RFF REPORT

Consumer Inattention and Demand for Energy Cost Savings

Benjamin Leard

AUGUST 2017

RESOURCES FOR THE FUTURE

Consumer Inattention and Demand for Energy Cost Savings

Benjamin Leard*

August 2017

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 energy savings exceeds the costs. This paper presents empirical evidence on the relationship between a potential source of undervaluation – consumer inattention – and demand for energy-efficient products. 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 undervalue fuel cost savings and attentive consumers fully value these savings. The results imply that designing energy efficiency policies requires careful consideration of consumer inattention.

Key Words: Inattention, Energy Efficiency, Discrete Choice

JEL Classification Numbers: C25, D46, L62, Q41

*Resources for the Future, 1616 P St. NW, Washington, D.C. 20036, e-mail: *leard@rff.org*.

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).

Most empirical evidence for a gap is in the form of consumer undervaluation of energy cost savings. The evidence compares values of willingness to pay (WTP) for reducing energy cost savings and the lifetime value of the associated savings. Estimates of WTP that fall below the lifetime value suggest undervaluation. Recent economics literature focusing on automobiles 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) use similar variation but find undervaluation, where consumers are willing to pay 76 cents for one dollar of fuel cost savings. 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 one dollar of fuel cost savings, suggesting undervaluation.

The conflicting evidence motivates an examination of underlying reasons why consumers may undervalue energy costs. The literature provides several causes of a gap, including

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

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 (Sallee, 2014; Turrentine and Kurani, 2007). Hardly any research tests these explanations. One exception is Bradford et al. (2014), who find a positive correlation between hyperbolic discounting and low demand for energy-efficient products.

I expand this literature by examining unique survey data to identify the relationship between consumer inattention and valuation of energy cost savings. I leverage discrete choice experiments accompanying the survey data to find that the average respondent undervalues energy 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 completely explains undervaluation, motivating careful consideration of consumer inattention in the design of policies aiming to increase energy efficiency.

2 Empirical Evidence on Inattention and Demand for Fuel Cost Savings in Automobiles

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 and preferences for autonomous vehicles.[2] The survey asked questions to elicit respondents' demographics and preferences for vehicle attributes. The original sample included 1,226 responses. After

[2]For a detailed explanation of the survey questions on autonomous vehicles, see Daziano et al. (2017).

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 characteristics, the sample represents the entire U.S. population well. Mean and median household incomes are $61,780 and $55,000, respectively, which are similar to estimates from the 2013 American Community Survey.[4] 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.[5]

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

[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).

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

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

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.
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. 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.[6] 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. Allcott (2011) finds that higher gasoline prices have a statistically significant and positive effect on consumer attention to fuel costs, implying that

[6] The VOAS included the following responses in addition to the first two responses above: (option 3) "I calculated some, but not as precisely as I did just now in this survey"; (option 4) "I calculated about the same as I did just now in this survey"; (option 5) "I calculated more precisely than I did just now during this survey."

the difference in inattention can at least partly be explained by the difference in survey dates. 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.

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.

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 Stated Preferences

The first form of evidence comes from multiple stated preference questions on WTP for hypothetical fuel cost savings over the course of five years from the purchase date. The stated preferences questions are worded exactly as 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.[7] 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.

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 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

[7] 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.

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).[8] 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. 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

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

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 at least 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 as the handling of an automobile, 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).[9] 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

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

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 – for example, Busse et al. (2013). This approach, however, requires a large number of observations and data on 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 vehicles, which differ by relevant vehicle attributes that are set by the researcher. Since the researcher sets the vehicle attributes that are seen by each respondent, unobserved attributes are not present and exogenous variation in vehicle attributes is set by the researcher. Another benefit of the experimental approach is that the design of the experiment yields statistical precision for the estimates of willingness to pay. The estimates are statistically precise because each respondent makes multiple choices under alternative choice settings where each choice setting has a different set of vehicle attributes.[10]

The purpose of the discrete choice experiments is to elicit willingness-to-pay estimates for automobile automation and energy efficiency. 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

[10] In most market transaction datasets, consumers are typically observed to make a single choice. Since most market transaction datasets are also cross-sectional, it is difficult to estimate distributions of preferences for vehicle attributes. Without panel data, second choice data are necessary for obtaining precise estimates of preferences (Berry et al., 2004).

