2}Front-Wheel-Drive/Rear-Wheel-Drive/All-Wheel-Drive. FWD is treated as the base category.
\textsuperscript{3}Automatic Transmission/Manual Transmission. AT is treated as the base category.
\textsuperscript{4}Vehicles included in the regression (light duty vehicles) fall into two large categories: passenger cars and light duty trucks. Pickup trucks, sport utility vehicles and vans are in the light duty truck (LDT) category. Other vehicles are in the passenger car category.
\textsuperscript{5}The variable “Luxury” takes 1 if the trim is classified as a luxury model in \textit{WARDS Automotive Yearbook}, and 0 otherwise. The variable “ABS/TC” is the sum of two dummy variables: it takes 2 if the trim has the anti-lock brake system and traction control as standard features, 1 if either of them is a standard feature, 0 otherwise.
Table 2: Results of Estimating Equation (1)

<table>
<thead>
<tr>
<th>Method:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(e)</td>
<td>-0.20*</td>
<td>0.17**</td>
<td>-0.44***</td>
<td>-0.15**</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.082)</td>
<td>(0.083)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>ln(w)</td>
<td>1.00***</td>
<td>0.52***</td>
<td>1.38***</td>
<td>0.96***</td>
</tr>
<tr>
<td></td>
<td>(0.095)</td>
<td>(0.077)</td>
<td>(0.080)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>ln(a)</td>
<td>0.89***</td>
<td>0.55***</td>
<td>0.78***</td>
<td>0.46***</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.040)</td>
<td>(0.045)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>LDT</td>
<td>-0.27***</td>
<td>-0.11***</td>
<td>-0.12***</td>
<td>-0.056***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.021)</td>
<td>(0.019)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>MT</td>
<td>-0.12***</td>
<td>-0.11***</td>
<td>-0.14***</td>
<td>-0.12***</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.013)</td>
<td>(0.015)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>AWD</td>
<td>0.23***</td>
<td>0.13***</td>
<td>0.16***</td>
<td>0.13***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.020)</td>
<td>(0.021)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>RWD</td>
<td>0.14***</td>
<td>0.053***</td>
<td>0.100***</td>
<td>0.058***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.018)</td>
<td>(0.019)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Luxury</td>
<td>0.39***</td>
<td>0.28***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ABS/TC</td>
<td>0.079***</td>
<td>0.076***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0099)</td>
<td>(0.0075)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>4.96***</td>
<td>7.11***</td>
<td>1.78***</td>
<td>3.71***</td>
</tr>
<tr>
<td></td>
<td>(0.66)</td>
<td>(0.53)</td>
<td>(0.58)</td>
<td>(0.48)</td>
</tr>
<tr>
<td>Observations</td>
<td>1177</td>
<td>1177</td>
<td>1177</td>
<td>1177</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.635</td>
<td>0.777</td>
<td>0.687</td>
<td>0.792</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
causing the unreasonable coefficient on $\ln(e)$. Indeed, WLS with the same regressors (column (4)) provides a reasonable coefficient (-0.15). This implies the advantage and importance of sales-weighting in obtaining a reasonable parameter estimate on fuel efficiency, as sales-weighted least squares can prevent the estimation to be driven too much by vehicles with small sales and outlying attributes. Previous hedonic studies of the automobile market mostly use OLS. Table 2 suggests that those studies obtaining an unreasonable estimate on fuel efficiency by OLS could have avoided it by applying WLS.

Second and more importantly, including variables for the luxury status and safety features changes the estimates drastically. There are various vehicle attributes that are desirable for consumers and affect the retail price, but are not well represented in columns (1) and (3), such as interior equipment, safety features, comfort and reliability. The variables Luxury and ABS/TC control for these attributes (at least to some extent). Regardless of the estimator used (OLS or WLS), the inclusion of Luxury and ABS/TC significantly reduces the magnitude of most of the other coefficients, and changes the sign of the OLS estimate on $\ln(e)$. This clearly implies strong correlations between attributes in columns (1) or (3) such as fuel economy, weight and horsepower (divided by weight) and attributes represented by Luxury and ABS/TC (e.g., interior equipment, safety features, comfort and reliability). Thus, regressions without variables to control for the latter attributes are most likely biased, and inferring MWTP for fuel economy (or other attributes) based on these regressions is misleading, as it cannot estimate the effect of changing fuel economy (or another attribute) only. Some previous studies (e.g., Arguea, Hsiao and Taylor, 1994; McManus, 2007) discuss the marginal price of fuel economy based on regressions without these variables, but the results in Table 2 imply the possibility of omitted variable bias in the estimates from these studies.

In connection with later sections, it is very important to note that correlation between fuel economy and attributes like interior equipment and safety features does not necessarily mean that production of fuel economy is technologically related with production of these attributes. Indeed, it would make more sense to consider that they are technologically independent (if the effect of weight increase from these attributes is accounted for by including weight as a regressor). Even though two attributes are technologically independent, consumer preferences may make them correlated in marketed vehicles. For example, fuel economy and safety features such as the anti-lock brake system and traction control seem technologically independent (once weight is included in the regression). On the other hand, everything else equal, consumers with higher demand for driving would prefer more fuel efficient vehicles, and they may also want more safety features because more driving increases the risk of involving in an accident. If this is the case, other attributes equal, more fuel efficient vehicles will be equipped with more safety features, and we will observe partial correlation between fuel economy and safety attributes. Section discusses technological independence of attributes in more detail.

In addition, Luxury and ABS/TC (and similar variables) may not be able to remove the omitted variable
bias well enough. Our Luxury and ABS/TC are simple discrete variables that take 0 or 1 (Luxury) or 0, 1 or 2 (ABS/TC). Indeed, data for attributes like interior equipment, safety features, comfort and reliability is mostly given, if any, in the form of dummy variables, in contrast to those attributes that can be expressed as continuous variables, such as fuel economy, weight and horsepower. These simple discrete variables may not be effective enough to take away the bias due to the strong correlations between attributes like interior equipment, safety features, comfort and reliability, and fuel economy (and others). Thus, the result in columns (2) or (4) may still contain substantial omitted variable bias, and the estimated marginal price of fuel economy may still be misleading as well.

These arguments show the difficulty of separating the effect on retail price of fuel economy from that of such attributes as interior equipment, safety features, comfort and reliability.

3 Background: Hedonic Cost Function

For understanding our approach, it will be useful to start from the vehicle production process. Thus, this section briefly considers the hedonic cost function of automobile production and discusses how vehicle attributes are related in the cost function.

A hedonic cost function is the supply-side counterpart of a hedonic price function. It describes the cost of producing a heterogeneous good as a function of its attributes. Consider the following hedonic cost function of producing a vehicle.

\[ c = h(e, q), \]  

(2)

where \( c \) is the total cost of producing the vehicle, \( e \) is fuel economy (measured in gallons per 100 miles) and \( q \) is a vector of other vehicle attributes.\(^6\)

We decompose the hedonic cost function \( h(e, q) \) into the sum of a function that involves \( e \) and another function that does not:\(^7\)

\[ h(e, q) = f(e, q_1) + g(q_1, q_2), \]  

(3)

where \( q = [q_1, q_2] \).

Function \( f(e, q_1) \) represents the part of \( c \) that is technologically related with fuel economy, so \( f \) is the (total) production cost of fuel economy. A vector of its arguments \( q_1 \) are not additively separable from \( e \) in the cost function, so that the marginal cost of fuel economy improvement (\( -\frac{\partial f}{\partial e} \)) depends on \( q_1 \).

Function \( g(q_1, q_2) \) represents the other part of \( c \) that is technologically independent of \( e \) and thus does not vary with \( e \). It has two types of arguments: \( q_1 \) and \( q_2 \). \( q_2 \) does not show up in \( f \), so it is completely

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\(^6\)As in most studies using the hedonic cost function approach, we assume constant returns to scale (i.e., production volume) in vehicle production, so that \( c \) does not depend on how many vehicles are produced by the firm, plant or production line.

