MEASURING AND MODELING FUTURE VEHICLE PREFERENCES: A PRELIMINARY STATED PREFERENCE SURVEY IN MARYLAND

Michael Maness*
Graduate Research Assistant
University of Maryland
Department of Civil and Environmental Engineering
1173 Glenn Martin Hall
College Park, MD 20742
Phone: 301-405-6864
Fax: 301-405-2585
Email: mmaness@umd.edu

Cinzia Cirillo
Assistant Professor
University of Maryland
Department of Civil and Environmental Engineering
1173 Glenn Martin Hall
College Park, MD 20742
Phone: 301-405-6864
Fax: 301-405-2585
Email: ccirillo@umd.edu

* corresponding author

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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. Understanding the impact of these factors, through vehicle ownership modeling, is critical for achieving environmental and economic goals. This study focuses on analyzing future demand for battery electric, hybrid electric, plug-in hybrid electric, alternative fuel, and gasoline vehicles over the short to medium term. To do this, this project proposes to use a novel stated preference survey design to analyze vehicle purchasing behavior in a dynamically changing marketplace. 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 designs correspond to changing vehicle technology, fueling options, and taxation policy. Between scenarios, the vehicle and fuel attributes dynamically change to mimic marketplace conditions. A pilot web-based survey was performed during fall 2010. Mixed logit models showed that the survey design allowed for estimation of important parameters in vehicle choice. The models showed that, among respondents in the sample, hybrid vehicles had nearly the same preference as new gasoline vehicles and that battery electric and plug-in hybrid vehicles became attractive with raising gasoline price. Respondents were able to depreciate their vehicles over the five-year hypothetical period. Taxation policy measures had some impact on changing vehicle preferences, but when presented in isolation, taxation policy can produce inconsistent results.

INTRODUCTION

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.

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.

The power of vehicle preference and ownership models is that the models can be used for a multitude of analysis including vehicle emissions and climate change, travel mode choice, vehicle miles traveled, vehicle use tax policy, analysis of vehicle fees and rebates, transportation sector energy usage, electric infrastructure demand, automobile industry outlook, and international trade.

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 (SP) 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 (*4*) 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 (*5*) 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. (*6*) 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. (*7*) surveyed households in Canada and California to compare 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 (*8*) 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. (*10,11*) 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. (*12*) 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) (*13*) and applying information cascade experiments to vehicle preference studies (*14*).

From a modeling perspective, discrete choice models have generally been used to analyze future vehicle preferences. Multinomial logit and nested logit models have been used extensively over the last 20 years (*1,3,6,8*). 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.

(*10*). Additional modeling frameworks have included cross-nested logit (*12*), hybrid choice (*5*), latent class (*11*), and multiple discrete-continuous extreme value models (*4*).

PURPOSE AND CONTRIBUTION

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 (*8*) or the next vehicle purchase (*2-7,9-12*). 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, BEV prices fell over a three years period and gasoline vehicle MPG 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.

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.

TABLE 1 Summary of Survey Methods

Time Frame	Summer – Fall 2010
Target Population	Suburban and Urban Maryland Households
Sampling Frame	Households with internet access in 5 Maryland counties
Sample Design	Multi-stage cluster design by county and zipcode
Use of Interviewer	Self-administered
Mode of Administration	Self-administered via the computer and internet for remaining respondents
Computer Assistance	Computer-assisted self interview (CASI) and web-based survey
Reporting Unit	One person age 18 or older per household reports for the entire household
Time Dimension	Cross-sectional survey with hypothetical longitudinal stated preference experiments
Frequency	One two-month phase of collecting responses
Levels of Observation	Household, vehicle, person

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.