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.[11] Each respondent faced eight choice situations, where each situation involved a different combination of alternative attributes. See Daziano et al. (2017) for more details on the survey design.

Two features of the survey make it representative of actual vehicle purchase settings faced by respondents making purchase decisions. First, the vehicle attributes are assigned according to general new vehicle attributes (e.g., hybrid vehicles have a low cost to drive 100 miles). Second, the vehicle purchase price values seen are tailored to each respondent according to stated price thresholds.[12] The purchase price was customized using a pre-experiment question on the respondent's willingness to spend in buying a new vehicle.[13]

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

[11]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).

[12]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.

[13]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.

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.[14] I use 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 schedules.[15] I estimate average VMT by model year of all cars in the NHTS using the *bestmile* variable and by following the methodology in Lu (2006). I estimate a survival rate as a function of vehicle age following Lu (2006). 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.[16] The estimated schedules appear in Table 4. 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 assume that respondents make choices based on maximizing their utility. I express the conditional indirect utility function for respondent i selecting vehicle j for choice occasion t as

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

[14] 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).

[15] 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).

[16] Lu (2006) uses the 2001 NHTS to estimate average VMT by age and class and uses R.L. Polk data from 1976 to 2002 to estimate vehicle survivability schedules. Using these schedules to assign expected VMT would lead to an underestimate of expected VMT, given that vehicles are being driven more miles and lasting longer than before (Bento et al., 2017).

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}. 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 cost savings. For these specifications, if respondent i fully values fuel costs, then $\phi_i = \mu_i$.[17] If $\phi_i < \mu_i$, then respondent i undervalues fuel costs. 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

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

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

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.[18] 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, varies according to observed respondent characteristics.

$$\mu_i p_{ijt} = \lambda_g p_{ijt}. \tag{9}$$

The coefficient λ_g represents the marginal utility of purchase price for respondent i in group g, where group g is defined by observed respondent characteristics, such as the level of attention toward fuel costs. I estimate a separate coefficient λ_g for each group g, such that μ_g represents a set of demographic group by purchase price interaction terms.

To allow for additional flexibility, I estimate models that allow ϕ_i to vary randomly within

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

subsets of respondents. For these specifications, the fuel cost component of utility is

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

The coefficient ρ_g has the same interpretation as λ_g, such that ρ_g represents a set of demographic group by fuel cost interaction terms. 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 5 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.[19] 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.

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

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 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.[20] The results of this estimation appear in column (3). The coefficient for PV Cost slightly increases in magnitude to -0.341, suggesting some 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.[21]

To estimate the relationship between inattention to fuel costs and willingness to pay for fuel cost savings, I re-estimate the models in Table 5 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 6. 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.

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

[21] 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.

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 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.[22]

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 7 based on preferred specifications.[23] 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 changing the sample of respondents. I report estimation results for alternative specifications that include restricted samples in Table 8. Each restriction is meant to test for hypothetical bias by omitting respondents who may lack

[22]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 heterogeneity likely leads to biased estimates of willingness to pay for fuel cost savings.

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

recent market experience or who may not be expecting to make a vehicle purchase decision in the near future. Calculated willingness-to-pay estimates reported in Table 9 show that across all of the restricted samples, attentive respondents fully value fuel cost savings, while inattentive respondents have low or nearly zero WTP.

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.

