MEASURING FUTURE VEHICLE PREFERENCES: A STATED PREFERENCE SURVEY APPROACH WITH DYNAMIC ATTRIBUTES AND MULTI-YEAR TIME FRAME

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ABSTRACT

The culmination of new vehicle technology, greater competition in energy markets, and government policies to reduce pollution and energy consumption will result in changes to the personal vehicle marketplace. To measure future vehicle preferences, stated preference surveys have been the dominant approach. Prior research has been limited to a narrow focus of accelerating respondents to a hypothetical next vehicle purchasing decision without mimicking the marketplace’s influence on this decision. To explore marketplace influences, this project proposes to use a novel stated preference survey design to analyze vehicle purchasing behavior in a dynamically changing marketplace through the use of dynamic attributes and a six-year hypothetical time window. The survey is divided into three parts: household characteristics, current vehicles, and stated preference. The stated preference section presents respondents with various hypothetical scenarios annually over a future six-year period using one of three experiments. The experiments correspond to changing vehicle technology, fueling options, and taxation policy. Between scenarios, the vehicle, fuel, and policy attributes dynamically change to mimic marketplace conditions. A pilot web-based survey was performed during fall 2010. Mixed logit models showed that respondents responded in behaviorally realistic ways and that the survey design allowed for estimation of important parameters in vehicle choice. Respondents were able to depreciate their vehicles over the five-year hypothetical period and place tradeoffs on the features of vehicles and fuel types. The insights from the survey are also used to suggest refinements to the survey methods and areas for further research.
INTRODUCTION

Predicting consumer preferences for future vehicles is important for industry and governments. Automobile companies and energy producers need to know how much and what kinds of products to sell in the marketplace in order to make a profit. Transportation planners need to know the vehicle characteristics of roadway users in order to create valid car ownership models to predict energy consumption and emissions. Government officials need to know what policies can encourage vehicle ownership that promotes a better environment, improves public health, reduces energy dependence, and promotes economic growth.

Stated preference (SP) survey approaches have been the predominant method to determine the demand for new motor vehicles. An early 1990s study used SP surveys to analyze clean-fuel vehicle adoption in California (1). In this study, respondents were presented with hypothetical scenarios with vehicles of varying attributes and asked them to choose their most preferred option. Since then, stated preference surveys have been used to analyze different types of new vehicles as well as various aspects of purchasing behavior. Studies have analyzed demand for battery electric, hybrid electric, plug-in hybrid electric, alternative fuel, and hydrogen fuel vehicles (1-14). Additionally, studies have concentrated on the effects of prior vehicle ownership (2), attitudes (3,4), the purchases of others (5,6), brand recognition (7), and survey framing effects (8,9).

Prior vehicle preference SP surveys have been limited in their concentration on a future vehicle purchasing decision without consideration of the marketplace conditions behind the decision. Driving households are at a crossroads. Various vehicle technologies have or will emerge in the market over the next five to ten years. Rising global oil demand is driving up energy prices and creating a competitive marketplace for alternative energy sources. Additionally, local and national governments are interested in using public policy to reduce dependence on oil, decrease air pollution, and combat climate change. These three conditions create an opportunity for changes in the automotive marketplace over the short to medium term.

The purpose of this study is to investigate future vehicle preferences over a dynamically changing landscape. To do this, the following tasks were proposed:

- Design a stated preference survey with dynamically changing vehicle technology and pricing, varying fueling options, and evolving taxation policy
- Administer a web-based survey pilot to determine if the survey design can collect data which allows for estimation of advanced discrete choice models with significant and plausible results
- Suggest enhancements to the survey instrument for a larger scale survey

This study makes contributions in the survey methods field through the use of a purchasing time window and dynamically changing attributes. Respondents were given scenarios over a six year time window and asked if they would make various purchases. Prior surveys typically looked at either a set time (6,12) or the next vehicle purchase (2-5,7-13). Those approaches isolated the vehicle purchase time from the actual environment. In this study, the survey design allowed the respondent to see the state of the hypothetical environment which allowed for modification of purchasing behavior as needed. This design also allowed for analysis of respondents’ depreciation of their current vehicle.

Dynamically changing attributes were used in the survey design to help mimic a real marketplace. The vehicle, fuel, and policy attributes change annually. For example, battery electric vehicle prices fell over a three years period and gasoline vehicle fuel economy increased.
annually. This type of survey design allows for analysis of possible “tipping points” in technological and price changes which may influence new vehicle adoption.

DEFINITIONS
The following is a brief description of acronyms used in this paper:
- **BEV** – battery electric vehicle, a vehicle that stores electricity in batteries as its only energy source
- **HEV** – hybrid electric vehicle, a vehicle which runs on gasoline but uses larger batteries to aid in the vehicle propulsion
- **PHEV** – plug-in hybrid electric vehicle, a vehicle which stores electricity from the power grid in batteries and includes a gasoline engine. This vehicle can run on battery power alone for short distances and then can switch to gasoline only operation when batteries are depleted.
- **AFV** – alternative fuel vehicle, a vehicle with an internal combustion engine that runs on a liquid fuel that is not gasoline or diesel (e.g. ethanol)
- **VMT** – vehicle miles traveled, a measure of the distance a vehicle travels
- **MPGe** – miles per gallon gasoline equivalent, a measure of the average distance traveled per unit of energy in one US gallon of gasoline

PREVIOUS RESEARCH
The transportation community has generally approached the task of predicting new vehicle preference via stated preference methods. Bunch et al. (1) performed a three phase survey in the early 1990s to analyze alternative fuel (AFV), flex-fuel, and battery electric vehicle (BEV) adoption in California. Phase two of the survey was a vehicle choice SP experiment where respondents were asked to choose among three different types of vehicle for a future vehicle purchase. The vehicles varied in terms of fuel type, fuel availability, refueling range, price, fuel cost, pollution, and performance.