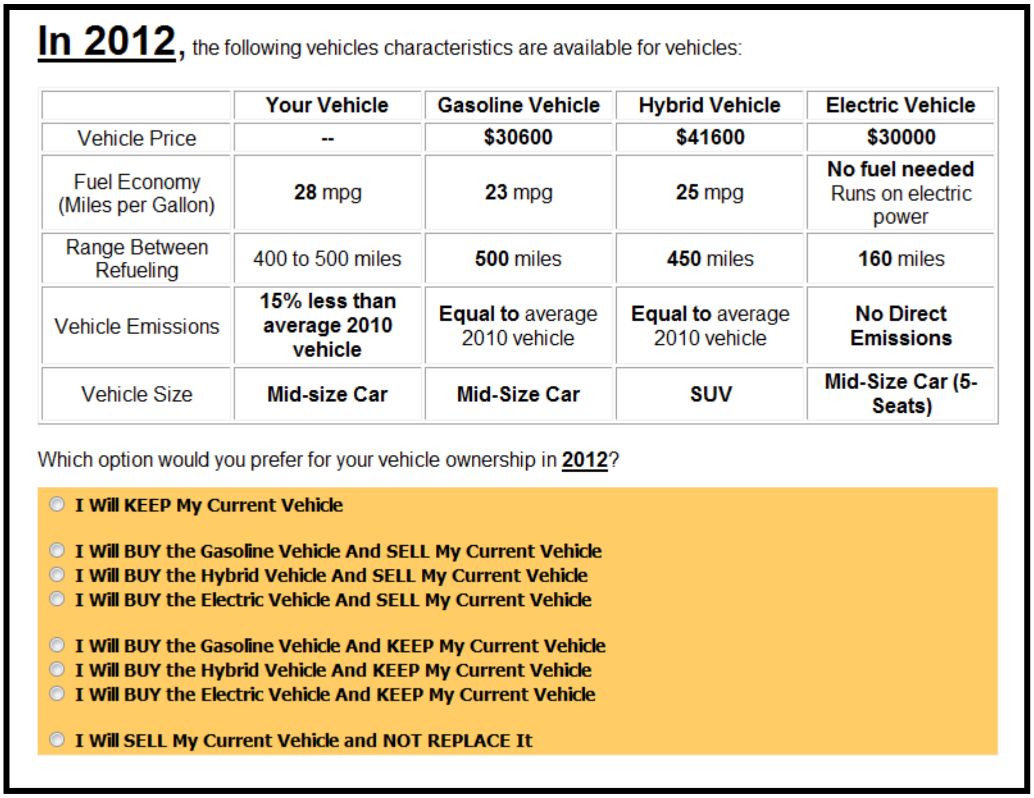
Vehicle Technology Experiment

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 manufacturers.

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.



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

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

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

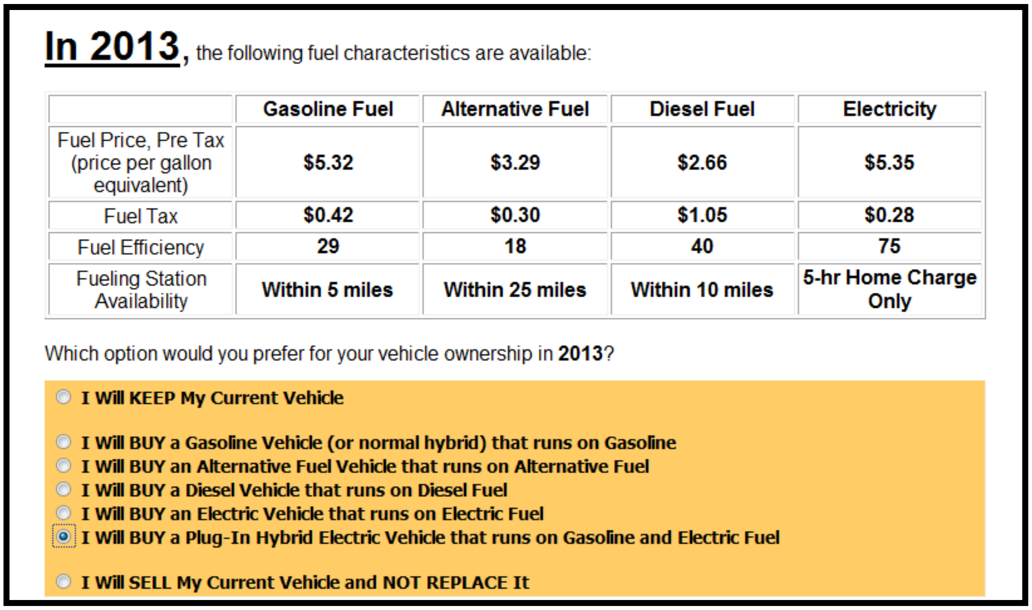
Fuel Type Experiment

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 electric). 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.



