Measuring Future Vehicle Preferences

Stated Preference Survey Approach with Dynamic Attributes and Multiyear Time Frame

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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 (SP) surveys have been the dominant approach. Prior research has been limited to a narrow focus of accelerating respondents' hypothetical next vehicle purchasing decisions without mimicking the influence of the marketplace on these decisions. To explore marketplace influences, this study proposes to use a novel SP survey design to analyze vehicle purchasing behavior in a dynamically changing marketplace through the use of dynamic attributes and a 6-year hypothetical time window. The survey is divided into three parts: household characteristics, current vehicles, and SP. The SP section presents respondents with various hypothetical scenarios annually over a future 6-year period with 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 individuals 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 5-year hypothetical period and place trade-offs 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.

Predicting consumer preferences for future vehicles is important for industry and government. 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 and 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 adoption of clean-fuel vehicles in California (*1*). In this study, respondents were presented with hypothetical scenarios with vehicles of varying attributes and asked to choose their most preferred option. Since then, SP 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*). In addition, 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 SP vehicle preference 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 5 to 10 years. Rising global oil demand is driving up energy prices and creating a competitive marketplace for alternative energy sources. In addition, 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 an SP 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 that allow for estimation of advanced discrete choice models with significant and plausible results; and
- 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 6-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, prices of battery electric

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vehicles fell over a 3-year 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 that may influence new-vehicle adoption.

The following terms used in the study are defined here:

- Battery electric vehicle (BEV). A vehicle that stores electricity in batteries as its only energy source;
- Hybrid electric vehicle (HEV). A vehicle that runs on gasoline but uses larger batteries to aid in the vehicle propulsion;
- Plug-in hybrid electric vehicle (PHEV). A vehicle that 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;
- Alternative-fuel vehicle (AFV). A vehicle with an internal combustion engine that runs on a liquid fuel that is not gasoline or diesel (e.g., ethanol);
- Vehicle miles traveled (VMT). The measure of distance a vehicle travels; and
- Miles per gallon gasoline (mpg) equivalent (mpge). The measure of average distance traveled per unit of energy in 1 U.S. gal of gasoline.

PREVIOUS RESEARCH

The transportation community has generally approached the task of predicting new-vehicle preference via SP methods. Bunch et al. performed a three-phase survey in the early 1990s to analyze AFV, flex-fuel, and BEV adoption in California (*1*). Phase 2 of the survey was a vehicle choice SP experiment in which 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. performed an SP survey with reflexive designs in the mid-1990s in California (*2*). In this experiment, it was hypothesized that certain multiple-vehicle households had a greater propensity toward 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% of California households could be hybrid households.

Ewing and Sarigöllü used SP methods and attitude analysis to study consumer preferences for BEVs and AFVs (*3*). 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. considered AFVs (diesel, natural gas, liquefied petroleum gas) and HEVs to estimate new-vehicle purchases and annual usage (*10*). Bolduc et al. used SP methods with psychometric data to analyze vehicle preferences in Canada (*4*). Hybrid choice models found that environmental concern and appreciation of new vehicle features had a significant influence on vehicle choice.

Mau et al. looked at vehicle preferences for HEVs and hydrogen–fuel cell vehicles using SP methods and a technology vintage model (*5*). The analysis confirmed their hypothesis that market share of new technology ("neighbor effect") affects personal vehicle preferences. Axsen et al. surveyed households in Canada and California to compare revealed-preference (RP) methods with SP-RP methods in determining hybrid vehicle preferences (*11*). 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 used an SP survey to calibrate a simulation-based model of household vehicle evolution (*12*). This survey presented respondents with 12 different vehicle options and asked for their preferred vehicle under current conditions, under higher fuel price conditions, and with environmental impact information. Eggers and Eggers conducted a web-based SP survey in Germany that concentrated on compact and subcompact vehicles for city driving (*7*). 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. used a web-based SP survey to study the effect of annual and usage-based emission fees on vehicle ownership (*8, 9*). The survey's alternative set included new gasoline, diesel, and hybrid vehicles. Respondent's current vehicle was presented next to the vehicles available to purchase but was not included as a possible alternative in order to reduce hypothetical bias. Hess et al. analyzed results from the California Vehicle Study, which asked respondents about the vehicle they likely planned to purchase next (*13*). By using this vehicle as an alternative as well as three other vehicles of varying sizes, fuel type, and drive train technology, respondents chose their preferred vehicle.