Despite those concerns, the results yield several findings relevant for understanding the demand for energy efficiency 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. Their results are based on a field experiment at a Ford dealership with individuals who were about to purchase a new automobile and an online survey. 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 greatly 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 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 are willing to pay significantly less for fuel cost savings. Encouraging these consumers to pay attention to fuel costs when making a purchase decision would likely increase fuel economy of vehicles on the road and reduce greenhouse gas emissions. Alternatively, policies can cause changes in relative vehicle prices and fuel economy that encourage all consumers to purchase vehicles with better fuel economy, including consumers inattentive to fuel costs. These are the mechanisms and motivating forces behind recently tightened fuel economy and greenhouse gas standards. Whether the private benefits to inattentive consumers in the form of fuel cost savings is worth the cost of imposing the standards remains a focal point of research, especially since sufficiently large undervaluation may justify these standards based on cost-benefit analysis (Fischer et al., 2007; Parry et al., 2014).

But the results found in the current paper suggest that not all consumers are inattentive, and those who are attentive appear to correctly value fuel cost savings associated with greater energy efficiency. Forcing these consumers to buy more fuel efficient vehicles through price and quality changes may be a private welfare cost, since these consumers are already making optimal investments in energy efficiency. Fuel economy and greenhouse gas standards do not intentionally encourage certain consumer groups to buy vehicles with higher fuel efficiency. Therefore, the standards create distributional effects that are typically left out of cost-benefit analyses, where inattentive consumers may benefit at the expense of attentive consumers. Assuming that all consumers lose or benefit by the same amount from tighter fuel economy standards based on a representative consumer framework remains a poor measurement of actual welfare effects, given the significant consumer heterogeneity found in the current paper and other prior literature, e.g., Jacobsen (2013). Ideally, future impact analyses will be able to incorporate relevant heterogeneity into assessing the costs and benefits of policies directed toward lowering gasoline consumption and greenhouse gas emissions in the transportation sector.

References

Allcott, H. (2011). Consumer perceptions and misperceptions of energy costs. *American Economic Review: Papers and Proceedings 101*(3), 98–104.

Allcott, H. and M. Greenstone (2012). Is there an energy efficiency gap? *Journal of Economic Perspectives 14*(5), 3–28.

Allcott, H. and K. Knittel (2017). Are consumers poorly informated about fuel economy? Evidence from two experiments. *NBER Working Paper No. 23076*, 1–62.

Allcott, H., S. Mullainathan, and D. Taubinsky (2014). Energy policy with externalities and internalities. *Journal of Public Economics 112*, 72–88.

Allcott, H. and N. Wozny (2014). Gasoline prices, fuel economy, and the energy paradox. *Review of Economics and Statistics 96*, 779–795.

Bento, A., L. Goulder, R. V. Hafen, and M. Jacobsen (2009). Distributional and efficiency impacts of increased us gasoline taxes. *American Economic Review 99*(3), 1–37.

Bento, A., S. Li, and K. Roth (2012). Is there an energy paradox in fuel economy? A note on the role of consumer heterogeneity and sorting bias. *Economics Letters 115*, 44–48.

Bento, A., K. Roth, and S. Zhou (2017). Vehicle lifetime trends and scrappage behavior in the used car market. *Energy Journal Forthcoming.*

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica 63*(4), 841–890.

Berry, S., J. Levinsohn, and A. Pakes (2004). Differentiated products demand systems from a combination of micro and macro data: The new car market. *Journal of Political Economy 112*(1), 68–105.

Bradford, D., C. Courtemanche, G. Heutel, P. McAlvanah, and C. Ruhm (2014). Time preferences and consumer behavior. *National Bureau of Economic Research Working Paper 20320*.

Busse, M., C. Knittel, and F. Zettelmeyer (2013). Are consumers myopic? evidence from new and used car purchases. *American Economic Review 103*(1), 220–256.

Coller, M. and M. B. Williams (1999). Eliciting individual discount rates. *Experimental Economics 2*(2), 107–127.

