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How Does Information in Fuel Economy Labels Affect Consumer Choice?

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Abstract

This paper examines the effect of different pieces of information in fuel economy labels on consumer choice using data from a discrete choice experiment. In the experiment, participants are randomly assigned to treatment groups and asked to make choices between vehicle alternatives. Fuel economy labels vary over treatment group. Individual-specific discount rates are elicited in the survey, allowing this analysis to disentangle the effects of information and discount rate on choice. The analysis estimates each individual's willingness to pay for a one dollar reduction in present value of operating costs, then examines how information affects the willingness to pay coefficient. I find that certain pieces of information, especially estimated cost information, increase willingness to pay. The degree of valuation is highly sensitive to discount rate. I find substantial overvaluation of fuel economy using individual discount rates and full valuation using a uniform 5% rate.

1 Introduction

Beginning in 1974, all new cars sold in the U.S. had to display fuel economy labels (EPA, 2011). The EPA created this program with the hope that it would encourage consumers to purchase more fuel efficient vehicles and save gasoline. The imperative for policy-makers to encourage fuel savings is higher than ever due to the threats of climate change. In 2014, passenger cars and light-duty trucks account for 20% of greenhouse gas emissions in the U.S (EPA,2016).

Since the seminal work of Hausman (1979), economists have noted that consumers may apply discount rates well above market interest rates in the purchase of energy using durable goods.[1] Nonetheless, if consumers undervalue fuel economy it is unclear why. Jaffe et al. (1994) have called this the "energy paradox," noting that it could have numerous explanations. Perhaps consumers naturally apply discount rates well above market interest rates when considering the trade-off between up-front cost and future fuel costs. Alternatively, consumers may be ill-informed about the value of future fuel costs. Numerous authors have noted that even though implied discount rates may be higher than market interest rates, consumer are not necessarily acting irrationally. Studies which found only slight undervaluation, such as that of Busse et al. (2013), have noted that implied discount rates are not significantly different then interest rates on car loans. If there is an under-provision of information on fuel economy, or if consumers make inaccurate future fuel cost calculations, then fuel economy labels may encourage more fuel efficient vehicle purchases, reduce gasoline consumption, and improve consumer welfare.

The literature on how information affects consumer choice of energy efficiency is sparse. Sallee (2013) wrote on "rational inattention," using a model that shows that consumers may be acting rationally by using high implied discount rates when information costs are high and preferences for other observable attributes is strong. He notes that consumers find it costly to translate information in existing fuel economy labels into expected fuel costs. Similarly, an experiment conducted by Larrick et al. (2008) demonstrates that consumers generally translate

[1] Evidence of undervaluation is truly a mixed bag. See Busse et al. (2013), Sallee et al. (2015), Linn et al. (2011) for evidence of full valuation or moderate undervaluation. See Green (2010) for a meta-analysis of the fuel economy valuation literature.

MPG into fuel costs incorrectly. They show that consumers tend to believe that the relationship between fuel cost and MPG is linear, when in reality, fuel cost is linear with gallons per mile. This should result in undervaluation for low fuel economy vehicles, and possible overvaluation for high fuel economy vehicles. These findings suggest that the role of information may be important, and that there could be increases to consumer welfare by providing better information (which consumers can use form more accurate beliefs about expected fuel costs).

I have not found a study to date which uses revealed preference data to study the effect of different pieces of information on energy efficiency investments. Perhaps the closest is the work of Alberini et al. (2014), who study whether the fuel economy label has an effect on price using data from the new car market in Switzerland. They do not consider the introduction of new information but instead exploit the fact that some models of cars near the cutoff between two discrete grades move from one fuel efficiency grade level to another depending on the year. They find that simply having an A grade on the label gives a 5% price premium. But, they find a smaller effect or no effect at all between the threshold of lower grade cars. They interpret this as evidence that consumers are willing to pay for "environmental friendliness."

My paper is heavily influenced by the work of Newell et al. (2014) who use a discrete choice experiment to understand how information in the US EnergyGuide labels affects household choice of water heaters. Like Newell et al. (2014), this study also elicits individual-specific discount rates and assigns participants to randomized treatment groups. They find that current EnergyGuide labels guide cost-minimizing choices given individual discount rates, but find modest undervaluation of future energy savings when future costs are calculated using a uniform 5% rate. They find that monetary information on future energy savings is perhaps the most important piece of information guiding cost-effective energy efficiency investments.

Fuel economy labels have evolved over time to help consumers process fuel economy information more easily. In 2013, the fuel economy label in the U.S. was overhauled, and now shows, *inter alia*, a discrete fuel usage rating, five year fuel savings compared to the average new vehicle, environmental impact information, and gallons per 100 miles (EPA, 2011). This paper will examine whether consumers respond to these information changes using experimental data.

In the experiment, I elicit individual discount rates, allowing me to disentangle the effect of information and discount rates on consumer choice. I elicit discount rates by asking survey participants to make a series of choices between present and future payments to narrow in on their point of indifference. If certain pieces of information move consumers closer to making a one-to-one trade off between up-front cost and future operating cost, then it would suggest that those pieces of information render fuel economy more salient to the consumer: that the consumer can use those pieces of information to translate fuel economy into a more accurate belief about future fuel costs. Further, it would suggest that policy makers should pay close attention to which pieces of information should be given to consumers.

I find significant overvaluation of future fuel costs using individual discount rates and full valuation using a uniform 5% rate. Willingness to pay was largely similar over treatment groups. But, I find that certain combinations of information increase willingness to pay. Further, I find that consumers *undervalue* fuel economy when they are given the linear form of fuel economy, gallons per 100 miles, without substantial estimated cost information.

The remainder of this paper is structured as follows. Section two presents a model of consumer choice among different automobiles as well as an econometric specification for estimating individual willingness to pay. Section three discusses the experimental design. Section four presents results. Section five concludes.

2 Theory

In this model, individual i chooses from a set of alternatives, J. The utility that consumer i gets from alternative j can be additively separated into a deterministic component (V_{ij}) and a stochastic component (ϵ_{ij}) following the random utility model of McFadden (1974). Thus,

$$U_{ij} = V_{ij} + \epsilon_{ij}. \tag{1}$$

The deterministic component, V_{ij}, is a function of price (p_j), observable vehicle attributes (X_j), and the present-discounted value of operating costs ($PVOC_{ij}$). Thus utility can be separated further into

$$U_{ij} = \alpha_i p_j + \beta_i PVOC_{ij} + \psi_i X_j + \epsilon_{ij} \tag{2}$$

where $PVOC_{ij} = \sum_{n=0}^{11} A_j \frac{1}{(1+r_i)^n}$. r_i is individual i's discount rate, and A_j is the annual operating cost on the label of vehicle j. In estimation, I assume that the planning horizon for operating costs (lifetime of the vehicle) is 12 years (which is reflected in the number of terms in the summand). The coefficients on price and present-value of operating costs are expected to be negative ($\alpha_i, \beta_i \leq 0$).