In 2013, the following fuel characteristics are available:

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

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

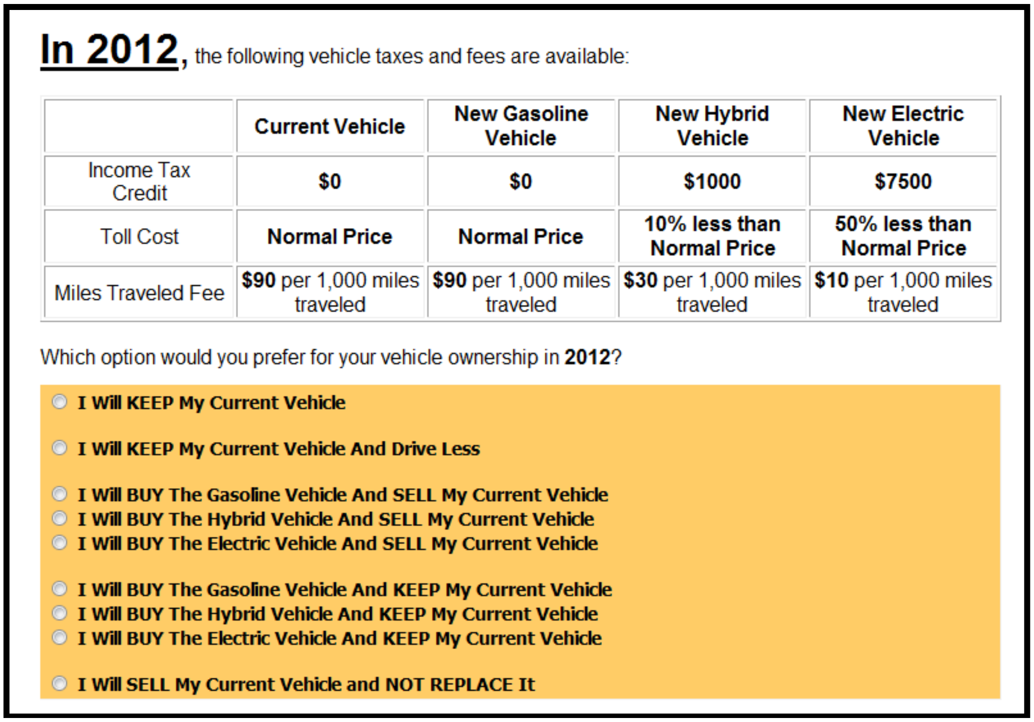
FIGURE 2 Fuel Type Experiment Example

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, hybrid, or electric) 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.



In 2012, the following vehicle taxes and fees are available:

	Current Vehicle	New Gasoline Vehicle	New Hybrid Vehicle	New Electric Vehicle
Income Tax Credit	$0	$0	$1000	$7500
Toll Cost	Normal Price	Normal Price	10% less than Normal Price	50% less than Normal Price
Miles Traveled Fee	$90 per 1,000 miles traveled	$90 per 1,000 miles traveled	$30 per 1,000 miles traveled	$10 per 1,000 miles traveled

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

FIGURE 3 Taxation Policy Experiment Example

MODEL STRUCTURE

To test the usability of the survey results for analysis, discrete choice methods were the basis of the modeling process. 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 as follows:

$$U_{nit} = \beta X_{nit} + [\, \eta_{ni} + \varepsilon_{nit} \,]$$

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

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

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

where:
$\mathrm{P}(\mathrm{i}|\mathrm{X}_{\mathrm{nit}}; \beta, \sigma)$ = 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 β, here assumed to be normal

RESULTS

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.