Kurani et al. (2) performed a stated preference survey with reflexive designs in the mid 1990s in California. In this experiment, it was hypothesized that certain multiple-vehicle households had a greater propensity towards BEVs (“hybrid household hypothesis”). The research found that the range limit on BEVs was not a binding travel constraint in many multiple-vehicle households and that the convenience of home refueling was an attractive quality of BEVs. The study estimated that 35 to 40 percent of California households could be “hybrid households.”

Ewing and Sarigöllü (3) used SP methods and attitude analysis to study consumer preferences for BEVs and AFVs. This study found that regulation alone was insufficient in creating demand for BEVs in Canada and that technological advances were essential. The research also found that price subsidies were effective and that tax credits would likely be effective as well. Ahn et al (10) looked at alternative fuel vehicles (diesel, natural gas, liquefied petroleum gas) and hybrid electric vehicles (HEVs) to estimate new vehicle purchases and annual usage. Bolduc et al. (4) used SP methods with psychometric data to analyze vehicle preferences in Canada. Hybrid choice models found that environmental concern and appreciation of new vehicle features had significant influence on vehicle choice.

Mau et al. (5) looked at vehicle preferences for HEVs and hydrogen fuel cell vehicles using SP methods and a technology vintage model. The analysis confirmed their hypothesis that market share of new technology (“neighbor effect”) affects personal vehicle preferences. Axsen
et al. (11) surveyed households in Canada and California to compare revealed preference (RP) - only methods with SP-RP methods in determining hybrid vehicles preferences. This study found that statistically, RP-only and RP-dominant models performed better, but that SP-dominant models provided better estimates for policy simulations and that willingness-to-pay estimates were more realistic.

Musti and Kockelman (12) used a SP survey to calibrate a simulation-based model of household vehicle evolution. This survey presented respondents with twelve different vehicles options and asked for their preferred vehicle under current conditions, under higher fuel price conditions, and with environmental impact information. Eggers and Eggers (9) conducted a web-based SP survey in Germany concentrated on compact and subcompact vehicles for city driving. Their choice set included a gasoline vehicle and three alternative drive train vehicles (combinations of HEV, BEV, and PHEV). The study also tailored the scenarios to respondents’ brand and vehicle class preferences.

Beck et al. (8,9) used a web-based SP survey to study the effect of annual and usage-based emissions fees on vehicle ownership. The survey’s alternative set included a new gasoline, diesel, and hybrid vehicles. Respondents’ current vehicle was presented next to the available vehicles to purchase but was not included as a possible alternative in order to reduce hypothetical bias. Hess et al. (13) analyzed results from the California Vehicle Study which asked respondents about the vehicle they likely planned to purchase next. Using this vehicle as an alternative as well as three other vehicles of varying sizes, fuel type, and drivetrain technology, respondents chose their preferred vehicle.

Additional approaches to studying future vehicle preferences have included exercises to design new vehicle (design games) (14) and applying information cascade experiments to vehicle preference studies (6).

SURVEY DESIGN

To analyze consumer preferences for future vehicles, a stated preference approach was adopted. A web-based survey was chosen primarily for its cost and administration time advantages. Table 1 summarizes the characteristics and methodology of the survey. The survey consisted of three sections: Household Characteristics, Current Vehicle, and Stated Preference. The Household Characteristics section gathered information about the respondents and their households. The Current Vehicle section asked respondents to describe various characteristics about their current vehicle, such as make and model, fuel economy, and vehicle price.

The Stated Preference portion of the survey involved presenting respondents with one of three stated choice experiments: Vehicle Technology, Fuel Type, and Taxation Policy. Each respondent randomly received one SP experiment. The Vehicle Technology experiment had a 50% chance of being displayed while the other two experiments each had a 25% chance.

Each stated choice experiment generated multiple SP observations over a six year time period, from 2010 to 2015. The variables in the scenarios changed from year to year when plausible. For example, vehicle price generally increased over time, hybrid vehicle tax credit decreased with time, and the range for gasoline vehicles remained constant. Two scenarios per year were presented for a total of 12 observations. Respondents were given the following instructions for this section:

- Make realistic decisions. Act as if you were actually buying a vehicle in a real life purchasing situation.
• Take into account the situations presented during the scenarios. If you would not normally consider buying a vehicle, then do not. But if the situation presented would make you reconsider in real life, then take them into account.

• Assume that you maintain your current living situation with moderate increases in income from year to year.

• Each scenario is independent from one another. Do not take into account the decisions you made in former scenarios. For example, if you purchase a vehicle in 2011, then in the next scenario forget about the new vehicle and just assume you have your current real life vehicle.

After the instructions, respondents were also given definitions of the vehicle types in the choice set and the attributes in the scenario table.

Vehicle Technology Experiment
The Vehicle Technology experiment focused on presenting respondents with varying vehicle characteristics and pricing in order to discover preferences for vehicle technology. This experimental design consisted of four alternatives and five variables with a choice set size of eight.

Four alternatives – current vehicle and a new gasoline, HEV, and BEV – were shown to respondents. These vehicle platforms were chosen because they appear to have a good chance for market share in the United States over the next five years. Gasoline vehicles are the traditional option, while hybrid electric vehicles have grown in market share in the US. While battery electric vehicles are new to the marketplace, there has been significant interest in exploring this paradigm by major automobile manufactures.

