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Abstract

Consumer undervaluation of energy cost savings is a common explanation for the energy efficiency gap, where markets fail to adopt fuel-saving technologies even though the value of the savings exceeds the costs. This paper presents empirical evidence on the relationship between a possible cause of empirical studies finding undervaluation – consumer inattention – and the demand for fuel cost savings in automobiles. Using survey data on respondents' attention to automobile fuel costs, attribute preferences, and discrete choice experiments, I find heterogeneity in inattention toward and willingness to pay for fuel cost savings. Estimates from discrete choice models suggest that inattentive consumers make choices as if they undervalue fuel cost savings and attentive consumers make choices as if they fully value these savings. The data show that respondent-specific characteristics that influence fuel costs, such as vehicle miles traveled, partly explain the degree of inattention, a finding that is consistent with models of rational inattention. The results imply that designing energy efficiency policies requires careful consideration of consumer inattention.

Key Words: Inattention, Energy Efficiency Gap, Discrete Choice

JEL Classification Numbers: C25, D46, L62, Q41

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1 Introduction

How markets value energy efficiency is crucial for evaluating the costs and benefits of energy policies. In markets without economic distortions, the price of greater energy efficiency reflects its benefits: reductions in energy costs are capitalized in higher purchase prices. In this setting, imposing binding energy efficiency programs reduces private welfare. With distortions, however, markets may undervalue energy efficiency, which has become known as the "energy paradox" or the "energy efficiency gap." For certain market distortions, imposing binding energy efficiency programs can increase private welfare.[1] These gains can dominate costs, a possibility that promotes aggressive policies. Government analyses of recent federal energy efficiency policies, including regulations for new light-, medium-, and heavy-duty vehicles, find this result, implying that the regulations benefit consumers without considering external costs and benefits (NHTSA, 2012, 2016).

A substantial body of empirical evidence for a gap is in the form of consumer undervaluation of fuel cost savings in automobiles. The evidence compares willingness to pay (WTP) for fuel cost savings and the lifetime value of the associated savings. Estimates of WTP that fall below the lifetime value suggest undervaluation. Recent economics literature has found conflicting evidence for undervaluation. Busse et al. (2013) and Sallee et al. (2016) identify WTP for fuel cost savings in new and used automobiles using gasoline price variation and find that consumers fully value fuel cost savings. Allcott and Wozny (2014) find undervaluation, where consumers are willing to pay 76 cents for one dollar of fuel cost savings.[2] Grigolon et al. (2018) use fuel price variation in Europe and find modest undervaluation. Leard et al. (2017) identify how consumers value increases in fuel economy using variation in fuel-saving technology adoption caused by tightening fuel economy standards. Their estimates imply that consumers are willing to pay 52 cents for

[1] See Allcott and Greenstone (2012) for an overview of this subject.

[2] This estimate is derived from the assumption that consumers form expectations of future fuel prices based on crude oil futures prices. The other two methods that they use, including a random walk and survey-based expectations, yield lower willingness to pay.

one dollar of fuel cost savings, suggesting undervaluation.

The conflicting evidence motivates an examination of underlying reasons why consumers may undervalue fuel cost savings. The literature provides several causes of a gap, including loss aversion (Greene, 2011; Greene et al., 2013), principal-agent issues (Davis, 2012), credit constraints (Golove and Eto, 1996), hyperbolic discounting (Heutel, 2015), self-control problems (Tsvetanov and Segerson, 2013), and consumer inattention (Allcott, 2011; Sallee, 2014; Turrentine and Kurani, 2007). Hardly any research tests these explanations with data. One exception is Bradford et al. (2014), who find a positive correlation between hyperbolic discounting and low demand for energy-efficient products.

I add to this literature by focusing on consumer inattention and leverage survey data that include experiments involving respondents choosing a new vehicle. Based on the discrete choice experiment data, I estimate random utility model preference parameters for vehicle price, fuel costs, and other attributes and use the estimated parameters to infer an implied willingness to pay for fuel cost savings. I then correlate respondent stated attention to fuel costs during their prior vehicle purchase to their valuation coefficient implied by their responses in the discrete choice experiments. This approach is related to an existing literature on the relationship between stated attention and implied WTP elicited from discrete choice experiments. Balcombe et al. (2015) find that stated attention diverges sharply from visual attention recorded from eye-tracking, but that stated attention is useful for incorporating into utility function estimation. I leverage this insight by estimating utility parameters as functions of stated attention. Another relevant paper in this literature is Cameron and DeShazo (2010), which provides a theoretical framework for how inattention to attributes may bias WTP toward zero and presents empirical evidence on the magnitude of this bias. While the survey data in the current paper are not rich enough to estimate how WTP may change if inattentive respondents become attentive, the data can reveal how estimated WTP for certain attributes are related to inattention. This is useful for understanding the role that inattention may play in empirical findings on the energy efficiency gap.

Based on the estimated coefficient estimates from the random utility models, I find that the average respondent undervalues fuel cost savings: he or she is willing to pay 45 cents to reduce present value lifetime fuel costs by one dollar. I find, however, that willingness to pay is strongly correlated with stated attention to fuel costs. Inattentive respondents make experimental choices as if they undervalue fuel costs, while attentive respondents make choices as if they fully value fuel costs.

This evidence suggests that the level of inattention may explain estimated undervaluation. The survey data also include information about factors influencing respondent-specific fuel costs, such as annual vehicle miles traveled. I find that these factors are correlated with the level of attention toward fuel costs, suggesting that the degree of inattention is a rational decision. Together these results motivate careful consideration of consumer inattention in the design of policies aiming to reduce fuel consumption from light-duty vehicles.

2 Evidence on the Relationship Between Inattention and Demand for Fuel Cost Savings

2.1 Data

To analyze the relationship between consumer inattention and demand for energy efficiency, I leverage data from a Qualtrics survey administered during September and October 2014. The survey asked respondents a series of questions about vehicle ownership, demographics, and preferences for vehicle attributes. The original sample included 1,226 responses. After cleaning the data by dropping observations with missing responses to demographics and relevant preference questions, 1,125 usable responses remain.[3]

Table 1 provides summary statistics of the sample. Based on observed household

[3] I drop households that do not report demographic information including education level, gender, age, income, political affiliation, employment status, and state. I also drop households that do not report a response to Question 9 of the survey (see text).

characteristics, the sample represents the entire U.S. population based on observed demographics.[4] Mean and median household incomes are $61,780 and $55,000, respectively, which are similar to estimates from the 2013 American Community Survey.[5] The sample's fraction of married adults is close to the U.S. marriage rate of around 50 percent. The unemployment rate of 5.15 percent is lower than but close to the reported national unemployment rate for September 2014 of 5.9 percent.[6]

The survey asked respondents to report information on the vehicle used most often by the respondent, including model year, make, model, series, and fuel type. I merge vehicle characteristics such as horsepower, weight, and city/highway fuel economy using characteristics data from Wards Automotive.