Discrete choice models were estimated using BIOGEME (*17*). Multinomial logit and mixed multinomial logit models were used with all mixed logit models presented 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. Next, modeling results are presented 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 vehicle was generally the preferred alternative for a new vehicle with the HEV closely following. 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 is likely more realistic as new technology generally suffers 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 value of range increases between the MNL and mixed logit models. This result suggests that the MNL model more conservatively predicts how much respondents value vehicle range. The change in the value of range between the MNL and mixed logit is similar to results from Bhat (*18*) but counter to Bhat (*19*) and Brownstone and Train (*11*).

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.

TABLE 2 Vehicle Technology Experiment Models

Variable [Units]	In Utility: Current	Gasoline	Hybrid	Electric	Model 1a Estimate (t-stat)	Model 1b Estimate (t-stat)	Model 1c Estimate (t-stat)
ASC – New Gasoline Vehicle		X			-1.330 (-4.55)	-1.090 (-3.15)	-1.320 (-3.28)
ASC – New Hybrid Vehicle			X		-1.130 (-2.98)	-1.160 (-2.24)	-1.760 (-2.93)
ASC – New Electric Vehicle				X	-1.370 (-4.80)	-2.290 (-4.59)	-3.450 (-5.70)
Purchase Price [$10,000]		X	X	X	-0.498 (-5.86)	-0.701 (-7.12)	-0.639 (-5.42)
Fuel Economy Change [MPG] (current vehicle MPG known)		X	X		0.038 (4.58)	0.054 (4.98)	0.039 (2.68)
Fuel Economy [MPG] (current vehicle MPG unknown)		X	X		0.009 *(1.69)	-0.004 **(-0.52)	-0.002 **(-0.21)
Recharging Range [100 miles]				X	0.308 (2.13)	0.668 (3.47)	0.909 (4.37)
Current Vehicle Age – Purchased New [years]	X				-0.097 (-5.57)	-0.134 (-5.74)	-0.123 (-4.34)
Current Vehicle Age – Purchased Used [years]	X				-0.053 (-3.20)	-0.050 (-2.08)	-0.059 (-2.02)
Minivan Dummy interacted with Family Households		X			0.886 *(1.95)	1.030 (2.24)	1.410 (2.75)
SUV Dummy interacted with Family Households		X			1.110 (3.41)	1.440 (4.22)	1.900 (4.77)
Non-Electric Vehicle Error Component (standard deviation)	X	X	X			2.530 (5.89)	2.400 (6.00)
Non-Hybrid Vehicle Error Component (standard deviation)	X	X		X		1.980 (6.79)	2.150 (6.71)
Vehicle Size (mean)	X	X	X	X			-0.435 (-2.42)
Vehicle Size (standard deviation)	X	X	X	X			1.090 (6.61)
Log Likelihood (no coefficients)					-1379.363	-1379.363	-1379.363
Log Likelihood (constants only)					-1088.104	-1088.104	-1088.104
Log Likelihood (at optimal)					-1011.789	-866.276	-819.608
Rho-squared					0.266	0.371	0.406
Adjusted Rho-squared					0.259	0.361	0.395
Number of Observations (Individuals)					995	995 (83)	995 (83)

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

Table 3 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.

TABLE 3 Vehicle Technology Experiment Calculations

	Model 1a (MNL)	Model 1b (Mixed)	Model 1c (Mixed)
Value of EV Range ($ / mile)	62	95	141
Depreciation – bought new ($ / year)	1,950	1,910	1,310
Depreciation – bought used ($ / year)	1,066	710	920
Value of Fuel Efficiency ($ / mpg)	760	770	610

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. 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 4. 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.

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. For the fuel type experiment, the difference between this depreciation was less than in the vehicle technology experiment.

The error component specification was significant which suggests that this is a possible technique of grouping the different vehicle types together. 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.

