Would You Consider a “Green” Vehicle? Anticipating Electric Vehicle Adoption Patterns and Emissions Impacts in Virginia

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Would You Consider a “Green” Vehicle? Anticipating Electric Vehicle Adoption Patterns and Emissions Impacts in Virginia

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Electric vehicles (EVs) have potential to decrease greenhouse gas (GHG) emissions and improve air quality and energy security. This study examines EV adoption patterns and preferences in Virginia at the zone (county) level and individual consumer level. The zonal level analysis is conducted using Virginia Department of Motor Vehicles (DMV) vehicle registration data from 2012 to 2016 while the individual multinomial logit (MNL) model is developed based on a stated preference (SP) vehicle choice survey across Virginia drivers in 2018. Model results indicate higher education attainment and preference for smaller vehicles are found to consistently have positive effects on EV adoption and preference in both the zonal level EV ownership model and individual level vehicle choice model. However, several factors’ relationship with EV adoption and preference are more complex since results from zonal- and individual-level analysis are not consistent. These nuances include: 1) individual-level analysis shows that males are more likely to be interested in both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) while the zonal-level analysis shows counties with higher percent of males are associated with higher BEV (but not PHEV) counts; 2) counties with older population are associated with more EV registrations, yet in the survey, younger people are more likely to show interest in EVs; 3) though vehicle registration data suggests higher charging port density increases the number of EVs in a county, individuals exhibit heterogeneous preferences on different charging infrastructure types: the presence of direct current fast charging (DCFC) stations and workplace charging increase only the utility of BEVs (but not PHEVs) while local public charging station availability is not statistically significant in individual preferences for EVs. Additionally, results from individual level MNL model indicate that: 1) individuals looking for PHEVs are less concerned about all-electric range than those seeking BEVs; 2) federal tax credit and state rebates together are critical to offset high purchase price premiums of EVs; 3) individuals with higher educational attainment show strong negative preference for vehicles with higher tailpipe CO₂ emissions; and 4) respondents are more likely to buy an EV as an addition to their household’s car fleet or as the first car to the household, compared to buying an EV to replace an existing vehicle.

The zonal EV ownership model predicts a 0.6% to 10% Virginia statewide EV adoption rate in 2025 depending on future charging infrastructure investment, with a 2.4% adoption rate under the most likely scenario. Local CO₂ emissions impact is also assessed in this study based on predictions on EV adoption and fuel economy improvement of ICEVs. When considering only tailpipe emissions, all Virginia counties are predicted to reduce CO₂ tailpipe emissions, with the highest decrease in a single county at 58% (relative change from 2016 to 2025). When also considering the emissions from electricity generation,
statewide CO₂ emissions are projected to decrease by 7.5% to 19.4%, with a 10.7% decrease under the most likely scenario. Overall, the projected CO₂ emission reduction benefits from EV adoption is much lower than that from the fuel economy improvement of internal combustion engine vehicles (ICEVs), due to the relatively low projected statewide EV adoption rate in the most likely scenario.

17. Key Words
Electric Vehicles, Choice Behavior, Revealed Preference, Stated Preference, Emissions, Virginia

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WOULD YOU CONSIDER A “GREEN” VEHICLE? ANTICIPATING ELECTRIC VEHICLE ADOPTION PATTERNS AND EMISSIONS IMPACTS IN VIRGINIA

ABSTRACT
Electric vehicles (EVs) have potential to decrease greenhouse gas (GHG) emissions and improve air quality and energy security. This study examines EV adoption patterns and preferences in Virginia at the zone (county) level and individual consumer level. The zonal level analysis is conducted using Virginia Department of Motor Vehicles (DMV) vehicle registration data from 2012 to 2016 while the individual multinomial logit (MNL) model is developed based on a stated preference (SP) vehicle choice survey across Virginia drivers in 2018. Model results indicate higher education attainment and preference for smaller vehicles are found to consistently have positive effects on EV adoption and preference in both the zonal level EV ownership model and individual level vehicle choice model. However, several factors’ relationship with EV adoption and preference are more complex since results from zonal- and individual-level analysis are not consistent. These nuances include: 1) individual-level analysis shows that males are more likely to be interested in both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) while the zonal-level analysis shows counties with higher percent of males are associated with higher BEV (but not PHEV) counts; 2) counties with older population are associated with more EV registrations, yet in the survey, younger people are more likely to show interest in EVs; 3) though vehicle registration data suggests higher charging port density increases the number of EVs in a county, individuals exhibit heterogeneous preferences on different charging infrastructure types: the presence of direct current fast charging (DCFC) stations and workplace charging increase only the utility of BEVs (but not PHEVs) while local public charging station availability is not statistically significant in individual preferences for EVs. Additionally, results from individual level MNL model indicate that: 1) individuals looking for PHEVs are less concerned about all-electric range than those seeking BEVs; 2) federal tax credit and state rebates together are critical to offset high purchase price premiums of EVs; 3) individuals with higher educational attainment show strong negative preference for vehicles with higher tailpipe CO2 emissions; and 4) respondents are more likely to buy an EV as an addition to their household’s car fleet or as the first car to the household, compared to buying an EV to replace an existing vehicle.

The zonal EV ownership model predicts a 0.6% to 10% Virginia statewide EV adoption rate in 2025 depending on future charging infrastructure investment, with a 2.4% adoption rate under the most likely scenario. Local CO2 emissions impact is also assessed in this study based on predictions on EV adoption and fuel economy improvement of ICEVs. When considering only tailpipe emissions, all Virginia counties are predicted to reduce CO2 tailpipe emissions, with the highest decrease in a single county at 58% (relative change from 2016 to 2025). When also considering the emissions from electricity generation, statewide CO2 emissions are projected to decrease by 7.5% to 19.4%, with a 10.7% decrease under the most likely scenario. Overall, the projected CO2 emission reduction benefits from EV adoption is much lower than that from the
fuel economy improvement of internal combustion engine vehicles (ICEVs), due to the relatively low projected statewide EV adoption rate in the most likely scenario.

1. INTRODUCTION
Plug-in electric vehicle (EV) sales are on the rise and growing EV adoption can be a key factor in helping regions achieve national- and state-level air quality standards for ozone and particulate matter, and ultimately carbon-emissions standards. In the Mid-Atlantic, purchasing an EV over a gasoline-powered medium sedan can reduce transportation greenhouse gas emissions by 60 percent (Rushlow et al., 2015). The ability to predict which households in which neighborhoods are most likely to adopt EVs can provide important insights and opportunities for power-gird planning, transportation investment, and air quality policy-making. However, unlike the choice to purchase a traditional gasoline-powered vehicle, the decision to adopt an EV is complicated by technology familiarity, vehicle availability, and charging infrastructure provision, etc. This report analyzes the characteristics which contribute to existing EV adoption patterns and factors which may impact future EV adoption patterns in the state of Virginia. Previous quantitative research forecasting regional or household EV ownership trends either used revealed preference (RP) or stated preference (SP) data. This study contributes to the existing literature by combining both RP and SP data for the same study area. The impacts of socio-demographics, charging infrastructure, vehicle traits, and travel pattern, etc. on EV adoption are examined from county level (RP)- and individual level (SP) data, respectively. An EV adoption prediction model is subsequently developed, from which, the local emissions impacts of EV adoption are evaluated.

This report is organized as follows: Section 2 summarizes existing EV adoption literature from an aggregate perspective (studies based on historical EV sales or vehicle registration data) and a disaggregate perspective (studies based on individual stated preferences). Section 3 presents a model of existing zonal-level EV ownership using RP vehicle registration data from Virginia Department of Motor Vehicles (VA DMV), and then predicts zonal EV adoption in Virginia in 2025 and subsequent impacts on local CO₂ emissions. In Section 4, the development, distribution, and results of a stated preference vehicle choice survey are presented, followed by models which demonstrate the factors which affect individual EV preference in Virginia. Lastly, Section 5 concludes this report with major findings and discussions on future work.

2. LITERATURE REVIEW
This literature review includes two parts which are relevant to this study. The first part reviews prior work on aggregate predictions at different spatial resolution levels using historical EV sales or vehicle registration data. In the second part, disaggregate-level EV adoption studies based on household/individual surveys are summarized.

Aggregate EV Adoption Studies
Aggregate EV adoption studies explores the effects of socio-demographics, policy, charging infrastructure etc. on EV market share at different geographic scales. For example, Sierzchula et
al. (2014) examined the EV market shares of 30 countries for the year 2012 using multiple linear regression analysis. The author concluded that charging infrastructure was the best predictor of a country’s EV market share. In contrast, broader socio-demographic variables such as income and education level were not good predictors of adoption levels. Due to the highly aggregate nature of this study, the authors suggest that future research should also examine EV adoption within a country to capture the spatial heterogeneity.

Focusing on all 50 states in US, Vergis and Chen (2014) developed multiple linear regression model to understand the impacts of social, economic, and policy factors on statewide EV market share. The authors found that the number of publicly available charging stations, environmentalism, gasoline and electricity prices, education level, vehicle miles traveled per capita, HOV lane access, and the presence of purchase incentives to be significantly correlated with EV market shares in U.S. states in 2013.

The Sierzchula et al. (2014) and Vergis and Chen (2014)’s studies above fail to differentiate between BEVs and PHEVs. Although there are many similarities between the two powertrain types, the differences between PHEVs and BEVs, such as the need for new charging infrastructure, may confound model results. Thus, more recent studies differentiated between the two vehicle types.

For instance, Vergis and Chen (2015) developed stepwise regression models for PHEV and BEV market share separately at the US state level. The authors conclude that the variables that contribute to the BEV markets may be different than those contributing to PHEV markets, indicating that policies that are aimed at promoting EVs in general, may not be equally effective in supporting both the BEV and PHEV markets. Similarly, Jin et al. (2014) monetized all major direct and indirect incentives offered and examined whether such incentives influenced state-level EV sales on different states in US. Stepwise regression analysis was conducted for PHEVs and BEVs separately. Results indicate that the total monetary benefit available to BEV owners has a strong positive correlation with BEV sales, but similar monetary benefit for PHEVs is not correlated with PHEV sales. Furthermore, the authors find that not all types of incentives affect BEV sales equally: the most effective incentives are subsidies, carpool lane access, and emissions testing exemptions initiatives. Similarly, on a state basis across US, Narassimhan and Johnson (2014) developed a random effects model to study the impacts of incentives, charging station density, and gasoline price on BEV and PHEV adoption. The authors concluded that state monetary incentives have no effect on PHEV sales, regardless of whether the state monetary incentives are offered as a tax credit, purchase rebate, or sales tax waiver. EV charging infrastructure, and gasoline price significantly increase both PHEV and BEV purchase. However, BEV purchase number are more sensitive to charging infrastructure and gasoline price than that of PHEV.

The highly aggregate studies above ignore spatial variation in EV adoption and cannot decipher the effects of zonal characteristics. In contrast, zone-level EV ownership models are more appropriate for local analysis, but these studies are limited in number. For example, Dimatulac and Maoh (2017), Chen et al. (2015), and Bansal et al. (2015) investigated the spatial distribution
characteristics of (non-plug-in) hybrid electric vehicles (HEVs) on a census tract basis using cross-sectional data. Local level analysis for plug-in EVs is even more limited. Zhou et al. (2017) developed multiple linear regression models to examine factors which affect BEV and PHEV adoption rates separately on a county basis in the U.S. using 2014 vehicle registration data. Results show that income, extreme temperature, vehicle incentives, and HOV lane subsidies affect both BEV and PHEV adoption. Interestingly, the authors found that charging infrastructure is statistically correlated with PHEV adoption, but not with BEV adoption.

Existing zonal level EV adoption studies have several limitations: 1) though several studies examine PHEV and BEV adoption separately, the univariate modeling framework fails to account for the commonalities between PHEV and BEV adoption patterns at a zonal level; 2) cross-sectional data are often used for model development, posing challenges for future EV adoption prediction; 3) existing studies often focus only on metropolitan areas and exclude rural areas. This study enriches the empirical evidence for zonal level EV adoption pattern and fills the EV adoption literature gap by developing a county-level bivariate EV ownership model based on Virginia DMV vehicle registration data from 2012 to 2016. This Virginia-based case study can provide a reference framework for other regions to conduct similar analysis using common state and national public datasets.

**Disaggregate EV Adoption Studies**

Table 1 summarize disaggregate level EV adoption studies. Researchers often use discrete choice modeling framework based on empirical consumer data to examine the influential factors of EV adoption. Due to the limited real-world EV purchase behavior, the stated preference survey approach is widely used. The survey typically asks respondents to make decisions among choice alternatives (e.g., EVs and ICEVs) by making trade-offs between attributes in several hypothetical scenarios. The attributes associated with alternatives often vary systematically via experiment design. Note that the limitation with any stated preference work is that actual respondent behavior may not correspond with the stated intent, so the developed models should be evaluated critically (Louviere et al., 2000).

Existing disaggregate EV adoption literature have examined several factors that impact EV purchase decisions: respondent-related variables (e.g., socio-demographics), vehicle choice alternative-related variables including monetary attributes (fuel cost, purchase cost, etc.), technical attributes (all-electric range, emissions, charging time, etc.), charging infrastructure attributes (charging station availability), and incentive policy attributes (one-time cash incentives, free parking, access to high occupancy vehicle [HOV] lanes, etc.).

With regard to respondents’ socio-demographic factors, many studies found that male (Anable et al, 2011, Egbue et al. 2012, Carley et al. 2013, Plötz et al. 2014, and Kim et al. 2014), younger (Ewing and Sarigöllü, 1998; Potoglou and Kanaroglou, 2007; Hidrue et al., 2011; Achtnicht et al., 2012; Ziegler, 2012; Li et al., 2013; Hackbarth and Madlener, 2013; Shin et al., 2015) and better educated individuals (e.g. Potoglou and Kanaroglou, 2007; Hidrue et al., 2011; Hackbarth and Madlener, 2013; Li et al., 2013; Kim et al., 2014) with higher income (e.g. Potoglou
and Kanaroglou, 2007; Caulfield et al., 2010; Musti and Kockelman, 2011; Link et al., 2012, Qian and Soopramanien, 2011), living in larger households (Knockaert, 2010; Musti and Kockelman, 2011, Qian and Soopramanien, 2011) are more likely to be interested in adopt EVs. However, due to varied study areas, data collection periods, experiment designs, and modeling technique, different studies often show mixed results. According to the comprehensive review work by Liao et al. (2017), it is so far unclear whether the impacts of age, gender, education attainment, income, and household composition are negative, positive, or significant at all, since there are supporting evidence for all claims. For example, the effect of gender variable (male) on EV adoption is found to be significantly negative by Jensen et al. (2013), and insignificant by Mohamed et al. (2016) and Kurani (2018). Hidrue et al. (2011)'s study in US found that higher income levels made respondents less inclined to own EVs, although the effect was statistically insignificant.

The impacts of financial, technical, and charging infrastructure attributes on EV adoption are generally found to be significant. Preference heterogeneity for those attributes are further examined. For example, regarding price taste heterogeneity, Ferguson et al. (2018) developed a latent class model and found that ICEV-oriented class was the most price sensitive. This result is in line with Hidrue et al. (2011) where the conventional vehicle class is much more purchase price sensitive than EV-oriented class. Some studies explore income effects on price preference. For example, Potoglou and Kanaroglou (2007) examined the effects of interaction term between purchase price and household income. They found that medium-income and “income-not reported” individuals considered purchase price more important than high-income individuals. As to the range preference heterogeneity, respondents with lower annual mileage showed lower preference on driving range of EVs. (Hoen & Koetse, 2014). Multiple car household showed a much lower WTP for driving range of EV than single car household (Jensen et al., 2013), as the multiple car household can rely on the other car if need arises for longer trips. Lastly, Ferguson et al. (2018) found that the effect of charging station availability was significant for both PHEV and BEV-oriented classes, but not for ICEV and HEV-oriented class. The authors argued that relative to charging station availability, ICEV and HEV-oriented class are more concerned about electric range, public charging time etc.