2.1.1 Inattention to Fuel Costs

The survey included questions on how respondents value fuel cost savings and their perceptions of fuel costs when they bought their most often used vehicle. To prime respondents to think about their vehicle purchase, the survey began by asking respondents about characteristics of the vehicle they drive most often, including the production year, the make, model, and trim, fuel type (e.g., gasoline), and annual mileage. The next survey question then addressed how attentive to fuel costs the respondents were when they bought their vehicle, which is similar to the question posed in the Vehicle Ownership and Alternatives Survey (VOAS) and presented in Table 1 of Allcott (2011):

Question 9: Think back to the time when you were deciding whether to purchase your current vehicle. At that time, how much did you think about fuel costs for your vehicle or other vehicles you could have bought?

1. I did not think about fuel costs at all.

[4] The original design of the survey was meant to represent the U.S. population of driver's license holders.

[5] source: http://www.census.gov/content/dam/Census/library/publications/2014/acs/acsbr13-02.pdf

[6] source: http://data.bls.gov/timeseries/LNS14000000

2. I did think some about fuel costs, but I did not do any calculation at all.

3. I made some calculations to compare fuel costs.

Summary results and correlations with the attributes of the vehicle held by each respondent are presented in Table 2. Of the 1,125 cleaned sample, 24 percent stated that they did not think about fuel costs at all, suggesting a significant fraction of vehicle owners were inattentive to fuel costs when purchasing their vehicle.[7] About 52 percent selected the second option, representing a partial attention response, and the remaining 24 percent selected the third option, representing a full attention response.

In Table 2, I present results from a series of regressions to understand how inattention to fuel costs influences the types of primary vehicles reported by respondents. Each specification corresponds to regression with a different vehicle characteristic as the dependent variable. I control for demographic and economic characteristics by including fixed effects for education level, gender, household head age, household income, political affiliation, employment status, and state of residence. The omitted group response to Question 9 – representing 24.4 percent of responses – is the response "I made some calculations to compare fuel costs." so that the marginal effects are interpreted relative to this group. Column (1) reports regression results where fuel economy, measured as highway and city combined miles per gallon, is the dependent variable. The marginal effect of answering Question 9 as inattentive to fuel costs is a lower combined fuel economy rating of about 3 miles per gallon, which is statistically significant at the 1 percent level.

[7] Allcott (2011) found this percentage to be 40 percent among participants in the VOAS data. This difference may be driven by three features that differentiate VOAS from the Qualtrics survey. First, prior to the attention question, the VOAS had several questions requesting the respondents to calculate fuel costs of the vehicles they own. Second, this survey provided more options to answering the question. These differences may have prompted different thought processes of the respondents, leading to differences in the options selected by the respondents. The third possible reason for differences in response proportions is when the surveys where administered. The VOAS was administered in October 2010, whereas the Qualtrics survey was completed in October 2014. Therefore, average fuel prices were likely higher for respondents in the VOAS. More than 50 percent of respondents report that the vehicle they use most often is no older than a 2007 model year. Between 2007 and 2014, gasoline prices averaged around \$3 to \$4 per gallon. Gasoline prices were much lower in the early 2000s, a time period when many respondents in the VOAS bought their vehicle. Regardless of the differences between the surveys, however, they both suggest that a large fraction of vehicle buyers were inattentive to fuel costs when they made their most recent purchase.

2.2 Relationship Between Inattention and Willingness-to-Pay for Fuel Cost Savings

In this subsection, I present two forms of evidence on the relationship between attention to fuel costs and WTP for fuel cost savings.

2.2.1 Evidence from Survey Questions

The first form of evidence comes from direct questions on WTP for hypothetical fuel cost savings over the course of five years from the purchase date. The questions are worded similar to a survey analyzed in Greene et al. (2013) and take the following form:

Consider that you are about to buy a new car. Suppose an optimal engine was available, just as good in all respects as the engine you may consider buying, but more fuel efficient. If the optimal engine would save you [dollar amount] in fuel over 5 years, how much EXTRA would you be willing to spend for the vehicle?

The survey has separate questions for the dollar amount, including $2,000 and $8,500. The $2,000 in savings represents the difference in fuel costs between two similar vehicles – for example, a 24 mpg and a 31 mpg vehicle each driven for 12,500 miles per year at $3.30 per gallon.[8] The $8,500 in savings represents a comparison of two extremely different vehicles – for example, an 18 mpg and a 70 mpg vehicle each driven for 12,500 miles per year at $3.30 per gallon. For each question, respondents were able to provide a dollar amount (rounded to the nearest dollar) representing their willingness to spend extra for the more fuel efficient version.[9]

To understand the relationship between inattention and willingness to pay, I regress the log of the stated willingness to pay for each level of fuel cost savings on the stated level of attention from Question 9 of the survey. To account for the effect of other observable

[8] According to the 2009 National Household Travel Survey, average vehicle miles traveled of new vehicles is about 12,500 per year over the first five years of a vehicle. The national average gasoline price when the Qualtrics survey was administered was about $3.30 per gallon.

[9] This question appears after a series of questions about the respondent's currently owned vehicle including how much they drive it so that respondents are primed to thinking about vehicle attributes.

characteristics on willingness to pay, I include the same set of demographic fixed effects that appear in the models in Table 2. The results of these regressions appear in Table 3. The coefficients for each attention variable are negative and statistically significant at the 5 percent level. The negative sign implies that inattentive respondents state that they are willing to pay less for fuel cost savings than attentive respondents. Since the dependent variables are logged, the coefficients are interpreted as semi-elasticities. Therefore, the inattentive respondents state that they are willing to pay about 31 percent and 37 percent less for fuel cost savings of $2,000 and $8,500 over five years, respectively, relative to attentive respondents.

If we interpret these values as differences in willingness to pay, then inattentive respondents appear to value undiscounted fuel cost savings substantially less than attentive consumers. Therefore, either inattentive respondents have high private discount rates, or they value the present value of fuel cost savings less. To identify which of these possibilities is more likely, I use data from the survey on elicited discount rates. Elicited discount rates are derived from a series of questions based on the multiple price list method Coller and Williams (1999).[10] The average discount rates for the inattentive, partially attentive, and attentive respondents are 14.9 percent, 12.3 percent, and 13.0 percent, respectively. Although discount rates are slightly higher for the inattentive respondents, this difference hardly explains the large gap in stated willingness to pay.

These results are derived from stated preference questions, which may lead to biased estimates of true willingness to pay and therefore do not represent preferences of respondents in a market setting. Hypothetical bias stems from situations where respondents do not have market experience (Hausman, 2012). In the current context, each respondent reported having purchased a vehicle. But not every respondent may have compared two vehicles based on their fuel costs. Respondents likely used alternative choice methods for narrowing down their choices, and the final few vehicles they considered may have had similar fuel costs.

[10]See Daziano et al. (2017) for details on how these discount rates are elicited.

Hypothetical bias tends to result in inflated estimates of willingness to pay (Hsiao et al., 2002; Morwitz et al., 2007). To explain the results from Table 3, the bias would need to be more pronounced among the attentive respondents, which is possible.

Another possible source of bias is the embedding effect, where "willingness to pay for the same good can vary over a wide range depending on whether the good is assessed on its own or embedded as part of a more inclusive package" (Kahneman and Knetsch, 1992). In the vehicle choice context, fuel economy is often related inversely to many desirable characteristics, such as horsepower or perceived safety. Some respondents may have responded to the willingness-to-pay question thinking that they would be trading off one or more of these characteristics to gain the stated fuel cost savings, as is the case when comparing two vehicles with different fuel economy ratings. This bias may be small, given the explicit statement within the question that all other characteristics of the vehicle are held fixed and only the engine is changed. But given that some optional engines trade-off performance characteristics (e.g., acceleration) with fuel economy, this bias may be large. But similar to the hypothetical bias, for the embedding effect to explain the stated preference results, the effect would need to be stronger for the inattentive respondents. These respondents may value performance-related characteristics more heavily than attentive respondents – as suggested by the vehicle attribute data in Table 2 – leaving this source of bias as a possibility.