The variables of interest in the vehicle technology experiment included vehicle price, fuel economy, refueling range, emissions, and vehicle size. Vehicle price, presented in U.S. dollars, depended on the size of the vehicle and increased annually. Fuel economy was presented in miles per gallon (MPG) for gasoline and hybrid vehicles. Refueling range was presented as the miles between refueling or recharging. Emissions were displayed as the percent difference in emissions in comparison to the average vehicle in 2010. Electric vehicles were stated to have no direct emissions. Vehicle sizes were based on the US EPA vehicle size system.

The choice set for the vehicle technology experiment included all permutations of buying or not buying a new vehicle (gasoline, hybrid, or electric) and selling or retaining the current vehicle.

Fuel Type Experiment
The Fuel Type experiment presented respondents with different fuel options to infer the effect of fuel characteristics on future vehicle purchases. This experimental design consisted of four alternatives and four variables with a choice set size of seven.

Four fuel types were shown to respondents – gasoline, alternative fuel, diesel, and electricity. These fuel types are currently established in Maryland’s marketplace – gasoline, alternative (ethanol), and diesel via fueling stations and electricity via the home.

The variables of interest in the fuel type experiment included fuel price, fuel tax, average fuel economy, refueling availability, and charging time. The fuel price and fuel tax were presented in US dollars per gallon or gallon equivalent for electric. The fuel economy was presented as the average expected fuel economy for a vehicle that runs on that fuel type and measured in MPG or MPGe (for BEVs). The refueling availability was presented as the average
distance to a refueling station from the respondent’s home. Charging time was presented as the
time it would take to recharge an electric vehicle from the home.

The choice set for this experiment included keeping and selling the respondent’s current
vehicle or buying a new gasoline, alternative fuel, diesel, battery electric, or plug-in hybrid
electric vehicle.

**Taxation Policy Experiment**
The taxation policy experiment presented respondents with different toll and tax policies to infer
their effect on future vehicle purchases. For the 2010 and 2011 scenarios, the experimental
design consisted of four alternatives and two variables with a choice set size of eight. For the
2012 through 2015 scenarios, the experimental design consisted of four alternatives, three
variables, and nine choices.

For reasons similar to the **Vehicle Technology** experiment, four alternatives – current
vehicle, new gasoline vehicle, new HEV, and new BEV – were shown to respondents. The
variables of interest in the taxation policy experiment included: income tax credits, toll cost, and
vehicle-miles traveled (VMT) fee (for scenario years 2012 through 2015). The income tax
credit, measured in US dollars, attempted to encourage adoption of new technology through
reducing one’s tax burden. Tax credits were shown for HEVs and BEVs based on current US
federal guidelines for credits. The toll cost variable was presented to respondents as the percent
reduction in normal toll prices for users of that vehicle type. The VMT tax rate was presented as
a cost in US dollars per 1000 miles traveled that would be collected by the respondent’s
insurance provider.

The choice set for the taxation policy experiment included all permutation of buying or
not buying a new vehicle (gasoline, HEV, or BEV) and selling or retaining the current vehicle.
For the 2012 through 2015 scenarios, an additional choice was added to keep one’s current
vehicle and drive less.

**DESCRIPTIVE STATISTICS**
A sample was collected using a multi-stage cluster design by county and zipcode with 141
completed surveys. The sample had the following descriptive statistics:

- Gender: 52% male
- Age: 41 years (median), 43 years (mean)
- Education: 76% with Bachelor degree or higher
- Income: $50k – $75k (median), 22% with incomes above $150k
- Vehicle Ownership: 1.9 (average), 2.0 (median)
- Primary Vehicle Age: 6.4 years (average), 6.0 years (median)
- Primary Vehicle Price: $23,763 (average, new), $11,367 (average, used)
- Intend to Purchase Vehicle within Five Years: 62%

This pilot sample was not intended to be representative of Maryland. The sample respondents
tended to be better educated and slightly older than average Marylanders but the households had
vehicle ownership and median incomes similar to other Maryland households.

**MODELS AND RESULTS**
Because of the study’s emphasis on testing the survey design and studying preferences, discrete
choice models were used to gain behavioral insight into the decision process and to test the
suitability of this survey design for analysis in a larger scale study. The models in this study are not intended for forecasting future demand.

Discrete choice models have generally been used to analyze future vehicle preferences. Multinomial logit (MNL) and nested logit models have been used extensively over the last 20 years (1,3,5,12). Brownstone and Train (15) used mixed logit and probit models to analyze vehicle preference data. Their research showed that the substitution patterns generated from these models were more realistic than the IIA assumption of multinomial logit models. Mixed logit frameworks were also used by Brownstone et al. (16) and Beck et al. (8).

The decision makers in each model were individual households and it was assumed that each respondent made decisions for the entire household. The general utility function structure used in estimating the model was the following:

\[ U_{nit} = \beta X_{nit} + [ \eta_{ni} + \epsilon_{nit} ] \]

where:
- \( U_{nit} \) = the utility for individual \( n \), alternative \( i \), and scenario \( t \)
- \( \beta \) = a vector of regressors corresponding to \( X_{nit} \)
- \( \eta_{ni} \) = a vector of flexible disturbances terms normally distributed with zero mean and standard deviation \( \sigma_\eta \) (vector)
- \( X_{nit} \) = a vector of observed characteristics for individual \( n \), alternative \( i \), and scenario \( t \)
- \( \epsilon_{nit} \) = error term with zero mean that is i.i.d. over alternatives, individuals, and scenarios

