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Evaluating Fuel Tax Revenue Impacts of Electric Vehicle Adoption in Virginia Counties: Application of a Bivariate Linear Mixed Count Model

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Abstract

Increasing electric vehicle (EV) shares and fuel economy pose challenges to a fuel tax-based transportation funding scheme. This paper evaluates such fuel tax revenue impacts using Virginia as a case study. First, a bivariate count model is developed using vehicle registration data in 132 counties from 2012 to 2016. Model results indicate strong correlation between presence of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) on a county basis. Counties with higher percent of males are associated with higher BEV (but not PHEV) counts. In contrast, higher average commute time is predicted to increase the number of PHEVs in each county, but not BEVs. Greater population density, population over 65, population with graduate degrees, and household size are found to increase PHEV and BEV counts, whereas more households with children is associated with fewer EVs. The analysis forecasts 0.6–10% statewide EV adoption by 2025, with an adoption rate of 2.4% in the most likely scenario. Nine scenarios, combining different predictions of EV adoption and fuel economy improvement, project 2025 statewide fuel tax revenue to decrease by 5–19%, relative to 2016 receipts. Furthermore, model results suggest that, on average, a light-duty vehicle in a rural area will pay 28% more in fuel taxes than its urban counterpart by 2025. The framework proposed here provides a reference for other regions to conduct similar analysis using public agency data in the vehicle electrification era.

Fuel tax revenue is the primary source of federal transportation funding for road infrastructure construction and maintenance in the United States. According to U.S. Congressional Budget Office estimates, Highway Trust Fund (HTF) tax revenue totaled $41 billion in fiscal year 2017, with fuel tax revenue ($35.3 billion) accounting for 86% of the total. However, fuel tax revenue is unsustainable in nature as a result of failure to adjust to inflation and vehicle fuel efficiency improvement. Since 2008, U.S. Congress has sustained highway spending by transferring $143 billion of general revenues to the HTF, including $70 billion in 2016 (*1*).

The current fuel tax revenue shortfall will be exacerbated with the adoption of electric vehicles (EVs), making it more difficult for the HTF to remain solvent. In 2017, EV stock in the U.S. exceeded 760,000, a 36% increase from 2016. In addition, EV sales market penetration crossed the 1% mark in 2017. Unlike internal combustion engine vehicles (ICEVs), EVs do not refuel with gasoline and thus do not contribute to fuel tax revenue. Researchers have estimated that EVs will account for about 60% of new car sales in US by 2040 (*2*). It is expected that the HTF will suffer great deficit in the mass vehicle electrification era if the current gas tax funding structure remains.

In addition to the financial solvency issues, fuel tax disproportionately affects rural populations, raising questions of geographic equity (*3*). U.S. Department of Transportation's National Household Travel Survey shows that rural households spend more on fuel than their urban or suburban counterparts, because of the lower vehicle fuel efficiency and greater vehicle miles traveled (VMT) (*4*). Despite faster rates of EV adoption in urban areas (*5*), no study has yet quantified the impact of EV adoption on fuel tax geographic equity.

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Motivated by these trends, this paper uses the state of Virginia as a case study to examine: (1) the impact of socio-demographic, travel behavior, and charging infrastructure characteristics on EV ownership on a county level; (2) the possible ranges of future fuel tax revenue impacts resulting from EV adoption trends and fuel economy improvement; (3) spatial distribution of projected future fuel tax revenue contribution per vehicle on a county basis.

Literature Review

This literature review includes two parts which are relevant to this study. The first part reviews prior work on EV adoption at different geographic scales. In the second part, previous studies on fuel tax revenue impacts of EV adoption are summarized.