Given that the stated preference results may be caused by standard biases present in stated preference questions, I supplement these results with discrete choice experiment methods that may partially mitigate these biases.

2.2.2 Evidence from Discrete Choice Experiments

A challenge in the differentiated product demand literature is identifying unbiased preferences for product attributes. The challenge arises because products typically have characteristics that consumers value, such a navigation system, that researchers do not observe. If these unobserved characteristics are correlated with observed characteristics, the estimated valuation of the observed characteristics will be biased. Berry et al. (1995) pioneered a method to handle this endogeneity problem in the discrete choice context, which requires instruments for the observed characteristics that are uncorrelated with unobserved characteristics.

Applying this method in the current context to recover willingness to pay for fuel cost savings requires several characteristics that are not available in the survey data. First, the method requires aggregate sales data (or at least an estimate of aggregate sales data).[11] Second, the method requires a valid instrument for each endogenous vehicle characteristic. The survey data includes a distribution of vehicle holdings: some were purchased new, and others were purchased used. The sample has about 100 respondents with new vehicles. The approach in Berry et al. (1995) could be applied to this sample, but the statistical precision would be low, given the small sample size. The survey data also lacks purchase price data, which has been shown to be necessary for obtaining accurate estimates of demand for fuel cost savings derived from discrete choice models (Langer and Miller, 2013).

An alternative to the revealed preference discrete choice approach is the reduced-form approach, such as Busse et al. (2013). This approach, however, requires a large number of observations and data on transaction prices and aggregate sales, as well as an exogenous source of variation in fuel costs. Moreover, the reduced form approach requires price and quantity data disaggregated by consumer type if the goal is to estimate preferences for subsamples of consumers. These requirements render the reduced form approach infeasible for the current setting.

Given these features, I use an experimental approach that has several advantages over using market data. The approach involves choice experiment methods, which are frequently used to elicit measures of willingness to pay for product attributes (McFadden, 1974; Newell and Siikamaki, 2014; Revelt and Train, 1998; Train, 2009). Respondents choose from a set of

[11] These data are necessary for constructing the empirical moment condition that aggregate sales shares equal predicted sales shares.

vehicles, which differ by values of relevant vehicle attributes that are set by the researcher.[12]

The purpose of the discrete choice experiments is to elicit willingness-to-pay estimates for vehicle attributes. In each experiment, respondents can choose one of four possible vehicles, where the vehicles differ along the following characteristics: fuel type, cost to drive 100 miles, purchase price, driving range, refueling time, and the level of automation. Figure 1 shows one possible choice menu that respondents saw when taking part in the experiment. I use cost to drive 100 miles to calculate the fuel costs of each alternative.[13] The fuel cost attribute is included in this manner to allow comparisons of costs among different powertrains that are currently available in the vehicle market, including plug-in electric and electric vehicles. Each respondent faced eight choice situations, where each situation involved a different combination of alternative attributes.[14]

This approach, however, is based on stated preferences, making it prone to the biases discussed in Section 2.2.1. One possible source of bias is that the experiments included choices among different vehicle powertrains, including plug-in electric and electric vehicles. This could bias parameter estimates if respondents generally would not consider these powertrains when making a purchase.

Two other features of the survey, however, reduce these biases by making the experiments close to actual vehicle purchase settings faced by respondents. First, the vehicle attributes are assigned according to new vehicle attributes available during the survey period (e.g., hybrid vehicles have a low cost to drive 100 miles). Second, the vehicle purchase price values

[12] One benefit of the experimental approach is that estimation of flexible discrete choice models is computationally feasible. This is because the experimental approach only requires including a small number of alternatives available for the respondent to choose from. In contrast, estimating discrete choice models using revealed preference data of vehicle purchases generally requires modeling a large number of alternatives, unless the researcher is willing to aggregate alternatives and their characteristics, creating a tradeoff between aggregation bias and computational feasibility. For example, in a given model year, over one thousand different new vehicle trims are available for consumers to purchase. Another benefit of the experimental approach is that estimates of random parameter standard deviations and the estimates of willingness to pay are generally more robust to specification selection. This is because each respondent faces many choice occasions, as opposed to single choice occasion in most revealed preference datasets.

[13] Respondents could perceive cost to drive 100 miles to include costs other than fuel, such as insurance costs. But these costs are small relative to fuel costs and are mostly independent of miles driven, as discussed in Bento et al. (2009).

[14] See Daziano et al. (2017) for more details on the survey design.

seen are tailored to each respondent according to stated price thresholds.[15] The purchase price was customized using a pre-experiment question on the respondent's willingness to spend in buying a new vehicle.[16]

Calculating the Present Value of Fuel Costs

The experimental data do not include the present value of fuel costs as an attribute. Instead, respondents see the cost to drive 100 miles as an attribute. I calculate the present value of fuel costs for each vehicle based on a series of standard assumptions adopted by previous studies. Letting z_{ijt} represent the present value of fuel costs for respondent i choosing vehicle j in choice occasion t, this value is expressed as

$$z_{ijt} = \mathbb{E}\left[\sum_{y=1}^{Y} \frac{cpm_{jyt} * VMT_{ijy}}{(1+\delta_i)^y}\right], \tag{1}$$

where y denotes year, Y, represents the expected life of the vehicle, cpm_{jyt} is the expected cost per mile of vehicle j in year y and choice occasion t (calculated by divided cost per 100 miles by 100), VMT_{ijy} is expected vehicle miles traveled (VMT) by respondent i in vehicle j in year y, δ_i is respondent i's private discount rate, and $\mathbb{E}$ is the expectation operator. I set the private discount rate equal to the elicited discount rate from the survey as discussed in Section 2.2.1.[17] I use estimates from Leard et al. (2017) for assumptions on annual VMT, which is based on annual VMT data from the 2009 National Household Travel Survey (NHTS) and proprietary data from R.L. Polk on annual scrappage rates from 2003–2014 to construct expected VMT schedules. Since the discrete choice experiment does not assign a class category, I use car data from each source to build the VMT and survivability

[15]The sample of the survey is further tailored to represent individuals who make vehicle purchase decisions by restricting those participating to individuals with drivers licenses and with at least one vehicle currently owned or leased.

[16]Respondents selected how much they would spend on buying their next vehicle, with options of $5,000 bins up to $60,000 and a bin for more than $60,000.

[17]The elicited discount rates for the sample of respondents ranges from 2 percent to 40 percent, with an average of 13 percent. This range and mean are similar to those found in Newell and Siikamaki (2015).

schedules.[18] See Leard et al. (2017) for more details.[19] I assume that the maximum lifespan of a vehicle is 35 years. Consistent with previous studies, I assume that VMT_{ijy} is independent of cpm_{jyt} and δ_i. The last variable to assign is expected cost per 100 miles, which I assume to be equal to the stated attribute from each experiment.