Next, following the work of Train et al. (2005), I rewrite the above equation in "willingness to pay (WTP) space" as:

$$U_{ij} = \alpha_i [p_j + \gamma_i PVOC_{ij} + \phi_i X_j] + \epsilon_{ij} \tag{3}$$

where $\gamma_i = \frac{\beta_i}{\alpha_i}$ and $\phi_i = \frac{\psi_i}{\alpha_i}$. Our variable of interest is γ_i, which represents how many dollars a participant would be willing to pay in upfront costs to reduce future operating costs by \$1. Thus, if individual i is making a cost-minimizing tradeoff between upfront costs and future operating costs, then $\gamma_i = 1$.

The probability that participant i selects alternative j from the three alternatives is equal to the probability that the utility person i derives from option j is greater than the utility she would derive from the other two options:

$$P_{ij} = P(U_{ij} > U_{ik}) = P(V_{ij} + \epsilon_{ij} > V_{ik} + \epsilon_{ik}) = P(\epsilon_{ik} - \epsilon_{ij} < V_{ij} - V_{ik}) \forall k \neq j \tag{4}$$

Obviously, different assumptions about the distribution of our errors and coefficients will lead to different distributions of this probability. If ϵ is IID type-I extreme value distributed across people and choices, and β is allowed to vary across decision-makers then P_{ij} can be written as the mixed logit model choice probability,

$$P_{ij} = \int \frac{exp(\alpha_i p_j + \beta_i PVOC_{ij})}{\sum_{k=1}^{3} exp(\alpha_i p_j + \beta_i PVOC_{ij})} f(\beta|\theta) d\beta \tag{5}$$

where $f(\beta|\theta)$ is the density function of β (Hole, 2013). In the experiment, each participant is asked to make 10 distinct choices between three vehicle alternatives in each choice. The probability of individual i making a given sequence of choices S_i is given by,

$$S_i = \int \prod_{t=1}^{T} \prod_{j=1}^{J} [\frac{exp(\alpha_i p_j + \beta_i PVOC_{ij})}{\sum_{k=1}^{3} exp(\alpha_i p_j + \beta_i PVOC_{ij})}]^{y_{ijt}} f(\beta|\theta) d\beta \tag{6}$$

where T is the set of choice occasions (in my experiment it consists of 10 distinct choice questions), and $y_{ijt} = 1$ if the individual i chose alternative j in choice situation t (Hole, 2013). The θ parameter can be estimated through simulated log-likelihood maximization

$$SLL = \sum_{n=i}^{I} ln(\frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j=1}^{J} [\frac{exp(\alpha_i p_j + \beta_i^{[r]} PVOC_{ij})}{\sum_{j=1}^{J} exp(\alpha_i p_j + \beta_i^{[r]} PVOC_{ij})}]^{y_{ijt}}) \tag{7}$$

where $\beta_i^{[r]}$ is the $r-$th draw for individual i from the estimated distribution of β.

Revelt and Train (1998) show that individual coefficients can be approximated using simulation as well. Let $\mathbf{y}_i$ and $\mathbf{x}_i$ be the given response pattern and characteristics of alternatives, respectively. Then I estimate $\hat{\beta}_i = E[\beta|\mathbf{y}_i, \mathbf{x}_i]$ as

$$\hat{\beta}_i \approx \frac{\frac{1}{R} \sum_{r=1}^{R} \beta_n^{[r]} \prod_{t=1}^{T} \prod_{j=1}^{J} [\frac{exp(\alpha_i p_j + \beta_i^{[r]} PVOC_{ij})}{\sum_{j=1}^{J} exp(\alpha_i p_j + \beta_i^{[r]} PVOC_{ij})}]^{y_{ijt}}}{\frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j=1}^{J} [\frac{exp(\alpha_i p_j + \beta_i^{[r]} PVOC_{ij})}{\sum_{j=1}^{J} exp(\alpha_i p_j + \beta_i^{[r]} PVOC_{ij})}]^{y_{ijt}}}. \tag{8}$$

Two individuals with the same discount rates and the same series of choices should be assigned the same individual coefficient on $PVOC$. Similarly, if one individual chooses *more* fuel economy than another individual with the same discount rate, then the former individual should be assigned a higher coefficient on $PVOC$.

Once each individual is assigned an individual coefficient on $PVOC$, I estimate their individual willingness to pay for a \$1 reduction in $PVOC$, $\hat{\gamma}_i$, as the ratio of their individual coefficient on $PVOC$, $\hat{\beta}_i$ and the fixed coefficient on price, α.

$$\hat{\gamma}_i = \frac{\hat{\beta}_i}{\alpha} \tag{9}$$

This paper aims to determine whether γ varies over treatment groups. As I noted earlier, cost-minimizing investments require that $\gamma = 1$ (signifying a one-to-one tradeoff between upfront costs and future fuel costs). Once each participant is assigned an individual $\hat{\gamma}$, I regress this coefficient on treatment group and individual characteristics as

$$\hat{\gamma}_i = \sum_{k=1}^{8} \lambda_k TREAT_k + \eta_i \mathbf{x}_i + \epsilon_i \tag{10}$$

where $TREAT_k$ is a dummy which equal one if participant i was in Treatment k, and $\mathbf{x}_i$ are a set of individual characteristics such as income, sex, education, etc.

3 Experimental Design

The use of stated preference data allows me to control for vehicle attributes which may be correlated with fuel economy. In each choice scenario, respondents are told that each vehicle is the same in all respects except for price and fuel economy. Many vehicle attributes which consumers have strong preferences for, such as size or luxury, are negatively correlated with fuel economy. Moreover, gathering revealed preference data on the effect of information changes is nearly an intractable problem. A researcher could theoretically gather purchase data for before and after label changes in different countries, but the data would be highly time-consuming to compile.[2]

Of course, the use of stated preference data has its own shortfalls. Perhaps the largest is the possibility that respondents do not select choices that they would in a real-world scenario. Lusk et al. (2006) compared actual retail sales and projected sales from an experiment in grocery and found that in the experiment, consumers give socially-motivated responses. Perhaps consumers in this experiment will overstate their preferences for fuel economy because of a negative social association with gas-guzzlers. This could bias our estimates of willingness to pay upwards.

3.1 Survey Sample

I distributed the survey via Amazon Mechanical Turk. Each participant was paid to take the survey. The survey took the vast majority of participants between 5 and 10 minutes to complete. The instructions told potential participants that they must reside in the U.S. and that they must have purchased a new car to participate. I impose these restrictions on participation to ensure that each participant could place choice decisions in a real-world context. Potential respondents in other countries would be likely to place fuel economy decisions in the context of their own country, with differing policies on vehicles and gasoline. Potential respondents in other countries would also have a hard time realistically making decisions with our units (U.S. dollars, gallons, miles). Respondents were automatically screened out if they were not using a U.S. IP address. If a respondent answered "no" to a question asking them if they had ever purchased a new car, the survey ended and they were not asked to make choice decisions. 604 respondents began taking the survey. Of those, 475 were eligible to finish taking the survey. Of those, 96.7% of participants finished the survey, leaving us with a final sample size of 459. Table 1 provides descriptive statistics on our sample. Overall, our results are comparable to U.S. adult demographics. For comparison, I include means from the 2015 Current Population Survey. On average, our respondents had higher annual incomes, and higher levels of education, but were

[2]The researcher would also have to gather data on fuel economy standards, changes in subsidy or tax policies, etc.

significantly less likely to be employed.