Davis, L. (2012). Evaluating the slow adoption of energy efficient investments: Are renters less likely to have energy efficient appliances? *The Design and Implementation of U.S. Climate Policy*.

Daziano, R., M. Sarrias, and B. Leard (2017). Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. *Transportation research Part C: Emerging Technologies* (78), 150–164.

Fischer, C., W. Harrington, and I. Parry (2007). Should autombile fuel economy standards be tightened? *Resources for the Future Discussion Paper* (04-53), 1–34.

Golove, W. and J. Eto (1996). Market barriers to energy efficiency: A critical reappraisal of the rationale for public policies to promote energy efficiency. *Berkeley, CA: Lawrence Berkeley national Laboratory: LBL-38059, UC-1322*.

Greene, D. L., D. Evans, and J. Hiestand (2013). Survey evidence on the willingness of U.S. consumers to pay to automotive fuel economy. *Energy Policy 61*, 1539–1550.

Hausman, J. A. (2012). Contingent valuation: From dubious to hopeless. *Journal of Economic Perspectives 26*(4), 43–56.

Heutel, G. (2015). Optimal policy instruments for externality-producing durable goods under present bias. *Journal of Environmental Economics and Management 72*, 54–70.

Hsiao, C., S. Baohong, and V. Morowitz (2002). The role of stated intentions in new product purchase forecasting. *Advances in Econometrics 16*, 11–28.

Jacobsen, M. (2013). Evaluating U.S. fuel economy standards in a model with producer and consumer heterogeneity. *American Economic Journal: Economic Policy 5*(2).

Kahneman, D. and J. Knetsch (1992). Valuing public goods: The purchase of moral satisfaction. *Journal of Environmental Economics and Management 22*(1), 57–70.

Langer, A. and N. Miller (2013). Automakers' short-run responses to changing gasoline prices. *Review of Economics and Statistics 95*(4), 1198–1211.

Leard, B., J. Linn, and Y. Zhou (2017). How much do consumers value fuel economy and performance? Evidence from technology adoption. *Resources for the Future Report*, 1–37.

Lu, S. (2006). Vehicle survivability and travel mileage schedules. *NHTSA Technical Report*, 1–37.

McFadden, D. (1974). *Conditional logit analysis of qualitative choice behavior.* Frontiers in Econometrics, edited by P. Zarembka. New York: Academic Press.

Morwitz, V., J. Steckel, and A. Gupta (2007). When do purchase intentions predict sales? *International Journal of Forecasting 23*(3), 347–364.

Newell, R. and J. Siikamaki (2014). Nudging energy efficiency behavior: The role of information labels. *Journal of the Association of Environmental and Resource Economists 1*(4), 555–598.

Newell, R. and J. Siikamaki (2015). Individual time preferences and energy efficiency. *American Economic Review Papers and Proceedings 105*(5), 196–200.

NHTSA (2012). Final regulatory impact analysis: Corporate average fuel economy for my 2017-my 2025 passenger cars and light trucks. *U.S. Department of Transportation,* *National Highway Traffic Safety Administration. Office of Regulatory Analysis and Evaluation, National Center for Statistics and Analysis, Washington, D.C.*.

NHTSA (2016). Greenhouse gas emissions and fuel efficiency standards for medium- and heavy-duty engines and vehicles - Phase 2: Regulatory impact analysis final rule. *Assessment and Standards Division Office of Transportation and Air Quality U.S. Environmental Protection Agency and National Highway Traffic Safety Administration U.S. Department of Transportation*.

Parry, I., D. Evams, and W. Oates (2014). Are energy efficiency standards justified? *Journal of Environmental Economics and Management 67*(2), 104–125.

Revelt, D. and K. Train (1998). Mixed logit with repeated choices: High-efficiency appliances. *Review of Economics and Statistics 80*(4), 647–657.

Sallee, J. (2014). Rational inattention and energy efficiency. *Journal of Law and Economics 57*(3), 781–820.