As for incentive policy attributes, the one-time cash incentives are generally effective (Hess et al. 2012; Higgins et al. 2017; Ferguson et al. 2018). However, the effects of other incentive policies are controversial. For example, the effectiveness of free parking on EV adoption is found to be significant by Ferguson et al. (2018), while Hess et al. (2012), Hoen and Koetse (2014), Potoglou and Kanaroglou (2007), and Qian and Soopramanien (2011) report no significance.

Previous quantitative research forecasting household/individual EV adoption trends tend to neglect one or more of the above influence factors. This research enriches the existing understanding of EV adoption by conducting stated preference survey in Virginia that captures household demographics, vehicle traits, infrastructure, and land use considerations, all of which influence vehicle choice. One unique contribution of this study is combining both RP and SP data to examine EV adoption patterns for the same study area (Virginia). Though zonal-level EV registration data can depict EV early adopters’ preferences accurately, the limited existing RP data
fails to capture the preferences of mainstream consumers who determine the success of mass EV adoption in the future. In addition, it is difficult to examine preferences on several vehicle-related attributes (e.g., range, purchase price, and fuel cost, etc.) based on the zonal-level RP data. Therefore, the enriched SP survey data are further collected and analyzed to explore the general consumers’ preferences on EVs in Virginia. Lastly, the combined SP and RP approach for the same study area can help uncover the commonalities and differences between stated interests and real-world behavior in the EV adoption domain.
Table 1 Summary on disaggregate EV adoption studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Region</th>
<th>Survey time</th>
<th>Target group</th>
<th>Number of Respondents</th>
<th>EV alternatives</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horne et al. (2005)</td>
<td>Canada</td>
<td>2002-2003</td>
<td>Respondents had access to a vehicle or commuted at least once per week</td>
<td>1150</td>
<td>Hydrogen</td>
<td>Multinomial logit (MNL)</td>
</tr>
<tr>
<td>Potoglou and Kanaroglou (2007)</td>
<td>Hamilton, Canada</td>
<td>2005</td>
<td>Participants with intention to purchase a vehicle in the next five years.</td>
<td>426</td>
<td>Alternative fuel vehicle (AFV)</td>
<td>Nested logit</td>
</tr>
<tr>
<td>Qian and Soopramanien (2011)</td>
<td>China</td>
<td>2009</td>
<td>General households</td>
<td>527</td>
<td>EV</td>
<td>MNL, nested logit</td>
</tr>
<tr>
<td>Hidrue et al. (2011)</td>
<td>US</td>
<td>2008-2009</td>
<td>-</td>
<td>3029</td>
<td>EV</td>
<td>Latent class model (LCM)</td>
</tr>
<tr>
<td>Jensen et al. (2013)</td>
<td>Denmark</td>
<td>2012</td>
<td>Households who had bought a car within the last 5 years or intended to buy a car within the next 5-year.</td>
<td>369</td>
<td>EV</td>
<td>Hybrid choice model (HCM)</td>
</tr>
<tr>
<td>Ito et al. (2013)</td>
<td>Japan</td>
<td>2010</td>
<td>People aged between 19 and 69</td>
<td>1531</td>
<td>EV, fuel cell vehicle (FCV)</td>
<td>MNL, nested Logit</td>
</tr>
<tr>
<td>Tanaka et al. (2014)</td>
<td>US and Japan</td>
<td>2012</td>
<td>General consumers</td>
<td>4202+4000</td>
<td>EV, PHEV, ICEV</td>
<td>Error component multinomial logit (ECML) model</td>
</tr>
<tr>
<td></td>
<td>Location</td>
<td>Year</td>
<td>Description</td>
<td>Sample Size</td>
<td>Vehicle Types</td>
<td>Methodology</td>
</tr>
<tr>
<td>--------</td>
<td>-----------------</td>
<td>-----------</td>
<td>-------------------------------------------------------------------------------</td>
<td>-------------</td>
<td>-----------------------------------------</td>
<td>------------------------------</td>
</tr>
<tr>
<td>Kim et al. (2014)</td>
<td>Netherlands</td>
<td>2012</td>
<td>Respondents who indicated their purchase intension of EVs</td>
<td>726</td>
<td>EV</td>
<td>HCM</td>
</tr>
<tr>
<td>Hoen &amp; Koetse (2014)</td>
<td>Netherlands</td>
<td>2011</td>
<td>Households with one or more cars</td>
<td>1903</td>
<td>Hybrid electric vehicle (HEV), PHEV, BEV, FCV, and flexi-fuel car</td>
<td>Mixed logit (MXL) model, MNL</td>
</tr>
<tr>
<td>Axsen et al. (2015)</td>
<td>Canada</td>
<td>2013</td>
<td>Households who have purchased a new vehicle in the past five years and use a vehicle regularly</td>
<td>1754</td>
<td>ICEV, HEV, PHEV, BEV</td>
<td>LCM and cluster analysis</td>
</tr>
<tr>
<td>Axsen et al. (2015)</td>
<td>Canada</td>
<td>2013</td>
<td>Households who have purchased a new vehicle in the past five years and use a vehicle regularly</td>
<td>1754</td>
<td>ICEV, HEV, PHEV, BEV</td>
<td>LCM and cluster analysis</td>
</tr>
<tr>
<td>Mohamed et al. (2016)</td>
<td>Canada</td>
<td>2015</td>
<td>Households with interest to purchase an economy car</td>
<td>3,505</td>
<td>PHEV, BEV</td>
<td>Structural equation model and cluster analysis</td>
</tr>
<tr>
<td>Hackbarth &amp; Madlener, (2016)</td>
<td>Germany</td>
<td>2011</td>
<td>Participants with intention to purchase a new car within the next year or made an actual vehicle purchase in the last 12 months</td>
<td>711</td>
<td>Natural gas vehicle (NGV), HEV, PHEV, BEV, biofuel vehicle (BV), and FCV</td>
<td>MNL, LCM</td>
</tr>
<tr>
<td>Ferguson et al. (2018)</td>
<td>Canada</td>
<td>2015</td>
<td>Households with interest to acquire a vehicle in future</td>
<td>20,520</td>
<td>ICEV, HEV, PHEV, BEV</td>
<td>LCM</td>
</tr>
<tr>
<td>------------------------</td>
<td>--------</td>
<td>------</td>
<td>--------------------------------------------------------</td>
<td>-------</td>
<td>-------------------</td>
<td>-----</td>
</tr>
<tr>
<td>Kwon et al. (2018)</td>
<td>Korea</td>
<td>2015</td>
<td>EV owners</td>
<td>216</td>
<td>EV</td>
<td>MNL</td>
</tr>
<tr>
<td>Mohamed et al. (2018)</td>
<td>Canada</td>
<td>2015</td>
<td>Households with interest to acquire a vehicle in future</td>
<td>15,392</td>
<td>EV</td>
<td>Structural equation model</td>
</tr>
</tbody>
</table>
3. ZONAL LEVEL EV OWNERSHIP ANALYSIS
Methodology and Data

The data used for the zonal EV ownership model development are collected from Virginia Department of Motor Vehicle (DMV), US Census Bureau, and Alternative Fuels Data Center (AFDC) in U.S. Department of Energy (DOE). The DMV dataset records make, model, model year, fuel type, zipcode, and county for each registered vehicle in Virginia in calendar years 2012, 2014, 2015, and 2016. The response variables (BEV and PHEV counts in each year on a county basis) are calculated based on the DMV dataset. Most predictor variables are collected from US Census Bureau during the same years as the DMV dataset, including county demographics (i.e., total population, age distribution, sex ratio, etc.), household attributes (i.e., household size, income, etc.), and commute characteristics (i.e. commute time, mode, etc.). In addition to census data, AFDC data is included in the predictor variables to describe the EV charging infrastructure in each county: the dataset contains specific information for each public charging station in US, including location, opening date, number of charging ports, etc. Finally, a panel dataset with 528 observations (132 counties with 4 years of data for each county) is obtained by merging datasets from various sources above. 80% of total 528 records (422 observations) are randomly selected for parameters estimation, and the remainder 20% of sample are used for model validation. All the response variables and predictor variables are aggregated on a county basis annually, with summary statistics shown in Table 2.

The county-level EV ownership model is specified using a bivariate, lognormal Poisson, linear mixed effects model framework. First, the bivariate approach allows the modeling of two response variables jointly, aiming to describe correlation between the number of BEVs and PHEVs per county. Correlation between the two response variables are captured by the covariance coefficients in the variance-covariance matrices of the random effects and residuals (see $\Sigma_u, \Sigma_e$ below). Second, the lognormal Poisson process is applied here to allow for observation-level dispersion (see $e$ below). By an exponential link function, the expected values of responses variables are modeled as a linear function of a set of predictor variables (see $X\beta$ below). Third, the mixed effects model structure includes not only the fixed effects, but also the random terms to capture county-specific effects (see $u$ below). The random terms allow for the correlation between observations in the same county. Specifically, the model is set up as equation (1):

$$E(Y) = \exp(X\beta + Zu + e)$$  \hspace{1cm} (1)

$Y$: matrix with counts per observation and per response variable (422 $\times$ 2)

$X$: fixed effects design matrix (including intercept; 422 $\times$ [# FixedPredictors + 1])

$\beta$: fixed effects coefficients (including intercept, [# FixedPredictors + 1] $\times$ 2)

$Z$: random effects design matrix (422 $\times$ 132)

$u$: county random effects (132 $\times$ 2)

$e$: residuals for random observation-level dispersion (422 $\times$ 2)
The random effects $u$ and residuals $e$ are assumed to follow multivariate normal distribution, as shown in equations (2):

$$u \sim N(0, \Sigma_u)$$
$$e \sim N(0, \Sigma_e)$$

$$\Sigma_u = \begin{pmatrix}
\sigma^2_{u, bev} & \sigma_{u, bev\& phev} \\
\sigma_{u, bev\& phev} & \sigma^2_{u, phev}
\end{pmatrix}$$

$$\Sigma_e = \begin{pmatrix}
\sigma^2_{e, bev} & \sigma_{e, bev\& phev} \\
\sigma_{e, bev\& phev} & \sigma^2_{e, phev}
\end{pmatrix}$$

For $\Sigma_u$, the diagonal elements are the variance in consistent “county” effects for BEV and PHEV counts, respectively. The off-diagonal elements are the covariance between these effects on the two response variables. For $\Sigma_e$, the diagonal elements are the residual variance for BEV and PHEV counts, respectively. The off-diagonal elements are the covariance between these residual variances on the two response variables. Model parameters in $\beta$, $\Sigma_u$, $\Sigma_e$ were estimated using Bayesian Markov Chain Monte Carlo (MCMC) sampling technique, as implemented in the MCMCglmm package (Hadfield, 2010) in R.

To predict number of BEVs and PHEVs by county in 2025, projections on predictor variables from the EV ownership model are needed. First, demographics projections are cited directly from the Weldon Cooper Center for Public Service (Demographics Research Group, 2018) which forecasts the Virginia demographics on a county basis from 2020 to 2040. Second, the household and commute variables are projected from historical trendlines between 2009 and 2016 based on Census data. Third, the charging infrastructure predictions are made based on charging infrastructure growth patterns in California (based on AFDC dataset), as the limited charging infrastructure currently in place in Virginia makes it difficult to make future projections.
Table 2 Summary statistics of model variables at the county level (N = 528)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Response Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Battery Electric Vehicles (BEVs)</td>
<td>9.03</td>
<td>1.00</td>
<td>44.10</td>
<td>0.00</td>
<td>770.00</td>
</tr>
<tr>
<td>Number of Plug-in Hybrid Electric Vehicles (PHEVs)</td>
<td>8.49</td>
<td>1.00</td>
<td>35.64</td>
<td>0.00</td>
<td>545.00</td>
</tr>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total population</td>
<td>62,209</td>
<td>25,638</td>
<td>121,381</td>
<td>2,230</td>
<td>1,132,887</td>
</tr>
<tr>
<td>Population density (# of people/sq. mi.)</td>
<td>856</td>
<td>101</td>
<td>1607</td>
<td>5.37</td>
<td>10,078</td>
</tr>
<tr>
<td>Percent of population over 65 years of age</td>
<td>16.81</td>
<td>17.25</td>
<td>4.93</td>
<td>5.80</td>
<td>36.10</td>
</tr>
<tr>
<td>Sex ratio (number of males per 100 females)</td>
<td>98.03</td>
<td>96.30</td>
<td>14.09</td>
<td>59.60</td>
<td>217.70</td>
</tr>
<tr>
<td>Percent of population with graduate degree</td>
<td>9.75</td>
<td>7.60</td>
<td>6.85</td>
<td>2.70</td>
<td>44.40</td>
</tr>
<tr>
<td><strong>Household</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median household income ($)</td>
<td>53,420</td>
<td>48,239</td>
<td>19,615</td>
<td>24,059</td>
<td>125,672</td>
</tr>
<tr>
<td>Percent of households with income higher than $100K</td>
<td>20.35</td>
<td>16.40</td>
<td>12.40</td>
<td>4.80</td>
<td>63.00</td>
</tr>
<tr>
<td>Percent of households with income higher than $150K</td>
<td>8.04</td>
<td>5.20</td>
<td>7.70</td>
<td>0.00</td>
<td>39.50</td>
</tr>
<tr>
<td>Percent of households with 1+ people &lt; 18 years old</td>
<td>29.61</td>
<td>29.15</td>
<td>5.73</td>
<td>14.80</td>
<td>49.20</td>
</tr>
<tr>
<td>Percent of households with 1+ people ≥ 60 years old</td>
<td>40.98</td>
<td>42.00</td>
<td>8.16</td>
<td>21.50</td>
<td>70.00</td>
</tr>
<tr>
<td>Average household size</td>
<td>2.49</td>
<td>2.47</td>
<td>0.23</td>
<td>1.75</td>
<td>3.37</td>
</tr>
<tr>
<td><strong>Commute</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average commute time (minutes)</td>
<td>27.36</td>
<td>26.80</td>
<td>6.34</td>
<td>14.50</td>
<td>42.70</td>
</tr>
<tr>
<td>Percent of workers who use public transit for commute</td>
<td>1.72</td>
<td>0.55</td>
<td>3.71</td>
<td>0.00</td>
<td>27.50</td>
</tr>
<tr>
<td><strong>Charging infrastructure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total number of charging ports</td>
<td>2.65</td>
<td>0.00</td>
<td>8.92</td>
<td>0.00</td>
<td>118.00</td>
</tr>
<tr>
<td>Charging ports density (#/sq. mi.)</td>
<td>0.04</td>
<td>0.00</td>
<td>0.22</td>
<td>0.00</td>
<td>3.97</td>
</tr>
</tbody>
</table>

**Zonal EV Ownership Model**

Table 3 shows the parameter estimates of EV ownership model. Here, population of each county is used as an exposure term, and socio-demographic, travel behavior, and charging infrastructure characteristics as predictor variables. The positive covariance coefficient in $\Sigma_u$ suggests that counties that have more registered BEVs consistently have more registered PHEVs. The correlation coefficient is 0.86 (calculated by $\sigma_{u,bev,phev} / (\sqrt{\sigma_{u,bev}^2 \times \sigma_{u,phev}^2})$) for BEV and PHEV counts, which demonstrates that correlation between these two response variables should be considered in the analysis. Similarly, the positive covariance coefficient in $\Sigma_e$ indicates that in specific years that a county registers many BEVs, it also registers many PHEVs.

Most predictor variables show consistent effects across both BEV and PHEV ownership models due to the commonalities between the two vehicle powertrain technologies. Population density is a statistically significant predictor for both BEV and PHEV models, though the parameter coefficient for PHEV model is lower than BEV. In a consumer preference study in Canada, Ferguson et al. (2018) found that BEV-orientation is strongly urban while a PHEV-orientation is more moderately urban and is also oriented to suburban areas. In rural areas where population density is low, residents prefer larger vehicles such as pickups and SUVs (Ferguson et
al., 2018). The EV market for such body types is immature from both the supply and demand perspectives at this point, with BEVs exhibiting even more limited model types than PHEVs.