Table 1: Descriptive Statistics of the Sample

Variable	Mean	SD	Median	Minimum	Maximum	CPS
Annual Income	48,839	26,813	42500	5,000	>100,000	30,176
Metropolitan area (yes,no)	0.86	0.38	1	0	1	
Employed (yes,no)	0.81	0.39	1	0	1	0.94
Education (bachelor's or higher)	0.72	0.45	1	0	1	0.39
Married (yes,no)	0.48	0.50	0	0	1	0.65
Sex (Male, Female)	0.52	0.50	0	0	1	0.49
Age	37.4	12.0	34	19	70	38

N=459

Note: Income was collected as a categorical variable. For example, if a participant earned $18,000 annually, then they would report that their income was in betwen $15,000 and $20,000. Binary variables assign 1 to "yes" and 0 to "no."

There was some concern that respondents would not take the time to adequately read the survey directions or think about their responses. The Amazon Mechanical Turk system pays participants to complete the survey without regard to the quality of their responses. In practice, this was not an issue. Mean response time was 4 minutes and 48 seconds. When I restricted the sample by screening out participants who took less than 3 minutes to complete the survey, the results were not affected. The choices and discount rates given by this group of participants were largely similar to the results collected from respondents who took longer to complete the survey.

3.2 General Structure and Survey Instructions

Participants were told that the purpose of the experiment was to better understand how consumers choose fuel economy. The survey consisted of three parts. The first asked participants general information about their income, car ownership history, education, and employment. The second part was used to assign each participant an individual discount rate. The third presented each participant with 10 different choice questions.

In the second section participants were told that the intent of this section of the survey was to better understand how they made intertemporal trade-offs. This section was used to assign each participant an individual-specific discount rate. Participants were asked to choose between two payments, payment one and payment two. The first payment was a lump sum delivered in one month, and payment two was a lump sum delivered in one year. Participants were given a series of choices between payment one and payment two, to reveal their point of indifference between payment one and two.

In the third part, participants were given ten choices where they were asked to choose between three vehicle alternatives. The instructions told respondents that they should select the vehicle option which they would purchase in a real world situation. It told participants that this meant selecting the option which they thought would be the most cost-effective. Since the only attributes to vary in each choice set was price and fuel economy, participants were asked to assume that the three alternatives were the same in all other respects (size, comfort, power, etc.). Participants were told that there was no risk of any car being a "lemon." Each car would have a lifetime of 12 years.

3.3 Discount Rate Elicitation

In this section, participants were asked to chose between two payments. The first payment was a \$1000 lump sum payment delivered in one month, and the second was a $\$1000 + \$x$ lump sum delivered in 1 year. I selected a lump sum of \$1000 to be similar to the trade-off decision that the participant would see in the choice sets.[3] Participants were told that they would receive the first payment in one month because previous researchers have found that discount rates tend to be inordinately high when participants are told that they would receive the money immediately (Newell, 2014). The one-year time horizon was chosen to reflect the long time horizon in the choice between up-front costs and future fuel costs. Depending on the participant's answer, the next question the participant saw changed. For example, if a participant said that they would rather receive $\$1,000$ in one year instead of $\$1,100$, then the next question that they would see would offer them a larger amount (converseley, if they prefered $\$1,000$, then then they would be

[3]The full choice set is shown in Table 8 in the appendix. You can see that alternatives in the same choice occasion differ in price by up to \$2100 and in annual fuel cost by up to \$298.

offered more money.)[4] Each survey participant was shown the following instructions:

> In this section you will be asked to choose between two possible lump-sum payments. Your first option in each question will be a $\$1,000$ check mailed to you in one month. Your second option will be a check of greater value mailed to you in one year from now. You can only choose one option. Both options are guaranteed to be delivered at their due day. You do not need to pay taxes on either. The only difference between the two checks is the delivery date and the payment amount. Please select the option which you would choose in a real world scenario.

The directions given to survey participants is quite similar to the language used by Newell et al (2014). Due to survey limitations, discount rate "resolution" decreases as discount rate increases. For discounts less than 0.4, I zero-in on a participant's point of indifference to a 0.01 level. For discounts of greater than 0.4, participants were assigned discount rates with less precision $(0.4, 0.45, 0.5, 0.5...0.7)$. No participant could be assigned a discount rate of higher than 0.7.[5]

3.4 Fuel Economy Label Treatments

The experiment was designed to evaluate the effectiveness of information on the label and not style[6]. I examine five different pieces of information; miles per gallon, gallons per 100 miles, estimated annual fuel cost, a five year fuel cost comparison, and a discrete grading system. Survey participants are randomly assigned to one of eight treatment groups show in Table 2. Treatments one and two only show a basic combined fuel economy in miles per gallon and gallons per 100 miles, respectively. Treatment three sees a label with gallons per 100 miles, estimated annual fuel cost, and the five year fuel cost comparison. Treatment four sees the same label as treatment three except that annual fuel cost has been replaced with a discrete fuel economy

[4] An example of the survey flow is shown in figure 7 in the appendix.

[5] The discount rate had to be capped at some level due to time constraints. In experiment test rounds, few participants had discount rates higher than 0.7.

[6] For example, I do not consider the effect of size or prominence of a piece on information on the label.

rating. Treatment five is the same as treatment four but fuel economy is given in MPG instead of miles per 100 gallons. Treatment six sees gallons per 100 miles, estimated annual fuel cost, and the discrete rating. Treatment seven sees every piece of information except for the discrete rating. Treatment 8 sees every piece of information. Table 7 in the appendix shows which pieces of information are in each treatment group. Once a participant was assigned to a treatment group, they were only shown labels corresponding to that treatment group. Each respondent was given the same choice set regardless of their treatment group. Participants were asked to make ten choices between three vehicle alternatives in each choice.

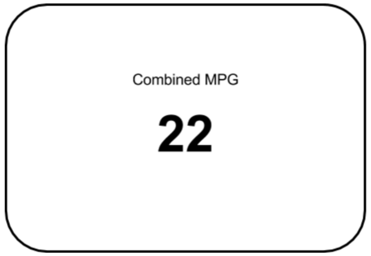
Estimated costs are calculated using the same assumptions that the EPA makes on 2016 fuel economy labels for gasoline vehicles: that gasoline prices remain $1.77 per gallon, that each vehicle drives 15,000 miles per year, and that each vehicle drives 55% of miles in the city and 45% of miles on the highway. The five-year fuel cost comparison tells the participant how much their estimated five year fuel costs deviate from the average new vehicle (25 MPG). If a vehicle has higher fuel economy than the average new vehicle, this piece of information says in bold font the estimated amount of money you will save in fuel costs over five years (conversely, if a vehicle had lower fuel economy then this piece of information would give an estimate of how much more money you would spend over five years). Estimated fuel cost information in the labels **is not** discounted. The discrete grade was assigned using the EPA grading system which was introduced on new car fuel economy labels in 2013.