Discrete Choice Model Development

To estimate willingness to pay with the experimental data, I adopt a random utility framework where respondent utility is a function of observed and unobserved attributes. I express the conditional indirect utility function for respondent i selecting vehicle j for choice occasion t as

$$U_{ijt} = x'_{ijt}\omega_{xi} - \mu_i p_{ijt} - \phi_i z_{ijt} + \varepsilon_{ijt}. \tag{2}$$

In Equation (2), ω_{xi} is a vector representing the change in utility from marginal improvements in the (nonmonetary) vehicle attributes that are captured in the vector x_{ijt}. I assume that these coefficients do not vary over choice occasions, but can vary over respondents. Variables p_{ijt} and z_{ijt} represent purchase price and a measurement of fuel costs, respectively. Parameters of interest are μ_i, interpreted as the marginal utility of income, and ϕ_i, interpreted as the change in utility from a marginal change in the negative of fuel costs, which is equivalent to a (positive) marginal change in fuel cost savings. In most of the specifications to follow, z_{ijt} is the present value of fuel costs. This represents the total fuel costs over the entire life of the vehicle, discounted to the present. For these specifications, if respondent i fully values fuel costs, then $\phi_i = \mu_i$.[20] If $\phi_i < \mu_i$, then respondent i undervalues fuel costs.

This model focuses on identifying how respondents value fuel cost savings relative to a lifetime fuel cost benchmark. This is a common benchmark in the economics literature because a particular set of parameter estimates ($\phi_i = \mu_i$) represent a rational consumer

[18]Using the car data is meant to serve as a conservative estimate of lifetime VMT, since trucks typically last longer and have higher annual VMT (Lu, 2006).

[19]I avoid using the VMT and survivability schedules from Lu (2006) because this study uses old VMT and scrappage data and because VMT and vehicle lifetimes have been increasing over time.

[20]This is because both p_{ijt} and z_{ijt} are monetary attributes at the time of purchase.

model (Allcott and Wozny, 2014; Leard et al., 2017; Sallee et al., 2016). In contrast, it is less common for valuations of other attributes, such as fuel type, to have an associated benchmark value.

In each specification, I assume that the idiosyncratic error term ε_{ij} is i.i.d. distributed Type 1 extreme value, so that predicted probabilities conditional on respondent i parameters take on the conditional logit form

$$L_{ijt}(\mu_i, \phi_i) = \frac{e^{x'_{ijt}\omega_{xi} - \mu_i p_{ijt} - \phi_i z_{ijt}}}{\sum_k e^{x'_{iht}\omega_{xi} - \mu_i p_{iht} - \phi_i z_{iht}}}. \tag{3}$$

Conditional on respondent i parameters, the probability of respondent i's series of choices is the product of logits (Revelt and Train, 1998):

$$S_i(\mu_i, \phi_i) = \prod_t L_{ijt}(\mu_i, \phi_i). \tag{4}$$

I estimate parameters with logit and mixed logit specifications. For the logit specifications, the log-likelihood function is

$$LL(\theta) = \sum_i \ln S_i(\theta), \tag{5}$$

where θ is the vector of parameters to be estimated. For the mixed logit specifications, I define the unconditional probability for the sequence of choices as

$$Q_i(\theta) = \int S_i(\mu_i, \phi_i) f(\mu_i, \phi_i|\theta) d\mu d\phi. \tag{6}$$

Since the integral has no closed-form solution, I simulate the probabilities using random draws r with the expression

$$\tilde{Q}_i(\theta) = \frac{1}{R} \sum_{r=1}^{R} S_i(\mu_i^{r|\theta}, \phi_i^{r|\theta}). \tag{7}$$

The simulated log likelihood function is

$$SLL(\theta) = \sum_i \ln \tilde{Q}_i(\theta). \tag{8}$$

I estimate several conditional logit and mixed logit models to test whether the results are sensitive to specification decisions. For the conditional logit models, all respondents are assumed to have the same preference parameters for price and non-price attributes, so that $\omega_{xi} = \overline{\omega_x}$, $\mu_i = \overline{\mu}$, and $\phi_i = \overline{\phi}$ for all i. In the estimation results, I denote these values as average utility coefficients.[21] For the mixed logit models, I estimate two sets of parameters: average utility that is common among all or a subset of the respondents, and utility that varies randomly among all or a subset of the respondents. In the estimation results, I denote the utility that is common among all or a subset of respondents as average utility coefficients. Within the context of the discrete choice model, I assume preference parameters for purchase price, μ_i, and fuel costs, ϕ_i, vary according to observed respondent characteristics. The preference parameter for purchase price is

$$\mu_i = \lambda_g h_{ig}. \tag{9}$$

The coefficient λ_g represents the marginal utility of purchase price for respondent i in group g, where group g is defined by the level of attention toward fuel costs. The variable h_{ig} is an indicator equal to one if respondent i is in group g and zero otherwise. I estimate a separate coefficient λ_g for each group g, such that λ_g represents a set of respondent group by purchase price interaction terms.

To allow for additional flexibility, I estimate models that allow ϕ_i to vary randomly within subsets of respondents. For these specifications, the fuel cost component of utility is

$$\phi_i z_{ijt} = \rho_g h_{ig} z_{ijt} + \sigma_i z_{ijt}. \tag{10}$$

[21] I estimate these models with maximum likelihood, which does not require simulation of choice probabilities.

The coefficient ρ_g has the same interpretation as λ_g, such that ρ_g represents the average marginal utility of fuel costs for all respondents in group g. The coefficient σ_i is the random component of utility, where σ_i is assumed to be normally distributed around zero.

Estimation Results

I first present estimates of the choice model parameters for the conditional logit specification where respondents are assumed to have the same preferences. For each specification, the sample contains eight choice occasions for every respondent in the cleaned sample, for a total of 9,000 total choice occasions. The estimates are obtained by maximum likelihood. In every specification, purchase price enters in thousands of dollars. Columns (1) and (2) in Table 4 show parameter estimates for two distinct definitions of the fuel cost variable. Column (1) has the fuel cost variable entering as the cost per 100 miles driven, in thousands of dollars.[22] The coefficients are estimated to have expected signs and most are statistically significant at the 5 percent level. Respondents dislike higher purchase price and cost per 100 miles, as indicated by the negative signs for each coefficient estimate; respondents like higher range and both levels of automation, and respondents prefer full automation over some or no automation. Column (2) displays qualitatively similar results, where PV Cost enters as a parameter and is calculated by equation (1). The coefficient PV Cost enters with the expected sign and the other coefficients are similar in magnitude to those in the specification in column (1). The magnitude of the PV Cost coefficient is about half as large as the magnitude of the purchase price coefficient. Since each corresponding variable is denominated in the same monetary units, this suggests that the average respondent undervalues fuel costs by about 60 percent.

This result, however, may stem from the lack of flexibility of the conditional logit model. Bento et al. (2012) find that not accounting for consumer heterogeneity in the discrete choice framework can bias the fuel cost coefficient estimate toward zero because of sorting, implying undervaluation when consumers fully value fuel costs. To account for this possibility, I

[22]This denomination makes this cost consistent with purchase price units.

estimate a mixed logit version of the specification in column (2) by allowing respondent preferences for fuel costs to vary randomly. I estimate the mean and standard deviation of a normally distributed coefficient for PV Cost.[23] The results of this estimation appear in column (3). The coefficient for PV Cost slightly increases in magnitude to -0.341, suggesting modest sorting bias is present in the conditional logit specification. But this estimate remains far smaller in magnitude than the purchase price coefficient.