There exists an extensive body of literature on EV adoption, and each study can be categorized into one of three geographic scales: individual/household, national/state, and zonal. For the individual/household-level studies, discrete choice models are typically used to explore determinants of EV purchase decisions. These disaggregate studies examine the impacts of respondent-related variables (e.g., socio-demographics) and vehicle choice alternative-related variables including financial 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.). Because of the varied study areas, data collection periods, experiment designs, and model specifications, the effects of socio-demographics on EV preference are mixed. It is so far unclear whether the effects of age, gender, education attainment, income, and household composition are negative, positive, or significant at all, as there is supporting evidence for all claims (*6*). For example, the effect of gender variable (male) on EV adoption is found to be significantly positive by Anable et al. (*7*), Egbue and Long (*8*), Carley et al. (*9*), Plötz et al. (*10*), and Kim et al. (*11*), significantly negative by Jensen et al. (*12*), and insignificant by Mohamed et al. (*13*) and Kurani (*14*). The impacts of financial, technical, and charging infrastructure attributes on EV adoption are generally found to be significant (6). As for incentive policy attributes, the one-time cash incentives are generally effective (*15–17*). 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. (*16*), whereas Hess et al. (*17*), Hoen and Koetse (*18*), Potoglou and Kanaroglou (*19*), and Qian and Soopramanien (*20*) report no significance. Because of limited real-world EV purchase behavior data, these disaggregate studies are often conducted using stated preference (SP) survey data, with the obvious limitation of the inherent biases in SP data.

Another group of EV adoption literature focuses on aggregate predictions at an international/national/state level using historical EV sales or vehicle registration data. Some recent examples include Sierzchula et al. (*21*), Jin et al. (*22*), Narassimhan and Johnson (*23*), Lutsey et al. (*24*), Vergis and Chen (*25*, *26*), and Soltani-Sobh, et al. (*27*). Such highly aggregate studies 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 previous studies are limited in number. For example, Dimatulac and Maoh (*28*), Chen et al. (*29*), and Bansal et al. (*30*) investigate 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. develop multiple linear regression models to examine factors which affect battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) adoption rates separately on a county basis in the U.S. using 2014 vehicle registration data (*31*). Results show that income, extreme temperature, vehicle incentives, and HOV lane subsidies affect both BEV and PHEV adoption. Interestingly, the authors find that charging infrastructure is statistically correlated with PHEV adoption, but not with BEV adoption. There are several limitations to this study: (1) univariate models developed in this study fail to allow for the commonalities between PHEV and BEV adoption patterns at a zonal level; (2) the cross-sectional data used in this paper fail to account for temporal effects of EV adoption; (3) this study focuses only on counties in metropolitan areas and excludes rural areas.

With the increasing rate of EV adoption, policymakers are interested in the subsequent impacts on fuel tax revenue. A few studies have examined fuel tax revenue impacts of EV adoption on a regional or national scale. Vasudevan and Nambisan evaluate the impacts of Corporate Average Fuel Economy (CAFE) regulations and HEV and alternative fuel vehicles (AFV) adoption on transportation funding at the U.S. national level (*32*). The New Sales Survivability model, along with new vehicle sales data and vehicle survivability data from 1980 to 2005, are used to estimate revenue projections for 2010–2025. Assuming that HEV and AFV sales will increase annually by 20% from base year 2009, results predict federal fuel tax revenues to decrease by 37% by 2025 (relative to 2009). Jenn et al. assess the effects of EV adoption on revenues at both individual state and U.S. national level (*33*). First, lifetime tax revenue of representative vehicle models of ICEVs and EVs are calculated on a marginal basis. Then, aggregate funding deficits resulting from EV adoption are estimated based on EV sales predictions from the U.S. Energy Information Administration. Results show that by 2025, total annual revenue generation decreases by \$200 to \$900 million depending on the EV adoption scenario. Chamberlin et al. predict statewide fuel tax revenue in Utah by 2040 (*34*). Three EV market penetration rates are assumed: less than 1%, 21%, and 32% of new vehicle sales. The Energy and Emissions Policy Analysis Tool from Federal Highway Administration (FHWA) is used to estimate the VMT and the resulting fuel consumption and fuel tax revenues. This study concludes that 2040 fuel tax revenue will decline by 40% from 2010 under the most likely EV market penetration scenario. Schleith examined the effects of EVs on a national scale by assuming three scenarios of EV sales growth rates from 2016: 5%, 10%, and 15% (*35*). Calculations for EV sales growth rates of 10% show a 5% reduction in the HTF in about 20 years. Although these previous studies have examined the fuel tax revenue impacts of EV adoption under various scenarios, they have two major limitations: (1) EV adoption rates are simply assumed based on general trends without rigorous econometric analysis; (2) fuel tax revenue results are highly aggregated on a national/state basis, failing to account for spatial differences on smaller geographic scales where transportation investment decisions are also made (city, county, metropolitan area, etc.).