3.5 Choice Set Design

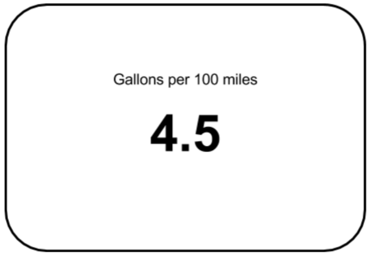
Survey participants were told to assume that the vehicles were the same in all respects except for price and fuel economy. All of the choices were within the price and fuel economy range of actual personal vehicles available on the market today. Descriptive statistics for the choices are shown it table 3. Average fuel economy was 25 MPG, exactly the mean for new cars today. A full list of choices in our set is given in the Appendix in Table 8. For each choice, the up-front cost and

Table 2: Treatment Labels

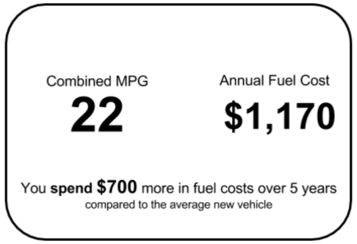
Treatment 1



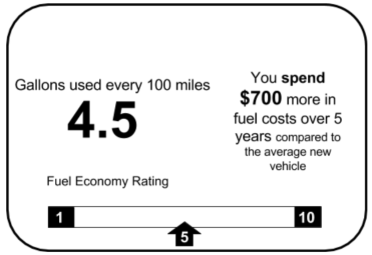
Treatment 2



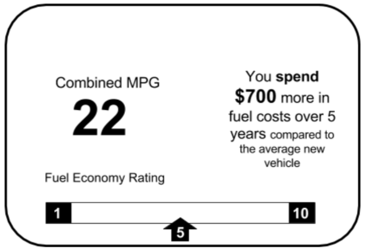
Treatment 3



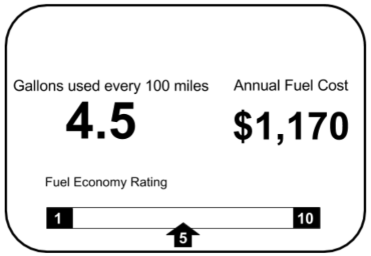
Treatment 4



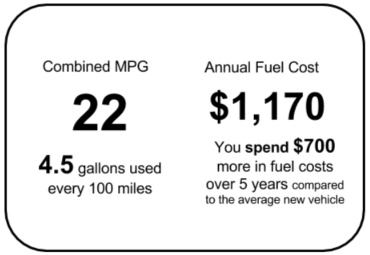
Treatment 5



Treatment 6



Treatment 7



Treatment 8

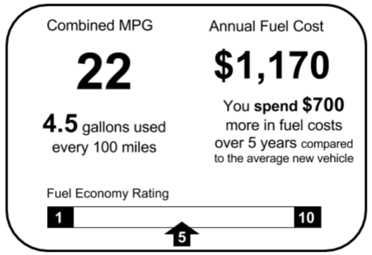
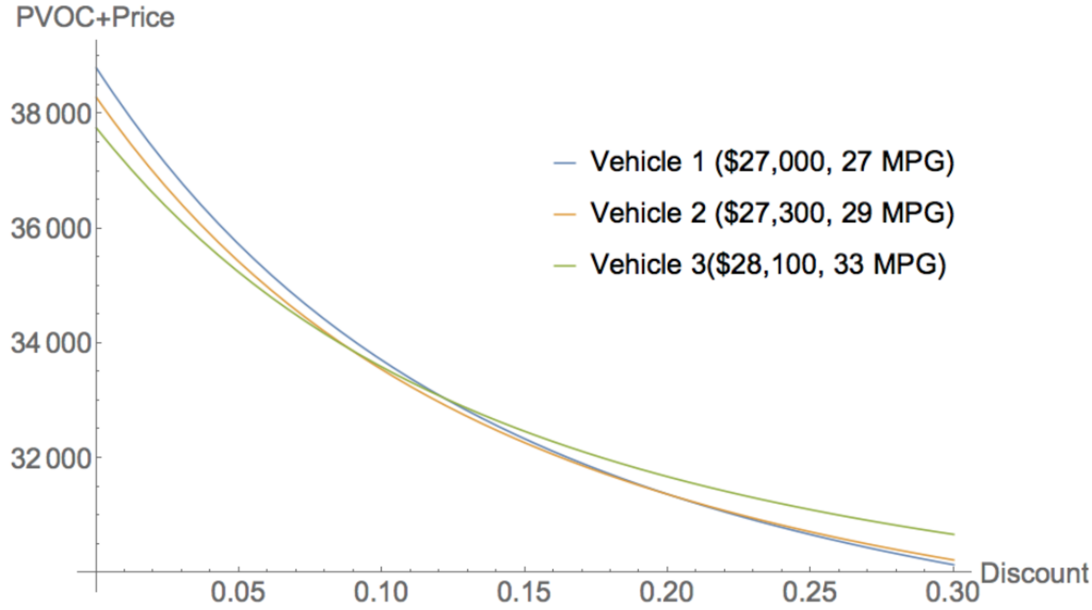


Figure 1: Sum of Up-Front Price and Present Value of Operating Cost for Three Alternatives Against Discount Rate



fuel efficiency for each of the three alternatives was similar. Each of the three alternatives would be plausible options for a consumer searching for a vehicle of that class.[7]

For each choice the relationship between price and fuel economy is strictly positive. In other words, the most expensive option was always the most fuel efficient and the cheapest option was always the least fuel efficient. For each choice, there was no "obvious" choice. That is, each alternative was the cost-minimizing choice for some reasonable range of discount rates. Figure 1 shows the sum of price and $PVOC$ as a function of discount rate for three alternatives. As you can see, the green option, which has a high up front cost and high fuel economy minimizes cost for low discount rates, while the blue option, which has a lower up front cost and lower fuel economy, minimizes costs for high discount rates.

[7]For example, one choice might be between three alternatives which could all be small sedans

Table 3: Descriptive Statistics of the Choice Set

Variable	Mean	Standard Deviation	Minimum	Maximum
Price	25,912	5,266	16,000	34,500
Annual Operating Cost	1048	254	661	1,613
PVOC (5% Discount)	10,335	2,501	6,520	15,909
PVOC (Individual Discount)	4,905	3,356	1,604	19,767
MPG	25	4.2	16	35

Note- Annual operating cost is calculated assuming 15,000 miles driven annually and that the price of gas is $1.77 per gallon. MPG is a combined estimate which assumes 55% of miles are driven in the city and 45% are driven on the highway.