For the MNL model, \( \eta_{ni} \) was not included in the specification for any variables. The mixed logit model for panel data had the following choice probabilities:

\[ P(i|X_{nit}; \beta, \sigma) = \int \prod_{t=1}^{T} \frac{e^{\beta X_{nit}}}{\sum_{j \in C} e^{\beta X_{njt}}} f(\beta|\sigma) d\beta \]

where:
- \( P(i|X_{nit}; \beta, \sigma) \) = the probability of choosing alternative \( i \) for decision maker \( n \)
- \( C \) = the choice set for the model
- \( T \) = the total number of scenarios
- \( f(\beta|\sigma) \) = is the density of \( \beta \), here assumed to be normal

Discrete choice models were estimated using BIOGEME (17). Multinomial logit and mixed multinomial logit models were used with all mixed logit models estimated with 2500 Halton draws. These results are not intended for predictive purposes but to show that the survey design can be used for behavioral modeling. The following sections present modeling results for each SP experiment.

**Vehicle Technology Experiment Results**

Three models of the vehicle technology experiment are presented in Table 2. Model 1a is a multinomial logit model. Model 1b is a mixed logit model with normally distributed error components analogous to a cross-nested logit setup. Model 1c expands on Model 1b by including a normally distributed random parameter for size preference.

The alternative specific constants (ASC) for the new vehicles are in comparison to the keeping the current vehicle alternative. All the constants are negative as expected since one’s current vehicle is likely a good match to a respondent’s preferences. A conventional gasoline
The constant for BEVs decreased (becomes more negative) as additional variables were added to the model. This result may be attributed to a wide variation in preferences for electric vehicles in the sample and vehicle sizes (since most electric vehicles are smaller). The decreasing preference for BEVs in the mixed logit models could be more realistic since new technology adoption may suffer from status quo bias.

The purchase price coefficient was negative as expected since increasing costs are prohibitive. The coefficients for current vehicle age were also negative as older vehicles are generally less attractive. The recharging range for electric vehicles was positive which follows the expectation that greater range makes BEVs usable for longer trips.

The new vehicle age coefficient was greater in magnitude than the used vehicle age coefficient which suggests that households that buy new vehicles place greater depreciation on their vehicles. Additionally, dummies for new gasoline SUV and minivans for households with children were positive as it was assumed that families have a preference for larger vehicles with utility and seating capacity.

For fuel economy, respondents were split into groups based on their knowledge of their current vehicle fuel economy. For respondents who knew their vehicle MPG, the difference between their current vehicle MPG and the MPG of the new vehicle was used for estimation. For respondents who did not know their vehicle MPG, the actual new vehicle MPG was used for estimation. The models showed that fuel economy had no significant influence on vehicle preferences for respondents without knowledge of their vehicle MPG. For households with knowledge of their vehicle MPG, the results from all models are positive as expected.

The error components for non-electric and non-hybrid vehicles are significant in both mixed logit models with the same ordering of magnitudes. This suggests that the following pairings of alternatives exists in decreasing order of covariance: current vehicle paired with new gasoline vehicle, new gasoline or current vehicle paired with new hybrid vehicle, new gasoline or current vehicle paired with new electric vehicle, and new hybrid vehicle paired with new electric vehicle.

The size variable corresponds to a value of 0 for a small vehicle, 1 for a midsize vehicle, or 2 for a large vehicle (large car, SUV, minivan, or pickup). This formulation allowed for estimation of a household’s preference for larger or smaller vehicles. Model 1c showed a preference in the sample for smaller primary vehicles with approximately 65% of the sample preferring smaller vehicles over larger vehicles. Emissions were excluded from the models as it was found to have an insignificant effect and was too correlated with vehicle fuel economy.

The bottom of Table 2 summarizes some additional findings in regards to respondents’ valuation of vehicle attributes. The three models varied in their predictions of respondents’ preferences for their current vehicle and the attributes of new vehicles. Model 1a suggested that consumers place less preference on their current vehicles and a greater willingness to pay for improving fuel efficiency. Model 1c suggested that consumers place greater preference on their current vehicle through lower depreciation and a smaller willingness to pay for improving fuel efficiency.

The value of electric vehicle range was found to vary from $62 per mile in model 1a to $141 per mile for model 1c. Model 1c more conservatively estimated how much each mile of range was worth to respondents. The value of fuel efficiency varied from $610 per mpg to $770 per mpg. Model 1c was most conservative about preferences for fuel efficiency while models 1b and 1a showed a similar preference.
Respondent’s vehicle depreciation was obtained by dividing the coefficient of vehicle age (new or used) by the coefficient of purchase price. The models found that respondents depreciated their current vehicle at a rate between $1,950 and $1,310 per year for vehicles purchased new. For respondents with used vehicles, depreciation was between $1,066 and $710 per year. The MNL model placed greater depreciation on both new and used vehicles than the mixed models. Model 1c showed less depreciation for new vehicles and the ratio between depreciation of new and used vehicles showed a closer level of depreciation that the other two models.

**Fuel Type Experiment Results**

Two models for the fuel type experiment are presented in Table 3. Model 2a is a multinomial logit model. Model 2b is a mixed logit model with normally distributed error components analogous to a nested logit. The scale of the utility increased in the mixed logit models.

Both models had similar orderings of alternative specific constants. The current vehicle was most preferred inherently followed by new gasoline vehicles. New diesel vehicles were inherently least preferred.