\(^7\)There is no loss of generality in this decomposition because it is possible to set \( q = q_1 \) and \( g(\cdot) = 0 \) if none of the elements in \( q \) is additively separable from \( e \).
additively separable from $e$. On the other hand, $q_1$ is also observed in $f$, so $g$ captures the part of the effect of $q_1$ on $e$ that is additively separable from $e$.

An example of attributes in $q_2$ would be safety devices such as air bags. The cost of marginally improving fuel economy is unlikely affected by whether or not the vehicle is equipped with air bags (once vehicle weight is included in $q_1$ and thus the possible effect of the weight increase from the air bags is accounted for). Thus, air bags do not enter $f$. On the other hand, the cost of installing a safety device is unlikely related with the level of fuel economy, once the effect of other attributes in $q$ is controlled for. Thus, $e$ does not enter $g$.

Vehicle weight would be a good example of attributes in $q_1$. Marginally improving fuel economy would be more costly with a vehicle of 4,000 lb and 20 miles per gallon than with a vehicle with 3,500 lb and 20 miles per gallon, as weight negatively affects fuel efficiency. This illustrates the dependence of $f$ on vehicle weight. On the other hand, vehicle weight would also affect $g$ because it simultaneously represents other attributes than weight itself. In virtually all studies (hedonic or discrete choice) that use vehicle weight as a regressor (including the regression in Section 2), this variable implicitly represents other attributes as well, such as vehicle size (and sometimes even the level of optional equipment). This multiple representation is necessary because in practice it is impossible to include all vehicle attributes as regressors. If we take vehicle size as an example, heavier vehicles are generally larger, so that they need more materials for producing the body, and have higher material costs. These material costs should be included in $g$, not $f$, because fuel economy is affected by weight itself, and what it comes from does not matter. For instance, a weight increase from loading rocks (found somewhere on the road) into the vehicle’s trunk has essentially the same effect on fuel economy as an equivalent weight increase due to an increase in vehicle size and material use (if the potential effect of a change in aerodynamic drag is ignored). Thus, it is possible that an attribute in $q_1$ appears both in $f$ and $g$. $f$ accounts only for how the attribute changes the cost of providing fuel economy, while $g$ accounts for how it changes the production cost in ways unrelated with fuel economy.

Other than vehicle weight, $q_1$ would include such attributes as horsepower, torque, body styles, drive systems (front-wheel drive, rear-wheel drive or four-wheel drive) and transmission types (manual or automatic). For each of the elements in $q_1$, it is possible to give an engineering explanation as to how it is related with fuel efficiency. What is important to note in connection with later sections is that these attributes affects the marginal cost of fuel economy improvement.

4 Theoretical Framework

This section discusses the theoretical framework of our approach to estimating the hedonic price function for fuel economy.

Let us consider a consumer who is buying a new automobile. The consumer’s choice problem is formulated
as:

$$\max_{z, q, m, e} u(z, q, m; \theta) \quad s.t. \quad y = z + H(e, q) + p \cdot m \cdot e.$$  \hspace{1cm} (4)

In the utility function $u(\cdot)$, $z$ is consumption of the numéraire good. $q$ is a vector of vehicle attributes. $m$ is the distance (measured in 100 miles) the consumer expects to travel with the vehicle (expected vehicle miles traveled (VMT)), and $\theta$ is a vector of her characteristics. In the budget constraint, $y$ is her income; $H(\cdot)$ is the hedonic price function for automobiles, one of whose arguments is $e$, fuel economy measured in gallons per 100 miles; and $p$ is expected gasoline price per gallon. Thus, the term $p \cdot m \cdot e$ is the total fuel cost the consumer expects to pay ($$/\text{gallon} \times \text{miles} \times \text{gallons/mile}$). For the moment, we consider only a single period in the problem. We will later introduce multiple periods to reflect the fact that consumers own vehicles over years and likely consider total fuel cost over the lifetime of their vehicles. Exogenous to the choice problem are $\theta$, $y$, $p$, and the shape of $u(\cdot)$ and $H(\cdot)$. The consumer chooses $z$, $q$, $m$ and $e$.

Note that $m$ enters $u(\cdot)$, but not $H(\cdot)$. That is, how much the consumer will drive the vehicle after purchase affects her utility, but not its price. On the other hand, I assume that $e$ enters $H(\cdot)$, but not $u(\cdot)$: The level of fuel economy influences vehicle prices, but good fuel economy does not directly increase her utility on its own. Consumers prefer better fuel economy only because it lowers fuel costs $p \cdot m \cdot e$. Although some consumers who are environmentally conscious may obtain utility directly from owning fuel efficient vehicles, this assumption will be valid for most consumers. It is this property of $e$ that enables the estimation approach we propose.

First order conditions of the consumer’s choice problem are:

$$\frac{\partial u(z, q, m; \theta)}{\partial z} = \lambda,$$

$$\frac{\partial u(z, q, m; \theta)}{\partial q_k} = \lambda \frac{\partial H(e, q)}{\partial q_k} \quad \forall k,$$

$$\frac{\partial u(z, q, m; \theta)}{\partial m} = \lambda p e,$$

$$pm = -\frac{\partial H(e, q)}{\partial e},$$

$$y = z + H(e, q) + p \cdot m \cdot e,$$

where $\lambda$ is the Lagrange multiplier for the budget constraint, and $q_k$ is the $k$-th element of $q$. The rational consumer’s vehicle choice should satisfy these equations in equilibrium.

Among these conditions, this study focuses on equation (5), which is the first order condition with respect to $e$. $pm$ is the fuel cost savings from a marginal improvement in fuel economy (i.e., MWTP for fuel economy). Similarly, $-\frac{\partial H(e, q)}{\partial e}$ is the price increase from a marginal improvement in fuel economy (i.e., marginal price of fuel economy). The equality implies that the marginal willingness to pay and the marginal price are equalized at the optimum.
As in the case of the hedonic cost function \( h(e, q) \) above, the hedonic price function \( H(e, q) \) can be decomposed into the sum of a function that involves \( e \) and another function that does not:

\[
H(e, q) = F(e, q) + G(q).^8
\]  

(6)

How are \( F \) and \( f \) (or \( G \) and \( g \)) related with each other? If the automobile market is perfectly competitive, the hedonic price function matches the hedonic cost function, so that \( F(e, q) = F(e, [q_1, q_2]) = f(e, q_1) \) and \( G(q) = G([q_1, q_2]) = g(q_1, q_2) \). In reality, the auto market is oligopolistic, so \( F \) and \( f \) (or \( G \) and \( g \)) will differ in accordance with automakers’ markup-setting strategies. Therefore, it may be possible that \( F \) is affected not only by \( e \) and \( q_1 \), but also by \( q_2 \). Still, it would be the case that \( e \) and \( q_1 \) affect \( F \) much more significantly than \( q_2 \), because \( e \) and \( q_1 \) affect \( F \) directly through the production technology \( f(e, q_1) \), while \( q_2 \) does not affect \( F \) technologically, but only indirectly through the automaker’s pricing strategy.

In the empirics below, we will analyze the effect of \( q_2 \) on \( f \) by first estimating \( f \) without variables representing \( q_2 \), and then including them. We will see that including these variables changes the result only slightly, implying small effects of \( q_2 \) on \( f \).