4 Results

4.1 Discount Rate Solicitation

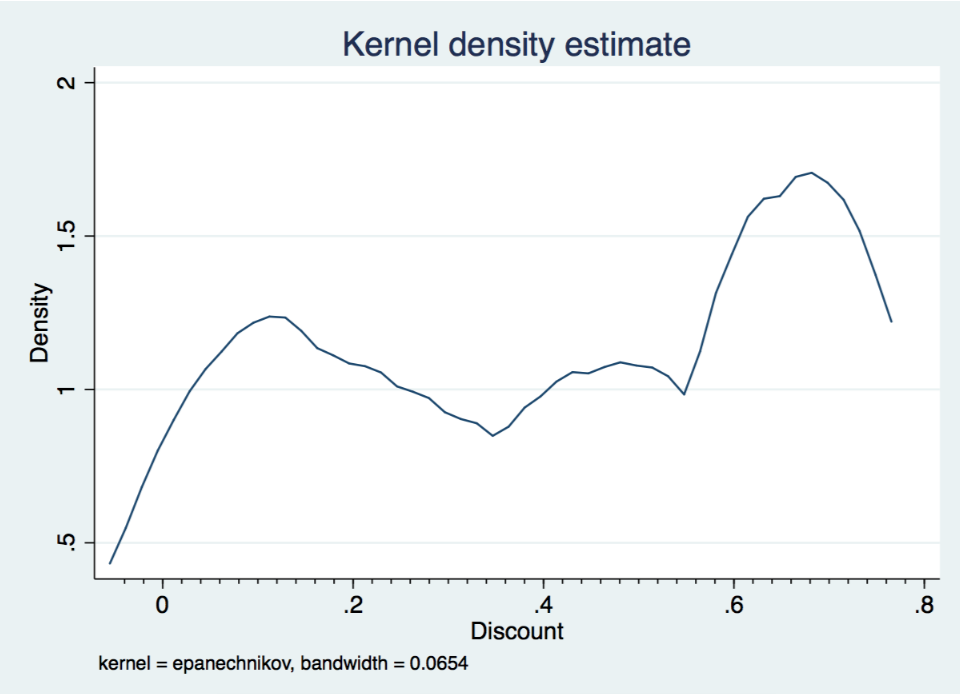
Discount rates were unusually high compared to discount rates solicited in the literature. Elicited discount rates tend to be significantly higher than market interest rates (Newell et al., 2014). Studies often find discount rates of 15% to 20%. During the preliminary testing of the survey, I found a mean discount rate of 0.24. In the final survey, the mean discount rate was 0.40, which is discouraging. Moreover, this mean was biased downward because a participant couldn't be assigned a discount rate of higher than 0.70 (presumably, some of the respondents would have had a higher discount rate).

The density plot of solicited discount rates is show below in Figure 2. The odd shape can be attributed to two survey design limitations. First, since I expected discount rates to be lower, the highest discount rate an individual could be assigned was 0.7 which explains the large hump around 0.7. Second, discount rate resolution decreased for high discount rates which explains the "lumpiness" of the right-hand side of the distribution.

4.2 Qualitative Observations on Choice

I begin presenting my results by providing some qualitative observations from the data. Figure 3 shows histograms by treatment for the proportion of times respondents chose the most fuel efficient outcome. The x-axis denotes proportion of times a respondent chose the most fuel

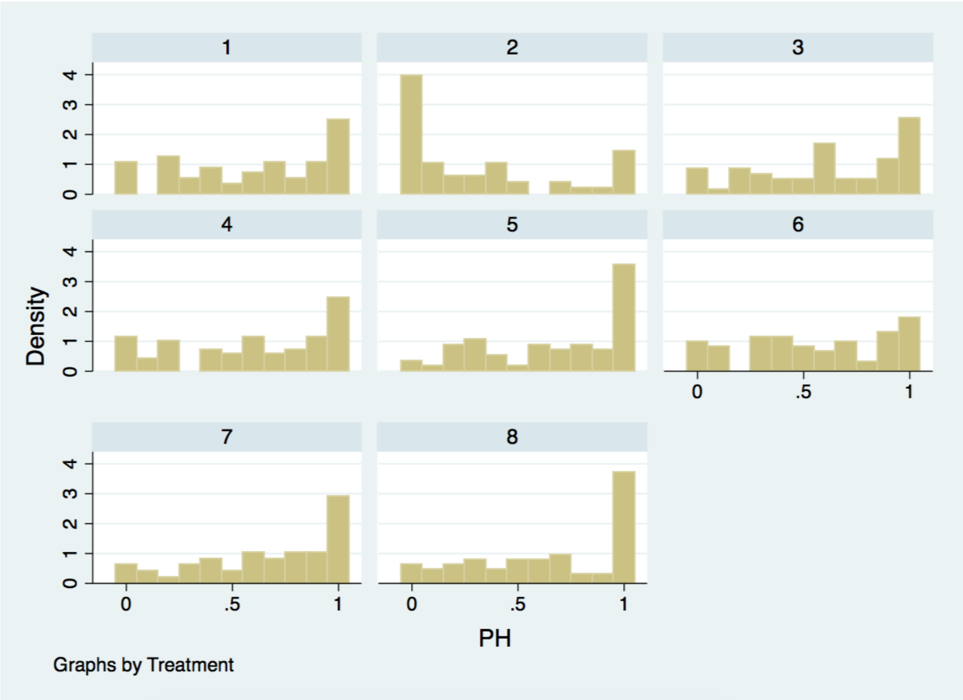
Figure 2: Distribution of Individual Discount Rates



efficient outcome. If a respondent selected the most fuel efficient option in all ten questions, then he would be placed in the ”1” bin. If a respondent selected the most fuel efficient option in five of the ten questions, then he would be placed in the ”0.5” bin.

There are some important observations to be made from this alone. For example, a very high proportion of respondents in treatments 5, 7, and 8 selected the most fuel efficient outcome in each choice scenario. Each of these treatments saw labels with MPG and the five year fuel cost comparison. Treatments 2 and 6 had lower proportions of respondents selecting the most fuel efficient options and these treatments were the only two which showed fuel economy in gallons per 100 miles without a five year fuel cost comparison. This evidence alone seems to suggest that certain pieces of information, especially estimated cost information, uniformly increases willingness to pay for reduced PVOC. These results are qualitatively similar to the results of Newell et al. (2014), who found that estimated cost information induces cost-effective choices while the lack of estimated cost information results in undervaluation.

Figure 3: Histograms by Treatment for the Proportion of Times Respondents Selected the Most Fuel Efficient Option



4.3 Willingness to Pay Estimation

I used the "mixlogit" package in STATA to produce the individual willingness to pay estimates with 500 Halton draws.[8] In my estimation, the coefficient on operating cost, β_i is allowed to vary across individuals. My estimates for the mixed logit model are shown in table 4. In the first model, individual operating cost is calculated using individual-specific discount rates which were elicited in the survey. In the second model, PVOC is calculated using a uniform 5% discount rate, following Newell et al. (2014).