The ratio between fuel price and electricity price (for BEVs) was similar between models. The electricity price coefficient suggested that respondents were less sensitive to electricity price than gasoline price. This may be attributed to lack of familiarity with electricity for fueling or a “rule of thumb.” The charging time of battery electric vehicles was significant with each hour of charge time being worth more than a dollar worth of fuel cost. Additionally, charge time for PHEVs was found to be insignificant. This may confirm that respondents realized that charging of PHEVs was less important since PHEVs run on gasoline when batteries are depleted.

The average fuel economy coefficient was positive as expected and significant. As with the vehicle technology experiment, vehicle age was a disutility with new vehicles depreciating faster than used vehicles. The error component specification was significant which suggests that this is a possible grouping that respondents placed between different vehicle type. The results suggested that households responsive to electric vehicles had a similar responsiveness to PHEV. Additionally, the three liquid fueling types (gasoline, diesel, and alternative fuel) were shown to have some similarities.

**Taxation Policy Experiment Results**

Two models for the taxation policy experiment are presented in Table 4. Model 3a is a multinomial logit model. Model 3b is a mixed logit model with a normally distributed error component analogous to a nested logit setup. As with the fuel type experiment, the mixed logit model had a larger scale in utility.

The alternative specific constants had a similar pattern between scenarios with new gasoline and hybrid vehicles having similar preference and new electric vehicles being the least preferred.

A vehicle-miles-traveled tax was found to have a negative effect on utility. This variable was interacted with respondent’s current annual mileage to estimate an annual VMT tax. The vehicle income tax deduction was interacted with the household’s current annual income to find the deduction’s value as a fraction of household income. This variable had a positive impact on utility for hybrid and electric vehicles as expected. The deductions were found to have significantly different effects on hybrid and electric vehicles. In the MNL model, the hybrid
vehicle deduction had a larger effect than the electric vehicle deduction, but in the mixed logit model the effects were reversed.

The toll discount variable had a positive impact on preferences for hybrid and electric vehicles with the effect being greater for households near toll facilities. This effect was only significant for households near toll facilities in the mixed logit model. As with the other two experiments, depreciation of the current vehicle was found to be significant and had a negative effect on the attractiveness of the current vehicle.

For the error component specification, the current vehicle error component was fixed for identification purposes (18). The error component for the new vehicles was found to be significant which shows that there is some correlation between all the new vehicle types.

**SUMMARY AND FUTURE RESEARCH**

This study showed that a stated preference study over a hypothetical dynamic environment can produce results that fit economic expectations (e.g. disutility of price). The approach shown in this paper uses a novel stated preference survey with dynamically changing vehicle, fuel, and policy attributes and multi-year time window. The research shows that respondents realistically depreciate their vehicles over the course of the experiments as well as consider trade-offs that may allow them to change their intended plans. Respondents were able to create trade-offs between different vehicle technology as well as the price of various fueling options.

The study exposed some areas for refinement of the survey, and based on the modeling and analysis, the following options are being considered for future surveys:

- **Incorporation of taxation policy variables into the other experiments.** The taxation policy experiment was felt to be the weakest of the three as there was a lack of context in the decision process. The experiment showed that VMT taxes could influence vehicle purchasing decisions but the results for vehicle deductions and tolls were inconsistent. The inconsistencies in the taxation policy experiment may suggest that advertising policies requires some contextual elements to affect behavior. To add context, possible incorporations include, adding the vehicle deduction into the vehicle technology experiment and adding the VMT tax into the fuel type experiment since vehicle usage also affects fuel usage.

- **Use MPGe for electric vehicles in the vehicle technology experiment.** During the model building process, there were concerns about how well MPGe would be interpreted by respondents. Therefore in this study, the fuel economy for BEV was included as a separate variable in the fuel type models but not in the vehicle technology experiment. This coefficient had a similar value to the fuel economy variable for vehicles that ran on liquid fuels. This result may suggest that respondents were able to comprehend the fuel economy of electric vehicles.

From the novel design used in this study, future avenues for research into the behavioral aspects of vehicle purchases and survey design are warranted. This study found disparities in vehicle purchase frequency between respondent who stated that they intended to buy and those who did not intend. This effect was not included in the models because of endogeneity with the choice task, but more research is needed to understand how prior intent affects respondents’ decisions. The models for the vehicle technology experiment showed that respondents with knowledge of their current vehicles’ fuel economy were receptive to the fuel economy attribute of new vehicles, while respondents without knowledge were not receptive. New research could delve into the indicators of one’s knowledge of vehicle attributes.

Additionally, research into the effect of varying the time frame of the survey and vehicle retention is needed. This study used a six-year time frame due to the commonly advertised 60-
month financing offers for new vehicles. Further research could determine how far forward respondents can reliability comprehend and mimic actual vehicle purchasing processes. In regards to vehicle retention, this study asked respondents to make their purchasing decisions independently of former decisions in order to reduce the complexity of the choice task and survey design. Future work should allow scenarios to depend on past decisions and increase the task to multiple purchasing opportunities. This would also require testing how many purchases to allow and the appropriate time frame lengths for accurate measurement.

ACKNOWLEDGEMENTS
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In 2012, the following vehicles characteristics are available for vehicles:

<table>
<thead>
<tr>
<th></th>
<th>Your Vehicle</th>
<th>Gasoline Vehicle</th>
<th>Hybrid Vehicle</th>
<th>Electric Vehicle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle Price</td>
<td>--</td>
<td>$30600</td>
<td>$41600</td>
<td>$30000</td>
</tr>
<tr>
<td>Fuel Economy (Miles per Gallon)</td>
<td>28 mpg</td>
<td>23 mpg</td>
<td>25 mpg</td>
<td>No fuel needed Runs on electric power</td>
</tr>
<tr>
<td>Range Between Refueling</td>
<td>400 to 500 miles</td>
<td>500 miles</td>
<td>450 miles</td>
<td>160 miles</td>
</tr>
<tr>
<td>Vehicle Emissions</td>
<td>15% less than average 2010 vehicle</td>
<td>Equal to average 2010 vehicle</td>
<td>Equal to average 2010 vehicle</td>
<td>No Direct Emissions</td>
</tr>
<tr>
<td>Vehicle Size</td>
<td>Mid-size Car</td>
<td>Mid-Size Car</td>
<td>SUV</td>
<td>Mid-Size Car (5-Seats)</td>
</tr>
</tbody>
</table>

Which option would you prefer for your vehicle ownership in 2012?