Dividing the fuel cost coefficient by the price coefficient implies that on average, respondents are willing to pay about 45 cents in a higher purchase price to reduce PV fuel costs by one dollar. This estimate is near the mean WTP estimate reported in Leard et al. (2017), but is lower than the estimates implied from the benchmark specifications in Allcott and Wozny (2014) and Sallee et al. (2016). The estimate, however, is similar in magnitude to alternative specifications in these studies.[24]

To estimate the relationship between inattention to fuel costs and willingness to pay for fuel cost savings, I re-estimate the models in Table 4 with interaction terms. The alternative specifications include interactions between the level of fuel cost attention, purchase price, and fuel costs. Estimation results of these specifications appear in Table 5. Column (1) reports coefficient estimates for the conditional logit specification. Each level of attention, denoted by no, some, and full attention – corresponding to respondents' choosing options 1, 2, or 3, respectively, for Question 9 of the survey – is interacted with the purchase price and fuel cost variables. Two results emerge. First, inattentive respondents have the highest purchase price sensitivity. Second, inattentive respondents have the lowest sensitivity to fuel costs. Together, this suggests that respondents inattentive to fuel costs are willing to pay the least amount for reductions in fuel costs. This result remains and becomes more pronounced when fuel costs are measured using the present value estimate. In column (2), we see that although

[23]In all mixed logit specifications, choice probabilities are simulated using 100 Halton draws.

[24]For example, alternative specifications in Allcott and Wozny (2014) that use contemporaneous fuel price data or survey data on expectations of fuel costs imply a willingness to pay of 55 cents and 51 cents, respectively. Sallee et al. (2016) find that consumers who purchase vehicles with at least 100,000 miles – roughly half of all vehicles in operation – are willing to pay about 30 cents for one dollar of fuel cost savings.

respondents who are partially or fully attentive to fuel costs are sensitive to changes in fuel costs, inattentive respondents are not; their coefficient estimate for the present value of fuel costs is close to zero. This pattern persists when unobserved heterogeniety in preferences for fuel costs is incorporated, as shown in column (3). Inattentive respondents are the most sensitive to purchase prices and the least sensitive to fuel costs.[25]

Implied average willingness to pay for reducing the present value of fuel costs by one dollar are computed by dividing the mean estimate of PV Cost coefficient for each group by the corresponding group's coefficient estimate of purchase price. These calculations, along with their confidence intervals, appear in Table 6 based on preferred specifications.[26] Inattentive respondents are willing to pay little for fuel cost reductions; the upper 95 percent confidence interval is only 2.7 cents. In contrast, respondents who reported making fuel cost calculations during their most recent vehicle purchase have an implied average willingness to pay of \$1.07 for reducing fuel costs by \$1, with a 95 percent confidence interval of \$0.75 to \$1.38. Respondents with some attention to fuel costs appear to undervalue fuel costs, but not nearly to the extent of the inattentive respondents. In fact, inattention completely explains undervaluation: if all respondents were fully attentive, WTP for fuel cost savings would suggest full valuation across the entire sample.

2.2.3 Robustness Checks

The estimated coefficients are robust to several sample restrictions. I report estimation results for alternative specifications that include restricted samples in Table 7. Each restriction is meant to test for bias by omitting respondents who may lack recent market experience or who may not be expecting to make a vehicle purchase decision in the near future. For example, the column labeled own young vehicle restricts the sample to include respondents who reported to drive most often a vehicle with model year between 2010

[25]The magnitude of the fuel cost coefficients modestly increases in the mixed logit specification, once again affirming the result in Bento et al. (2012) that omitting unobserved heterogeniety likely leads to biased estimates of willingness to pay for fuel cost savings.

[26]Confidence intervals are calculated using the delta method.

and 2014, implying that these respondents made a relatively recent purchase. Restricting the sample to these respondents reduces recall bias present in the attention to fuel costs question. Calculated willingness-to-pay estimates reported in Table 8 show that across all of the restricted samples, attentive respondents have preference parameters that imply full valuation of fuel cost savings, while inattentive respondents have low implied valuation.

2.2.4 Discussion

Several caveats apply to the results from the discrete choice experiments. First, the implied WTP for inattentive respondents may be affirming that these respondents are inattentive to fuel costs during the choice experiments. An ideal experiment would elicit inattentive respondents to become attentive to the attribute, then elicit WTP for the attribute. The first elicitation was attempted using a series of questions about fuel costs and hypothetical willingness to pay for fuel cost savings, but proof of this elicitation is not apparent. Future survey designs focusing on estimating WTP for fuel cost savings require detailed care to ensure that both margins of elicitation are achieved.

Second, estimates of WTP are derived from hypothetical choice situations. These choice situations may lead to hypothetical bias, as some respondents may never consider purchasing a vehicle with the attributes presented to them. The tailoring of the price attribute only partially alleviates this issue; ideally, every attribute for all of the possible choice occasions should be tailored to respondents, based on either their stated preferences or their observed vehicle holdings (or both). Note, however, that the design of these experiments involves an inherent trade-off between realism and usefulness. At the extreme, every possible vehicle characteristic, such as the type of material of the interior of the vehicle, could be included and tailored to each respondent. But including all possible characteristics would make precise estimation of preference parameters infeasible, given the sample size.

Third, other types of behavior may be correlated with respondent inattention and WTP for fuel cost savings. For example, loss aversion may be an underlying cause of undervaluation of and inattention to attributes that appear risky, which is the case for fuel cost savings (Greene, 2011; Greene et al., 2013). Ideally, all factors would be controlled for to isolate the impact of each type on WTP for fuel cost savings. The current work motivates incorporating all of these effects in future surveys and experiments.

Fourth, the inattention response may be correlated with respondent characteristics that affect WTP. This concern is partly alleviated by the robustness of the results to sample restrictions, but it cannot be completely alleviated. This highlights the benefits of quasi-experimental designs that are able to randomly assign attention treatment to respondents (Allcott and Knittel, 2017).

Despite those concerns, the results yield several findings relevant for understanding the demand for fuel cost savings and for designing energy efficiency policy. The fact that inattention is strongly correlated with undervaluation suggests that policies designed to increase energy efficiency should incorporate design features that account for attention to energy costs. For example, providing more detailed information on energy costs to consumers may encourage more consumers to be attentive to energy costs and purchase more energy-efficient products. Using an experimental setting where survey respondents decided among water heaters, Newell and Siikamaki (2014) found that providing energy cost information had significant effects on consumer willingness to pay for energy cost savings. They find that failing to provide energy cost information causes consumers to undervalue energy costs, but providing basic information on the economic value of energy efficiency leads to full valuation. Allcott and Knittel (2017), however, find that consumers do not respond to alternative forms of information about energy costs provided immediately prior to making a new vehicle purchase. These conflicting conclusions suggest that the type of product may influence the efficacy of informational treatments.

The results also imply that consumers show substantial heterogeneity in their WTP for fuel cost savings: inattentive respondents make vehicle choices as if they undervalue energy efficiency, whereas fully informed respondents make rational choices on average.