Surprisingly, models predict counties with more older population to have more EVs. For a one standard deviation increase in the percent of population over 65 years of age, the number of BEVs and PHEVs in the county are predicted to increase by 324% and 196%, respectively, holding all other variables at mean values. This result is contrary to many disaggregate-level EV preference studies (see, e.g. Hidrue et al., 2011; Ziegler et al., 2012; Carley et al., 2013; Ferguson et al., 2018) which find that young or middle-aged consumers are more likely to show interest in EVs. The author note that these disaggregate EV studies are mainly based on consumers’ stated preference which may not fully represent real market behavior. On the other hand, a revealed preference studies (Farkas et al., 2018) supports our finding that EV owners tend to be older than ICEV owners.

Controlling for all other variables, counties with higher percentage of residents with graduate degrees are associated with more EVs, which is consistent with Hidrue et al. (2011), Egbue et al. (2012), and Ferguson et al. (2018), etc., all individual/household level studies which found a positive relationship between increased educational attainment and preference for EVs. When income and education variables are incorporated into the EV ownership model simultaneously, education-related variables were found to be statistically significant while income was not (due to high correlation between the two variables). Hence, only education-related variables are included in the final model specification here.

A greater percentage of households with children (under 18) exerts a negative effect on predicted county-level EV counts. For an one standard deviation increase in percent of households with children, the number of BEVs and PHEVs are predicted to decrease by 37% and 34%, respectively, holding all other variables at mean values. This finding is supported by Brownstone and Fang (2009), which found higher ownership rates of vans, SUVs, and pick-up trucks in California households with young children. As of 2016, consumers considering large vehicles have far fewer choice when seeking an EV vs. an ICEV.

Increase in average household size is positively correlated with number of EVs in a county. For an one standard deviation increase in average household size, the BEV and PHEV counts in the county are predicted to increase by 197% and 149%, respectively, holding all other variables at mean values. This result is consistent with Plötz et al. (2014), which report that multimember families are more likely to be EV adopters. Empirical evidence for early adopters from Norway shows that most consumers who purchase EVs buy it as an addition to their household’s car fleet (Klöckner et al., 2013). Larger households tend to be multi-car households, and may be more likely to adopt EVs than single-car households. In this sense, multi-car households are less likely to be limited by the driving range of EVs as they have alternative vehicles. However, Hidrue et al. (2011) report no significant relationship between multi-car households and EV preference.

Public transit commute share appears to have a negative influence on EV ownership in these models. This is possibly because counties with higher public transit share may represent counties with higher share of low income households (since income variables are not included in
the final model specification). The EV’s purchase price premium (over ICEVs) is a barrier for adoption among low income households. Another possible explanation is that given the same average household size, a household in a high public transit access county may own fewer vehicles than a household in a low transit access county, which goes back to the previous discussion on multi-car households being more open to adopting EVs (when compared to single car households).

The model predicts higher public charging port density to increase both BEV and PHEV counts in a county, with the coefficient for BEV higher than that for PHEV, indicating that BEV ownership is more sensitive to charging infrastructure than PHEV. This result seems logical, as BEVs are solely powered by electricity, higher availability of public charging facilities can help travelers overcome the “range anxiety” barrier to EV adoption. For one standard deviation increase in the charging port density, the BEV and PHEV counts in the county are predicted to increase by 18% and 14%, respectively, holding all other variables at mean values. Note that the marginal effect of one standard deviation increase in charging port density is much lower than the marginal effects of socio-demographic variables, owning to the limited charging port density in Virginia with correspondingly low standard deviation.

However, two predictor variables, sex ratio and average commute time, show mixed effects across BEV and PHEV adoption. Counties with higher percent of males are associated with higher numbers of BEVs, but not PHEVs. Although many disaggregate EV preference studies (see, e.g., Anable et al, 2011; Egbue et al. 2012; Carley et al. 2013; Plötz et al. 2014) report that males are more likely to be interested in EVs, some studies (see, e.g., Mohamed et al., 2016; Kurani, 2018) argue that there is no evidence of gender impact on EV adoption intention. Interestingly, higher average commute time increases the number of predicted PHEVs in each county, but not BEVs. For PHEVs, this can be explained by the energy cost savings associated with powering the vehicle on electricity rather than gasoline. Commute time is a proxy for commute distance. Commuters traveling longer distances pay more for fuel and have greater savings potential from owning PHEVs. Lane et al. (2018) show that such economic benefit contributes to consumers’ interest in purchasing or leasing PHEVs. But for BEVs, the range anxiety, frequently cited in the literature as a key barrier in EV adoption (Egbue et al., 2012), offsets the fuel saving benefits, potentially making the commute time a statistically insignificant variable for county-level BEV adoption.

To validate the EV ownership model, prediction performances are compared across four models: (I) bivariate count model (coefficients showed in Table 3); (II) bivariate count model with spatial lagged charging port density component (binary weight matrix); (III) bivariate count model with spatial lagged charging port density component (1/distance weight matrix); (IV) univariate count model. Model II and model III with spatial lagged X component aim to capture the “neighbor effects” in EV adoption (shown at a census block level in Chen et al. (2015)), assuming that number of EVs in a county are impacted by charging port density in its neighboring counties. Mean Average Error (MAE) and Root Mean Square Error (RMSE) are used to measure the differences between predicted and observed EV count. As shown in the last part in Table 3, the bivariate count model outperforms the univariate count models. Considering the simplicity, model I (without spatially lagged X components) is used for EV number prediction in the fuel tax
revenue impacts portion of this analysis. The reason that incorporating neighbor effects into the county-basis model does not improve model prediction performance is possibly due to the modifiable area unit problem (MAUP) (Openshaw, 1984) when aggregating household-based vehicle choice phenomena into county districts, a potential limitation to zone-level count modeling.

Table 3 Coefficients estimates for bivariate county-level EV ownership model

<table>
<thead>
<tr>
<th>Predictor Variables of Model I</th>
<th>Vehicle Type</th>
<th>Mean</th>
<th>Lower-95% CI</th>
<th>Upper-95% CI</th>
<th>Marginal Effect* (100%)</th>
<th>pMCMC **</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>BEV</td>
<td>-33.168</td>
<td>-41.603</td>
<td>-24.706</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PHEV</td>
<td>-27.149</td>
<td>-34.406</td>
<td>-20.231</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Natural logarithm of population density</td>
<td>BEV</td>
<td>0.640</td>
<td>0.327</td>
<td>0.936</td>
<td>2.237</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>PHEV</td>
<td>0.440</td>
<td>0.210</td>
<td>0.674</td>
<td>1.203</td>
<td>0.001</td>
</tr>
<tr>
<td>Percent of population over 65 years of age</td>
<td>BEV</td>
<td>0.268</td>
<td>0.139</td>
<td>0.390</td>
<td>3.236</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>PHEV</td>
<td>0.207</td>
<td>0.113</td>
<td>0.313</td>
<td>1.964</td>
<td>0.000</td>
</tr>
<tr>
<td>Number of males per 100 females</td>
<td>BEV</td>
<td>0.045</td>
<td>0.021</td>
<td>0.071</td>
<td>2.237</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>PHEV</td>
<td>0.013</td>
<td>-0.012</td>
<td>0.037</td>
<td>0.308</td>
<td></td>
</tr>
<tr>
<td>Percent of population with graduate degree</td>
<td>BEV</td>
<td>0.149</td>
<td>0.095</td>
<td>0.212</td>
<td>1.874</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>PHEV</td>
<td>0.122</td>
<td>0.074</td>
<td>0.162</td>
<td>1.328</td>
<td>0.000</td>
</tr>
<tr>
<td>Percent of households with 1+ people &lt; 18 years old</td>
<td>BEV</td>
<td>-0.084</td>
<td>-0.152</td>
<td>-0.018</td>
<td>-0.370</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>PHEV</td>
<td>-0.072</td>
<td>-0.121</td>
<td>-0.019</td>
<td>-0.337</td>
<td>0.008</td>
</tr>
<tr>
<td>Average household size</td>
<td>BEV</td>
<td>4.555</td>
<td>2.461</td>
<td>6.559</td>
<td>1.972</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>PHEV</td>
<td>3.911</td>
<td>2.310</td>
<td>5.512</td>
<td>1.486</td>
<td>0.000</td>
</tr>
<tr>
<td>Average commute time</td>
<td>BEV</td>
<td>0.013</td>
<td>-0.048</td>
<td>0.069</td>
<td>0.679</td>
<td></td>
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<tr>
<td></td>
<td>PHEV</td>
<td>0.052</td>
<td>0.009</td>
<td>0.094</td>
<td>0.386</td>
<td>0.021</td>
</tr>
<tr>
<td>Percent of workers who use public transit for commute</td>
<td>BEV</td>
<td>-0.138</td>
<td>-0.251</td>
<td>-0.024</td>
<td>-0.390</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>PHEV</td>
<td>-0.102</td>
<td>-0.188</td>
<td>-0.018</td>
<td>-0.317</td>
<td>0.014</td>
</tr>
<tr>
<td>Charging port density (# / sq. mi.)</td>
<td>BEV</td>
<td>0.689</td>
<td>0.312</td>
<td>1.123</td>
<td>0.182</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>PHEV</td>
<td>0.587</td>
<td>0.255</td>
<td>0.947</td>
<td>0.142</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Random effects (county effects)

- $\sigma_{u, \text{bev}}^2$: 1.807, 0.96, 2.807
- $\sigma_{u, \text{phev}}^2$: 0.805, 0.312, 1.325
- $\sigma_{u, \text{bev & phev}}$: 1.042, 0.4531, 1.684

Residuals (within-county effects)

- $\sigma_{e, \text{bev}}^2$: 0.418, 0.268, 0.589
- $\sigma_{e, \text{phev}}^2$: 0.3376, 0.2025, 0.4717
- $\sigma_{e, \text{bev & phev}}$: 0.3345, 0.2053, 0.4623

DIC: 2815

Model Validation

<table>
<thead>
<tr>
<th>Model</th>
<th>BEV MAE</th>
<th>BEV RMSE</th>
<th>PHEV MAE</th>
<th>PHEV RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model I: Bivariate count model</td>
<td>2.25</td>
<td>4.45</td>
<td>1.86</td>
<td>3.25</td>
</tr>
<tr>
<td>Model II: Bivariate count model with spatial lagged X (binary weight)</td>
<td>2.28</td>
<td>4.32</td>
<td>1.87</td>
<td>3.32</td>
</tr>
<tr>
<td>Model III: Bivariate count model with spatial lagged X (1/distance weight)</td>
<td>2.22</td>
<td>4.72</td>
<td>1.77</td>
<td>3.14</td>
</tr>
</tbody>
</table>

20
**Model IV: Univariate count model**

<table>
<thead>
<tr>
<th></th>
<th>2.25</th>
<th>4.75</th>
<th>1.91</th>
<th>3.61</th>
</tr>
</thead>
</table>

* Marginal effect of one standard deviation increase in predictor variable.
** The posterior probability of the coefficient is not different from zero.

### 2025 Zonal EV Ownership Prediction

Based on demographics projections from the Weldon Cooper Center, predictor variables (total population, population density, percent of population over 65 years of age, and sex ratio) are cited as the input variables in EV ownership model to predict 2025 EV counts by county. Then, the other predictor variables (percent of population with graduate degrees, percent of households with children, average household size, average commute time, and percent of workers who use public transit for commute) are predicted based on historical trends from 2009 to 2016, using Census data. The five independent variables show a linear change (increase or decrease) in the past eight years, and a linear trendline is fitted to predict these independent variables through 2025 (with R² values ranging from 0.89 to 0.99).

Since there is limited charging infrastructure in Virginia currently, it is difficult to predict charging port density based on each county’s own historical trendline. Thus, the charging port density in Virginia in 2025 is predicted by referencing charging infrastructure deployment trendlines in California. First, the counties in California and Virginia are categorized into four quantiles based on charging port density. Then, the mean charging port density of each quantile is calculated for the comparison between California and Virginia. As shown in Figure 1, charging port density in Virginia appears to be roughly four years behind that in California. Specifically, the charging port density in Virginia in 2017 is close to California’s 2013 level. To capture the uncertainty in future charging infrastructure investment in Virginia, three scenarios are examined in this study. One scenario assumes the charging infrastructure development in Virginia follows the same rate as California, thus the charging port density in Virginia in 2025 will be close to California’s projected 2021 level. The other two scenarios capture a conservative scenario (no further investment in charging infrastructure, density remains the same as 2017 Virginia levels) and a more aggressive case (Virginia catches up to California’s projected 2025 charging infrastructure level). Lastly, California’s projected charging port densities in 2021 and 2025 (by quantile) are obtained by fitting a two-order polynomial function based on California’s historic trendline (with R² values ranging from 0.98 to 0.99).

After inputting all the predictor variables into the EV ownership model, the total number of BEVs and PHEVs for each county in Virginia in 2025 are predicted: 1) for the conservative scenario (at 2017 Virginia charging infrastructure levels), the model estimates 45,364 EVs total statewide, accounting for 0.64% of total vehicle fleet; 2) for the most likely scenario following California’s projected 2021 charging infrastructure levels, the model estimates 166,016 EVs statewide, accounting for 2.36% of total vehicle fleet; 3) for the most aggressive scenario (charging port densities are the same as California’s 2025 level), model estimates 721,870 EVs statewide, accounting for 10.27% of total vehicle fleet. For comparison, EV Adoption predicts U.S. national annual EV new sales market share up to 2025 and Virginia would have about 244,000 EVs in stock in 2025 if the state EV market share follows the national average (EVAwdopt, 2018).
Figure 1 A comparison of charging port density between California and Virginia

Figure 2 shows the predicted spatial distribution of EV adoption rates for the most likely scenario (following California’s projected 2021 charging infrastructure levels) of Virginia counties. Though the EV adoption rates in most counties in 2025 are predicted to be less than 1%, a few counties show relatively high adoption rates, and are concentrated in and near large and medium metropolitan areas, such as the Washington DC, Richmond, Hampton Roads, and Charlottesville metropolitan areas. Other high EV adoption counties are distributed along the interstate highways, where many public charging stations (especially DC fast charging stations) are deployed.
Zonal Emission Impacts Evaluation

Based on EV ownership prediction from previous section, 2025 carbon footprint impacts in Virginia are evaluated. First, mobile emissions from personal vehicles (only considering tailpipe emissions) impacts are evaluated at the county level. Then, the emission impacts considering electricity generation for EV charging are analyzed.

Impacts on Tailpipe Emissions

A “bottom-up” approach is used to calculate CO₂ tailpipe emissions. Vehicles are divided into three categories: BEVs, PHEVs, and ICEVs. The specific parameters used for tailpipe CO₂ emission calculation for each vehicle category are discussed as follows:

BEVs have zero tailpipe emissions. For PHEVs, the utility factor of the 2017 Chevrolet Volt (0.76) is used here as this model shows the highest adoption rate among all PHEVs in Virginia. The utility factor refers to the fraction of total VMT driven in electric mode for PHEVs. PHEVs emit no CO₂ from tailpipe when operating in electric mode. The calculation of CO₂ tailpipe emissions during hybrid electric-gasoline mode is the same as ICEVs.

For ICEVs, CO₂ tailpipe emissions are calculated based on fuel consumption which is dependent on fuel economy and VMT. Given the volatile nature of fuel economy improvement in the long term, three scenarios of ICEV’s fuel economy are developed, as shown in Figure 3. The first conservative scenario assumes the fuel economy will remain stagnant from MY 2017 to 2025.

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1 A gallon of gasoline produces 8,887 grams CO₂ emissions when burned (EIA, 2018).
The second (most likely) scenario assumes the fuel economy follows the historic growth rate since MY 2005. The last aggressive scenario assumes the fuel economy will be in compliance with the proposed (but not passed) CAFE standards for MY 2017 - MY 2025 released in August 2012 by US EPA and NHTSA. Combining the new vehicles’ fuel economy for each model year and the vehicle age distribution in each county in 2016, the fleet average fuel economy for each county in Virginia in 2016 can be calculated. Assuming the vehicle age distribution in 2025 remains the same as in 2016, the projected fleet average fuel economy for each county in 2025 is shown in Figure 4 for the most likely fuel economy improvement scenario.