Table 4: Mixed Logit Estimation of Choice

	Model 1 (Individual Discount Rate)				Model 2 (Uniform 5%)			
Variable	Coefficient	S.E.	Z	$P > \|z\|$	Coefficient	S.E.	Z	$P > \|z\|$
Price	-0.0033	0.0002	-14.35	0.000	-0.0041	0.0002	-17.48	0.000
PVOC	-0.0097	0.0006	-15.89	0.000	-0.0041	0.0002	-20.12	0.000

Since price is a fixed parameter, expected willingness to pay of individual i for a $1 reduction

[8]Halton draws are simply a way to generate pseudorandom numbers for use in simulation. The use of halton draws is the default in the mixlogit package.

in $PVOC$ is

$$E[WTP_i] = \frac{E[\beta_i]}{\alpha},$$

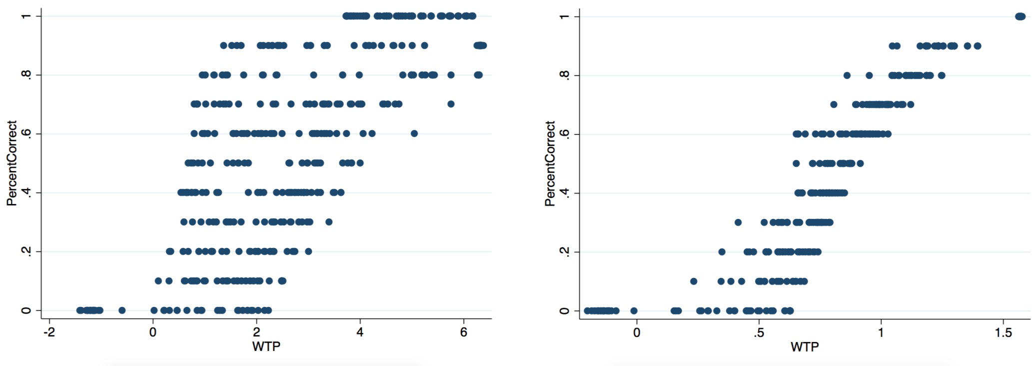
where β_i is individual i's estimated coefficient on $PVOC$ and α is the fixed coefficient estimated on price. Thus, average WTP is simply given by the ratio of the two coefficients in table 4. I find full valuation when operating costs are calculated using a uniform 5% rate (mean WTP of \$0.99 for \$1 reduction in PVOC) and significant overvaluation using individual discount rates (mean WTP of \$2.94 for \$1 reduction in PVOC). This is an interesting result in itself, suggesting that consumers likely fully-value fuel economy.

To test goodness of fit, I use individual coefficients to produce individual choice probabilities using the "mixlpred" command in the mixlogit package. Coefficients from model 1 correctly predicted 58% of responses and coefficients from model 2 correctly predicted 59% of responses. Since participants were asked to choose between three alternatives in each choice scenario, the model did significantly better than random. Nonetheless, both models display some heteroscedasticity in that they both over predict the most fuel efficient outcome. In figure 4 you can see that the model predicted a higher percentage of responses for respondents assigned higher willingness to pay coefficients. Nonetheless, the individual willingness to pay estimates do capture relative willingness to pay between participants. As expected, if one individual choose more fuel efficient choices then another individual with the same discount rate, then the former would be assigned a higher WTP estimate. Thus, even though the model of fuel economy choice is not perfect, it does capture variation across individuals and correctly orders participants in WTP based on their observed choices.

4.4 Willingness to Pay Variation Across Treatment Groups

Next, I examine how individual WTP estimates vary based on treatment. From my qualitative analysis of choices by treatment group, treatments with the five year fuel cost are expected to have significantly higher WTP. Willingness to pay distributions for each treatment group are

Figure 4: Scatter Plot of Percentage of Choices Predicted Correctly Against Individual WTP Estimates in Model 1 and Model 2, Respectively



(a) Model 1 (b) Model 2

shown for individual discount rates and uniform %5 rates in figures 5 and 6, respectively.

I test whether mean WTP has statistically significant differences across treatment groups. I simply regress WTP by treatment group dummies and a number of individual-characteristic covariates. Table 5 displays these results. Most pairwise comparisons between treatment groups are statistically indistinguishable. For example, Treatments 7 and 8 are statistically indistinguishable from each other in both model 1 and model 2 (because their standard error intervals overlap). In fact, treatment 2, which only shows participants miles per 100 gallons, is the only treatment group which is statistically distinct from other treatment groups.

In my qualitative analysis, I visually picked out treatments 5, 7,and 8 for having especially high proportions of respondents choosing the most fuel efficient options. Are these groups statistically different from others, even if they are very similar to each other? Each of these treatment groups shows participants both MPG and the five-year fuel cost comparison. To test this, I regress willingness to pay on a dummy which equals one if the participant saw both MPG and the five year fuel cost comparison and the individual characteristics used in the previous regressions. Results are reported in Table 6. The mean for groups which did not see these two pieces of information together was significantly lower in both models. In model 2, where PVOC is calculated with a uniform 5% rate, participants who don't see these two pieces of information significantly *undervalue* fuel economy.

Table 5: OLS of Willingness to Pay by Treatment Group

$n = 459$	Model 1 (Individual Discount Rates)				Model 2 (Uniform 5%)			
Covariate	Coefficient	Std. Err.	t	P> $\|t\|$	Coefficient	Std. Err.	t	P> $\|t\|$
Treatment 1 (yes,no)	3.26***	0.50	6.54	0.000	0.79***	0.12	6.82	0.000
Treatment 2 (yes,no)	1.65***	0.51	3.24	0.001	0.41***	0.12	3.46	0.001
Treatment 3 (yes,no)	3.36***	0.49	6.82	0.000	0.80***	0.11	6.98	0.000
Treatment 4 (yes,no)	3.27***	0.48	6.77	0.000	0.81***	0.11	7.13	0.000
Treatment 5 (yes,no)	3.81***	0.51	7.48	0.000	0.92***	0.12	7.70	0.000
Treatment 6 (yes,no)	3.15***	0.50	6.34	0.000	0.75***	0.12	6.43	0.000
Treatment 7 (yes,no)	3.46***	0.49	7.04	0.000	0.89***	0.11	7.78	0.000
Treatment 8 (yes,no)	3.55***	0.47	7.49	0.000	0.91***	0.11	8.17	0.000
Married (yes,no)	-0.47***	0.19	-2.43	0.016	-0.14***	0.04	-3.08	0.002
Employed (yes,no)	-0.21	0.24	-0.88	0.381	0.006	0.056	0.11	0.916
Sex	-0.47***	0.18	-2.66	0.008	-0.04	0.04	-1.07	0.289
Bachelor's Degree (yes,no)	-0.16	0.19	-0.80	0.42	0.013	0.045	0.30	0.766
Income	-2.78×10^{-7}	3.64×10^{-6}	-0.08	0.94	8.40×10^{-7}	8.51×10^{-7}	0.99	0.324
Metropolitan	0.16	0.24	0.65	0.51	0.058	0.056	1.03	0.304
Age	0.009	0.008	1.22	0.22	0.005***	0.002	2.70	0.007
R^2	0.11				0.12			
F	3.95***				4.37***			