- [ ] I WILL KEEP My Current Vehicle
- [ ] I WILL BUY the Gasoline Vehicle And SELL My Current Vehicle
- [ ] I WILL BUY the Hybrid Vehicle And SELL My Current Vehicle
- [ ] I WILL BUY the Electric Vehicle And SELL My Current Vehicle
- [ ] I WILL BUY the Gasoline Vehicle And KEEP My Current Vehicle
- [ ] I WILL BUY the Hybrid Vehicle And KEEP My Current Vehicle
- [ ] I WILL BUY the Electric Vehicle And KEEP My Current Vehicle
- [ ] I WILL SELL My Current Vehicle and NOT REPLACE It

**FIGURE 1  Vehicle Technology Experiment Example**
In 2013, the following fuel characteristics are available:

<table>
<thead>
<tr>
<th></th>
<th>Gasoline Fuel</th>
<th>Alternative Fuel</th>
<th>Diesel Fuel</th>
<th>Electricity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel Price, Pre Tax</td>
<td>$5.32</td>
<td>$3.29</td>
<td>$2.66</td>
<td>$5.35</td>
</tr>
<tr>
<td>(price per gallon</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>equivalent)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fuel Tax</td>
<td>$0.42</td>
<td>$0.30</td>
<td>$1.05</td>
<td>$0.28</td>
</tr>
<tr>
<td>Fuel Efficiency</td>
<td>29</td>
<td>18</td>
<td>40</td>
<td>75</td>
</tr>
<tr>
<td>Fueling Station</td>
<td>Within 5 miles</td>
<td>Within 25 miles</td>
<td>Within 10 miles</td>
<td>5-hr Home Charge Only</td>
</tr>
<tr>
<td>Availability</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Which option would you prefer for your vehicle ownership in 2013?

- I WILL KEEP My Current Vehicle
- I WILL BUY a Gasoline Vehicle (or normal hybrid) that runs on Gasoline
- I WILL BUY an Alternative Fuel Vehicle that runs on Alternative Fuel
- I WILL BUY a Diesel Vehicle that runs on Diesel Fuel
- I WILL BUY an Electric Vehicle that runs on Electric Fuel
- I WILL BUY a Plug-In Hybrid Electric Vehicle that runs on Gasoline and Electric Fuel
- I WILL SELL My Current Vehicle and NOT REPLACE It

**FIGURE 2 Fuel Type Experiment Example**
In 2012, the following vehicle taxes and fees are available:

<table>
<thead>
<tr>
<th></th>
<th>Current Vehicle</th>
<th>New Gasoline Vehicle</th>
<th>New Hybrid Vehicle</th>
<th>New Electric Vehicle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income Tax Credit</td>
<td>$0</td>
<td>$0</td>
<td>$1000</td>
<td>$7500</td>
</tr>
<tr>
<td>Toll Cost</td>
<td>Normal Price</td>
<td>Normal Price</td>
<td>10% less than Normal Price</td>
<td>50% less than Normal Price</td>
</tr>
<tr>
<td>Miles Traveled Fee</td>
<td>$90 per 1,000 miles traveled</td>
<td>$90 per 1,000 miles traveled</td>
<td>$30 per 1,000 miles traveled</td>
<td>$10 per 1,000 miles traveled</td>
</tr>
</tbody>
</table>

Which option would you prefer for your vehicle ownership in 2012?

- I WILL KEEP My Current Vehicle
- I WILL KEEP My Current Vehicle And Drive Less
- I WILL BUY The Gasoline Vehicle And SELL My Current Vehicle
- I WILL BUY The Hybrid Vehicle And SELL My Current Vehicle
- I WILL BUY The Electric Vehicle And SELL My Current Vehicle
- I WILL BUY The Gasoline Vehicle And KEEP My Current Vehicle
- I WILL BUY The Hybrid Vehicle And KEEP My Current Vehicle
- I WILL BUY The Electric Vehicle And KEEP My Current Vehicle
- I WILL SELL My Current Vehicle and NOT REPLACE IT
<table>
<thead>
<tr>
<th>TABLE 1</th>
<th>Summary of Survey Methods</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time Frame</strong></td>
<td>Summer – Fall 2010</td>
</tr>
<tr>
<td><strong>Target Population</strong></td>
<td>Suburban and Urban Maryland Households</td>
</tr>
<tr>
<td><strong>Sampling Frame</strong></td>
<td>Households with internet access in 5 Maryland counties</td>
</tr>
<tr>
<td><strong>Sample Design</strong></td>
<td>Multi-stage cluster design by county and zipcode</td>
</tr>
<tr>
<td><strong>Use of Interviewer</strong></td>
<td>Self-administered</td>
</tr>
<tr>
<td><strong>Mode of Administration</strong></td>
<td>Self-administered via the computer and internet for remaining respondents</td>
</tr>
<tr>
<td><strong>Computer Assistance</strong></td>
<td>Computer-assisted self interview (CASI) and web-based survey</td>
</tr>
<tr>
<td><strong>Reporting Unit</strong></td>
<td>One person age 18 or older per household reports for the entire household</td>
</tr>
<tr>
<td><strong>Time Dimension</strong></td>
<td>Cross-sectional survey with hypothetical longitudinal stated preference experiments</td>
</tr>
<tr>
<td><strong>Frequency</strong></td>
<td>One two-month phase of collecting responses</td>
</tr>
<tr>
<td><strong>Levels of Observation</strong></td>
<td>Household, vehicle, person</td>
</tr>
</tbody>
</table>
### TABLE 2 Vehicle Technology Experiment Models