Figure 3 Fuel economy improvement scenarios
Combining three EV levels of adoption prediction and three future fuel economy improvement levels, nine scenarios were designed as shown in Table 4. Figure 5 shows the tailpipe emissions reduction for each county for the most likely scenario (Scenario 5). All counties exhibit CO₂ tailpipe emissions reduction, with the highest tailpipe emissions decrease up to 58% in City of Williamsburg (relative change from 2016 to 2025). The counties with high tailpipe emissions reduction are mainly concentrated in dense metropolitan regions such as Washington DC, Richmond, and Hampton Roads etc. where EV adoption and fuel economy improvement are predicted to be higher than rural areas.

<table>
<thead>
<tr>
<th>EV Charging Infrastructure</th>
<th>Fuel Economy</th>
<th>Growth stagnant (stays at Virginia 2017 levels)</th>
<th>Follows likely rate</th>
<th>Follows aggressive rate (matches California levels)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stagnant since 2017</td>
<td>Stagnant since 2017</td>
<td>Scenario 1</td>
<td>Scenario 2</td>
<td>Scenario 3</td>
</tr>
<tr>
<td>Linear increase based on historical trend</td>
<td>Linear increase based on historical trend</td>
<td>Scenario 4</td>
<td>Scenario 5</td>
<td>Scenario 6</td>
</tr>
<tr>
<td>Compliant with proposed CAFE standards</td>
<td>Compliant with proposed CAFE standards</td>
<td>Scenario 7</td>
<td>Scenario 8</td>
<td>Scenario 9</td>
</tr>
</tbody>
</table>
Emission Impacts Considering Electricity Generation

Though EVs do not emit tailpipe emissions, electricity generation produces emissions at power plants. The electricity consumption of EVs depends on their energy efficiency and VMT. For BEVs, energy efficiency is assumed to be 30 kWh/100mi (per 2018 Nissan Leaf\(^1\) specifications) for the analysis. To adjust for the transmission and distribution losses when electricity travels from the power plant to where it is used by the consumer (e.g., at the outlet), the US average regional grid loss factors (4.48%) from Emission & Generation Resource Integrated Database (eGRID2016) is used here. For PHEVs, the energy efficiency in electric mode is assumed to be 31 kWh/100mi (per 2018 Chevrolet Volt\(^2\) specifications).

Statewide Virginia average CO₂ emission rates (kg/MWh) of electricity generation from 1996 to 2016 are taken from the eGRID2016. The missing values (noted in Figure 6) for several years are filled by linear interpolation. Overall, average CO₂ emission rates show a decreasing trend over the past 20 years. As shown in Figure 6, Virginia’s average CO₂ emission rate from electricity generation is 369.138 kg/MWh in 2016, decreasing by 30% from the 1996 rates. Two 2025 power plant average emission rate scenarios are then developed. The first conservative scenario assumes the 2025 average CO₂ emission rate from electricity generation remains at the 2016 level. The second scenario assumes it follows linear decrease trend of the past 20 years. The linear extrapolation based on historical data predicts the average CO₂ emission rate from electricity generation to be 288 kg/MWh in 2025 in Virginia.

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\(^1\) Nissan Leaf is the most popular BEV in Virginia per DMV records.

\(^2\) Chevrolet Volt is the most popular PHEV in Virginia per DMV records.
Figure 6 Average emission rate of electricity generation power plants.
Note: the red dots are interpolation for those years with missing values; The dashed line represents linear extrapolation based on historical data from 1996 to 2016.

When assuming the conservative scenario (average emission rate from electricity generation remains at the 2016 level), Figure 7 shows the CO₂ emission reduction evaluation for each scenario from Table 4. Statewide CO₂ emissions from personal vehicles are projected to decrease by 7.38% to 18.78% depending on EV adoption and fuel economy improvement levels, with a 10.56% decrease for the most likely scenario (Scenario 5). Within that 10.56% decrease, 1.45% reduction can be attributed to EV adoption and 9.1% reduction can be attributed to fuel economy improvement of ICEVs.
**Figure 7 2025 statewide CO₂ emissions reduction from 2016 (emission factors of electricity generation keeps 2016 level)**

Results from Figure 7 assumes emission factor of electricity generation in 2025 remains the same as 2016 level. When the power plants’ average CO₂ emission rate are projected to follow the linear decrease trend in Figure 6, CO₂ emission reduction in 2025 are presented in Figure 8. The statewide CO₂ emissions are projected to decrease by 7.45% to 19.39% compared to year 2016. The most likely scenario (Scenario 5) predicts a 10.68% emission reduction. More specifically, for the 10.68% emission reduction, EV adoption contributes to 1.58% while fuel economy improvement contributes to 9.10%. In 2025, EVs still account for a small portion of total vehicle fleet under the most likely scenario, and thus the statewide emission reduction benefits from EV adoption is minor compared to the effects of fuel economy improvement even when electricity generation becomes greener. EVs have the potential to contribute to greater emissions reductions under Scenario 3, 6, and 9 (emissions reductions ranging from 13.45% to 19.39%), but these three scenarios require more aggressive investment on charging infrastructure.
Figure 8 2025 statewide CO₂ emissions reduction from 2016 (projected 2025 emission factor of electricity generation)
4. INDIVIDUAL VIRGINIAN’S PREFERENCES ON EV PURCHASE

Zonal level analysis in section 3 based on EV registration data can provide insights for EV adoption over time in Virginia, but it fails to examine the effects of several vehicle-related attributes, such as battery range, emissions, and purchase and operational costs, etc. In this section, results of a stated preference survey are presented to show the factors which affect individual EV preferences in Virginia, including vehicle technical characteristics, charging infrastructure, vehicle ownership and operating cost, incentives, and respondents’ socio-demographic characteristics.

Survey Design and Distribution

Survey structure

The five-part web-based survey was implemented through Qualtrics. Estimation survey completion time was between 15 to 20 minutes (See appendix A for a sample survey).

- Part 1: Household socio-demographics
- Part 2: Future vehicle purchase plan and household vehicle fleet inventory
- Part 3: Educational material to familiarize respondents with different vehicle powertrain technologies and EV’s technical characteristics, cost and policies.
- Part 4: Stated preference choice experiments where respondents are asked to select the one vehicle they would most likely purchase from four alternatives (ICEV, HEV, PHEV, and BEV) based on hypothetical scenarios.
- Part 5: Respondents’ experience and attitudes.

Choice Experiment Design

Before the stated preference experiments, respondents were asked which vehicle body type their household would most likely to purchase. This approach (respondents choosing vehicle type before engaging in choice experiment) was also used by Higgins et al. (2017) in Canada which found that respondents exhibited heterogeneous EV preferences across different body types. This approach also makes the choice experiment alternatives more relevant to respondents by allowing attribute levels to differ across vehicle body types. This survey divides vehicle body type into five segments: subcompact/compact car, mid/full size car, small/medium SUV, standard/large SUV or minivan, and pick-up truck. Responses to questions about vehicle body type preference and VMT play an important role in the customization of the different choice scenarios for each respondent.

Figure 9 shows a typical choice scenario presented to respondents. Each respondent is asked to choose one from four vehicle powertrain technology (ICEV, HEV, PHEV, and BEV) based on four vehicle attribute categories: vehicle technical attributes (battery-only range, fuel economy, and CO2 emissions); charging infrastructure availability (DC fast charging station spacing along interstate highway, local charging at workplace/school, and local charging at other destinations); cost (purchase price, fuel cost, maintenance cost, and use fee); and incentives (federal tax credit and state rebates). Battery-only range, fuel economy, purchase price, federal tax credit and state rebates are specific to different vehicle body types, while CO2 emissions, fuel cost, and maintenance cost were calculated based on vehicle body type and VMT. The general attributes...
that remain consistent across vehicle body types are charging station availability, fuel price, and vehicle use fees.

The levels for each attribute are determined by widely-known vehicle models in US market. To make the survey more realistic to respondents, those who select pick-up truck (6% of respondents) are excluded from participating in the choice experiment since there are no available pick-up truck EV models for reference. Appendix B shows attribute levels used for experiment design for the four remaining vehicle body types. Taking the subcompact/compact car for example, the attribute levels result in a full factorial design of $2^9 \times 3^6$ choice scenarios. SAS’s “MktEx macro” function is used to generate a main-effects fractional factorial design and the number of choice scenarios are set to be 36 (Kuhfeld, 2005). The D-efficiency is 100%, indicating that the design is balanced and orthogonal. The 36 choice scenarios are then divided into six blocks while each block has six choice scenarios. Each respondent is randomly assigned one block with six choice scenarios while each choice scenario presents all four vehicle powertrain technologies.

Figure 9 Typical choice scenario for mid/full size car
Survey Distribution
A pilot survey was conducted in February 2018. 15 respondents provided feedback regarding duration, language, and presentation of the survey. 5 out of the 15 respondents are EV owners whose contact information was collected from the 2017 National Drive Electric Week event in Crozet, Virginia. The EV owners’ feedback ensures attribute levels in the survey are realistic. To make sure the survey does not contain EV terminology that are difficult to understand for general consumers, the pilot survey also solicited 10 responses from non-EV owners.

The survey was then revised based on pilot survey feedback. The formal survey was conducted from March to May 2018 by a two-prong approach: a general respondent pool via a professional survey service (Survey Sample International [SSI]) and an EV-specific respondent pool via distribution on relevant listservs (such as Virginia Clean Cities alliance, Facebook groups of EV owners in various Virginia cities). For the general respondent pool distribution, the SSI’s quota system ensured the respondent sample met statewide distribution of certain socio-demographics (income, and rural/suburban/urban ratio). Then, targeted approach for the EV-specific respondent pool oversampled EV owners due to the currently low EV adoption rates (less than 0.1%) in Virginia. A total 957 responses were received, including 927 complete responses (80 from EV owners, and 877 from non-EV owners).

Comparison between EV owners and non-EV owners
Table 5 compares the socio-demographics and household characteristics between EV owner sample, non-EV owner sample and the general Virginia population. Overall, the non-EV owner sample descriptive statistics match up well with the Virginia general population. The one exception is education attainment. 59% of non-EV owners in the survey sample hold bachelor’s degree or higher while only 37% of the general Virginia population hold the same level of education. Next, socio-demographics, household characteristics, charging infrastructure, and attitude and experience are compared between EV owners and non-EV owners.

Table 5 Comparison between survey sample and population

<table>
<thead>
<tr>
<th>Variable</th>
<th>EV owners (N = 80)</th>
<th>Non-EV owners (N = 877)</th>
<th>Virginia general population</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>81%</td>
<td>43%</td>
<td>49%</td>
</tr>
<tr>
<td>Female</td>
<td>19%</td>
<td>57%</td>
<td>51%</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18 to 24 years</td>
<td>1%</td>
<td>6%</td>
<td>9%</td>
</tr>
<tr>
<td>25 to 34 years</td>
<td>19%</td>
<td>23%</td>
<td>19%</td>
</tr>
<tr>
<td>35 to 44 years</td>
<td>28%</td>
<td>17%</td>
<td>18%</td>
</tr>
<tr>
<td>45 to 54 years</td>
<td>22%</td>
<td>14%</td>
<td>19%</td>
</tr>
<tr>
<td>55 to 64 years</td>
<td>17%</td>
<td>20%</td>
<td>16%</td>
</tr>
</tbody>
</table>
### Education

<table>
<thead>
<tr>
<th></th>
<th>Less than high school graduate</th>
<th>High school graduate (includes equivalency)</th>
<th>Some college, no degree</th>
<th>Associate's degree</th>
<th>Bachelor's degree</th>
<th>Graduate or professional degree</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1%</td>
<td>4%</td>
<td>10%</td>
<td>5%</td>
<td>38%</td>
<td>43%</td>
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<td>20%</td>
<td>10%</td>
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<td>25%</td>
<td>20%</td>
<td>7%</td>
<td>21%</td>
<td>16%</td>
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### Employment

<table>
<thead>
<tr>
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<th>Full time</th>
<th>Part time</th>
<th>Not employed</th>
<th>Retired</th>
<th>Student</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>78%</td>
<td>53%</td>
<td>62%</td>
<td>14%</td>
<td>20%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
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</table>

### Income

<table>
<thead>
<tr>
<th></th>
<th>Less than $25,000</th>
<th>$25,000 - $34,999</th>
<th>$35,000 - $49,999</th>
<th>$50,000 - $74,999</th>
<th>$75,000 - $99,999</th>
<th>$100,000 - $149,999</th>
<th>$150,000 - $199,999</th>
<th>$200,000 - $249,999</th>
<th>$250,000 - $299,999</th>
<th>$300,000 and over</th>
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</thead>
<tbody>
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<td></td>
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<td>3%</td>
<td>5%</td>
<td>8%</td>
<td>13%</td>
<td>19%</td>
<td>19%</td>
<td>16%</td>
<td>10%</td>
<td>9%</td>
</tr>
<tr>
<td></td>
<td>11%</td>
<td>10%</td>
<td>14%</td>
<td>17%</td>
<td>17%</td>
<td>17%</td>
<td>9%</td>
<td>3%</td>
<td>1%</td>
<td>1%</td>
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</table>

### Household size

<table>
<thead>
<tr>
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<th>1</th>
<th>2</th>
<th>3 or more</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>11%</td>
<td>20%</td>
<td>26%</td>
</tr>
<tr>
<td></td>
<td>31%</td>
<td>39%</td>
<td>34%</td>
</tr>
<tr>
<td></td>
<td>58%</td>
<td>41%</td>
<td>40%</td>
</tr>
</tbody>
</table>

### Number of vehicles

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3 or more</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
<td>6%</td>
<td>6%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>14%</td>
<td>37%</td>
<td>31%</td>
<td>33%</td>
</tr>
<tr>
<td></td>
<td>54%</td>
<td>40%</td>
<td>38%</td>
<td>17%</td>
</tr>
<tr>
<td></td>
<td>33%</td>
<td>17%</td>
<td>25%</td>
<td>25%</td>
</tr>
</tbody>
</table>

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*Socio-demographics*

There is an obvious gender difference between EV owners and non-EV owners in the survey sample. Males dominate EV owners, accounting for 81% of the 80 respondents. In contrast, the gender ratio is much more balanced for non-EV owners (43% male). Second, half of EV owners fall into middle-aged group (35-55 years old) while only about 30% of non-EV owners are middle-
aged. Third, most of the EV respondents hold a higher education degree. The percent of EV owners with a bachelor’s degree or higher (80%) is much greater than the percent of non-EV owners that with the same education level (about 60%). Fourth, about 80% EV respondents are full-time employed, compared to only half of non-EV owners are. In summary, EV owners are more likely to be male, middle-aged, with a higher education level and full-time employment.

**Household Characteristics**
EV owners are more likely to fall into higher income segments. Specifically, more than 70% of EV respondents' household income are higher than $100,000. For comparison, the same income category only accounts for 32% of non-EV owners. Second, most of EV owners report larger households. About 60% of EV respondents have a household with three or more people. In contrast, the proportion of three or more household size is only about 40% for the non-EV owners. Third, EV owners are more likely to emerge in multi-car households as about 90% of EV respondents own at least two vehicles. In contrast, only 57% non-EV owners holds two vehicles or more. Fourth, regarding to housing tenure, 90% of EV respondents report owning the house, compared to the fact that 70% of non-EV owners own the house. Fifth, 80% of EV respondents report that their houses are detached, while 66% non-EV respondents’ houses are detached. Lastly, most of EV owners (65%) report the garage availability while only about 30% of non-EV owners do. The results are expected as larger households are more likely to be multi-car households, and higher income households exhibit higher rates of car ownership. Specific to EV ownership, owning a detached house with a garage makes charging much easier and thus increase the possibility of purchasing an EV.