This heterogeneity has important policy implications. An efficient policy would encourage inattentive consumers to purchase more efficient products while not influencing the decisions of the attentive consumers (Allcott and Greenstone, 2012; Allcott et al., 2014). This is because policies that distort all consumer choices lead to private welfare losses for consumers who fully value fuel costs. Some policies, including subsidies for alternative fuel vehicles, may be poor at targeting individuals that undervalue fuel costs. Subsidies for electric vehicles, for example, likely target consumers who fully value fuel costs, since these households are more likely to substitute between buying a conventional vehicle with high fuel economy and an electric vehicle. Other policies, such as gas guzzler taxes, may be relatively good at targeting inattentive consumers, since they influence the prices only of vehicles that are more popular among consumers who pay less attention to fuel costs.

3 Factors Explaining Inattention

So far this paper has summarized evidence suggesting that inattention varies considerably among households, and the amount of attention paid to fuel cost savings is strongly correlated with inferred demand for these savings. But inattention may be rationalized by characteristics of the household. For example, households that drive less than the average commuter face a lower fuel cost for all of the vehicles that they consider owning or leasing. Therefore, when making a decision about fuel economy, fuel cost savings from buying a high fuel economy vehicle are relatively small. In the context of a rational attention model (e.g., Sallee (2014)), households with few miles traveled have less incentive to pay attention to fuel costs when buying a vehicle.

In this section, I evaluate how characteristics of the household are related to their reported level of attention to fuel costs. This is facilitated by several questions appearing in the Qualtrics survey, including the model year and annual miles traveled of the held vehicle, whether the vehicle is owned or leased, and what the respondents expect future gasoline prices to be in five years.[27]

Table 9 reports coefficient estimates from a multinomial logit model where the outcome variable is the response to the inattention question in the survey. The base outcome is full attention so that the coefficient estimates are relative to this response. The explanatory variables are estimated with expected signs, although the estimates are noisy for some of the coefficient estimates. The coefficient estimates show that annual vehicle miles traveled have a negative effect on the likelihood of being inattentive to fuel costs. This suggests that respondents that do not drive much are less likely to pay attention to fuel costs. Other coefficient estimates have similar interpretations. Respondents with higher elicited discount rates are more likely to be inattentive, and those with newer vehicles are less likely to be inattentive. These results are consistent with models of rational inattention, where the choice to be attentive is a function of respondent-specific characteristics defining fuel costs. Lower fuel costs imply a lower financial return from paying attention and a greater likelihood of being inattentive. The lack of strong statistical precision for several of the coefficient estimates, however, suggests that other behavioral models of inattention may also explain respondent behavior in this context.

4 Conclusion

In this paper, I present evidence on the relationship between consumer inattention and mean WTP for energy cost savings. The data suggest that nearly a quarter of respondents are inattentive to automobile fuel costs when making a purchase decision, and that these respondents make choices as if they are willing to pay significantly less for fuel cost savings. This behavior appears to be consistent with models of rational inattention, where consumers that face higher driving costs are more likely to pay attention to these costs when purchasing a vehicle. Policies that reduce the costs of paying attention are therefore likely to increase fuel economy of vehicles on the road. Whether these policies improve welfare, however, depends

[27] The gasoline price expectation question is based on the survey data analyzed in Anderson et al. (2013).

on the administrative costs and the responsiveness of inattentive consumers to changes in the costs of attention.

Alternatively, policies like fuel economy and greenhouse gas standards force increases in fuel economy for the entire fleet of new vehicles. These policies encourage inattentive consumers to buy vehicles with lower fuel costs, saving them money without changing their attention toward these costs. This result, however, depends on how manufacturers adopt fuel-saving technologies across their fleets in response to the policies, which is out of the scope of the current paper.

The results found in the current paper suggest that many consumers are fully attentive to fuel cost savings, appearing to correctly value fuel cost savings associated with lower fuel costs. If manufacturers designed vehicles only for these consumers, it would be expected that manufacturers would adopt all cost-effective methods of increasing fuel economy and an energy efficiency gap would not exist. In this setting, a fuel economy standard would lower private consumer welfare. But these consumers may still benefit from fuel economy standards if manufacturers are making fuel economy investment decisions based on preferences of the majority of consumers. If most consumers ignore or undervalue fuel cost savings, then it may not be profitable for manufacturers to direct fuel-saving technology toward boosting fuel economy. This motivates accurately modeling heterogeneous consumer demand for fuel economy when evaluating manufacturer and consumer responses to fuel economy standards.

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Table 1: Sample Demographic Statistics of Qualtrics Survey Respondents

Variable	Mean (S.D.)
Household size	2.71 (1.32)
Age of respondent	47.47 (13.51)
Number of children	1.42 (1.35)
Household income (2014 $)	61,780 (42,290)
Number of vehicles held by household	1.59 (0.79)
Characteristics of Vehicle Driven Most Often by Respondent	**Mean (S.D.)**
Fuel economy (miles per gallon)	24.93 (5.72)
Horsepower	186.49 (57.58)
Weight (pounds)	3,456 (671.36)
Torque (pounds-feet)	197.78 (66.83)
Respondent Demographics	**Percentage**
Male	51.28
Female	48.72
Married	55.02
Widowed	2.84
Divorced	13.60
Single	20.98
Living with partner	7.56
High school diploma	98.58
Some college experience	77.51
Bachelors degree	38.67
Masters or professional degree	12.36
Full time ($\geq$ 30 hours per week) job	67.73
Part time job	8.44
Homemaker	7.82
Student	0.89
Retired	9.96
Unemployed but actively looking for work	5.15
Household income $\leq \$30,000$	22.93
Household income $> \$30,000$ and $\leq \$60,000$	34.84
Household income $> \$60,000$ and $\leq \$90,000$	21.60
Household income $> \$90,000$	20.62

Table 2: Relationships Between Fuel Cost Inattention and Vehicle Attribute Choice

Variables	Percentage of Sample	(1) Miles per Gallon	(2) Horsepower	(3) Weight	(4) Torque
Did not think about fuel costs at all	24.10	-3.17***	15.96***	202.00***	21.56***
		(0.57)	(5.28)	(62.43)	(6.33)
Thought some about fuel costs, no calculations made	51.50	-1.99***	9.06**	111.62**	10.09*
		(0.51)	(4.60)	(48.72)	(5.33)
Constant		34.62***	124.03***	1,846.05***	99.51**
		(3.765)	(44.33)	(433.32)	(45.33)
Demographic Fixed Effects		Y	Y	Y	Y
Observations	1,125	1,125	1,125	1,125	1,125
R-squared		0.23	0.23	0.22	0.21

Notes: The column titled Percentage of Sample denotes the fraction of households reporting a response to Question 9 of the survey. For example, 24.1 percent of respondents reported that they did not think about fuel costs at all when they bought their most-often-used vehicle. Each specification corresponds to regression with a different vehicle characteristic as the dependent variable. Miles per gallon is measured as the combined city and highway fuel economy rating. Horsepower is measured in foot-pounds per second. Weight is measured in pounds, and torque is measured in pound-feet. Demographic fixed effects include education level, gender, household head age, household income, political affiliation, employment status, and state of residence. The omitted group response to Question 9 is the response "I made some calculations to compare fuel costs" such that the marginal effects are interpreted relative to this group. Robust standard errors are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Relationship Between Fuel Cost Inattention and Stated Willingness to Pay for Fuel Cost Savings