With the decomposition of \( H \), equation (5) now becomes,

\[
\alpha m = -\frac{\partial F(e, q)}{\partial e}.
\]  

(7)

Up to this point we have assumed that the consumer uses the vehicle in a single period. In reality, each vehicle is used over years, so the consumer’s willingness to pay for a marginal fuel economy improvement will depend on the present value of fuel cost savings over the life of the vehicle. With this consideration, the left-hand side of equation (7) is replaced with the the present value of fuel cost savings from a marginal fuel economy improvement, which we model as

\[
\sum_{t=0}^{L} d^t \cdot p_t \cdot s^t m,
\]  

(8)

where \( L + 1 \) is the length of the vehicle’s life (in years), \( d \) is the annual discount factor, \( p_t \) is the expected gasoline price at time \( t \), \( m \) is the expected VMT for the first year and \( s \) is one minus the annual rate of VMT reduction. We assume that consumers expect future gasoline prices to stay at the current level.\(^9\) Then, equation (7) is replaced with

\[
\frac{1 - (ds)^{L+1}}{1 - ds} \alpha m = -\frac{\partial F(e, q)}{\partial e}.
\]  

(9)

\( \alpha m \) is multiplied by a factor \(( A \equiv \frac{1 - (ds)^{L+1}}{1 - ds} )\) that accounts for the vehicle’s lifetime and the consumer’s

\(^8\)There is no loss of generality in this decomposition because we can set \( G(q) = 0 \) if none of the elements in \( q \) is additively separable from \( e \).

\(^9\)The current price is the best predictor if gasoline prices follow a random walk.
discounting of future fuel cost savings. We assume that $d$ and $s$, and thus $A$, are common to all consumers.

5 Estimation Procedure

We will use equation (9) to estimate the marginal and total price of fuel economy ($-\frac{\partial F}{\partial e}$ and $F$) as a function of fuel economy and other vehicle attributes.

Suppose that we have data on $q$, $e$ and $Apm$ for each vehicle in the data set. Then, we can estimate $\frac{\partial F(e,q)}{\partial e}$ by making reasonable assumptions on its functional form and finding parameter values that best fit the observed market outcomes ($q$, $e$ and $Apm$) to equation (9). Using the estimated parameters, we calculate the fitted value of the marginal price of fuel economy of each model, or the average of marginal willingness to pay for fuel economy among consumers choosing the model. After estimating $\frac{\partial F(e,q)}{\partial e}$, we use the parameter estimates to recover $F(e,q)$, which gives us the total price of fuel economy, or the portion of the vehicle price attributable to fuel economy, as a function of fuel economy $e$ and other vehicle attributes $q$.

This procedure contrasts with the standard hedonic approach. In the standard approach, using data on vehicle price and attributes, we first estimate the hedonic price function for automobiles, $H(e,q)$, by regressing vehicle price on various attributes. Then, the marginal price of fuel economy is obtained as the first derivative of the estimated hedonic price function with respect to fuel economy. We have already argued that this approach does not work very well in evaluating the value of fuel economy.

Our approach discussed above proceeds in the opposite order. Fuel economy price, $F(e,q)$, is not explicitly observed. Instead, marginal willingness to pay for fuel economy $Apm$ is observed. Thus, we start from using the first order condition with respect to $e$ (equation (9)), and then recover the information on the hedonic price function for fuel economy, $F(e,q)$. Essentially, $F$ is recovered as an envelope of numerous consumers’ observed marginal willingness to pay for fuel economy. Note that this is possible because the left-hand side of equation (9) does not depend on (the derivative of) the utility function $u(\cdot)$ because $e$ does not enter $u$ but appears only in the budget constraint. Likewise, the left-hand side is independent of $z(= y - H - pme)$ and $\theta$, so we need not include individual (or household) income and characteristics in the estimation. In usual hedonic models, the attribute we are interested in (e.g., environmental quality) directly enters the utility function, so that first order condition with respect to that attribute involves (the derivative of) $u(\cdot)$, $z$ and $\theta$. As is widely known, this dependence on $u(\cdot)$, $z$ and $\theta$ significantly complicates the estimation procedure. In this study, we exploit an unusual situation that equation (9) is independent of $u(\cdot)$, $z$ and $\theta$ and estimate the unobserved total price of fuel economy $F(e,q)$.

---

10 You might be concerned about the fact that $q$, $e$ and $Apm$ are endogenous in the sense that consumers choose these values simultaneously. But the hedonic price function (and hence the marginal hedonic price function) is a locus of equilibrium points and not a behavioral function, so simultaneity is not a problem here. See Bockstael and McConnell (2006, p.175) for more details.
With this method of starting from the first order condition with respect to \(e\), we can extract information only on \(F(\cdot)\), the part of vehicle price associated with fuel economy, because \(G(\cdot)\) drops off through differentiation and does not show up in equation (9). This is impossible with the standard approach, since attributes other than \(e\), especially \(q_{11}\), affect both \(F\) and \(G\), and there is no way separating their effect on \(F\) from that on \(G\). If our focus is on fuel economy related issues, \(F(e, q)\) includes sufficient information. And information on \(G\) is not only redundant but possibly even confusing. Our approach makes it possible to separate \(F\) from unwanted \(G\).

In the following estimation, I assume that the hedonic (total) price function for fuel economy \(F(\cdot)\) takes the translog form as follows:

\[
\ln(F_i) = \beta_1 + \beta_2 \ln(e_i) + \beta_3 \ln(w_i) + \beta_4 \ln(a_i) + \frac{\beta_5}{2} \ln(e_i)^2 + \frac{\beta_6}{2} \ln(w_i)^2 + \frac{\beta_7}{2} \ln(a_i)^2 + \beta_8 \ln(e_i) \ln(w_i) + \beta_9 \ln(e_i) \ln(a_i) + \beta_{10} \ln(w_i) \ln(a_i) + \delta \cdot (\text{other controls}),
\]

where the subscript \(i\) indexes vehicle model \(i\), \(e_i\) is fuel economy (gallons per mile), \(w_i\) is vehicle weight and \(a_i\) is acceleration capacity (horsepower divided by weight). Other controls include dummy variables for drive systems (FWD/RWD/AWD), transmission types (AT/SAT/MT), and vehicle categories (passenger car/light duty truck).

With this specification, equation (9) becomes,

\[
A_{pim_i} = -\{\beta_2 + \beta_5 \ln(e_i) + \beta_8 \ln(w_i) + \beta_9 \ln(a_i)\} \frac{F_i}{e_i}^{11}
\]

Eliminating \(F_i\) in equation (11) by using equation (10), rearranging terms and adding the error \(\varepsilon_i\), we have the following equation to be estimated by nonlinear least squares:

\[
A_{pim_i} = -\{\beta_2 + \beta_5 \ln(e_i) + \beta_8 \ln(w_i) + \beta_9 \ln(a_i)\}
\times \exp\{\beta_1 + (\beta_2 - 1) \ln(e_i) + \beta_3 \ln(w_i) + \beta_4 \ln(a_i) + \frac{\beta_5}{2} \ln(e_i)^2 + \frac{\beta_6}{2} \ln(w_i)^2
\times + \frac{\beta_7}{2} \ln(a_i)^2 + \beta_8 \ln(e_i) \ln(w_i) + \beta_9 \ln(e_i) \ln(a_i) + \beta_{10} \ln(w_i) \ln(a_i)
\]

\[
+ \delta \cdot (\text{other controls})\} + \varepsilon_i.
\]

As explained in detail below, we construct (a proxy for) \(m_i\) from a survey data set. That is, \(m_i\) is the sample average VMT of all model \(i\) vehicles in the data set. The frequency observed in the survey differs across \(i\). For example, a model with a relatively large market share will be observed more frequently in the survey. \(m_i\) is likely to be more accurate (i.e., close to the population average VMT of model \(i\)) if it is based on more observations. Therefore, the difference in frequency across \(i\) should be reflected in the heteroskedasticity of

\[^{11}\text{Gasoline prices depend on } i \text{ because different vehicles require different types of gasoline.}\]
the error term $\epsilon_i$. To take account of this, we estimate equation (12) with weighted nonlinear least squares, where weight comes from each model’s frequency of observations in the sample.