**Charging Infrastructure**
**Figure 10** shows responses to the availability of workplace charging and public charging station near respondents’ house. Most of respondents report no workplace charging no matter they are EV owners or not. Only about 30% of EV respondents report the availability of charging stations at their workplace, and such percentage is even lower for non-EV respondents. For public charging infrastructure near the respondent’s home, 86% of EV owners report availability, while such proportion is only 26% for non-EV owners. Perhaps more importantly, about half of non-EV owners report they do not know the availability of public charging stations near their home, compared to only 5% for EV owners.
Figure 10 Charging infrastructure characteristics of EV-owners vs. Non-EV owners

**Attitude & Experience**

The survey asks respondents’ attitudes towards technology, risk-taking and environment. **Figure 11 (a)** shows the response for “I consider myself an early adopter when it comes to new technology”. 80% of EV owners express a positive attitude (strongly agree or agree) towards new technology adoption while most of non-EV owners hold a neutral or negative attitude. Second, as shown in **Figure 11 (b)**, 65% EV owners strongly agree or agree with the statement “I consider myself a risk-taker”, while only 30% non-EV owners show the same attitude towards this statement. Third, most of the EV-owners (56%) strongly agree with that “I consider myself an environmentally-conscientious person”, compared to the 16% of non-EV owners. **Figure 11 (d)** indicates that about 70% of EV owners strongly agree with the statement “global climate change is a serious threat to humanity”, while only 35% of non-EV owners express the same attitude.

**Figure 11 (e)** and **Figure 11 (f)** show respondents’ experiences with ridehailing and car-sharing memberships. The difference between EV owners and non-EV owners are less significant, though higher percent of EV owners reported that “they use ride-hailing service” and “they are a member of carsharing service” than non-EV owners. Lastly, **Figure 11 (g)** and **Figure 11 (h)** show attitudes towards driverless vehicle technology. About 90% of EV respondents report that “they pay close attention to the latest news about driverless vehicle technology”, while such percentage is about 50% for non-EV respondents. Similarly, more than 70% of EV respondents report they feel comfortable riding in driverless vehicles, compared to the 36% of non-EV respondents do.
(a) I consider myself an early adopter when it comes to new technology.

(b) I consider myself a risk-taker.

(c) I consider myself an environmentally-conscientious person

(d) Global climate change is a serious threat to humanity

(e) I use ride-hailing services (such as Uber or Lyft)

(f) I am a member of carsharing service (such as Zipcar or Car2go)
(g) I pay close attention to latest news about driverless vehicle technology.

(h) I would feel comfortable riding in a self-driving vehicle (given the vehicle and software has passed safety checks)

Figure 11 Attitude and experience of EV-owners vs. Non-EV owners

Discrete Choice Model
A multinomial logit model (MNL) is developed to examine the effects of alternative-specific attribute and respondent-specific characteristics on vehicle powertrain choice. Table 6 shows the parameter estimates, odds ratio and model fit information of the MNL model. The alternative specific constants (ASCs) are statistically significant. The negative sign of ASCs indicate that generally, respondents are more likely to buy a ICEV than a HEV, PHEV, or BEV, and the ASCs’ magnitude show the disutility for HEV, PHEV, and BEV increase respectively. The following section presents the detailed results for the effects of alternative attributes and respondent characteristics on vehicle powertrain choice.

As expected, higher purchase price reduces the utility of all alternatives. Furthermore, the sensitivity to purchase price vary across respondent segments. The interaction term of purchase price and income in Table 6 indicates that respondents in the high income segment (defined as household income of $100,000 or greater) is less sensitive to purchase price than others. Such an income effect was also reported by Potoglou and Kanaroglou (2007), Mabit and Fosgerau (2011), Hess et al. (2012), and Hackbarth and Madlener (2013), etc.

As expected, model results indicate greater annual fuel cost is associated with reduction in utilities of the respective vehicle choices. This result is consistent with studies that use either fuel cost per mile (Jensen et al., 2013) or weekly/annual fuel cost (Axsen et al., 2015; Higgins et al., 2017) as the attribute in choice experiments. Interestingly, Musti & Kockelman (2011) found that the fuel cost term was not statistically significant in the SP choice model, but did show up in the RP choice model, demonstrating the potential bias in stated preference approach.

In addition to fuel cost, the choice experiments in this study also present fuel economy and CO₂ emission attributes of vehicles. These three attributes (fuel economy, fuel cost, and CO₂ emissions) are highly correlated, as the fuel cost and CO₂ emissions are calculated based on fuel economy in the choice experiment design. Although the final model (which showed the best fit)
presented in this report only includes fuel cost, models that only include fuel economy or CO₂ emission attribute were also tested. For the model that only includes fuel economy, the effect of increasing fuel economy is positive on probability of vehicle choice (though without statistically significance). For the model that only includes tailpipe CO₂ emissions¹ attribute, increasing CO₂ emission reduces utility of a vehicle choice significantly. The negative effects of emissions were also reported by Potoglou and Kanaroglou (2007) in Canada, Hackbarth and Madlener (2013) in Germany, and Tanaka et al. (2014) in US and Japan. However, Ferguson et al. (2018) found the annual tailpipe CO₂ was an insignificant vehicle attribute in Canada. Though most studies reported the negative effects of emissions on vehicle choice, such optimistic result pales by Bunch et al. (1993)’s finding that respondents are more likely to express environmental concern in stated preference surveys while actual behavior might be different. 

Unlike fuel cost, maintenance cost by itself does not show statistical significance in the final model specification. This differs from findings in Ferguson et al. (2018)’s study in Canada, which reported that annual vehicle maintenance costs were negatively associated with utility and that the effect of maintenance cost were strongest for the BEV-oriented class since BEV-oriented class would be aware of the relative simplicity of BEVs and their advantage of fewer moving parts to maintain. Some studies (e.g., Mabit and Fosgerau, 2011) also combined the fuel cost and maintenance cost as the overall operational cost attribute which was found to be negatively affect the decision to purchase a vehicle.

With regard to financial incentives, both federal tax credit and state rebates increase the utility of EVs, which is consistent with existing studies (e.g., Hess et al. 2012; Higgins et al. 2017; Ferguson et al. 2018, etc.) where various tax reduction policies are generally found to be effective. Note that federal tax credit or states rebates alone cannot offset purchase price. There is a higher disutility for an increase in purchase price compared to the utility of the same monetary increase in federal tax credit or state rebates. Similar results were also reported by Higgins et al. (2017) where cash incentives could not cancel out purchase price for six of seven vehicle body types. For these respondents, this is even true for high-income segments who are less sensitive to purchase price. This stands in contrast to findings from Higgins et al. (2017), in which respondents who select luxury vehicles exhibit greater utility of every $1,000 increase in cash incentives than the disutility of a $1,000 increase in purchase price.

Model results suggest increasing battery range is associated with greater utility for BEVs, but not for PHEVs. Similarly, the DCFC stations along interstate highway and workplace charging also increase the utility only for BEVs (but not for PHEVs), though the effect of workplace charging is only marginally significant. Since PHEVs can operate in gasoline mode when the battery is depleted, respondents are perhaps less concerned about the battery range and charging infrastructure. Interestingly, the zonal level analysis in section 3 indicates that higher public charging port density to increase both BEV and PHEV counts in a county significantly, with the

¹ The use of tailpipe emissions in this study rather than well-to-wheel emissions enables respondents to be more aware of functionality difference between EVs and ICEVs.
coefficient for BEV higher than that for PHEV, indicating that BEV ownership is more sensitive to charging infrastructure than PHEV.

Surprisingly, model results suggest the availability of local public charging station does not increase the utility of EVs. This is possibly because EVs do most of their charging at home (US DOE, 2018) and the local travel mostly fall within the EVs’ battery range. Thus, local public charging seems not as important to EV preference as workplace charging or fast charging along interstate highway. However, the implication of this finding should come with caution: most of survey respondents in this study are non-EV owners who might not be familiar with charging stations, and thus making it difficult to examine the effects of charging stations based on their stated preference choice. Additionally, since current EV-owners (early adopters) are more likely to own their homes and have garages, local charging availability may not be as important to them. But local charging infrastructure may become more relevant as if EV adoption is to spread to those without garage availability at home. The authors note that future discrete choice modeling work should differentiate EV owners and non-EV owners among Virginia respondents to yield more comprehensive results.

While gender does not affect respondent preference between HEVs and ICEVs, there exists statistically significant differences between males and females on the utility of EVs (both BEV and PHEV) compared to ICEVs. Model results show males are more likely to be interested in EVs than females, which is consistent with most EV adoption studies (see, e.g., Anable et al, 2011, Egbue et al. 2012, Carley et al. 2013, Plötz et al. 2014, and Kim et al. 2014, etc.) though a few studies (Mohamed et al., 2016; Kurani, 2018) reported no gender effects. Furthermore, compared to the middle-aged group, young people (defined as age 35 or younger) are 1.5 times more likely to be interested in newer vehicle powertrain technology (non-ICEV) while the older age group (defined as age 55 and older) are 1.7 times less likely to show interest in non-ICEVs. Although most other stated preference EV studies have also found young people to be more likely to show interest in EVs, the zonal EV ownership model in section 3 indicates that counties with older populations are associated with more registered EVs. Such discrepancy between individual-level studies (SP) and county-level analysis (RP) demonstrates the potential bias of SP data. Perhaps younger people are more interested in EVs, but thus far, they are not yet buying them in greater rates compared to those more senior in age.

Respondents with bachelor’s degree or higher levels of educational attainment are associated with greater utilities of HEVs, PHEVs, and BEVs, compared to ICEVs. This model result is in line with the county-level EV registration analysis and most disaggregate EV SP studies (e.g. Potoglou and Kanaroglou, 2007; Hidrue et al., 2011; Hackbarth and Madlener, 2013; Li et al., 2013 etc.). Furthermore, the statistically significant interaction variable of education and CO2 emissions indicates that more educated respondents dislike vehicles with high emissions, compared to those respondents with lower education levels. This is expected as the highly educated are more likely to show environmental concern (Klineberg et al., 1998). In addition, when controlling for education in the final model specification, higher household income only increases
the utility of BEVs while the income effect is not significant for HEV and PHEV alternatives compared to the reference ICEV alternative.

Compared to respondents looking to replace an existing vehicle, those who are purchasing an additional vehicle or the first vehicle in their household exhibit statistically significant increases in utilities of PHEVs and BEVs. Specifically, the odds ratio of 2.46 for “purchase as the first vehicle” variable indicates that those who are anticipating purchasing their first car are 2.46 times more likely to choose a BEV than those looking to replace an existing vehicle. Ferguson et al. (2018) reported a similar result based on latent class analysis: those seeking an incremental vehicle were more likely to be assigned to the BEV-oriented class.

Lastly, respondents seeking a subcompact/compact car exhibit higher utilities for HEVs, PHEVs and BEVs. Specifically, compared to other vehicle body types (full-size car, SUVs, and vans), those who are seeking for a subcompact/compact car are 1.3, 1.6, 1.8 time more likely to buy HEV, PHEV, and BEV, respectively. This result suggests that EVs are more attractive to respondents looking for small vehicles, though EV manufactures are extending their production line to large vehicle segments. Also, those who are interested in small vehicles prefer HEVs compared to ICEVs. This is a relevant result that echoes results from Higgins et al. (2017) which developed separate models for each vehicle body type.

Table 6 Multinomial logit model results

<table>
<thead>
<tr>
<th>Alternative</th>
<th>Alternative specific constant</th>
<th>HEV</th>
<th>0.736</th>
<th>0.087</th>
<th>-8.476</th>
<th>0.479</th>
<th>0.000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alternative specific constant</td>
<td>PHEV</td>
<td>-1.318</td>
<td>0.109</td>
<td>-12.133</td>
<td>0.268</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Alternative specific constant</td>
<td>BEV</td>
<td>-2.102</td>
<td>0.161</td>
<td>-13.077</td>
<td>0.122</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>All-electric range</td>
<td>BEV</td>
<td>0.162</td>
<td>0.046</td>
<td>3.546</td>
<td>1.176</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>DC fast charging station</td>
<td>BEV</td>
<td>0.218</td>
<td>0.077</td>
<td>2.821</td>
<td>1.244</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td>Workplace charging</td>
<td>BEV</td>
<td>0.115</td>
<td>0.074</td>
<td>1.541</td>
<td>1.122</td>
<td>0.123</td>
<td></td>
</tr>
<tr>
<td>Purchase price ($10,000)</td>
<td>ALL</td>
<td>-0.863</td>
<td>0.066</td>
<td>-13.115</td>
<td>0.422</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Purchase price * household income &gt; $100,000</td>
<td>ALL</td>
<td>0.248</td>
<td>0.097</td>
<td>2.570</td>
<td>1.281</td>
<td>0.010</td>
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<tr>
<td>Fuel cost</td>
<td>ALL</td>
<td>-0.363</td>
<td>0.125</td>
<td>-2.906</td>
<td>0.696</td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td>CO2 emission * graduate degree</td>
<td>ALL</td>
<td>-0.073</td>
<td>0.027</td>
<td>-2.715</td>
<td>0.930</td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td>Federal tax credit ($1,000)</td>
<td>ALL</td>
<td>0.047</td>
<td>0.009</td>
<td>5.082</td>
<td>1.048</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>State rebates ($1,000)</td>
<td>ALL</td>
<td>0.061</td>
<td>0.021</td>
<td>2.909</td>
<td>1.063</td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>PHEV</td>
<td>0.203</td>
<td>0.075</td>
<td>2.707</td>
<td>1.225</td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>BEV</td>
<td>0.388</td>
<td>0.079</td>
<td>4.914</td>
<td>1.474</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Age &lt;= 35</td>
<td>Non-ICEV</td>
<td>0.419</td>
<td>0.077</td>
<td>5.424</td>
<td>1.520</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Age &gt;= 56</td>
<td>Non-ICEV</td>
<td>-0.401</td>
<td>0.070</td>
<td>-5.731</td>
<td>0.670</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Purchase as an additional vehicle</td>
<td>PHEV</td>
<td>0.331</td>
<td>0.097</td>
<td>3.424</td>
<td>1.392</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Purchase as an additional vehicle</td>
<td>BEV</td>
<td>0.219</td>
<td>0.104</td>
<td>2.103</td>
<td>1.245</td>
<td>0.035</td>
<td></td>
</tr>
<tr>
<td>Purchase as the first vehicle</td>
<td>PHEV</td>
<td>0.609</td>
<td>0.229</td>
<td>2.657</td>
<td>1.839</td>
<td>0.008</td>
<td></td>
</tr>
<tr>
<td>Purchase as the first vehicle</td>
<td>BEV</td>
<td>0.900</td>
<td>0.224</td>
<td>4.011</td>
<td>2.460</td>
<td>0.000</td>
<td></td>
</tr>
</tbody>
</table>
5. CONCLUSIONS AND FUTURE WORK

Conclusions
This study investigates EV adoption patterns in Virginia from two levels. First, Virginia DMV vehicle registration data from 2012 to 2016 are used to develop EV ownership model at the zonal (county) level. The impacts of zonal characteristics, such as population density, gender ratio, average household size, and charging ports density etc. on EV registration counts in a county are examined. Second, an individual level EV stated preference survey focusing on Virginians was conducted in 2018. The survey data are then used to develop MNL models to uncover Virginian’s individual heterogeneous preferences for EVs.

The individual level analysis shows that males are more likely to be interested in both BEVs and PHEVs than females, a result also reported by many other EV adoption SP studies (e.g., Anable et al, 2011, Egbue et al. 2012, Carley et al. 2013, Plötz et al. 2014, and Kim et al. 2014, etc.). Similarly, zonal-level analysis indicates that counties with higher percent of males are associated with higher number of BEV registration. A slight difference is that the county-level model found no statistically significant relationship between PHEV counts and the percent of males in a county. Such discrepancy can be explained by the difference between individual preference and household real-world vehicle purchase (which is often a comprised decision of household members of both sexes). As to effects of age on EV adoption, county-level and individual-level analysis show mixed results. Counties with greater percent of population over 65 years of age tend to have more EVs. This result is supported by a revealed preference study (Farkas et al., 2018) in Maryland that EV owners tend to be older than ICEV owners. However, compared to the middle-aged individuals, the MNL individual choice model shows that older individuals are less likely to show interest in new vehicle technology (HEVs, PHEVs and BEVs) while young individuals are more likely to be interested in non-ICEVs, a result consistent with most disaggregate-level EV adoption SP studies (see, e.g. Hidrue et al., 2011; Ziegler et al., 2012; Carley et al., 2013; Ferguson et al., 2018). These contradictory results may reflect the inherent bias of
stated preference approach, as the stated preference may not truly reflect respondents’ real-world vehicle choice behavior.