Variables	(1) log(WTP \$2,000)	(2) log(WTP \$8,500)
Did not think about fuel costs at all	-0.31**	-0.37***
	(0.12)	(0.11)
Thought some about fuel costs, no calculations made	-0.19*	-0.266***
	(0.099)	(0.082)
Constant	8.29***	6.56***
	(0.88)	(0.51)
Demographic Fixed Effects	Y	Y
Observations	722	708
R-squared	0.24	0.27

Notes: Each specification corresponds to a regression with responses to the stated preferences questions on willingness to pay for fuel cost savings. The values of these responses are logged such that the coefficient estimates are interpreted as percentage differences in willingness to pay relative to the omitted group response to Question 9. Demographic fixed effects include education level, gender, household head age, household income, political affiliation, employment status, and state of residence. The omitted group response to Question 9 is the response "I made some calculations to compare fuel costs" such that the marginal effects are interpreted relative to this group. Robust standard errors are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Estimates of Average Respondent Preferences

Average Utility Coefficients	(1) Logit	(2) Logit	(3) Mixed Logit
Purchase Price (1,000$)	-0.0760***	-0.0751***	-0.0755***
	(0.00390)	(0.00388)	(0.00395)
PV Cost (1,000$)		-0.0317***	-0.0341***
		(0.00534)	(0.00606)
Cost Per 100 Miles ($)	-0.0721***		
	(0.0205)		
Range (Miles)	0.00203***	0.00200***	0.00209***
	(0.000492)	(0.000491)	(0.000509)
Some Automation	0.267***	0.266***	0.266***
	(0.0352)	(0.0352)	(0.0352)
Full Automation	0.378***	0.377***	0.377***
	(0.0351)	(0.0351)	(0.0352)
Refueling Time (Hours)	-0.00403	-0.00511	-0.00483
	(0.00923)	(0.00921)	(0.00927)
Hybrid	-0.413**	-0.103	-0.0942
	(0.162)	(0.0671)	(0.0687)
Plug-in Hybrid	0.311	0.679***	0.725***
	(0.293)	(0.241)	(0.250)
Electric	-0.565*	-0.0889	-0.0800
	(0.303)	(0.209)	(0.213)
Random Coefficient S.D.			
PV Cost (1,000$)			0.0419*
			(0.0231)
Choice Occasions	9,000	9,000	9,000
Log Likelihood	-11,406	-11,394	-11,394

Notes: Each of the 1,125 respondents in the sample has eight choice occasions, for a total of 9,000 choice occasions. Purchase price and PV Cost variables are scaled to units of $1,000 to facilitate convergence of the estimation. The mixed logit specification uses 100 Halton draws to compute the simulated logit probabilities. The random coefficient is assumed to be approximated by a normal distribution such that the standard deviation estimate is interpreted as the estimated standard deviation of a normal distribution. Standard errors are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Estimates of Heterogeneous Respondent Preferences

Average Utility Coefficients	(1) Logit	(2) Logit	(3) Mixed Logit
No Attention*Purchase Price (1,000$)	-0.0852***	-0.0860***	-0.0901***
	(0.00777)	(0.00699)	(0.00767)
Some Attention*Purchase Price (1,000$)	-0.0766***	-0.0768***	-0.0776***
	(0.00525)	(0.00493)	(0.00502)
Full Attention*Purchase Price (1,000$)	-0.0666***	-0.0617***	-0.0622***
	(0.00699)	(0.00633)	(0.00647)
No Attention*PV Cost (1,000$)		-0.000432	-0.00129**
		(0.000399)	(0.000617)
Some Attention*PV Cost (1,000$)		-0.0207***	-0.0233***
		(0.00632)	(0.00653)
Full Attention*PV Cost (1,000$)		-0.0554***	-0.0664***
		(0.00799)	(0.0101)
No Attention*Cost Per 100 Miles ($)	-0.0510**		
	(0.0219)		
Some Attention*Cost Per 100 Miles ($)	-0.0635***		
	(0.0210)		
Full Attention*Cost Per 100 Miles ($)	-0.103***		
	(0.0217)		
Range (Miles)	0.00204***	0.00198***	0.00216***
	(0.000493)	(0.000492)	(0.000519)
Some Automation	0.266***	0.266***	0.266***
	(0.0352)	(0.0352)	(0.0353)
Full Automation	0.377***	0.376***	0.381***
	(0.0351)	(0.0351)	(0.0355)
Refueling Time (Hours)	-0.00380	-0.00503	-0.00415
	(0.00923)	(0.00921)	(0.00934)
Hybrid	-0.387**	-0.0564	-0.0413
	(0.162)	(0.0676)	(0.0707)
Plug-in Hybrid	0.338	0.723***	0.799***
	(0.294)	(0.242)	(0.255)
Electric	-0.540*	-0.0352	-0.0381
	(0.304)	(0.209)	(0.220)
Random Coefficient S.D.'s			
No Attention*PV Cost (1,000$)			-0.00979***
			(0.00190)
Some Attention*PV Cost (1,000$)			0.00365
			(0.0287)
Full Attention*PV Cost (1,000$)			0.0679***
			(0.0226)
Choice Occasions	9,000	9,000	9,000
Log Likelihood	-11,463	-11,458	-11,330

Notes: Each of the 1,125 respondents in the sample has eight choice occasions, for a total of 9,000 choice occasions. Purchase price and PV Cost variables are scaled to units of $1,000 to facilitate convergence of the estimation. The random coefficients are assumed to be approximated by normal distributions such that the standard deviation estimates are interpreted as estimated standard deviations of normal distributions. The mixed logit specification uses 100 Halton draws to compute the simulated logit probabilities. Standard errors are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Implied Average Willingness to Pay for Reducing the Present Value of Operating Costs by $1

Model	Respondent Group	Estimate	Lower 95% C.I.	Upper 95% C.I.
Mixed Logit Table 4	All Respondents	$0.451	$0.291	$0.612
Mixed Logit Table 5	No Attention	$0.014	$0.002	$0.027
Mixed Logit Table 5	Some Attention	$0.300	$0.140	$0.460
Mixed Logit Table 5	Full Attention	$1.067	$0.753	$1.381

Notes: Estimates are reported in dollars and are derived by dividing the coefficient estimate for PV cost by the associated coefficient for purchase price. All of the estimates are derived based on models presented in column (3) of Tables 4 and 5. Confidence intervals are computed using the delta method.