The multiplicative factor $A$, which accounts for the length of vehicle life and the consumer’s discounting of future fuel cost savings, affects only $\beta_1$ and does not change the relative magnitude of the marginal price of fuel economy across different vehicle models. At first, we ignore $A$ and estimate the relative marginal price ($-\frac{\partial \hat{F}(e_q)}{\partial e} \equiv -\frac{\partial F(e_q)}{\partial e} / A$) by regressing just $pm$ on $e$ and $q$. That is, we estimate

$$p_i m_i = -\left\{ \beta_2 + \beta_5 \ln(e_i) + \beta_8 \ln(w_i) + \beta_9 \ln(a_i) \right\} \times \exp\left(\tilde{\beta}_1 + (\beta_2 - 1) \ln(e_i) + \beta_3 \ln(w_i) + \beta_4 \ln(a_i) + \frac{1}{2} \beta_5 \ln(e_i)^2 + \frac{1}{2} \beta_6 \ln(w_i)^2ight) + \frac{1}{2} \beta_7 \ln(a_i)^2 + \beta_8 \ln(e_i) \ln(w_i) + \beta_9 \ln(e_i) \ln(a_i) + \beta_{10} \ln(w_i) \ln(a_i) + \delta \cdot (\text{other controls}) + \tilde{\epsilon}_i,$$

(13)

where $\tilde{\beta}_1 = \beta_1 - \ln(A)$ and $\tilde{\epsilon}_i = \epsilon_i / A$. In other words, estimating (13) gives the marginal value of fuel economy in case consumers take only the fuel costs of the first year into account.

After estimating equation (13), we estimate the multiplicative factor $A$ and the discount factor $d$ by combining the predicted relative marginal price of fuel economy and findings from National Research Council [NRC] (2002) and Environmental Protection Agency [EPA] (2009). Based on engineering estimates of benefits and costs of various fuel efficient technologies summarized in NRC (2002), and market penetration rates of different technologies given in EPA (2009), we estimate the marginal price of fuel economy for the average vehicle. Then, we estimate $A$, by dividing this engineering-based estimate of the average vehicle’s marginal price of fuel economy by the average vehicle’s predicted relative marginal price of fuel economy ($-\frac{\partial \hat{F}(e_q)}{\partial e}$, where $\bar{e}$ and $\bar{q}$ are sales-weighted average values). Plugging this $\hat{A}$, along with parameter values of $s$ and $L$, into the relation $A = \frac{1 - (dsL)^{k+1}}{1 - ds}$, we obtain an estimate of the discount factor $d$.

Finally, we estimate the magnitude of model $i$’s marginal price of fuel economy by

$$-\frac{\partial \hat{F}(e_i, q_i)}{\partial e} = -\frac{\partial \hat{F}(e_i, q_i)}{\partial e} \hat{A}.$$

(14)

Similarly, using $\hat{A}$ and estimates from equation (13), we can estimate the magnitude of model $i$’s total price of fuel economy, $\hat{F}(e_i, q_i)$. 

14
6 Data

We apply the above model to model year (MY) 2001 gasoline-engine passenger cars and light duty trucks marketed in the United States.\textsuperscript{12} We need data on vehicle attributes ($e$ and $q$), vehicle owners’ expectation on vehicle use ($m$, $s$ and $L$) and gasoline prices ($p$). Lastly, in order to estimate $A$, we will use engineering-based estimates of the marginal price of fuel economy.

### Table 3: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-reported VMT</td>
<td>14,942</td>
<td>9,493</td>
<td>500</td>
<td>76,000</td>
</tr>
<tr>
<td>Odometer-based VMT</td>
<td>14,660</td>
<td>8,805</td>
<td>45</td>
<td>73,452</td>
</tr>
<tr>
<td>Fuel economy (gallons/100 miles)</td>
<td>4.97</td>
<td>1.02</td>
<td>2.85</td>
<td>7.55</td>
</tr>
<tr>
<td>Weight (lb)</td>
<td>4,056</td>
<td>781</td>
<td>2,375</td>
<td>6,000</td>
</tr>
<tr>
<td>Horsepower/Weight (hp/lb)</td>
<td>0.048</td>
<td>0.006</td>
<td>0.033</td>
<td>0.099</td>
</tr>
<tr>
<td>LDT</td>
<td>0.518</td>
<td>0.499</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>MT</td>
<td>0.086</td>
<td>0.138</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>SAT</td>
<td>0.003</td>
<td>0.031</td>
<td>0</td>
<td>0.483</td>
</tr>
<tr>
<td>AWD</td>
<td>0.237</td>
<td>0.294</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>RWD</td>
<td>0.238</td>
<td>0.319</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

The number of observations is 1616.

Though in the theoretical model $m$ is the distance each vehicle is expected to be driven for the first year, no data is available on the owner’s expected VMT. Therefore, we use a surveyed vehicle’s estimated VMT as a proxy for $m$, which is obtained from the 2001 National Household Travel Survey (NHTS), a national survey conducted by the Federal Highway Administration. This survey contains information on the vehicle(s) each surveyed household owns (such as make, model and model year) and the estimated annual VMT of the vehicle(s). We will look at only MY 2001 vehicles. Two types of VMT estimates will be used in the estimation. The first is self-reported VMT (SVMT) (Table 3, row 1), which is based on the owner’s recollection on his vehicle’s annual VMT. The second is odometer-based VMT (OVMT) (Table 3, row 2), which is derived from two odometer readings of the same vehicle on two different dates (usually a few months apart from each other). Like the approach taken in the NHTS, we exclude from the sample 78 observations (passenger cars or light trucks) whose two VMT measures are extremely different. This leaves us 1,616 observations.\textsuperscript{13} Since vehicles are identified only up to the vehicle model level in the 2001 NHTS and equation (13) is estimated at the this level, we calculate the average VMT by vehicle model.

For vehicle attributes ($e$ and $q$), we will use the Environmental Protection Agency (EPA)’s “Fuel Economy

\textsuperscript{12}Non-gasoline engine vehicles such as hybrid vehicles, which were introduced to the U.S. market at around that time, and diesel engine vehicles are excluded from the sample. Flex fuel vehicles are included.

\textsuperscript{13}Observations are excluded if $|\text{SVMT-OVMT}| > 10,000$ miles and $(\text{SVMT} > 4\times \text{OVMT}$ or $\text{SVMT} < 0.25 \times \text{OVMT}$).
Test Car List Data” for MY 2001. This is the original fuel economy test data administered by the EPA and is used to determine the fuel economy label values available to consumers. The data set covers more than 1,000 vehicle configurations and provides information on vehicle attributes associated with fuel economy or vehicle emissions (e.g., vehicle weight, engine characteristics, transmissions, drive systems, emission control systems), and test results (fuel economy values and pollutant emissions). Table 1 summarizes variables from this data set (rows 3-8). In the following regressions, the data is aggregated to the vehicle model level, as vehicles are identified only up to this level in the 2001 NHTS. Model level average values are calculated by using sales at the configuration level as weights.

Gasoline price data are obtained from the Energy Information Administration. The annual average price for year 2000 is used as a proxy for the expected future gasoline price \( p \) that consumers held when purchasing a MY 2001 vehicle.\(^{14}\) We assume homogeneous consumers, so that all consumers are assumed to have the same expectation about future gasoline prices. For vehicles requiring premium gasoline, its annual average price ($1.639) is used. For others, the average regular gasoline price ($1.462) is used.

An engineering estimate of the marginal price of fuel economy for the average vehicle (this estimate is denoted by \( K \)) is constructed with findings from National Research Council [NRC] (2002) and Environmental Protection Agency [EPA] (2009). Based on meetings and interviews with representatives of automotive manufacturers and component and subsystem suppliers, and through published engineering studies, NRC (2002) estimates the rate of fuel economy improvement and the incremental retail price from (separately) applying various fuel efficient technologies. EPA (2009) gives statistics on market penetration rates of these technologies over time. As explained in detail in Appendix A, based on these studies we estimate that \( K \) is $35-$45.