In terms of effects of education and household income, counties with greater percent of more educated population are associated with more EVs, which is consistent with the results from the individual-level vehicle choice survey. The stated preference survey also uncovered that individuals with higher educational attainment show negative preference for tailpipe CO2 emissions (vehicles with higher CO2 emissions exhibit statistically significant lower utilities for those with graduate degrees, but not for respondents in other education attainment categories). Furthermore, controlling for education variables, the MNL model results suggest that households with higher income (defined as household income greater than $100,000) have higher probabilities of buying BEVs and they are less sensitive to the vehicle purchase price. Note that the income effects on EV adoption are mixed among existing studies: Potoglou and Kanaroglou (2007), Caulfield et al. (2010), Musti and Kockelman (2011), Link et al. (2012) and Qian and Soopramanien (2011), etc. reported that households with higher income are more likely to show interest in EVs. In contrast, household income was not observed to be a significant variable of vehicle powertrain choice by Hidrue et al. (2011) in US, Axsen et al. (2015) and Ferguson et al. (2018) in Canada. The correlation between educational attainment and household income and the statistically significant interaction variable between higher educational attainment and disfavor towards higher emissions may explain some of the inconsistency in previous studies’ findings, and points to a complex relationship between education, income, and environmental conscientiousness and the subsequent impact on EV adoption behavior.

The individual level vehicle choice model provides insights to the decreasing utility of purchase price and increasing utility of monetary incentives on vehicle choice. The federal tax credit or states rebates alone cannot offset purchase price, as there is a higher disutility for increasing in purchase price than the utility of increasing federal tax credit or state rebates. This is even true for high-income consumers who are less sensitive to purchase price. However, the combined utility of increasing federal tax credit and state rebates are greater than the disutility of an increase in purchase price. In early 2018, Virginia proposed a bill (House Bill No. 469) that stipulates 10% of the purchase price of an electric vehicle to be given to buyers as a tax credit up to $3500. However, this bill was not passed. Furthermore, the full federal tax credit will not be available when 200,000 qualified EVs have been sold in the United States by each manufacturer (which has already begun to affect Tesla and GM EVs). With more and more automakers hitting the 200,000-delivery threshold in the future and no state rebates available for EVs, Virginia will be in a disadvantageous position in increasing EV adoption compared to states which offer state-level financial incentives.

Counties with higher percent of household with children (under 18) shows lower EV registration counts. Brownstone and Fang (2010) reported that those households with children showed higher ownership rates of vans, SUVs, and pick-up trucks in California. As of 2016, consumers considering large vehicles have far fewer options when seeking an EVs vs. an ICEV. A relevant finding from the individual-level vehicle choice model is that respondents in a market
for a subcompact/compact car show significant higher utility of EVs compared to other vehicle body types. With more vehicle manufactures are extending their production line to large vehicle segments, EV adoption should expect to improve among other classes of vehicles. Model results from the individual vehicle choice survey also indicate that respondents are more likely to buy an EV as an addition to their household’s car fleet or as the first car to the household, compared to buying an EV to replace an existing vehicle. This result is evident in the results of Ferguson et al. (2018) in Canada where those seeking an incremental vehicle are far more likely to be assigned to the BEV-oriented class. A similar finding from early adopters in Norway also shows that most consumers who purchase EVs buy it as an addition to their existing vehicle fleet (Klöckner et al., 2013). Interestingly, those who are looking for the first car to their household also show preference for EVs. Potentially, first-time car buyers are younger and hence are more likely to show interest in new vehicle technology. However, as discussed previously, existing EV owners in Virginia are more likely to belong to older age groups.

The county-level EV ownership model predicts higher public charging port density to increase both BEV and PHEV counts in a county, with the coefficient for BEV higher than that for PHEV, indicating BEV registration counts is more sensitive to charging infrastructure than PHEV. The different charging infrastructure effects on BEV and PHEV adoption are further corroborated by individual-level analysis. The DCFC charging station along interstate highways and workplace charging is predicted to affect BEV adoption, but not PHEV adoption. This result seems logical as BEVs are solely powered by electricity. The availability of charging infrastructure helps travelers to overcome the “range anxiety” barrier to EV adoption. Surprisingly, model results indicate the availability of local public charging station does not increase the utility of EVs, which can be explained by the fact that EVs do most of their charging at home and the local travel may generally fall into the EVs’ range. The authors note the limitation of individual-level finding about charging infrastructure: non-EV owners from the sample may not be knowledgeable about EV charging stations and thus the charging infrastructure effects are hard to examine based on the stated preferences.

As to all-electric range, MNL model results from the stated preference survey show that this factor is statistically significant for BEVs, but not for PHEVs. There are two possible explanations for the insignificant effect on PHEV preference. First, PHEVs can also be powered by gasoline when the battery is depleted, thus potentially eliminating range anxiety issues (though a recent study has indicated that PHEV owners suffer from a different type of anxiety called “gas anxiety” (Ge et al., 2018). The second reason is that the effect of range is diluted by the effect of fuel cost for PHEVs. Greater all-electric range of PHEVs is associated with higher utility factor and thus more fuel cost savings.

In summary, both the zonal level EV ownership model and the individual vehicle choice model seem to confirm that greater education attainment and preference for a smaller vehicle exert positive effects on EV adoption. However, other factors’ relationships with EV ownership and preference are more complex, including gender, age, and charging infrastructure, where intentions (from SP data) are not in line with or even contradicts actions (from RP data).
The zonal EV ownership model was also used in this analysis to predict a 0.6% to 10% statewide EV adoption rate in 2025 in Virginia depending on future charging infrastructure investment, with a 2.4% adoption rate under the most likely scenario. Despite the mixed model results regarding effects of charging infrastructure on EV adoption in the individual vehicle preference model, such a large range across zonal EV adoption predictions demonstrates the importance of charging infrastructure investment in promoting state-wide EV adoption. In addition, EV adoption displays spatial differences across Virginia. Urban areas are predicted to have more EVs in 2025 compared to their rural counterparts. Also, counties predicted with dense EV adoption tend to be located along the major transportation corridors where many public charging stations (especially DCFC stations) are deployed.

Using the zonal EV ownership model, a CO2 emissions impact analysis is conducted based on predictions on EV adoption and fuel economy improvement of ICEVs. When considering only tailpipe emissions, Virginia counties exhibit CO2 emissions reductions ranging from 4% to 58% (relative change from 2016 to 2025). As dense metropolitan regions such as Washington DC, Richmond, and Hampton Roads are predicted to have higher EV adoption and faster fuel economy improvement among ICEVs, these areas will correspondingly enjoy more CO2 emissions reduction. When consider the emissions from electricity generation and assuming the average emission rate follows linear decrease trend, statewide CO2 emissions are projected to decrease by 7.45% to 19.39% depending on EV adoption and fuel economy improvement levels, with a 10.68% decrease for the most likely scenario. However, due to relatively low statewide EV adoption (2.4%) under the most likely scenario, only 1.58% of the 10.68% emissions reduction can be attributed to EV adoption while 9.10% of emissions reduction can be attributed to fuel economy improvement of ICEVs.

Note that this analysis only focuses on local (within Virginia) emission impacts and does not consider the emissions from vehicle manufacturing, and fuel production and transportation.

**Study Limitations and Future Work**

As discussed throughout the report, there are several limitations to this work. For the zonal level EV ownership analysis, the EV ownership model is developed using data from 2012 to 2016 where charging infrastructure levels are relatively low. The authors note the limitation of using such a model to project EV counts for significantly higher charging infrastructure levels, though predictions in this paper are limited to the year 2025. For the individual EV stated preference analysis, the MNL model developed in this report holds a strong assumption of independence from irrelevant alternatives (IIA), which may not represent real-world conditions.

The research can also be enhanced by several extensions. For example, future work will develop more advanced discrete choice models to avoid the restrictive IIA property of the logit model and recognizing differences in individual households’ vehicle choice sets. In addition, preferences analysis specific to EV owners vs. non-EV owners will be conducted to explore the charging infrastructure preferences heterogeneity. Lastly, emission impacts evaluation will be conducted beyond the scope of Virginia by allowing for the full life-cycle emissions.
REFERENCE


APPENDIX A SURVEY QUESTIONNAIRES

Virginia Electric Vehicles Adoption Survey

Survey Purpose
This survey is part of a research conducted by T. Donna Chen, PhD, at University of Virginia and Rajesh Paleti, PhD, at Old Dominion University. The research is funded by Mid-Atlantic Transportation Sustainability University Transportation Center (MATS UTC) with the purpose of understanding electric vehicle adoption process and evaluating its air quality impacts in the State of Virginia.

Survey Contents
This survey is comprised of 4 parts and is anticipated to take 15 to 20 minutes to complete.

1) Information about your household socioeconomic, demographic characteristics.
2) Information about your current household vehicles and your future vehicle purchase plan.
3) You will be asked to fill out six choice games where they are shown hypothetical vehicle profiles and asked to choose which vehicle you prefer.
4) Information about your experience about electric vehicles.

Confidentiality
The data collected for this research does not include any personally identifiable information about you.

Right to Ask Questions & Contact Information
If you have any questions about this research, please feel free to ask them by contacting the Principal Investigators at: tdchen@virginia.edu or rpaleti@odu.edu. If you have questions later, or you are interested in our research results, please contact the Principal Investigators in accordance with the contact information listed above.

Tip
Survey display is optimized for computer or tablet screen. Questions may be difficult to read on a smartphone.
Before starting the survey, it would be helpful to overview below table if you are not familiar with the following vehicle powertrain technologies.

<table>
<thead>
<tr>
<th>Vehicle Type</th>
<th>Details</th>
</tr>
</thead>
</table>
| Internal Combustion Engine Vehicle (ICEV)        | • Powered by an internal combustion engine.  
• Fueled solely by gasoline.                       |
| Hybrid Electric Vehicle (HEV)                    | • Powered by internal combustion engine and battery together.  
• Battery cannot be plugged in.  
• Battery is charged by regenerative braking and internal combustion engine.  
• Consume less fuel than ICEVs.  
• Produce fewer emissions than ICEVs.               |
| Plug-in Hybrid Electric Vehicle (PHEV)           | • Have larger batteries than HEVs  
• Battery can be charged by plugging in to an electric power source, by regenerative braking, and by the internal combustion engine.  
• Unable to take full advantage of fuel efficiency without charging |
| Battery Electric Vehicle (BEV)                   | • Run on electricity alone.  
• No internal combustion engine  
• One or more electric motors  
• Larger batteries compared to HEV and PHEV. Charged by plugging in and regenerative braking. |

In this survey, you may see the term “electric vehicles” which refers to both Plug-in Hybrid Electric Vehicle (PHEV) and Battery Electric Vehicle (BEV).
Part 1 Household Socio-demographics

1. **Including yourself**, how many household members of all ages live in your household?
   - ☐ 1
   - ☐ 2
   - ☐ 3
   - ☐ 4
   - ☐ 5
   - ☐ 6
   - ☐ More than 6

2. Please tell us about information about you and your household members.

<table>
<thead>
<tr>
<th></th>
<th>You</th>
<th>Household Member #2</th>
<th>#...</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>(Type in)</td>
<td>(Type in)</td>
<td>_____</td>
</tr>
<tr>
<td>Employment</td>
<td>☐ Full time</td>
<td>☐ Part time</td>
<td>☐ Retired</td>
</tr>
<tr>
<td></td>
<td>☐ Not-employed</td>
<td>☐ Student</td>
<td>☐ Pre-school child</td>
</tr>
<tr>
<td>Has driver’s license?</td>
<td>☐ YES</td>
<td>☐ NO</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>☐ Female</td>
<td>☐ Male</td>
<td>☐ other</td>
</tr>
</tbody>
</table>

3. Information about your income can help us to understand vehicle choices. Please choose the range that includes the approximate **annual HOUSEHOLD income before taxes**.
   - ☐ Less than $25,000
   - ☐ $25,000 - $34,999
   - ☐ $35,000 - $49,999
   - ☐ $50,000 - $74,999
   - ☐ $75,000 - $99,999
   - ☐ $100,000 - $149,999
   - ☐ $150,000 - $199,999
   - ☐ $200,000 - $249,999
   - ☐ $250,000 - $299,999
   - ☐ $300,000 and over

4. Which of the following best describes the **highest education level** obtained by you?
   - ☐ Less than high school graduate
   - ☐ High school graduate (includes equivalency)
   - ☐ Some college, no degree
Associate's degree

Bachelor's degree

Graduate or professional degree

5. Do you own or rent your primary residence?
   - Own
   - Rent
   - Other

6. Which of the following best describe your primary residence?
   - Detached (Example: Single family house)
   - Semi-detached (Example: Duplex)
   - Attached (Example: Townhouse)
   - Apartment/Condo (Example: Housing unit within a complex)
   - Mobile

7. The zipcode of your primary residence?
   ______

8. Your primary residence is in?
   - Urban area
   - Suburban area
   - Rural

9. To get a better idea about the transportation infrastructure and land use attributes around your primary residence, please name an intersection near your primary residence by giving two street names.
   ______ and _______
Part 2 Future Vehicle Purchase Plan and Household Vehicles Inventory

10. In your household, who is the primary decision-maker for purchasing a vehicle?
   - Me
   - Another household member
   - Both myself and another/other household member(s) contribute equally to the decision.

11. When do you expect your household to purchase the next vehicle?
   - Less than one year from now
   - Between 1 and 2 years from now
   - Between 2 and 3 years from now
   - Between 3 and 5 years from now
   - Greater than 5 years from now
   - I do not know

12. Please tell us about your approximate budget to your next vehicle purchase (Dropdown menu, from less than $10,000 to more than $100,000)

13. The vehicle you are going to purchase will be?
   - A replacement to one of your current vehicles.
   - An additional vehicle to your household’s vehicle fleet.
   - The first vehicle of your household.

14. The vehicle you are going to purchase will be mainly used by?
   - Myself
   - Another household member
   - Shared among household members

Questions 15-22 is only for those who answer “myself” or “shared among household members” in question 14.

15. On a typical day, what is your major destination? (single answer question)
   - Workplace
   - Attending school
   - Entertainment/shopping etc. place
   - Stay at home
   - Other destinations

16. Does your workplace have charging outlets/stations? (This question is only for those who answer “Workplace” in question 15)
   - Yes
   - No
   - Do not know

17. Does your school have charging outlets/stations? (This question is only for those who answer “Attending school” in question 15)
   - Yes
   - No
18. What’s the charger type at your workplace? (This question is only for those who answer YES in question 16)
   - Level 1 (110V)
   - Level 2 (220V)
   - DC fast charging (480V)
   - Do not know

19. What’s the charger type at your school? (This question is only for those who answer YES in question 17)
   - Level 1 (110V)
   - Level 2 (220V)
   - DC fast charging (480V)
   - Do not know

20. On a typical day, what is your most often used transportation mode to your major destination? (skip this question if respondents choose “stay at home” in question 14)
   - Drive alone
   - Carpool
   - Public transportation (excluding taxicab)
   - Walk or bike
   - Taxicab
   - Motorcycle or other means

21. On a typical day, how many miles ONE WAY do you travel from home to your major destination (including any regular intermediate stops, such as pick-up/drop off children)? (skip this question if respondent choose “stay at home” in question 14)
   - Drill down: from less than 1 mile – more than 50 miles

22. How many days per week do you drive to your major destination? (This question is for those who answer “drive alone” or ”carpool” in Question 19)
   - 1
   - 2
   - 3
   - 4
   - 5
   - 6
   - 7

Questions 23-30 is only for those who answer “another household member” in question 14.