Table 7: Alternative Samples for Mixed Logit Models

Average Utility Coefficients	(1) Own Young Vehicle	(2) Purchase Soon	(3) Next Purchase New	(4) Purchase New Soon
No Attention*Purchase Price (1,000$)	-0.0392***	-0.0928***	-0.100***	-0.0927***
	(0.0147)	(0.0107)	(0.0104)	(0.0134)
Some Attention*Purchase Price (1,000$)	-0.0707***	-0.0730***	-0.0708***	-0.0685***
	(0.00800)	(0.00695)	(0.00625)	(0.00814)
Full Attention*Purchase Price (1,000$)	-0.0635***	-0.0519***	-0.0650***	-0.0542***
	(0.00915)	(0.00824)	(0.00754)	(0.00944)
No Attention*PV Cost (1,000$)	0.00132	-0.00243**	-0.00182**	-0.00241*
	(0.00146)	(0.00113)	(0.000852)	(0.00134)
Some Attention*PV Cost (1,000$)	-0.0111	-0.0299***	-0.0219***	-0.0251*
	(0.0103)	(0.0112)	(0.00827)	(0.0128)
Full Attention*PV Cost (1,000$)	-0.0719***	-0.0623***	-0.0747***	-0.0770***
	(0.0150)	(0.0148)	(0.0120)	(0.0175)
Range (Miles)	0.00122	0.00190***	0.00194***	0.00216**
	(0.000820)	(0.000734)	(0.000636)	(0.000848)
Some Automation	0.233***	0.240***	0.259***	0.255***
	(0.0536)	(0.0460)	(0.0426)	(0.0535)
Full Automation	0.349***	0.400***	0.427***	0.424***
	(0.0539)	(0.0462)	(0.0424)	(0.0535)
Refueling Time (Hours)	-0.000317	-0.00493	-0.00451	-0.00842
	(0.0139)	(0.0122)	(0.0111)	(0.0139)
Hybrid	0.140	0.217**	-0.0248	0.193*
	(0.111)	(0.0973)	(0.0861)	(0.112)
Plug-in Hybrid	0.569	0.926**	0.728**	1.049**
	(0.402)	(0.360)	(0.312)	(0.416)
Electric	-0.194	0.0141	-0.108	0.196
	(0.346)	(0.306)	(0.268)	(0.354)
Random Coefficient S.D.'s				
No Attention*PV Cost (1,000$)	0.0147***	0.0162***	-0.0118***	-0.0148***
	(0.00447)	(0.00286)	(0.00252)	(0.00323)
Some Attention*PV Cost (1,000$)	-0.00594	0.0520	0.0147	0.0390
	(0.0636)	(0.0339)	(0.0467)	(0.0464)
Full Attention*PV Cost (1,000$)	0.0768***	0.111***	0.0635**	0.103***
	(0.0286)	(0.0259)	(0.0262)	(0.0288)
Choice Occasions	3,552	5,000	6,048	3,600
Log Likelihood	-4,608	-6,416	-7,692	-4,646

Notes: Each column has estimates for the mixed logit specification estimated on a subsample of respondents. Column (1) restricts the sample to respondents who reported to drive most often a young vehicle of model year between 2010 and 2014, implying that these models are at most four years old. Column (2) restricts the sample to respondents who reported wanting to purchase their next vehicle within two years. Column (3) restricts the sample to respondents who stated that they would buy a new vehicle when they made their next purchase. Column (4) restricts the sample to respondents who reported wanting to purchase a new vehicle within two years of the survey date. Purchase price and PV Cost variables are scaled to units of $1,000 to facilitate convergence of the estimation. The random coefficients are assumed to be approximated by normal distributions so that the standard deviation estimates are interpreted as estimated standard deviations of normal distributions. The mixed logit specifications use 100 Halton draws to compute the simulated logit probabilities. Standard errors are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Alternative Samples Implied Average Willingness to Pay for Reducing Present Value of Operating Costs by $1

Sample	Respondent Group	Estimate	Lower 95% C.I.	Upper 95% C.I.
Own Young Vehicle	No Attention	$-0.034	$-0.121	$0.054
	Some Attention	$0.156	$-0.125	$0.437
	Full Attention	$1.132	$0.655	$1.611
Purchase Soon	No Attention	$0.026	$0.004	$0.048
	Some Attention	$0.410	$0.120	$0.700
	Full Attention	$1.200	$0.630	$1.770
Next Purchase New	No Attention	$0.018	$0.003	$0.033
	Some Attention	$0.309	$0.088	$0.529
	Full Attention	$1.150	$0.780	$1.518
Purchase New Soon	No Attention	$0.026	$0.001	$0.052
	Some Attention	$0.366	$0.011	$0.721
	Full Attention	$1.422	$0.749	$2.094

Notes: Estimates are reported in dollars and are derived by dividing the coefficient estimate for PV cost by the associated coefficient for purchase price. All of the estimates are derived based on models presented in columns (1)–(4) in Table 7. The sample Own Young Vehicle represents implied WTP from column (1), which restricts the sample to include respondents who reported to drive most often a young vehicle of model year between 2010 and 2014, implying that these models are at most four years old. The sample Purchase Doon represents implied WTP from column (2), which restricts the sample to include respondents who stated that they would purchase their next vehicle within two years. The sample Next Purchase New represents implied WTP from column (3), which restricts the sample to include respondents who reported that they would purchase a new vehicle when they made their next purchase. The sample Purchase New Soon represents implied WTP from column (4), which restricts the sample to include respondents who reported wanting to purchase a new vehicle within two years of the survey date. Confidence intervals are computed using the delta method.

Table 9: Relationship Between Fuel Cost Inattention and Factors Influencing Fuel Costs

Did not think about fuel costs at all		
Variable	Coefficient	(S.E.)
Vehicle Miles Traveled	-0.14*	(0.08)
Discount Rate	1.41*	(0.72)
Gas Price Expectation	-0.04	(0.40)
Lease	0.98**	(0.49)
Model Year	-0.12***	(0.02)
Income	-0.37	(0.22)
Thought some about fuel costs, no calculations made		
Variable	Coefficient	(S.E.)
Vehicle Miles Traveled	-0.12**	(0.06)
Discount Rate	-0.23	(0.63)
Gas Price Expectation	0.03	(0.08)
Lease	0.50	(0.44)
Model Year	-0.03*	(0.02)
Income	-0.49***	(0.18)
Observations	1,125	
Log pseudolikelihood	-1,115.18	

Notes: This specification corresponds to a maximum likelihood estimation of a multinomial logit model. The outcome variable is one of three responses to Question 9. The base outcome is "I made some calculations to compare fuel costs" such that the coefficient estimates are interpreted relative to this group. The variable annual miles is defined as annual average miles driven with the held vehicle, denominated in thousands of miles for scaling purposes. The variable discount rate is the elicited discount rate from the survey's discount rate experiment. The variable gas price expectation is the response to the question "what do you think the gasoline price will be in five years from today?" The variable lease is equal to one if the held vehicle is currently being leased. The variable model year is the model year of the held vehicle. The variable income is the respondent's annual household income in hundreds of thousands of dollars. Robust standard errors are reported in parentheses. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 1: Presentation of Discrete Choice Experiment

	Hybrid Vehicle Gasoline **HEV**	Plug-in Hybrid Electric Gasoline-Electricity **PHEV**	Electric Vehicle **BEV**	Gasoline Vehicle **GAS**
Cost to Drive 100 Miles	**$8.80**	**$5.50**	**$3.20**	**$15.20**
Price	**$25,000**	**$37,000**	**$26,000**	**$20,000**
Driving Range	**590 miles** Gasoline	**15 miles / 520 miles** Gasoline Only	**150 miles** Electricity	**550 miles** Gasoline
Refueling Time	**5 minutes**	**2 hours / 5 minutes** (electricity) (gas)	**8 hours**	**5 minutes**
Driverless Package	**Some Automation**	**Full Automation**	**No Automation**	**No Automation**