<table>
<thead>
<tr>
<th>Variable [Units]</th>
<th>Current Gasoline</th>
<th>Hybrid</th>
<th>Electric</th>
<th>Model 1a Estimate (t-stat)</th>
<th>Model 1b Estimate (t-stat)</th>
<th>Model 1c Estimate (t-stat)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASC – New Gasoline Vehicle</td>
<td>X</td>
<td></td>
<td></td>
<td>-1.330</td>
<td>(-4.55)</td>
<td>-1.090</td>
</tr>
<tr>
<td>ASC – New Hybrid Vehicle</td>
<td>X</td>
<td></td>
<td></td>
<td>-1.130</td>
<td>(-2.98)</td>
<td>-1.160</td>
</tr>
<tr>
<td>ASC – New Electric Vehicle</td>
<td></td>
<td></td>
<td>X</td>
<td>-1.370</td>
<td>(-4.80)</td>
<td>-2.290</td>
</tr>
<tr>
<td>Purchase Price [$10,000]</td>
<td>X X X</td>
<td></td>
<td></td>
<td>-0.498</td>
<td>(-5.86)</td>
<td>-0.701</td>
</tr>
<tr>
<td>Fuel Economy Change [MPG] (current vehicle MPG known)</td>
<td>X X</td>
<td></td>
<td></td>
<td>0.038</td>
<td>(4.58)</td>
<td>0.054</td>
</tr>
<tr>
<td>Fuel Economy [MPG] (current vehicle MPG unknown)</td>
<td>X X</td>
<td></td>
<td></td>
<td>0.009</td>
<td>*(1.69)</td>
<td>-0.004</td>
</tr>
<tr>
<td>Recharging Range [100 miles]</td>
<td>X</td>
<td></td>
<td></td>
<td>0.308</td>
<td>(2.13)</td>
<td>0.668</td>
</tr>
<tr>
<td>Current Vehicle Age – Purchased New [years]</td>
<td>X</td>
<td></td>
<td></td>
<td>-0.097</td>
<td>(-5.57)</td>
<td>-0.134</td>
</tr>
<tr>
<td>Current Vehicle Age – Purchased Used [years]</td>
<td>X</td>
<td></td>
<td></td>
<td>-0.053</td>
<td>(-3.20)</td>
<td>-0.050</td>
</tr>
<tr>
<td>Minivan Dummy interacted with Family Households</td>
<td>X</td>
<td></td>
<td></td>
<td>0.886</td>
<td>*(1.95)</td>
<td>1.030</td>
</tr>
<tr>
<td>SUV Dummy interacted with Family Households</td>
<td>X</td>
<td></td>
<td></td>
<td>1.110</td>
<td>(3.41)</td>
<td>1.440</td>
</tr>
<tr>
<td>Non-Electric Vehicle Error Component (standard deviation)</td>
<td>X X X</td>
<td></td>
<td></td>
<td>2.530</td>
<td>(5.89)</td>
<td>2.400</td>
</tr>
<tr>
<td>Non-Hybrid Vehicle Error Component (standard deviation)</td>
<td>X X X</td>
<td></td>
<td></td>
<td>1.980</td>
<td>(6.79)</td>
<td>2.150</td>
</tr>
<tr>
<td>Vehicle Size (mean)</td>
<td>X X X X</td>
<td></td>
<td></td>
<td>-0.435</td>
<td>(-2.42)</td>
<td></td>
</tr>
<tr>
<td>Vehicle Size (standard deviation)</td>
<td>X X X X</td>
<td></td>
<td></td>
<td>1.090</td>
<td>(6.61)</td>
<td></td>
</tr>
</tbody>
</table>

### Model Statistics

- Log Likelihood (no coefficients): -1379.363
- Log Likelihood (constants only): -1088.104
- Log Likelihood (at optimal): -1011.789
- Rho-squared: 0.266
- Adjusted Rho-squared: 0.259
- Number of Observations (Individuals): 995

### Calculated Measures of Valuations

- Value of EV Range ($ / mile): 62
- Depreciation – bought new ($ / year): 1,950
- Depreciation – bought used ($ / year): 1,066
- Value of Fuel Efficiency ($ / mpg): 760

Note: Coefficients are significant to the 95% level or 90% level*, unless otherwise denoted**
## TABLE 3 Fuel Type Experiment Models