In order to estimate the discount factor \( d \), we need to assume parameter values of \( s \), one minus the annual rate of VMT reduction, and \( L + 1 \), the length of vehicle life. Following NRC (2002), we take \( r = 0.955 \). We use three values of \( L + 1 \): 10, 15 and 20. We will see that for \( L \) large enough (e.g., \( L \geq 9 \)), changing \( L \) affects \( d \) only slightly.

7 Results

7.1 Estimating the Relative Magnitude of Marginal Prices of Fuel Economy

Table 4 reports the result of weighted nonlinear least squares estimation of equation (13) for different dependent variables and specifications. Regression (1) is our base model, and regressions (2)-(4) will be discussed later for robustness checks.

Regression (1) uses self-reported VMT (SVMT) to construct the dependent variable. It includes dummy

\(^{14}\)Generally, MY 2001 vehicles began to be in the market in late (calendar year) 2000.
Table 4: Estimation of Equation (13)

<table>
<thead>
<tr>
<th>Coeff.</th>
<th>In Eq. (10), coeff. of:</th>
<th>(1) SVMT</th>
<th>(2) SVMT</th>
<th>(3) OVMT</th>
<th>(4) OVMT</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\tilde{\beta}_1)</td>
<td>—</td>
<td>-128.7</td>
<td>-122.2</td>
<td>-81.0</td>
<td>-69.0</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(89.0)</td>
<td>(90.9)</td>
<td>(88.0)</td>
<td>(90.0)</td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>(\ln(e))</td>
<td>-39.5**</td>
<td>-37.5*</td>
<td>-26.3</td>
<td>-23.3</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(19.4)</td>
<td>(19.7)</td>
<td>(18.6)</td>
<td>(18.7)</td>
</tr>
<tr>
<td>(\beta_3)</td>
<td>(\ln(w))</td>
<td>41.5*</td>
<td>40.3*</td>
<td>26.2</td>
<td>24.0</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(23.3)</td>
<td>(23.7)</td>
<td>(22.5)</td>
<td>(22.9)</td>
</tr>
<tr>
<td>(\beta_4)</td>
<td>(\ln(a))</td>
<td>11.4</td>
<td>13.4</td>
<td>6.27</td>
<td>9.50</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(11.6)</td>
<td>(11.5)</td>
<td>(12.5)</td>
<td>(12.2)</td>
</tr>
<tr>
<td>(\beta_5)</td>
<td>(\frac{1}{2} [\ln(e)]^2)</td>
<td>-6.29**</td>
<td>-6.02**</td>
<td>-4.26</td>
<td>-3.85</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(2.75)</td>
<td>(2.78)</td>
<td>(2.64)</td>
<td>(2.63)</td>
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<tr>
<td>(\beta_6)</td>
<td>(\frac{1}{2} [\ln(w)]^2)</td>
<td>-6.41*</td>
<td>-6.21*</td>
<td>-4.16</td>
<td>-3.83</td>
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<td>&amp;</td>
<td></td>
<td>(3.29)</td>
<td>(3.34)</td>
<td>(3.16)</td>
<td>(3.18)</td>
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<tr>
<td>(\beta_7)</td>
<td>(\frac{1}{2} [\ln(a)]^2)</td>
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<td>-1.34</td>
<td>-0.42</td>
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<tr>
<td>&amp;</td>
<td></td>
<td>(1.63)</td>
<td>(1.57)</td>
<td>(1.89)</td>
<td>(1.77)</td>
</tr>
<tr>
<td>(\beta_8)</td>
<td>(\ln(e) \ln(w))</td>
<td>6.32**</td>
<td>6.01**</td>
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<td>(2.86)</td>
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<td>1.52*</td>
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<td>1.06</td>
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<tr>
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<td>(0.82)</td>
<td>(0.84)</td>
<td>(0.81)</td>
<td>(0.82)</td>
</tr>
<tr>
<td>(\beta_{10})</td>
<td>(\ln(w) \ln(a))</td>
<td>-1.64</td>
<td>-1.65</td>
<td>-1.42</td>
<td>-1.45</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(1.33)</td>
<td>(1.34)</td>
<td>(1.34)</td>
<td>(1.34)</td>
</tr>
<tr>
<td>(\delta_{LDT})</td>
<td>LDT</td>
<td>0.0019</td>
<td>-0.014</td>
<td>0.065</td>
<td>0.045</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(0.063)</td>
<td>(0.063)</td>
<td>(0.061)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>(\delta_{RWD})</td>
<td>RWD</td>
<td>-0.023</td>
<td>-0.034</td>
<td>0.042</td>
<td>0.027</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(0.076)</td>
<td>(0.077)</td>
<td>(0.075)</td>
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<tr>
<td>(\delta_{AWD})</td>
<td>AWD</td>
<td>0.0021</td>
<td>0.012</td>
<td>-0.022</td>
<td>-0.010</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(0.089)</td>
<td>(0.089)</td>
<td>(0.088)</td>
<td>(0.088)</td>
</tr>
<tr>
<td>(\delta_{MT})</td>
<td>MT</td>
<td>0.16</td>
<td>0.17</td>
<td>0.0024</td>
<td>0.013</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>(\delta_{SAT})</td>
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<td>0.15</td>
<td>-0.74</td>
<td>-0.78</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(0.50)</td>
<td>(0.50)</td>
<td>(0.74)</td>
<td>(0.74)</td>
</tr>
<tr>
<td>(\delta_{Luxury})</td>
<td>Luxury</td>
<td>-0.12*</td>
<td>-0.16**</td>
<td>-0.12</td>
<td>-0.16**</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(0.068)</td>
<td>(0.068)</td>
<td>(0.068)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>(\delta_{ABS/TC})</td>
<td>ABS/TC</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
</tr>
<tr>
<td>&amp;</td>
<td></td>
<td>(0.040)</td>
<td>(0.039)</td>
<td>(0.040)</td>
<td>(0.039)</td>
</tr>
<tr>
<td># of obs</td>
<td>158</td>
<td>158</td>
<td>158</td>
<td>158</td>
<td></td>
</tr>
</tbody>
</table>

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Weighted nonlinear least squares estimation of equation (13). VMT \((m_i)\) in the dependent variable is based on self-reported VMT in regressions (1) and (2), and odometer-based VMT in regressions (3) and (4).

variables that seem technologically related with fuel economy as discussed in Section 3: the light duty truck status, transmission types and drive systems. Several coefficients are statistically significant (although with
the translog specification, coefficients are often jointly significant even when they are not individually). In particular, most coefficients of variables related with fuel economy \((e)\) and vehicle weight \((w)\) are statistically significant at the 5 or 10% level \((\beta_2, \beta_3, \beta_5, \beta_6, \beta_8 \text{ and } \beta_9)\).

Rather than analyzing the relative marginal price implied by Table 4 in detail, we will first estimate the multiplicative factor \(A\) and the discount factor \(d\). Using \(\hat{A}\), we will estimate the marginal price of fuel economy and analyze how it differs across vehicles.