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

SURVEY DESIGN

To analyze consumer preferences for future vehicles, an SP approach was adopted. A web-based survey was chosen, primarily for the advantages of its cost and administration time. 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

TABLE 1 Summary of Survey Methods

Characteristic	Details
Time frame	Summer–fall 2010
Target population	Suburban and urban Maryland households
Sampling frame	Households with Internet access in five Maryland counties
Sample design	Multistage cluster design by county and zip code
Use of interviewer	Self-administered
Mode of administration	Self-administered via computer and Internet for remaining respondents
Computer assistance	Computer-assisted self interview and web-based survey
Reporting unit	One person aged 18 or older per household reports for entire household
Time dimension	Cross-sectional survey with hypothetical longitudinal stated preference experiments
Frequency	One 2-month phase of collecting responses
Levels of observation	Household, vehicle, person

current vehicle section asked respondents to describe various characteristics about their current vehicle, such as make and model, fuel economy, and price.

The SP 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, whereas the other two experiments each had a 25% chance.

Each stated-choice experiment generated multiple SP observations over a 6-year time period, from 2010 to 2015. The variables in the scenarios changed from year to year when plausible. For example, the vehicle price generally increased over time, the 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 it into account.
- Assume that you maintain your current living situation with moderate increases in income from year to year.
- Each scenario is independent from the others. Do not take into account the decisions you made in former scenarios; for example, if you purchased 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 their preferences for vehicle technology. This experimental design consisted of four alternatives and five variables with a choice set size of eight.

Four alternatives—the current vehicle and a new gasoline vehicle, HEV, or 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 5 years. Gasoline vehicles are the traditional option, whereas HEVs have grown in market share in the United States. Although BEVs 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 refuelings or rechargings. Emissions were displayed as the percent difference in emissions in comparison with the average vehicle in 2010. Electric vehicles were stated to have no direct emissions. Vehicle sizes were based on the U.S. Environmental Protection Agency 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 (see Figure 1).

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 Example of vehicle technology experiment.

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. The following fuel types are currently established in Maryland's marketplace: gasoline, alternative (ethanol), 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 U.S. dollars per gallon or gallon equivalent for electric cars. The fuel economy was presented as the average expected fuel economy for a vehicle that runs on that fuel type and measured in miles per gallon (mpg) or mpg gasoline equivalent (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 vehicle, AFV, diesel vehicle, BEV, or PHEV (Figure 2).

Taxation Policy Experiment

The taxation policy experiment presented respondents with different toll and tax policies to infer their effects 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 those for the vehicle technology experiment, four alternatives were shown to respondents: current vehicle, new gasoline vehicle, new HEV, and new BEV. The variables of interest in the taxation policy experiment included income tax credits, toll cost, and VMT fee (for scenario years 2012 through 2015). The income tax credit, measured in U.S. dollars, attempted to encourage adoption of new technology through reducing the individual's tax burden. Tax credits were shown for HEVs and BEVs on the basis of current U.S. 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 U.S. dollars per 1,000 mi traveled that would be collected by the respondent's insurance provider.

The choice set for the taxation policy experiment included all permutations 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 the current vehicle and drive less (Figure 3).

DESCRIPTIVE STATISTICS

A sample was collected with a multistage cluster design by county and zip code 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's degree or higher;
- Income: $50,000 to $75,000 (median) and 22% with incomes more than $150,000;
- Vehicle ownership: 1.9 (average) and 2.0 (median);
- Primary vehicle age: 6.4 years (average) and 6.0 years (median);
- Primary vehicle price: $23,763 (average, new) and $11,367 (average, used); and
- Intent to purchase vehicle within 5 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 those of other Maryland households.

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 Example of fuel type experiment.

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 Example of taxation policy experiment.