Sallee, J., S. West, and W. Fan (2016). Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations. *Journal of Public Economics 134*, 61–73.

Train, K. (2009). *Discrete Choice Methods with Simulation* (2nd ed.). Cambridge University Press.

Tsvetanov, T. and K. Segerson (2013). Re-evaluating the role of energy efficiency standards: A behavioral economics approach. *Journal of Environmental Economics and Management, 66*(2), 347–363.

Turrentine, T. S. and K. S. Kurani (2007). Car buyers and fuel economy? *Energy Policy 35*(2), 1213–1223.

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	24.1	-3.171***	15.96***	202.0***	21.56***
		(0.573)	(5.277)	(62.43)	(6.330)
Thought some about fuel costs, no calculations made	51.5	-1.985***	9.061**	111.6**	10.09*
		(0.507)	(4.599)	(48.72)	(5.334)
Constant		34.62***	124.0***	1,846***	99.51**
		(3.765)	(44.33)	(433.3)	(45.33)
Demographic Fixed Effects		Y	Y	Y	Y
Observations	1,125	1,125	1,125	1,125	1,125
R-squared		0.228	0.227	0.222	0.213

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	-0.306**	-0.372***
	(0.123)	(0.105)
Thought some about fuel costs, no calculations made	-0.185*	-0.265***
	(0.0985)	(0.0821)
Constant	8.287***	6.563***
	(0.875)	(0.514)
Demographic Fixed Effects	Y	Y
Observations	722	708
R-squared	0.241	0.265

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: Estimated Vehicle Miles Traveled and Survival Rates

Vehicle Age (years)	VMT	Survival Rate	VMT*Survival Rate
1	13,379.31	1.00	13,342.37
2	12,963.11	0.99	12,891.07
3	12,562.98	0.99	12,433.65
4	12,178.60	0.98	11,962.76
5	11,809.65	0.97	11,471.81
6	11,455.83	0.96	10,956.08
7	11,116.81	0.94	10,413.42
8	10,792.27	0.91	9,844.62
9	10,481.91	0.88	9,253.34
10	10,185.40	0.85	8,645.58
11	9,902.435	0.82	8,088.59
12	9,632.69	0.76	7,368.92
13	9,375.86	0.71	6,650.43
14	9,131.61	0.65	5,949.24
15	8,899.65	0.59	5,278.96
16	8,679.64	0.54	4,650.01
17	8,471.27	0.48	4,069.40
18	8,274.23	0.43	3,540.98
19	8,088.22	0.38	3,065.96
20	7,912.89	0.33	2,643.43
21	7,747.94	0.29	2,270.96
22	7,593.06	0.26	1,945.12
23	7,447.93	0.22	1,661.92
24	7,312.23	0.19	1,417.10
25	7,185.64	0.17	1,206.42
26	7,067.86	0.15	1,025.78
27	6,958.56	0.13	871.37
28	6,857.43	0.11	739.71
29	6,764.15	0.09	627.67
30	6,678.41	0.08	532.46
31	6,599.89	0.07	451.66
32	6,528.27	0.06	383.13
33	6,463.24	0.05	325.05
34	6,404.49	0.04	275.84
35	6,351.69	0.04	234.15

Notes: The VMT schedule is estimated from 2009 National Household Travel Survey (NHTS) data, and the survivability schedule is estimated from proprietary data from R.L. Polk on scrappage rates from 2003–2014. Since the discrete choice experiment does not assign a class category, I use car data from each source to build the VMT and survivability schedules. Both schedules are estimated following the methodology in Lu (2006).

Table 5: 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 6: 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 7: 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 5	All Respondents	$0.451	$0.291	$0.612
Mixed Logit Table 6	No Attention	$0.014	$0.002	$0.027
Mixed Logit Table 6	Some Attention	$0.300	$0.140	$0.460
Mixed Logit Table 6	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 5 and 6. Confidence intervals are computed using the delta method.

Table 8: 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 9: 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 8. 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.

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