### 7.2 Estimating the Multiplicative Factor and Discount Rate

For the (hypothetical) vehicle with the sales-weighted average attributes, we have two estimates of the incremental price of a 1% fuel economy improvement. Our model, using VMT and vehicle attributes, gives

\[
A\left[-\frac{\partial \hat{F}(e,q)}{\partial e}\right]_{100},
\]

where \(\frac{\partial \hat{F}(\cdot)}{\partial e}\) is the predicted relative marginal price of fuel economy and \(\bar{e}\) and \(\bar{q}\) are sales-weighted average values. The engineering estimate \((K)\) based on NRC (2002) and EPA (2009) is $35-$45, as explained in detail in Appendix A. We estimate the multiplicative factor \(A\) by equating these two estimates and solving for \(A\). With the engineering-based estimate of $35-$45, we obtain \(A\) for three different values of \(K\) (35, 40 and 45). The discount factor \(d\) is then estimated using the relationship

\[
A = \frac{1}{1 - ds},
\]

and the discount rate \(r\) is given by

\[
r = \frac{1}{d - 1}.
\]

Table 5 shows the estimates of \(A\), \(d\) and \(r\) for different values of the average vehicle’s marginal price of fuel economy \((K)\) and the length of vehicle life \((L+1)\), with \(s = 0.955\). Table 5 also shows WP, the ratio of willingness to pay (WTP) for a marginal fuel economy improvement (or the marginal price of fuel economy) to the expected present value (PV) of fuel cost savings from the same improvement. WTP is given by

\[
WP = \frac{1 - (ds)^{L+1}}{1 - ds},
\]

and PV by

\[
PV = \frac{1 - (vs)^{L+1}}{1 - vs}.
\]

Thus,

\[
WP = \frac{1 - (ds)^{L+1}}{1 - ds} / \frac{1 - (vs)^{L+1}}{1 - vs}.
\]

(15)

WTP/PV< 1 implies consumers’ undervaluation of fuel economy, while WTP/PV > 1 implies overvaluation. The lower WTP/PV(< 1), the larger the degree of consumers’ undervaluation is.

<table>
<thead>
<tr>
<th>(K): engineering estimate of marginal price of fuel economy, (L+1): length of vehicle life, (A): multiplicative factor, (d): discount factor, (r): discount rate, WP: WTP/PV</th>
<th>(35)</th>
<th>(40)</th>
<th>(45)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(L+1)</td>
<td>(A)</td>
<td>(d)</td>
<td>(r)</td>
</tr>
<tr>
<td>10</td>
<td>3.03</td>
<td>0.71</td>
<td>0.41</td>
</tr>
<tr>
<td>15</td>
<td>3.03</td>
<td>0.70</td>
<td>0.42</td>
</tr>
<tr>
<td>20</td>
<td>3.03</td>
<td>0.70</td>
<td>0.43</td>
</tr>
</tbody>
</table>
The multiplicative factor $A$ is estimated around 3-4, so for a marginal fuel economy improvement, consumers are on average willing to pay three to four times more than the fuel cost savings from that improvement rewarded in the first year.

The estimates of the discount rate $r$ and the WTP/PV ratio imply that consumers discount future fuel cost savings very fast. The discount rate $r$ is estimated to be 26-43%, depending on $K$ and $L$. This range is much higher than the real interest rate we use (7%). We also find that the choice of $L$ (the length of vehicle life) has almost no effect on $r$ (or $d$). Future fuel cost savings are discounted so fast that savings realized after 10 years or later have little value. The WTP/PV ratio is around 0.35-0.60. Consumers are willing to pay for only 35-60% of the present value of total fuel cost savings over the life of the vehicle. These numbers are consistent with the so-called Energy Paradox that consumers significantly undervalue long-term energy cost savings from energy efficiency improvements.

### 7.3 Estimating the Magnitude of Marginal Prices of Fuel Economy

With the predicted relative marginal price of fuel economy ($-\frac{\partial \hat{F}(e, n)}{\partial e}$) derived from column (1) of Table 4 and an estimate of the multiplicative factor $\hat{A}$ at hand, we now estimate the magnitude of each model’s marginal price of fuel economy by multiplying them together. In the following we show the results based on $\hat{A}$ from the middle case of $K = 40$ ($\hat{A} = 3.46$). The (model-level, unweighted) average price of fuel economy improvement of 0.1 gallon per 100 miles is estimated to be $\$74.7$ (in 2000 U.S. dollars), and the standard deviation of $\$7.8$. In other words, on average, consumers are willing to pay $\$74.7$ for an improvement of 0.1 gallon per 100 miles. Figure 1 plots the estimated marginal price ($-\frac{\partial \hat{F}}{\partial e}$) against fuel economy (gallons per 100 miles) to roughly see what models tend to face larger marginal willingness to pay for fuel economy.
Table 6: Statistics of Estimated Total Price of Fuel Economy ($F$)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5%</td>
<td>1069</td>
<td>1091</td>
<td>1405</td>
<td>1521</td>
</tr>
<tr>
<td></td>
<td>(362)</td>
<td>(366)</td>
<td>(616)</td>
<td>(772)</td>
</tr>
<tr>
<td>25%</td>
<td>1485</td>
<td>1537</td>
<td>1893</td>
<td>2000</td>
</tr>
<tr>
<td></td>
<td>(587)</td>
<td>(635)</td>
<td>(726)</td>
<td>(847)</td>
</tr>
<tr>
<td>50%</td>
<td>1887</td>
<td>1904</td>
<td>2342</td>
<td>2408</td>
</tr>
<tr>
<td></td>
<td>(745)</td>
<td>(646)</td>
<td>(939)</td>
<td>(1167)</td>
</tr>
<tr>
<td>75%</td>
<td>2251</td>
<td>2289</td>
<td>2812</td>
<td>2886</td>
</tr>
<tr>
<td></td>
<td>(640)</td>
<td>(755)</td>
<td>(1063)</td>
<td>(1285)</td>
</tr>
<tr>
<td>95%</td>
<td>3281</td>
<td>3167</td>
<td>3922</td>
<td>3816</td>
</tr>
<tr>
<td></td>
<td>(967)</td>
<td>(1031)</td>
<td>(1583)</td>
<td>(1817)</td>
</tr>
<tr>
<td>Mean</td>
<td>1942</td>
<td>1951</td>
<td>2407</td>
<td>2474</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>641</td>
<td>620</td>
<td>726</td>
<td>701</td>
</tr>
<tr>
<td>Observations</td>
<td>158</td>
<td>158</td>
<td>158</td>
<td>158</td>
</tr>
</tbody>
</table>

The total price of fuel economy ($F$) is estimated using equation (10), the estimated coefficients in the corresponding column of Table 4 and the corresponding $\hat{A}$. The table reports the mean, standard deviation and selected percentiles of $\hat{F}$, treating a vehicle model as one observation. In parentheses are the standard errors of $\hat{F}$ for the corresponding vehicle models that result from randomness in the estimated coefficients of Table 4.

Figure 2: Total Price of Fuel Economy and Fuel Economy

and thus have larger marginal prices of fuel economy due to higher VMT or the use of premium gasoline. Figure 1 shows that less fuel efficient ($\approx$ larger and heavier) vehicles tend to have higher marginal prices. The average marginal price for passenger cars only is $71.5, while that for light duty trucks is $79.8.
The total price of fuel economy ($F$) can be recovered using equation (10), the estimated coefficients in column (1) of Table 4 and $\hat{A} = 3.46$. Column (1) of Table 6 reports selected percentiles, the mean and standard deviation of the total price of fuel economy ($F$) predicted by the base regression (column (1) of Table 4), treating a vehicle model (e.g., Toyota Camry) as one observation. The values in parentheses are the standard errors of $\hat{F}$ for the corresponding vehicle models that result from randomness in the estimated coefficients of Table 4. The (model-level, unweighted) average is estimated to be $1,942$ (in 2000 U.S. dollars), and the standard deviation is $642$. As in the case of $-\frac{\partial \hat{F}}{\partial e}$ above, Figure 2 plots $\hat{F}$ against fuel economy (gallons per 100 miles) to roughly see what vehicles likely have larger $F$. Generally, less fuel efficient ($\approx$ larger and heavier) vehicles tend to have larger $F$. That is, they tend be priced higher for fuel economy.