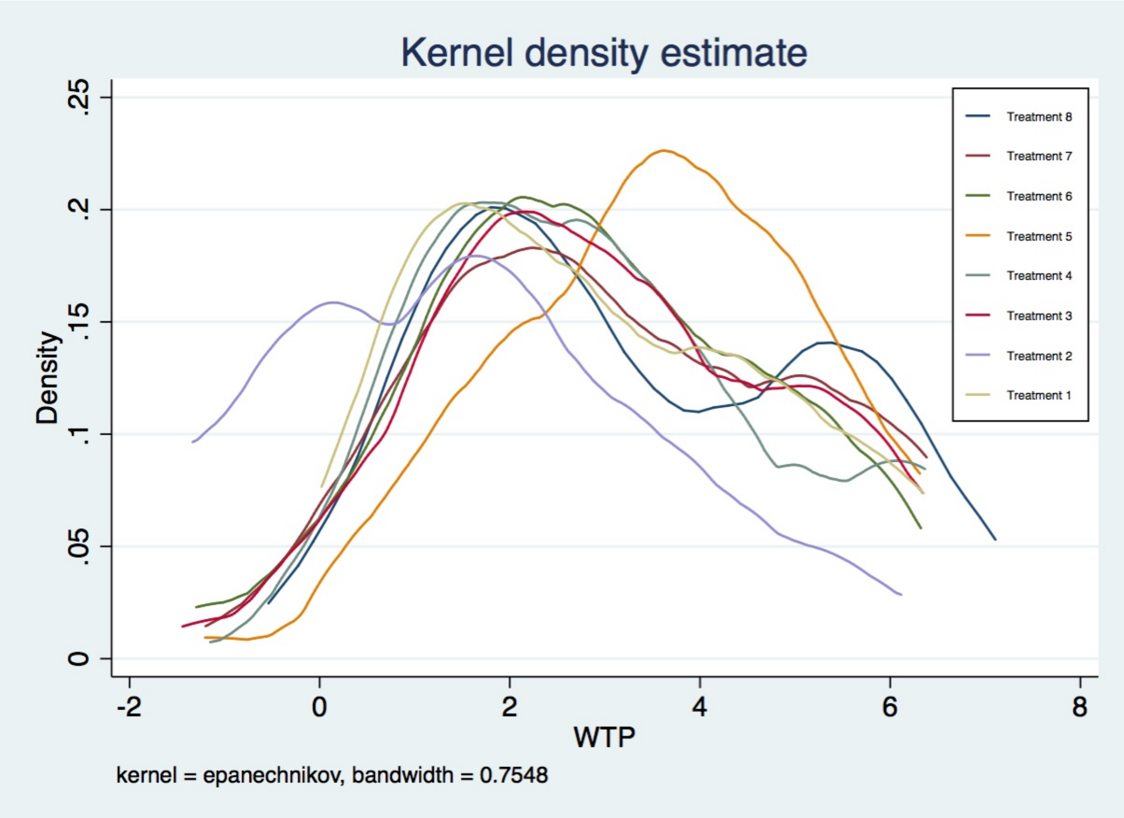
Note- Each treatment coefficient is the mean willingness to pay in that treatment group. The number of observations is 459. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 6: OLS on the Effect of Including MPG and Five-year Fuel Cost Comparison on WTP

	Model 1				Model 2			
Variable	Coefficient	S.E.	Z	$P > \|z\|$	Coefficient	S.E.	Z	$P > \|z\|$
MPG and Five-year	0.500***	0.188	2.66	0.008	0.120***	0.044	2.73	0.007
Constant	3.082***	0.450	6.85	0.000	0.773***	0.106	7.31	0.000
Metropolitan (yes,no)	0.128	0.246	0.52	0.603	0.049	0.058	0.85	0.395
Income	$1.16 * 10^{-7}$	$3.73 * 10^{-6}$	0.03	0.975	$9.29 * 10^{-7}$	$8.76 * 10^{-7}$	1.06	0.289
Bachelor's (yes,no)	-0.144	0.197	-0.73	0.464	0.016	0.046	0.34	0.737
Age	0.006	0.008	0.78	0.437	0.004**	0.002	2.11	0.035
Married (yes,no)	-0.443***	0.183	-2.24	0.025	-0.13***	0.05	-2.81	0.005
Employed (yes,no)	-0.146	0.242	-0.60	0.547	0.013	0.057	0.22	0.824
Sex (Male,Female)	-0.444	0.183	-2.43	0.016	-0.040	0.043	-0.92	0.36
R^2	0.04				0.04			
F	2.37**				2.37**			

Note- The number of observations is 459. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

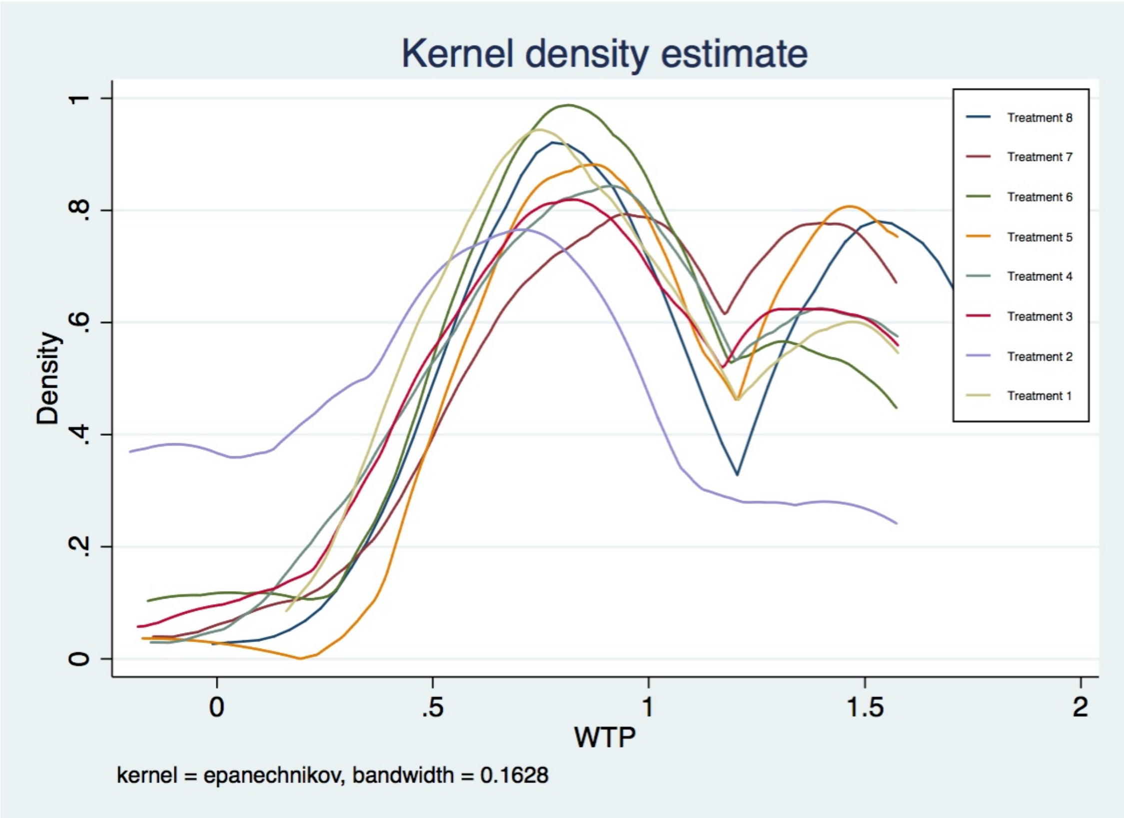
Figure 5: Willingness to Pay Distributions by Treatment Group Calculated with Individual Discount Rates