23. For the household member that will mainly use the new vehicle, what is his or her major destination on a typical day?
   - Workplace
   - Attending school
24. For the household member that will mainly use the new vehicle, does his or her workplace has charging outlets/stations? (This question is only for those who answer “Workplace” in question 23)
   - Yes
   - No
   - Do not know

25. For the household member that will mainly use the new vehicle, does his or her school has charging outlets/stations? (This question is only for those who answer “Attending school” in question 23)
   - Yes
   - No
   - Do not know

26. For the household member that will mainly use the new vehicle, what’s the charger type at his or her workplace? (This question is only for those who answer YES in question 24)
   - Level 1 (110V)
   - Level 2 (220V)
   - DC fast charging (480V)
   - Do not know

27. For the household member that will mainly use the new vehicle, what’s the charger type at his or her school? (This question is only for those who answer YES in question 25)
   - Level 1 (110V)
   - Level 2 (220V)
   - DC fast charging (480V)
   - Do not know

28. For the household member that will mainly use the new vehicle, what is the most often used transportation mode to his/her major destination on a typical day? (skip this question if respondents choose “stay at home” in question 23)
   - Drive alone
   - Carpool
   - Public transportation (excluding taxicab)
   - Walk or bike
   - Taxicab
   - Motorcycle or other means

29. For the household member that will mainly use the new vehicle, how many miles ONE WAY does he or she travel from home to his or her major destination on a typical day (including any regular intermediate stops, such as pick-up/drop off children)? (skip this question if respondent choose “stay at home” in question 22)
Drill down menu: from less than 1 mile to more than 50 miles

30. For the household member that will mainly use the new vehicle, how many days per week does he or she drive to his or her major destination? (This question is for those who answer “drive alone”/”carpool” in Question 27).

- 1
- 2
- 3
- 4
- 5
- 6
- 7

31. Which of the following body types would you be most interested in purchasing for your next vehicle? (Please choose carefully since the choice experiments part will be tailored for you based on your answer to this question)

- Subcompact or compact car
- Mid/Full size car
- Small/Medium SUV¹
- Standard/Large SUV or Minivan²
- Pick-up truck

32. You have mentioned that you would like to purchase a (piped from question 31) for your next vehicle. How many miles do you plan to drive **ANNUALLY** for this new vehicle to purchase?

- Less than 5,000 miles
- 5,001 miles to 7,000 miles
- 7,001 miles to 9,000 miles
- 9001 miles to 11000 miles
- 11001 miles to 13000 miles
- 13001 miles to 15000 miles

---

¹ Seating capacity: 5
² Seating capacity: 7
33. How many motorized vehicles (DO NOT include motorcycles) does your household CURRENTLY own/lease?

- 0
- 1
- 2
- 3
- 4
- 5 or more

34. You have mentioned that there are _ motorized vehicles in your household. Please tell us about the information about these vehicles in your household.

<table>
<thead>
<tr>
<th># 1 vehicle</th>
<th>#2 vehicle</th>
<th>#...</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MAKE, MODEL</strong></td>
<td>(Please type in), (Please type in)</td>
<td></td>
</tr>
<tr>
<td>Model year</td>
<td>(Select by slider)</td>
<td></td>
</tr>
<tr>
<td>Year of Purchase</td>
<td>(Select by slider)</td>
<td></td>
</tr>
</tbody>
</table>

**Vehicle powertrain technology**
- Internal combustion engine vehicle (ICEV)
- Hybrid electric vehicle (HEV)
- Plug-in hybrid electric vehicle (PHEV)
- Battery electric vehicle (BEV)
- Other, please specify.

**Do you own or lease this vehicle?**
- Own
- Lease

**When you purchased this vehicle, it was**
- New
- Used

**Where do you park this vehicle?**
- Garage
- Carport
- Driveway/off street
- On the street
- Parking lot
- Other

You have mentioned that the vehicle your household is going to purchase in the future will be a replacement to one of your current vehicles. Which one will be replaced? (This question is only for those who choose “replacement” in question 12)
35. You have mentioned that your household owns electric vehicles. What's the charger type at your home? (this question is only for households who have electric vehicles)
   - Level 1 (110V)
   - Level 2 (220V)
   - No charging outlet available at home

36. Please tell us about the distance to the nearest public electric vehicle charging station from your house.
   - Less than 1 mile
   - 1-5 miles
   - >5 miles
   - No charging stations around my house
   - Do not know the availability

37. What’s the charger type at the nearest charging station from your house? Please select all that apply. (this question is only for those who answer less than 1 mile or 1-5 mile, or > 5 miles in Question 36)
   - Level 1 (110V)
   - Level 2 (220V)
   - DC fast charging (480V)
   - Do not know

**Part 3 Choice Experiments for Household Next Vehicle Purchase**

In this part, you will complete 6 choice tasks based on several vehicle attributes. If you are not familiar with attributes associated with electric vehicles, please read the descriptions carefully before moving forward in the survey.

38. **Battery-only Range & Charging**
   - When the electric vehicle is fully charged, this value represents the approximate number of miles that can be travelled by battery power alone before the vehicle must be recharged. Below figure shows the battery-only ranges of three popular electric vehicle models in US market certified by Environmental Protection Agency (EPA).

   ![Electricity, 151 miles](image)
   ![Electricity, 238 miles](image)
   ![Electricity, 315 miles](image)

   - Charging equipment for plug-in electric vehicles (PHEVs or BEVs) is classified by the rate at which the batteries are charged. Charging time varies based on how depleted the battery is, how much energy it holds, the type of battery, and the type of charger. Below table shows typical application examples for different charger types.
<table>
<thead>
<tr>
<th>Charger types</th>
<th>Charging Speed</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1 (110V)</td>
<td>2 to 5 miles of range per 1 hour of charging</td>
<td>Charging at home</td>
</tr>
<tr>
<td>Level 2 (220V)</td>
<td>10 to 20 miles of range per 1 hour of charging</td>
<td>Charging at workplace</td>
</tr>
<tr>
<td>Level 3 Direct Current (DC)</td>
<td>60 to 80 miles of range per 20 minutes of charging</td>
<td>Public fast charging station</td>
</tr>
<tr>
<td>Fast Charging (480V)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

39. **Purchase Cost vs. Incentives**
• Purchase Price.
  o In the current US market, an electric vehicle is **about $10,000 to $20,000 more expensive** than its conventional internal combustion vehicle counterpart.
  o In some choice games below, you may see the purchase price of an electric vehicle is the same as a conventional internal combustion vehicle. Such choice games represent **future scenarios** when the price of an electric vehicle is competitive to a conventional internal combustion vehicle thanks to the battery cost decrease and electric vehicles production scale effect.

• Federal Tax Credit
  o BEV and PHEV purchased in or after 2010 may be eligible for a federal income tax credit of **up to $7,500**. The credit amount will vary based on the capacity of the battery used to power the vehicle.
  o Almost all Battery Electric Vehicles (BEVs) qualify for the full $7,500 federal tax credit.
  o Most of PHEVs are only eligible for a $4000-$5000 federal tax credit as their battery-only range is lower than 30 miles.

• State Incentives
  o In January, 2018, there is a proposed bill (not approved yet) in the Virginia legislature for a state electric vehicle tax credit in the amount of **10% of purchase price (up to $3500)** on PHEVs and BEVs.
  o California provides rebates of **$2500 for BEVs and $1500 for PHEVs**.

40. Operational/Maintenance Cost & Fees

• Cost to drive 25 miles
  o On a national average, for a midsize vehicle, it costs less than half as much to travel 25 miles in a Battery Electric Vehicle (BEV) than an Internal Combustion Engine Vehicle (ICEV).
Some utilities offer even cheaper electricity rates at night, which can further reduce recharging costs of electric vehicles.

- **Maintenance Cost**: Electric vehicles typically require less maintenance than internal combustion engine vehicles because:
  - The battery, motor, and associated electronics require little to no regular maintenance
  - There are fewer fluids to change
  - Brake wear is significantly reduced due to regenerative braking
  - There are far fewer moving parts relative to a conventional gasoline engine

- **Annual EV Use Fee**
  - Electric vehicle use fees are often developed as a means to pay for transportation infrastructure, which has traditionally been supplied by a gas tax.
  - Several states charge such fees, varying from $50 to $200 annually. Virginia currently charge $64/year/vehicle for Battery Electric Vehicles (BEV).

**Great! You have reviewed the materials of electric vehicle attributes. Now you are prepared to conduct the choice games.**
For each vehicle body type (except pick-up truck) in question 31, six blocks are developed, and each block has six choice experiments. After respondents select their preferred vehicle body type, one of the six blocks for that specific body type will be randomly presented to the respondents.

The tables below show one of the six blocks for subcompact/compact car. You mentioned that you would most likely purchase a subcompact/compact car (piped from question 31) for your next vehicle and that plan to drive 12,000 miles (piped from question 32) for this vehicle. Please carefully review each vehicle and all its attributes below. And then please select the ONE vehicle you would most likely purchase.
### Vehicle Technical Specs

<table>
<thead>
<tr>
<th></th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fuel Economy</strong></td>
<td>30 mpg</td>
<td>45 mpg</td>
<td>45 mpg (gas-mode)</td>
<td></td>
</tr>
<tr>
<td><strong>Annual Tailpipe CO₂ Emissions</strong></td>
<td>3.56 tonnes</td>
<td>2.37 tonnes</td>
<td>0.57 tonnes</td>
<td>0</td>
</tr>
<tr>
<td><strong>Battery-only Range</strong></td>
<td>0</td>
<td>0</td>
<td>50 miles</td>
<td>250 miles</td>
</tr>
</tbody>
</table>

### Charging Station Availability

**Long Distance Travel Charging**  
*(Charging rate is 60 to 80 miles of range per 20 minutes of charging)*

- DC Fasting Charging
  - Station Spacing along Interstate Highways

<table>
<thead>
<tr>
<th></th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fast charging station every 70 miles</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Fast charging station every 70 miles</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Local Charging Station Availability**  
*(Charging rate is 10 to 20 miles of range per 1 hour of charging)*

- Major Destinations  
  - *(workplace/school)*
- Other Destinations  
  - *(shopping center, restaurant etc.)*

<table>
<thead>
<tr>
<th></th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>YES</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>YES</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>15% (1 in 6 destinations)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>15% (1 in 6 destinations)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Cost

**One-time Purchase Cost**

<table>
<thead>
<tr>
<th></th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Purchase Price</strong></td>
<td>$17,000</td>
<td>$23,000</td>
<td>$17,000</td>
<td>$24,500</td>
</tr>
</tbody>
</table>

**Annual Cost**

<table>
<thead>
<tr>
<th></th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fuel/Charging</strong></td>
<td>$800</td>
<td>$530</td>
<td>$440</td>
<td>$390</td>
</tr>
<tr>
<td><strong>Maintenance/Repair</strong></td>
<td>$820</td>
<td>$738</td>
<td>$656</td>
<td>$410</td>
</tr>
<tr>
<td><strong>Electric Vehicle Use Fee</strong></td>
<td>$0</td>
<td>$0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### One-time Incentives

<table>
<thead>
<tr>
<th></th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Federal Tax Credit ($)</strong></td>
<td></td>
<td></td>
<td>$7,500</td>
<td>$7,500</td>
</tr>
<tr>
<td><strong>State Rebates ($)</strong></td>
<td>$0</td>
<td>$0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**You would most likely to purchase**  

- ○ | ○ | ○ | ○ | ○

Note: gasoline price and electricity price used to calculate fuel cost are $2/gallon and 11.08 cents/kWh.
Choice Experiment 2

### Vehicle Technical Specs

<table>
<thead>
<tr>
<th></th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fuel Economy</strong></td>
<td>40 mpg</td>
<td>60 mpg</td>
<td>60 mpg (gas-mode)</td>
<td></td>
</tr>
<tr>
<td><strong>Annual Tailpipe CO2 Emissions</strong></td>
<td>2.67 tonnes</td>
<td>1.78 tonnes</td>
<td>0.96 tonnes</td>
<td>0</td>
</tr>
<tr>
<td><strong>Battery-only Range</strong></td>
<td>0</td>
<td>0</td>
<td>20 miles</td>
<td>120 miles</td>
</tr>
</tbody>
</table>

### Charging Station Availability

**Long Distance Travel Charging**  
*Charging rate is 60 to 80 miles of range per 20 minutes of charging*

- **DC Fast Charging**  
  Station Spacing along Interstate Highways
  - Fast charging station every 100 miles
  - Fast charging station every 100 miles

**Local Charging Station Availability**  
*Charging rate is 10 to 20 miles of range per 1 hour of charging*

- **Major Destinations**  
  (workplace/school)
  - NO
  - NO

- **Other Destinations**  
  (shopping center, restaurant etc.)
  - 30% (1 in 3 destinations)
  - 30% (1 in 3 destinations)

### Cost

**One-time Cost**

- **Purchase Price**
  - $17,000
  - $23,000
  - $32,000
  - $32,000

**Annual Cost**

- **Fuel/Charging**
  - $750
  - $500
  - $500
  - $390

- **Maintenance/Repair**
  - $820
  - $738
  - $738
  - $410

- **Electric Vehicle Use Fee**
  - $100
  - $200

### One-time Incentives

- **Federal Tax Credit ($)**
  - $4,500
  - $7,500

- **State Rebates ($)**
  - $3,200
  - $3,200

**You would most likely to purchase**

- ○
- ○
- ○
- ○
- ○

Note: gasoline price and electricity price used to calculate fuel cost are $2.50/gallon and 11.08 cents/kWh.
Choice experiment 3

<table>
<thead>
<tr>
<th></th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel Economy</td>
<td>40 mpg</td>
<td>60 mpg</td>
<td>60 mpg (gas-mode)</td>
<td></td>
</tr>
<tr>
<td>Annual Tailpipe CO2 Emissions</td>
<td>2.67 tonnes</td>
<td>1.78 tonnes</td>
<td>0.96 tonnes</td>
<td>0</td>
</tr>
<tr>
<td>Battery-only Range</td>
<td>0</td>
<td>0</td>
<td>20 miles</td>
<td>120 miles</td>
</tr>
</tbody>
</table>

**Charging Station Availability**

Long Distance Travel Charging
(Charging rate is 60 to 80 miles of range per 20 minutes of charging)

- DC Fasting Charging Station Spacing along Interstate Highways
  - Fast charging station every 40 miles

Local Charging station availability
(Charging rate is 10 to 20 miles of range per 1 hour of charging)

- Major Destinations (workplace/school)
  - NO

- Other Destinations (shopping center, restaurant etc.)
  - 15% (1 in 6 destinations)
  - 15% (1 in 6 destinations)

**Cost**

**One-time Cost**

- Purchase Price
  - ICEV: $17,000
  - HEV: $23,000
  - PHEV: $17,000
  - BEV: $17,000

**Annual Cost**

- Fuel/Charging*
  - ICEV: $900
  - HEV: $600
  - PHEV: $550
  - BEV: $390
- Maintenance/Repair
  - ICEV: $820
  - HEV: $738
  - PHEV: $656
  - BEV: $574
- Electric Vehicle Use Fee
  - ICEV: $0
  - HEV: $100

**One-time Incentives**

- Federal Tax Credit ($)
  - ICEV: $4,500
  - HEV: $7,500
- State Rebates ($)
  - ICEV: $0
  - HEV: $0

You would most likely to purchase

- ICEV
- HEV
- PHEV
- BEV

Note: gasoline price and electricity price used to calculate fuel cost are $3/gallon and 11.08 cents/kWh.
Choice experiment 4

<table>
<thead>
<tr>
<th><strong>Vehicle Technical Specs</strong></th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fuel Economy</strong></td>
<td>30 mpg</td>
<td>45 mpg</td>
<td>45 mpg (gas mode)</td>
<td></td>
</tr>
<tr>
<td><strong>Annual Tailpipe CO2 Emissions</strong></td>
<td>3.56 tonnes</td>
<td>2.37 tonnes</td>
<td>0.57 tonnes</td>
<td>0</td>
</tr>
<tr>
<td><strong>Battery-only Range</strong></td>
<td>0</td>
<td>0</td>
<td>50 miles</td>
<td>60 miles</td>
</tr>
</tbody>
</table>