Figure 3 plots the relationship between the estimated total price of fuel economy $\hat{F}$ and the retail price. It shows a strong positive correlation between the two prices. This is interesting because we do not use any information on retail prices in estimating $\hat{F}$. Generally, 5-10% of the retail price is estimated to be attributable to fuel economy. Moreover, while light duty trucks show a relatively proportional relationship between the two prices, passenger cars present a nonlinear relationship in the sense that expensive luxury cars do not have proportionally high total prices of fuel economy. This suggests that luxury and non-luxury cars do not differ so much in terms of $F$, so that retail price differences between them mostly come from differences in the portion unrelated with fuel economy, $G$. 

Figure 3: Total Price of Fuel Economy and Retail Price
8 Robustness

We check the robustness of the above results in two respects. First, we estimate the same regression by using a different VMT measure. Second, we check whether the inclusion of variables that are technologically unrelated with fuel economy drastically changes the results.

8.1 Using Odometer-based VMT

We construct the dependent variable from odometer-based, rather than self-reported, VMT and do the same procedure as in the last section. Figure 4 compares self-reported VMT (SVMT) and odometer-based VMT (OVMT) for the 1,616 vehicles in our sample. Clearly, the two measures are positively correlated (the correlation coefficient is 0.66), but for many observations there is a wide disparity between them. Therefore, estimating with OVMT will provide a robustness check of the above results with SVMT.

![Figure 4: Self-reported VMT (SVMT) and Odometer-based VMT (OVMT)](image)

Column (3) of Table 4 shows the result of estimating equation (13) with using OVMT to construct the dependent variable. This regression is comparable to column (1). Obviously, OVMT gives less precise estimates than SVMT. None of the coefficients of regressors associated with $e$ or $w$, which are mostly significant with SVMT, are significant at the 10% level. (Their p-values are mostly between 0.1 and 0.2.) This difference implies that SVMT is a better proxy for (the first year’s) expected VMT at the time of purchase (i.e., $m$ in the theoretical model of Section 4).

Though less precise, OVMT-based predicted values and estimates are in many cases very close to SVMT-based predicted values and estimates. First, OVMT estimates $\hat{A} = 3.56$ and $\hat{d} = 0.76$ for $K = 40$ and $L + 1 = 14$, while SVMT gives $\hat{A} = 3.46$ and $\hat{d} = 0.75$. Using these estimates of $A$, Figure 5 compares
the OVMT-based predicted marginal price of fuel economy and the SVMT-based marginal price. It shows that for most vehicles these two predictions are similar. The (model-level, unweighted) average from OVMT is $74.6, while that from SVMT is $74.7. We also compare the total price of fuel economy predicted by OVMT and SVMT in Table 6 and Figure 6. Each column of Table 6 reports selected percentiles, the mean and standard deviation of the total price of fuel economy ($F$) calculated from the estimates in the corresponding column of Table 4. OVMT gives larger $\hat{F}$ than SVMT, as well as larger standard errors (given in parentheses). Yet, Figure 6, which plots OVMT-based $\hat{F}$ against SVMT-based $\hat{F}$, shows that they are very highly correlated.
These comparisons of OVMT-based and SVMT-based estimates confirm the robustness of the results discussed in the last section, and also suggest that SVMT is a better measure to use in estimating how fuel economy is valued in the market.

8.2 Including Variables Technologically Unrelated with Fuel Economy

For the standard approach discussed in Section 2, we see that the result is very sensitive to the inclusion of those variables that seem to be technologically unrelated with fuel economy, such as the luxury status and safety features. Table 2 shows that including these regressors drastically changes the coefficients of \( \ln(e) \), \( \ln(w) \) and \( \ln(a) \).

For our approach, the theoretical model suggests that the variables technologically independent of fuel economy (\( q_2 \)) unlikely have a large effect on the results based on equation (9). This is because \( q_2 \) does not affect \( F \) through production technology, but only indirectly, if any, through the automaker’s pricing strategy. We test whether our approach is also sensitive to attributes in \( q_2 \) by additionally including variables for the luxury status (Luxury) and safety features (ABS/TC).

Columns (2) and (4) of Table 4 show the result of estimating equation (13) with Luxury and ABS/TC. Column (2) uses SVMT and column (4) uses OVMT for constructing the dependent variable. While Luxury is estimated to have a significantly negative effect,\(^{15}\) other coefficients do not change significantly from columns (1) or (3). This makes a clear contrast with the standard approach in Table 2.

Figure 7 plots the predicted total price of fuel economy \( \hat{F} \) calculated from column (1) of Table 4 against \( \hat{F} \) from column (2). Also, columns (2) and (4) of Table 6 show some statistics of \( \hat{F} \) obtained from the corresponding columns of Table 4. From Figure 7 and Table 6, we find that \( \hat{F} \) is robust to including Luxury and ABS/TC.

These observations provide support for the validity of our approach. Unlike the estimates from the standard approach, the results in Section 7 are insensitive to including Luxury and ABS/TC, representatives of attributes that are technologically independent of fuel economy (i.e., \( q_2 \)). This insensitivity is consistent with our theoretical framework and suggests that our approach has succeeded in separately analyzing the value of fuel economy (the “\( F \)” part) without the complication from the price of other attributes (the “\( G \)” part).

9 Conclusion

This paper has proposed an alternative hedonic approach to estimating how fuel economy is valued in the market. The basic idea is that we can observe a proxy for a consumer’s marginal willingness to pay for her

\(^{15}\)The negative coefficient of Luxury implies that other things equal, a buyer of a luxury vehicle is on average less willing to pay for a marginal improvement of the vehicle’s fuel economy basically because it is (on average) driven less than a non-luxury vehicle.
vehicle’s fuel economy by using its VMT (and gasoline prices). With the theoretical prediction that marginal willingness to pay equals marginal price at an optimum, this is equivalent to observing each vehicle’s marginal price of fuel economy with error. By taking the steps of the standard hedonic method backward, we estimate the marginal and total price of fuel economy as a function of vehicle attributes such as fuel economy and weight.

An important advantage of our approach over the standard hedonic approach is that ours is much less likely affected by omitted variables bias from attributes technologically unrelated with fuel economy such as interior quality and safety features (i.e., attributes denoted by $q_2$). As discussed in Section 2, fuel economy is strongly correlated with $q_2$, largely due to consumer preferences (though not due to production technology). Thus, omitting these attributes in the standard hedonic regression of vehicle price on vehicle attributes, which usually happens because it is difficult to represent these attributes well enough in regressions, results in a biased estimate of marginal price of fuel economy. Our approach makes it possible to separate the portion of vehicle price that varies with fuel economy ($F$) from the portion that does not ($G$). This is because in our approach we first estimate $\frac{\partial F}{\partial e}$, and then recover $F$ using information on $\frac{\partial F}{\partial e}$. The effect of a vehicle attribute on the fuel-economy-unrelated portion of vehicle price ($G$) can be separated because it does not affect $\frac{\partial F}{\partial e}$. We have shown in Section 8 that the estimates and predictions from our approach are robust to including variables that represent $q_2$.

We have applied this procedure to MY 2001 new vehicles sold in the U.S. With additionally using engineering-based estimates of the average MY 2001 vehicle’s marginal price of fuel economy, we estimate that consumers discount future fuel cost savings at the annual rate of 26-43%, much higher than usual rates of return on investment. A fuel efficiency improvement of 0.1 gallon per 100 miles is estimated to increase

Figure 7: Total Price of Fuel Economy with and without Luxury and ABS/TC (2000 U.S. $)
vehicle price by, on average, $74.7 in 2000 U.S. dollars (for the middle case of the discount rate of 34%). Larger vehicles tend to have higher marginal prices of fuel economy, basically because these vehicles are driven more miles, so buyers of these vehicles are more willing to pay for fuel economy. The average total price of fuel economy is estimated at $1,950 (for the case of the discount rate of 34%). Larger vehicles tend to have higher total prices of fuel economy as well, which implies that the cost spent for fuel economy is higher in these vehicles than in smaller vehicles. The estimated total prices of fuel economy suggest that for most vehicles around 5-10% of their retail price is attributable to fuel economy.