TABLE 4 Fuel Type Experiment Models

Variable [Units]	In Utility: Current	Gasoline	AFV	Diesel	BEV	PHEV	Model 2a Estimate (t-stat)	Model 2b Estimate (t-stat)
ASC – New Gasoline Vehicle		X					-3.410 (-10.08)	-8.810 (-6.81)
ASC – New Alternative Fuel Vehicle (AFV)			X				-4.380 (-12.38)	-9.940 (-7.66)
ASC – New Diesel Vehicle				X			-4.830 (-11.67)	-10.300 (-7.84)
ASC – New Battery Electric Vehicle (BEV)					X		-3.990 (-2.38)	-9.230 (-4.07)
ASC – New Plug-In Hybrid Electric Vehicle (PHEV)						X	-4.510 (-3.31)	-10.100 (-4.79)
Fuel Price [$]	X	X	X	X			-0.800 (-6.91)	-1.160 (-7.79)
Gasoline Price – PHEV [$]						X	-0.423 (-2.83)	-0.358 (-2.02)
Electricity Price – BEV [$]					X		-0.518 (-2.42)	-0.762 (-3.02)
Electricity Price – PHEV [$]						X	-0.261 *(-1.79)	-0.569 (-2.79)
Charge Time – BEV [hours]					X		-0.700 (-3.49)	-0.917 (-3.68)
Charge Time – PHEV [hours]						X	-0.048 **(-0.38)	-0.164 **(-0.87)
Average Fuel Economy [MPG, MPGe]		X	X	X	X	X	0.021 (3.11)	0.039 (3.91)
Current Vehicle Age – Purchased New [years]	X						-0.114 (-4.21)	-0.395 (-4.21)
Current Vehicle Age – Purchased Used [years]	X						-0.095 (-4.03)	-0.377 (-3.86)
Current Vehicle Error Component (standard deviation)	X							2.290 (3.90)
Electric Vehicle Error Component (standard deviation)					X	X		2.300 (3.92)
Liquid Fuel Vehicle Error Component (standard deviation)		X	X	X				3.460 (4.91)
Log Likelihood (no coefficients)							-901.255	-901.255
Log Likelihood (constants only)							-667.735	-667.735
Log Likelihood (at optimal)							-597.008	-443.640
Rho-squared							0.338	0.508
Adjusted Rho-squared							0.322	0.489
Number of Observations (Individuals)							503	503 (42)

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

Taxation Policy Experiment Results

Two models for the taxation policy experiment are presented in Table 5. 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 (*20*). 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.

TABLE 5 Taxation Policy Experiment Models

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

FUTURE WORK

Based on the modeling work and analysis, the following options are being considered for future surveys:

- *Eliminate the taxation policy experiment.* This 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 were inconsistent as the hybrid and electric vehicle deductions did not have a similar effect and relative ordering of their magnitudes differed between models. Additionally, there were inconsistencies in the significance of tolling policy on vehicle preferences between the two models as well.
- *Incorporation of taxation policy variables into the other experiments.* The inconsistencies in the taxation policy experiment may suggest that advertising policies

requires some contextual elements to be most effective and to achieve expected aims. For example, incorporating the vehicle deduction into the vehicle technology experiment may have a greater impact in context than in isolation. Incorporating the VMT tax into the fuel type experiment would also be advisable as vehicle usage also affects fuel usage.

- *Use MPGe for electric vehicles in the vehicle technology experiment.* During the model building process, the fuel economy for BEV was included as a separate variable in the fuel type models. 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 understand MPG equivalency and that including that variable in the vehicle technology experiment would yield consistent results.

CONCLUSION

Technological gains, environmental concerns, and energy prices have created an opportunity to expand consumers' vehicle options. Over the next five to ten years, the automobile landscape will be filled with not only conventional gasoline vehicles but also with battery electric, hybrid electric, plug-in hybrid electric, and other alternative fuel vehicles. An understanding of the perceptions of consumers will be important for diversifying the vehicle pool.

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 showed that respondents realistically depreciating their vehicles over the course of the experiments as well as considered trade-offs that may have allowed 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 showed that policy measures have some impact on vehicle preferences, but that in isolation, policy measure may exhibit inconsistencies.

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