**Charging Station Availability**

**Long Distance Travel Charging**
(Charging rate is 60 to 80 miles of range per 20 minutes of charging)

- DC Fast Charging Station Spacing along Interstate Highways
  - Fast charging station every 70 miles

**Local Charging Station Availability**
(Charging rate is 10 to 20 miles of range per 1 hour of charging)

- Major Destinations (workplace/school)
  - NO
- Other Destinations (shopping center, restaurant etc.)
  - 0%
  - 0%

**Cost**

**One-time Cost**
- **Purchase Price**
  - $17,000
  - $23,000
  - $24,500
  - $24,500

**Annual Cost**
- **Fuel/Charging**
  - $1,000
  - $670
  - $470
  - $390
- **Maintenance/Repair**
  - $820
  - $738
  - $656
  - $410
- **Electric Vehicle Use Fee**
  - $100
  - $100

**One-time Incentives**
- **Federal Tax Credit ($)**
  - $0
  - $0
- **State Rebates ($)**
  - $2,450
  - $2,450

**You would most likely to purchase**
- ○
- ○
- ○
- ○

Note: gasoline price and electricity price used to calculate fuel cost are $2.5/gallon and 11.08 cents/kWh.
Choice experiment 5

<table>
<thead>
<tr>
<th>Vehicle Technical Specs</th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel Economy</td>
<td>40 mpg</td>
<td>60 mpg</td>
<td>60 mpg (gas-mode)</td>
<td></td>
</tr>
<tr>
<td>Annual Tailpipe CO₂ Emissions</td>
<td>2.67 tonnes</td>
<td>1.78 tonnes</td>
<td>0.43 tonnes</td>
<td>0</td>
</tr>
<tr>
<td>Battery-only Range</td>
<td>0</td>
<td>0</td>
<td>50 miles</td>
<td>60 miles</td>
</tr>
</tbody>
</table>

**Charging Station Availability**

**Long Distance Travel Charging**
*(Charging rate is 60 to 80 miles of range per 20 minutes of charging)*

- DC Fasting Charging Station Spacing along Interstate Highways
  - Fast charging station every 40 miles
  - Fast charging station every 40 miles

**Local Charging Station Availability**
*(Charging rate is 10 to 20 miles of range per 1 hour of charging)*

- Major Destinations *(workplace/school)*
  - YES
  - YES

- Other Destinations *(shopping center, restaurant etc.)*
  - 30% (1 in 3 destinations)
  - 30% (1 in 3 destinations)

**Cost**

**One-time Cost**

- **Purchase Price**
  - $17,000
  - $23,000
  - $24,500
  - $32,000

**Annual Cost**

- **Fuel/Charging**
  - $600
  - $400
  - $410
  - $390

- **Maintenance/Repair**
  - $820
  - $738
  - $738
  - $574

- **Electric Vehicle Use Fee**
  - $100
  - $100

**One-time Incentives**

- **Federal Tax Credit ($)**
  - $0
  - $0

- **State Rebates ($)**
  - $0
  - $0

**You would most likely to purchase**

- ○
- ○
- ○
- ○

Note: gasoline price and electricity price used to calculate fuel cost are $2/gallon and 11.08 cents/kWh.
Choice experiment 6

<table>
<thead>
<tr>
<th>Vehicle Technical Specs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fuel economy</strong></td>
</tr>
<tr>
<td>---------------------</td>
</tr>
<tr>
<td>30 mpg</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Annual Tailpipe CO2 Emissions</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>3.56 tonnes</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Battery-only Range</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Charging Station Availability</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Long Distance Travel Charging</strong> (Charging rate is 60 to 80 miles of range per 20 minutes of charging)</td>
</tr>
<tr>
<td>• DC Fasting Charging Station Spacing along Interstate Highways</td>
</tr>
<tr>
<td>Fast charging station every 100 miles</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Local Charging Station Availability</strong> (Charging rate is 10 to 20 miles of range per 1 hour of charging)</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Major Destinations (workplace/school)</td>
</tr>
<tr>
<td>• Other Destinations (shopping center, restaurant etc.)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>One-time Cost</strong></td>
</tr>
<tr>
<td>• Purchase Price</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Annual Cost</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>• Fuel/Charging*</td>
</tr>
<tr>
<td>• Maintenance/Repair</td>
</tr>
<tr>
<td>• Electric Vehicle Use Fee</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>One-time Incentives</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>• Federal Tax Credit ($)</td>
</tr>
</tbody>
</table>

You would most likely to purchase ○ ○ ○ ○ ○

Note: gasoline price and electricity price used to calculate fuel cost are $3/gallon and 11.08 cents/kWh.
41. Please rate the importance of the following attributes you considered through the above six choice games.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Unimportant</th>
<th>Somewhat unimportant</th>
<th>Neutral</th>
<th>Somewhat important</th>
<th>Very important</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel economy (mpg)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual CO₂ emissions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Battery-only range</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DC Fast Charging station spacing along interstate highways</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local major destinations (workplace/school) charging availability</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local destinations (except for workplace/school) charging availability</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Purchase price</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual fuel/charging cost</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual maintenance/repair cost</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual EV use fee</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Federal tax credit</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State rebates</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

42. In addition to the attributes listed in the choice scenarios, are there any other attributes which influence your decision when purchasing a new vehicle? Please list in the box below.
**Part 4 Experience**

In this part, we will ask some general questions about your experience associated with electric vehicles.

43. How have you been exposed to plug-in electric vehicles? Please select all that apply.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Never exposed to electric vehicles</td>
<td>Seen EV in ads, social media.</td>
<td>Seen EVs in parking lots, seen charging stations</td>
<td>Seen neighbors, friends, colleagues, etc. drive electric vehicles.</td>
<td>Sat in an electric vehicle</td>
<td>Own/lease</td>
</tr>
</tbody>
</table>

44. Please rate how much you agree with the following statements.

<table>
<thead>
<tr>
<th>I consider myself an early adopter when it comes to new technology.</th>
<th>Strongly disagree</th>
<th>Disagree</th>
<th>Neutral</th>
<th>Agree</th>
<th>Strongly agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>I consider myself a risk-taker.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I consider myself an environmentally-conscientious person</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global climate change is a serious threat to humanity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

45. Please select Yes or No for the following statements.

<table>
<thead>
<tr>
<th>I use ride-hailing services (such as Uber or Lyft)</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>I have used ride-hailing services' ridesharing option (such as Uberpool or Lyftline)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I am a member of carsharing service (such as Zipcar or Car2go)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I pay close attention to latest news about driverless vehicle technology.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I would feel comfortable riding in a self-driving vehicle (given the vehicle and software has passed safety checks).</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

46. If you have additional thoughts about the survey, please share them with us here.

___
## APPENDIX B ATTRIBUTE LEVELS FOR EXPERIMENT DESIGN

### Table B-1 Attribute levels for subcompact/compact car

<table>
<thead>
<tr>
<th>Attributes</th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Vehicle Technical Specification</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Battery-only Range (mile)</td>
<td></td>
<td></td>
<td>20, 50</td>
<td>60, 120, 250</td>
</tr>
<tr>
<td>Fuel economy (mpg)</td>
<td>Level 1 (30 for ICEV, 45 for HEV), Level 2 (40 for ICEV, 60 for HEV)</td>
<td>Same as HEV</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual CO₂ emissions (ton)</td>
<td>Calculated</td>
<td>Calculated</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td><strong>Charging Station Availability</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DC fast charging station spacing along interstate highways</td>
<td></td>
<td>40 miles, 70 miles, 100 miles</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local charging station availability at workplace/school</td>
<td></td>
<td>YES, NO</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local charging station availability at other destinations (restaurant, shopping center)</td>
<td></td>
<td>0%</td>
<td>15%, (1 in 6 destinations)</td>
<td>30%, (1 in 3 destinations)</td>
</tr>
<tr>
<td><strong>Cost ($)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Purchase Price</td>
<td>17,000 (Base)</td>
<td>23,000</td>
<td>Base + 15,000, Base + 7,500, Base</td>
<td>Base + 15,000, Base + 7,500, Base</td>
</tr>
<tr>
<td>Annual fuel/charging cost</td>
<td>Calculated</td>
<td>Calculated</td>
<td>Calculated</td>
<td>Calculated</td>
</tr>
<tr>
<td>Annual maintenance/repair cost</td>
<td>Base (calculated)</td>
<td>Base*90%</td>
<td>Base*90%</td>
<td>Base*70%</td>
</tr>
<tr>
<td>Annual EV use fee</td>
<td></td>
<td>0, 100</td>
<td>100, 200</td>
<td></td>
</tr>
<tr>
<td><strong>Incentives ($)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Federal tax credit</td>
<td></td>
<td>0, 4,500/7,500¹</td>
<td></td>
<td></td>
</tr>
<tr>
<td>State rebates</td>
<td></td>
<td>0, 10% of purchase price</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

¹ For PHEV, if battery-only range is 50 miles, federal tax credit will be $7,500; if range is 20 miles, then federal tax will be $4,500. For BEV, the federal tax credit will always be $7,500.
<table>
<thead>
<tr>
<th>Attributes</th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle Technical Specification</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Battery-only Range (mile)</td>
<td></td>
<td>15, 30</td>
<td>100, 200, 300</td>
<td></td>
</tr>
<tr>
<td>Fuel economy (mpg)</td>
<td>Level 1 (30 for ICEV, 45 for HEV), Level 2 (40 for ICEV, 60 for HEV)</td>
<td>Same as HEV</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual CO₂ emissions (ton)</td>
<td>Calculated</td>
<td>Calculated</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Charging Station Availability</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DC fast charging station spacing along interstate highways</td>
<td>40 miles, 70 miles, 100 miles</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local charging station availability at workplace/school</td>
<td>YES, NO</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local charging station availability at other destinations (restaurant, shopping center)</td>
<td>0%, 15%, (1 in 6 destinations) 30%, (1 in 3 destinations)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cost ($)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Purchase Price</td>
<td>22,000 (Base)</td>
<td>27,000</td>
<td>Base + 11,000, Base + 5,500, Base</td>
<td>Base + 10,000, Base + 5,000, Base</td>
</tr>
<tr>
<td>Annual fuel/charging cost</td>
<td>Calculated</td>
<td>Calculated</td>
<td>Calculated</td>
<td></td>
</tr>
<tr>
<td>Annual maintenance/repair cost</td>
<td>Base (calculated)</td>
<td>Base*90%</td>
<td>Base<em>90% Base</em>80%</td>
<td>Base<em>70% Base</em>50%</td>
</tr>
<tr>
<td>Annual EV use fee</td>
<td>0, 100</td>
<td></td>
<td>100, 200</td>
<td></td>
</tr>
<tr>
<td>Incentives ($)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Federal tax credit</td>
<td></td>
<td>0, 4,500/7,500¹</td>
<td></td>
<td></td>
</tr>
<tr>
<td>State rebates</td>
<td></td>
<td>0, 10% of purchase price</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

¹ For PHEV, federal tax is be $4,500. For BEV, the federal tax credit is $7,500.
Table B-3 Attribute levels for small/medium SUV

<table>
<thead>
<tr>
<th>Attributes</th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Vehicle Technical Specification</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Battery-only Range (mile)</td>
<td></td>
<td></td>
<td>15, 30</td>
<td>100, 200, 300</td>
</tr>
<tr>
<td>Fuel economy (mpg)</td>
<td></td>
<td></td>
<td>Level 1 (25 for ICEV, 35 for HEV), Level 2 (35 for ICEV, 50 for HEV)</td>
<td>Same as HEV</td>
</tr>
<tr>
<td>Annual CO₂ emissions (ton)</td>
<td></td>
<td>Calculated</td>
<td>Calculated</td>
<td>0</td>
</tr>
<tr>
<td><strong>Charging Station Availability</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DC fast charging station spacing along interstate highways</td>
<td></td>
<td></td>
<td>40 miles, 70 miles, 100 miles</td>
<td></td>
</tr>
<tr>
<td>Local charging station availability at workplace/school</td>
<td></td>
<td></td>
<td>YES, NO</td>
<td></td>
</tr>
<tr>
<td>Local charging station availability at other destinations (restaurant, shopping center)</td>
<td></td>
<td></td>
<td>0%, 15%, (1 in 6 destinations), 30%, (1 in 3 destinations)</td>
<td></td>
</tr>
<tr>
<td><strong>Cost ($)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Purchase Price</td>
<td>24,000 (Base)</td>
<td>27,000</td>
<td>Base + 10,000, Base + 5,000, Base</td>
<td>Base + 16,000, Base + 8,000, Base</td>
</tr>
<tr>
<td>Annual fuel/charging cost</td>
<td>Calculated</td>
<td></td>
<td>Calculated</td>
<td>Calculated</td>
</tr>
<tr>
<td>Annual maintenance/repair cost</td>
<td>Base (calculated)</td>
<td>Base*90%</td>
<td>Base<em>90%, Base</em>80%</td>
<td>Base<em>70%, Base</em>50%</td>
</tr>
<tr>
<td>Annual EV use fee</td>
<td>0, 100</td>
<td></td>
<td></td>
<td>100, 200</td>
</tr>
<tr>
<td><strong>Incentives ($)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Federal tax credit</td>
<td></td>
<td></td>
<td>0, 4,500/7,500$^1</td>
<td></td>
</tr>
<tr>
<td>State rebates</td>
<td></td>
<td></td>
<td>0, 10% of purchase price</td>
<td></td>
</tr>
</tbody>
</table>

^1 For PHEV, federal tax credit is $4,500. For BEV, the federal tax credit is $7,500.
### Table B-4 Attribute levels for standard SUV & Minivan

<table>
<thead>
<tr>
<th>Attributes</th>
<th>ICEV</th>
<th>HEV</th>
<th>PHEV</th>
<th>BEV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Vehicle Technical Specification</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Battery-only Range (mile)</td>
<td></td>
<td></td>
<td>15, 35</td>
<td>100, 200, 300</td>
</tr>
<tr>
<td>Fuel economy (mpg)</td>
<td></td>
<td>Level 1 (20 for ICEV, 25 for HEV), Level 2 (30 for ICEV, 35 for HEV)</td>
<td>Same as HEV</td>
<td></td>
</tr>
<tr>
<td>Annual CO₂ emissions (ton)</td>
<td>Calculated</td>
<td>Calculated</td>
<td></td>
<td>0</td>
</tr>
<tr>
<td><strong>Charging Station Availability</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DC fast charging station spacing along interstate highways</td>
<td></td>
<td></td>
<td>40 miles, 70 miles, 100 miles</td>
<td></td>
</tr>
<tr>
<td>Local charging station availability at workplace/school</td>
<td></td>
<td>YES, NO</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local charging station availability at other destinations (restaurant, shopping center)</td>
<td></td>
<td>0%</td>
<td>15%, (1 in 6 destinations) 30%, (1 in 3 destinations)</td>
<td></td>
</tr>
<tr>
<td><strong>Cost ($)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Purchase Price</td>
<td>28,000 (Base)</td>
<td>31,000</td>
<td>Base + 13,000, Base + 6,500, Base</td>
<td>Base + 20,000, Base + 10,000, Base</td>
</tr>
<tr>
<td>Annual fuel/charging cost</td>
<td>Calculated</td>
<td>Calculated</td>
<td>Calculated</td>
<td>Calculated</td>
</tr>
<tr>
<td>Annual maintenance/repair cost</td>
<td>Base (calculated)</td>
<td>Base*90%</td>
<td>Base<em>90%, Base</em>80%</td>
<td>Base<em>70%, Base</em>50%</td>
</tr>
<tr>
<td>Annual EV use fee</td>
<td>0, 100</td>
<td>100, 200</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Incentives ($)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Federal tax credit</td>
<td>0, 4,500/7,500¹</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State rebates</td>
<td>0, 10% of purchase price</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

¹ For PHEV, if battery-only range is 35 miles, federal tax credit will be $7,500; if range is 15 miles, then federal tax will be $4,500. For BEV, the federal tax credit will always be $7,500.