References


A List of Variables

\[ A = \frac{1-(de)_{L+1}}{1-ds} \]

\(a\) Horsepower per pound of a vehicle
\(c\) Production cost of a vehicle
\(d\) Annual discount factor
\(e\) Fuel economy of a vehicle (in miles per gallon)
\(F\) Part of \(H\) that involves \(e\) as an argument
\(f\) Part of \(c\) that is technologically related with fuel economy of a vehicle
\(G\) Part of \(H\) that does not involve \(e\) as an argument
\(g\) \(= c - f\)
\(H\) Retail price of a vehicle (in US dollars)
\(h\) Hedonic cost function of producing a vehicle
\(K\) Engineering-based cost estimate based on NRC (2002)
\(L + 1\) Length of a vehicle’s life (in years)
\(m\) (Expected) vehicle miles traveled (in 100 miles)
\(p\) (Expected) gasoline price per gallon
\(q\) Vector of vehicle attributes other than fuel economy
\(q_1\) Vehicle attributes that are arguments of both \(f\) and \(g\) functions
\(q_2\) Vehicle attributes that are arguments of \(g\) functions only
\(r\) Discount rate. \(r = \frac{1}{d} - 1\)
\(s\) One minus annual rate of VMT reduction
\(w\) Weight of a vehicle (in pounds)
\(z\) Consumption of the numéraire good
\(\theta\) Consumer characteristics
B List of Abbreviations

ABS Anti-lock brake system
AT Automatic transmission
AWD All wheel drive
LDT Light duty trucks
MT Manual transmission
MWTP Marginal willingness to pay
MY Model year
NHTS National Household Travel Survey
OVMT Odometer-based VMT
PV Present value
SAT Semi-automatic transmission
SVMT Self-reported VMT
VMT Vehicle miles traveled
WP WTP divided by PV
WTP Willingness to pay

C Engineering Estimates of the Marginal Price of Fuel Economy

Here we analyze two reports on automobile fuel economy (National Research Council, 2002; Environmental Protection Agency, 2014) and estimate the marginal price of fuel economy for the average vehicle from an engineering, rather than economic, point of view. We will consider a number of fuel efficient technologies that were available or expected to be available in 2001. Among these technologies we want to identify “marginal” technologies at that time which automakers chose to or not to use in their models for a marginal fuel economy adjustment. Then, engineering estimates of the benefit and cost of the “marginal” technologies allow us to estimate the marginal price of fuel economy for the average vehicle.

Various technologies are available to improve fuel economy. For example, NRC (2002) gives a comprehensive list of new technologies, and also engineering estimates of fuel economy gains and retail price increases from applying each technology. These estimates are based on engineering, rather than economics, in the sense that they are constructed through meetings and interviews with representatives of automotive manufacturers and component and subsystem suppliers, and through published engineering studies. Also, EPA (2009) provides data on market penetration trends of a number of old and new fuel efficient technologies.

16NRC’s (2002) list of fuel efficient technologies includes: engine friction reduction; low friction lubricants; multi-valve, overhead camshafts; variable valve timing; variable valve timing and lift; cylinder deactivation; engine accessory improvement; supercharging and downsizing; five-speed (or six-speed) automatic transmissions; continuously variable transmissions; aerodynamic drag reduction; improved rolling resistance; intake valve throttling; camless valve actuation; variable compression ratio; automated shift manual transmissions; integrated starter generators; 42 volt electrical systems; electric power steering.
Among these technologies, we want to identify “marginal” technologies for model year (MY) 2001 vehicles. Automakers can adjust the level of fuel economy of a vehicle by choosing a combination of fuel efficient technologies used in the vehicle. Marginal technologies are those that automakers likely add to or remove from the combination when they marginally adjust the vehicle’s fuel economy. Efficiency gains and price increases from these marginal technologies determine the marginal price of fuel economy.

What kind of technologies are marginal? Relatively old technologies (e.g. front-wheel-drive, port fuel injection and lockup transmissions) are so mature and common that their penetration rates have been very high and stable since the mid-1990s at the latest (EPA, 2009). They have become the default settings and it is unlikely that these technologies are added to or removed from a vehicle for the purpose of marginal fuel economy adjustment. On the other hand, new technologies that were rarely observed in the market in 2001 could not be marginal technologies, either. New technologies will still be more costly or unstable. It is unlikely that these new technologies were applied to a wide variety of vehicles for marginally improving fuel economy. Thus, marginal technologies are those that were used in not a few vehicles in 2001, but not so commonly that they had become default settings. For vehicles with these technologies, they were one of the last fuel efficient technologies applied. For vehicles without these technologies, they would be used if a marginal fuel economy improvement was needed.

Based on EPA (2009), we consider three technologies (multi-valve, overhead camshaft valve trains; variable valve timing; and five-speed automatic transmissions) as “marginal” in MY 2001. Statistics from EPA (2009) shows that 49% of new cars and trucks in MY 2001 were equipped with a multi-valve, overhead camshaft valve train; 20% were with a variable valve timing system, which is generally added to models with a multi-valve, overhead camshaft valve train; 11% (of MY 2001 new cars and trucks with an automatic transmission) were with a five-speed automatic transmission. Other technologies discussed in NRC (2002) were rarely observed in the market at that time, or we do not have data to show how widely they were used. Therefore, at the time of MY 2001, multi-valve, overhead camshaft valve trains, variable valve timing, and five-speed automatic transmissions were likely to be among those technologies that were applied to or removed from each model for marginally adjusting fuel economy.

Table 7: “Marginal” Fuel Efficient Technologies

<table>
<thead>
<tr>
<th></th>
<th>(1) Efficiency gain (%)</th>
<th>(2) Price increase ($)</th>
<th>(3) Mean $ /Mean %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multi-valve, overhead camshaft</td>
<td>2-5</td>
<td>105-140</td>
<td>35.0</td>
</tr>
<tr>
<td>Variable valve timing</td>
<td>2-3</td>
<td>35-140</td>
<td>35.0</td>
</tr>
<tr>
<td>Five-speed automatic transmission</td>
<td>2-3</td>
<td>70-154</td>
<td>44.8</td>
</tr>
</tbody>
</table>
Table 7 shows engineering estimates of efficiency gains and price increases from the marginal technologies, provided by NRC (2002). The first two columns give estimated ranges of the rate of fuel economy improvement and of the incremental retail price from applying each of the three marginal technologies. Remember that these estimates are based on engineering, rather than economics, in the sense that they are constructed through meetings and interviews with representatives of automotive manufacturers and component and subsystem suppliers, and through published engineering studies. NRC (2002) gives estimated ranges because the effect of each technology differs across vehicle models, depending on various factors, especially vehicle attributes. For example, it may be the case that variable valve timing is more effective and less costly for smaller cars. Unfortunately, further information is not available on how the rate of fuel economy improvement and the incremental retail price are related with vehicle attributes, so we cannot observe engineering estimates for each model. Alternatively, we assume that the effect of each technology on the (hypothetical) vehicle with the average attributes is well approximated by the midpoints of the ranges. Dividing the average incremental price by the average rate of fuel economy improvement, column (3) of Table 7 gives our engineering estimate of the price of a 1% fuel economy improvement for the average vehicle. The marginal price estimates from the three technologies should not be so different from one another. Indeed, column (3) shows that they stay in a $10 range ($35-$45), providing support for our approach. Based on these results, we use $35-$45 as our (interval) estimate of the marginal price of fuel economy for the average MY 2001 vehicle.

\[17\] NRC (2002) also uses the midpoints of the ranges in deriving its estimates.