<table>
<thead>
<tr>
<th>Variable [Units]</th>
<th>In Utility</th>
<th>Current</th>
<th>Gasoline</th>
<th>AFV</th>
<th>Diesel</th>
<th>BEV</th>
<th>PHEV</th>
<th>Model 2a Estimate (t-stat)</th>
<th>Model 2b Estimate (t-stat)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASC – New Gasoline Vehicle</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-3.410 (-10.08)</td>
<td>-8.810 (-6.81)</td>
</tr>
<tr>
<td>ASC – New Diesel Vehicle</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-4.830 (-11.67)</td>
<td>-10.300 (-7.84)</td>
</tr>
<tr>
<td>ASC – New Battery Electric Vehicle (BEV)</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-3.990 (-2.38)</td>
<td>-9.230 (-4.07)</td>
</tr>
<tr>
<td>ASC – New Plug-In Hybrid Electric Vehicle (PHEV)</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-4.510 (-3.31)</td>
<td>-10.100 (-4.79)</td>
</tr>
<tr>
<td>Fuel Price [$]</td>
<td>X X X X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.800 (-6.91)</td>
<td>-1.160 (-7.79)</td>
</tr>
<tr>
<td>Gasoline Price – PHEV [$]</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.423 (-2.83)</td>
<td>-0.358 (-2.02)</td>
</tr>
<tr>
<td>Electricity Price – BEV [$]</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.518 (-2.42)</td>
<td>-0.762 (-3.02)</td>
</tr>
<tr>
<td>Electricity Price – PHEV [$]</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.261 (-1.79)</td>
<td>-0.569 (-2.79)</td>
</tr>
<tr>
<td>Charge Time – BEV [hours]</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.700 (-3.49)</td>
<td>-0.917 (-3.68)</td>
</tr>
<tr>
<td>Charge Time – PHEV [hours]</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>**(-0.048 (-0.38))</td>
<td>**(-0.164 (-0.87))</td>
</tr>
<tr>
<td>Average Fuel Economy [MPG, MPGe]</td>
<td>X X X X X X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.021 (3.11)</td>
<td>0.039 (3.91)</td>
</tr>
<tr>
<td>Current Vehicle Age – Purchased New [years]</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.114 (-4.21)</td>
<td>-0.395 (-4.21)</td>
</tr>
<tr>
<td>Current Vehicle Age – Purchased Used [years]</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.095 (-4.03)</td>
<td>-0.377 (-3.86)</td>
</tr>
<tr>
<td>Current Vehicle Error Component (standard deviation)</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.290 (3.90)</td>
<td>2.300 (3.92)</td>
</tr>
<tr>
<td>Electric Vehicle Error Component (standard deviation)</td>
<td>X X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.300 (3.92)</td>
<td>3.460 (4.91)</td>
</tr>
</tbody>
</table>

### Model Statistics

- Log Likelihood (no coefficients): -901.255
- Log Likelihood (constants only): -667.735
- Log Likelihood (at optimal): -597.008
- Rho-squared: 0.338
- Adjusted Rho-squared: 0.322
- Number of Observations (Individuals): 503 (42)

Note: Coefficients are significant to the 95% level or 90% level*, unless otherwise denoted**
### TABLE 4 Taxation Policy Experiment Models

<table>
<thead>
<tr>
<th>Variable [Units]</th>
<th>In Utility</th>
<th>Model 3a Estimate (t-stat)</th>
<th>Model 3b Estimate (t-stat)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Current Gasoline Hybrid Electric</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASC – New Gasoline Vehicle</td>
<td>X</td>
<td>-3.410 (-10.53)</td>
<td>-7.170 (-6.03)</td>
</tr>
<tr>
<td>ASC – New Hybrid Vehicle</td>
<td>X</td>
<td>-3.460 (-11.52)</td>
<td>-7.090 (-5.94)</td>
</tr>
<tr>
<td>ASC – New Electric Vehicle</td>
<td>X</td>
<td>-3.960 (-11.01)</td>
<td>-7.590 (-6.17)</td>
</tr>
<tr>
<td>Hybrid Vehicle Deduction [$] divided by Household Income [$1000]</td>
<td>X</td>
<td>0.395 (3.62)</td>
<td>0.093 (2.71)</td>
</tr>
<tr>
<td>Electric Vehicle Deduction [$] divided by Household Income [$1000]</td>
<td>X</td>
<td>0.135 (4.42)</td>
<td>0.245 (2.02)</td>
</tr>
<tr>
<td>VMT Tax interacted with annual mileage [$100]</td>
<td>X X X X</td>
<td>-0.127 (-4.68)</td>
<td>-0.186 (-5.14)</td>
</tr>
<tr>
<td>Toll Discount [%] (for households near toll facilities)</td>
<td>X X</td>
<td>0.019 **(1.34)</td>
<td>0.065 (2.76)</td>
</tr>
<tr>
<td>Toll Discount [%] (for households not near toll facilities)</td>
<td>X X</td>
<td>0.010 **(1.64)</td>
<td>0.005 **(0.75)</td>
</tr>
<tr>
<td>Current Vehicle Age (new) interacted with Annual Mileage [years x 1000 miles]</td>
<td>X</td>
<td>-0.018 (-6.79)</td>
<td>-0.049 (-5.24)</td>
</tr>
<tr>
<td>Current Vehicle Age (used) interacted with Annual Mileage [years x 1000 miles]</td>
<td>X</td>
<td>-0.005 (-2.12)</td>
<td>-0.026 (-2.47)</td>
</tr>
<tr>
<td>New Vehicle Error Component (standard deviation)</td>
<td>X X X</td>
<td>3.760 (4.90)</td>
<td>0.000 (Fixed)</td>
</tr>
<tr>
<td>Current Vehicle Error Component (fixed to 0)</td>
<td>X</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Model Statistics**

- Log Likelihood (no coefficients) -565.608 -565.608
- Log Likelihood (constants only) -456.740 -456.740
- Log Likelihood (at optimal) -396.381 -308.081
- Rho-squared 0.299 0.455
- Adjusted Rho-squared 0.282 0.436
- Number of Observations (Individuals) 408 408 (34)

Note: Coefficients are significant to the 95% level or 90% level*, unless otherwise denoted**