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 and nested logit models have been used extensively over the past 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 independence from irrelevant alternatives 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:

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

where

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

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

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

where

$P(i|X_{nit};\beta,\sigma)$ = probability of choosing alternative i for decision maker n,
C = choice set for model,
$j \in C$ = alternative j in choice set C,
T = total number of scenarios, and
$f(\beta|\sigma)$ = density of β, here assumed to be normal.

Discrete choice models were estimated by using BIOGEME (*17*). Multinomial logit and mixed multinomial logit models were used with all mixed logit models estimated with 2,500 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.

Results of Vehicle Technology Experiment

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 with the alternative for keeping the current vehicle. All

TABLE 2 Vehicle Technology Experiment Models

Parameter	Alternative: Current	Gasoline	Hybrid	Electric	Model 1a Estimate (*t*-Statistic)	Model 1b Estimate (*t*-Statistic)	Model 1c Estimate (*t*-Statistic)
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 ($10,000)	—	X	X	X	−0.498 (−5.86)	−0.701 (−7.12)	−0.639 (−5.42)
Fuel economy change (mpg) (current vehicle mpg known)	—	X	X	—	0.038 (4.58)	0.054 (4.98)	0.039 (2.68)
Fuel economy (mpg) (current vehicle unknown)	—	X	X	—	0.009 (1.69)*	−0.004 (−0.52)**	−0.002 (−0.21)**
Recharging range (100 mi)	—	—	—	X	0.308 (2.13)	0.668 (3.47)	0.909 (4.37)
Current vehicle age, purchased new (years)	X	—	—	—	−0.097 (−5.57)	−0.134 (−5.74)	−0.123 (−4.34)
Current vehicle age, purchased used (years)	X	—	—	—	−0.053 (−3.20)	−0.050 (−2.08)	−0.059 (−2.02)
Minivan dummy interacted with family households	—	X	—	—	0.886 (1.95)*	1.030 (2.24)	1.410 (2.75)
SUV dummy interacted with family households	—	X	—	—	1.110 (3.41)	1.440 (4.22)	1.900 (4.77)
Nonelectric vehicle error component (standard deviation)	X	X	X	—	— —	2.530 (5.89)	2.400 (6.00)
Nonhybrid vehicle error component (standard deviation)	X	X	—	X	— —	1.980 (6.79)	2.150 (6.71)
Vehicle size (mean)	X	X	X	X	— —	— —	−0.435 (−2.42)
Vehicle size (standard deviation)	X	X	X	X	— —	— —	1.090 (6.61)
Model statistics							
Log likelihood (no coefficients)					−1,379.363	−1,379.363	−1,379.363
Log likelihood (constants only)					−1,088.104	−1,088.104	−1,088.104
Log likelihood (at optimal)					−1,011.789	−866.276	−819.608
Rho-squared					.266	.371	.406
Adjusted rho-squared					.259	.361	.395
Number of observations (individuals)					995	995 (83)	995 (83)
Calculated measures of valuations							
Value of EV range ($/mi)					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

NOTE: Coefficients are significant to the 95% level, unless otherwise noted. — = not applicable.
*$.10 \le p < .05$; ** $p < .10$.

the constants were negative as expected since one's current vehicle is likely a good match with one'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 (became 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 for 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 since 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 coefficient for new-vehicle age was greater in magnitude than that for the used-vehicle age, which suggests that households that buy new vehicles place greater depreciation on their vehicles. In addition, dummies for new gasoline sport utility vehicles and minivans for households with children were positive since 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's fuel economy. For respondents who knew their vehicle's mpg, the difference between their current

vehicle's mpg and the mpg of the new vehicle was used for estimation. For respondents who did not know their vehicle's fuel economy, the actual new-vehicle fuel economy was used for estimation. The models showed that fuel economy had no significant influence on vehicle preferences for respondents without knowledge of their vehicle's fuel economy. For households with knowledge of their vehicle's fuel economy, the results from all models were positive as expected.

The error components for nonelectric and nonhybrid vehicles were significant in both mixed logit models with the same ordering of magnitudes. This finding suggests that the following pairings of alternatives exist 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, sport utility vehicle, 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 since they were found to have an insignificant effect and were too correlated with vehicle fuel economy.