5 Conclusions

This paper evaluates how five pieces of information in fuel economy labels affects consumer choice. I was able to disentangle the effects of discounting and information on choice by individually soliciting discount rates. Willingness to pay is largely similar across treatment groups. But, there are some important differences. Treatment groups which saw a five year fuel cost comparison and fuel economy in MPG have significantly higher willingness to pay for fuel economy investments. Participants which saw fuel economy in gallons per 100 miles without the five-year fuel cost estimate have significantly lower willingness to pay for reduced $PVOC$ then other respondents. This is likely attributable to the fact that consumers rarely see fuel economy expressed like this. MPG is the standard way to express fuel economy in the U.S. If the standard was expressing fuel economy in gallons per 100 miles, I likely wouldn't have found such undervaluation in these

Figure 6: Willingness to Pay for a $1 Reduction in PVOC: Distributions by Treatment Group Calculated with Uniform Discount Rates



treatment groups. This result seems to contradict previous experimental studies like that of Larrick et al. (2008) which suggest that consumers are able to process fuel economy in linear terms more efficiently.

Perhaps the most striking result is the staggering mean overvaluation of $PVOC$ given individual discount rates and perfect mean valuation of $PVOC$ with a uniform 5% discount rate. This result suggests that consumers are fully valuing fuel economy, but reaching that full valuation in a roundabout way. They overvalue fuel economy given their own discount rates, but perfectly value fuel economy given "reasonable" discount rates.

The largest caveat in this research likely relates to the survey design. While a mean discount rate of 0.41 is not unprecedented, it is quite high[9]. If the survey design biased each individual's

[9]Researchers have found discount rates in excess of 100% in experimental settings. See Newell et al. (2014) for a brief summary of discount rate findings in the experimental literature.

discount rate upwards, then each person's willingness to pay for PVOC would be *overstated.* Further, Lusk et al. (2006) noted that respondent's answers in a stated preference survey may be socially motivated. Again, this would bias the estimates of WTP for reduced PVOC upwards.

Nonetheless, this research does suggest that current fuel economy labels likely guide cost-minimizing consumer choices. Estimated cost information, especially, seems to guide cost-effective choices. Furthermore, this research suggests that policy-makers could improve consumer welfare by extending the labeling scheme to used-cars, which is currently only voluntary in the U.S.

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8 Appendix

Table 7: Treatment Groups

Treatment Group	1	2	3	4	5	6	7	8
MPG	X				X		X	X
Gallons/100 Miles		X	X	X		X	X	X
Discrete Rating				X	X	X		X
Annual Fuel Cost			X			X	X	X
Five year comparison			X	X	X		X	X

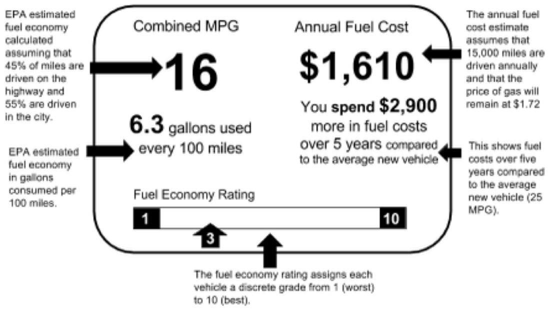
Table 8: Vehicle Choice Set

Choice	Option	Combined MPG	Price	Estimated Annual Fuel Cost	EPA Discrete Rating
1	1	20	27000	1290	4
	2	22	27750	1173	5
	3	26	29200	992	6
2	1	16	23000	1613	3
	2	18	23700	1433	4
	3	20	24800	1290	4
3	1	27	27000	956	6
	2	29	27300	890	7
	3	33	28100	782	8
4	1	30	30000	860	7
	2	33	30300	782	8
	3	38	30950	679	9
5	1	23	33000	1122	5
	2	24	33500	1075	5
	3	28	34500	921	7
6	1	22	25000	1173	5
	2	23	25200	1122	5
	3	26	26300	992	6
7	1	32	16000	806	8
	2	35	16300	737	8
	3	39	17000	662	9
8	1	27	17500	956	6
	2	29	17850	890	7
	3	31	18200	832	7
9	1	23	24500	1122	5
	2	25	24800	1032	6
	3	28	25500	921	7
10	1	16	30000	1613	3
	2	18	31000	1433	4
	3	20	32100	1290	4

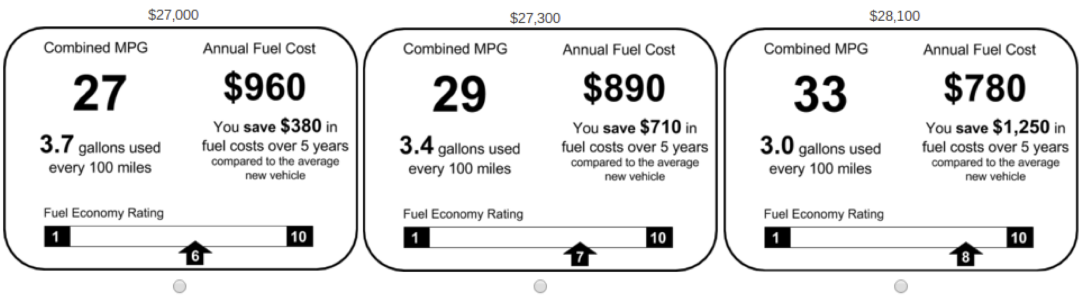
Figure 7: Example of the Survey Flow

In this section of the survey you will be asked, in each question, to choose between three vehicle alternatives. You will see each vehicle's price and information on its fuel economy (pictured below). Please carefully consider the tradeoffs between price and fuel economy and select the option that you would choose in a real-world scenario. You may assume that these vehicles are the same in all respects except for price and fuel economy. None of these vehicles will be "lemons." You may assume that they will last for 12 years.

You may assume that you drive around 15,000 miles per year, and that the price of gasoline will stay at current prices ($1.72/gallon) .



Please select the vehicle option which you would choose as if you were selecting between these three alternatives. You may assume that these vehicles are the same in every respect except for fuel economy and price.



Please select the vehicle option which you would choose as if you were selecting between these three alternatives. You may assume that these vehicles are the same in every respect except for fuel economy and price.