At the bottom of Table 2 some additional findings with regard to respondents' valuation of vehicle attributes are summarized. 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 lesser 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/mpg to $770/mpg. Model 1c was most conservative about preferences for fuel efficiency, and 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 vehicles 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 multinomial logit 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 than the other two models.

Results of Fuel Type Experiment

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 ASC. 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 to gasoline price. This finding may be attributed to lack of familiarity with electricity for fueling or a "rule of thumb." The charging time of BEVs was significant with each hour of charge time being worth more than a dollar's worth of fuel cost. In addition, charge time for PHEVs was found to be insignificant. This finding may confirm that respondents realized that charging of PHEVs was less important since PHEVs run on gasoline when batteries are depleted.

The coefficient for average fuel economy was positive as expected and significant. As in 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 types. The results suggested that households responsive to electric vehicles had a similar responsiveness to PHEVs. The three liquid fueling types (gasoline, diesel, and alternative fuel) were also shown to have some similarities.

Results of Taxation Policy Experiment

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

A VMT tax was found to have a negative effect on utility. This variable was interacted with the 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 multinomial logit 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; this finding shows that there is some correlation between all the new vehicle types.

SUMMARY AND FUTURE RESEARCH

This study showed that an SP study over a hypothetical dynamic environment can produce results that fit economic expectations (e.g., disutility of price). The approach shown here uses a novel SP survey with dynamically changing vehicle, fuel, and policy attributes and multiyear time window. The research shows that respondents realistically depreciate their vehicles over the course of the

TABLE 3 Fuel Type Experiment Models

Parameter	Alternative						Model 2a Estimate (*t*-Statistic)	Model 2b Estimate (*t*-Statistic)
	Current	Gasoline	AFV	Diesel	BEV	PHEV		
ASC, new gasoline vehicle	—	X	—	—	—	—	−3.410 (−10.08)	−8.810 (−6.81)
ASC, new 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 BEV	—	—	—	—	X	—	−3.990 (−2.38)	−9.230 (−4.07)
ASC, new 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)
Model statistics								
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							.338	.508
Adjusted Rho-squared							.322	.489
Number of observations (individuals)							503	503 (42)

NOTE: Coefficients are significant to the 95% level, unless otherwise noted. — = not applicable.
*$.10 \le p < .05$; ** $p < .10$.

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 technologies as well as the price of various fueling options.

The study exposed some areas for refinement of the survey; on the basis of 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 believed to be the weakest of the three since 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 require 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 of 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 BEVs was included as a separate variable in the fuel type models but not in the vehicle technology experiment. This coefficient had a value similar to the fuel economy variable for vehicles that ran on liquid fuels. This

TABLE 4 Taxation Policy Experiment Models

Parameter	Alternative: Current	Gasoline	Hybrid	Electric	Model 3a Estimate (*t*-Statistic)	Model 3b Estimate (*t*-Statistic)
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 ($1,000)	—	—	X	—	0.395 (3.62)	0.093 (2.71)
Electric vehicle deduction ($) divided by household income ($1,000)	—	—	—	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 × 1,000 mi)	X	—	—	—	−0.018 (−6.79)	−0.049 (−5.24)
Current vehicle age (used) interacted with annual mileage (years × 1,000 mi)	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)
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					.299	.455
Adjusted rho-squared					.282	.436
Number of observations (individuals)					408	408 (34)

NOTE: Coefficients are significant to the 95% level, unless otherwise noted. — = not applicable.
*$.10 \le p < .05$; ** $p < .10$.

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 respondents who stated that they intended to buy and those who did not. 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 vehicle's fuel economy were receptive to the fuel economy attribute of new vehicles, whereas respondents without knowledge were not receptive. New research could delve into the indicators of one's knowledge of vehicle attributes.

In addition, research into the effect of varying the time frame of the survey and vehicle retention is needed. This study used a 6-year time frame because of the commonly advertised 60-month financing offers for new vehicles. Further research could determine how far forward respondents can reliably comprehend and mimic actual vehicle purchasing processes. With regard 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 design would also require testing how many purchases to allow and the appropriate time frame lengths for accurate measurement.

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