To the authors' knowledge, this paper is the first to integrate the zonal (county-level) EV ownership model into the estimation of fuel tax revenue impacts. This study fills the EV adoption literature gaps by developing a county-level bivariate EV ownership model using panel data, allowing for the correlation between PHEV and BEV adoption. Though the study uses Virginia-based data, many other regions face the same questions regarding sustainable transportation funding as EV market penetration grows. This case study provides a reference framework for other regions to conduct similar analyses on fuel tax revenue impacts in the vehicle electrification era using common state and national datasets.

Methodology and Data

In this paper, the fuel tax revenue impacts of EV adoption and fuel economy improvement in 2025 in Virginia are estimated on a county basis, as shown in the methodology framework in Figure 1. First, based on multiple statewide data sources, a bivariate EV ownership model is developed to predict number of BEVs and PHEVs in each county. Second, different levels of ICEVs' fleetwide average fuel economy are predicted considering the uncertainty of fuel economy improvements. Third, nine scenarios are developed by combing different EV adoption levels and fuel economy improvement levels. Fuel tax revenue impacts are then evaluated for each scenario.

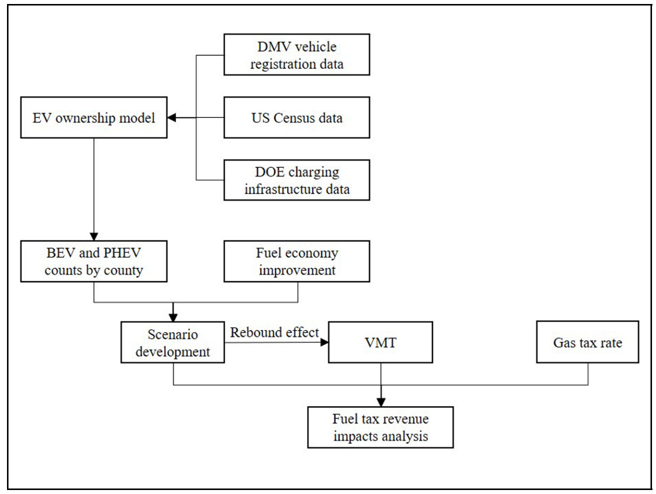

Figure 1. Methodology framework.

EV Ownership Model

The data used for EV ownership model development are collected from Virginia Department of Motor Vehicle (DMV), U.S. Census Bureau, and Alternative Fuels Data Center (AFDC) in the U.S. Department of Energy. 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 the U.S. 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 are 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 the U.S., including location, opening date, number of charging ports, and so forth. Finally, a panel dataset with 520 observations (130 counties with 4 years of data for each county) is obtained by merging datasets from various sources above. Of the total of 520 records, 80% (416 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 1.

The county-level EV ownership model is specified using a bivariate, lognormal Poisson, linear mixed effects

Table 1. Summary Statistics of Model Variables at the County Level (N = 520)

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

Note: SD = standard deviation; Min. = minimum; Max. = maximum.

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 is captured by the covariance coefficients in the variance–covariance matrices of the random effects and residuals (see Σ_u, Σ_e below). Second, the log-normal 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:

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

Y: matrix with counts per observation and per response variable (422×2)

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

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

Z: random effects design matrix (422×132)

u: county random effects (132×2)

e: residuals for random observation-level dispersion (422×2)

The random effects u and residuals e are assumed to follow multivariate normal distribution, as shown in Equation 2:

$$\begin{aligned} &u \sim N(0, \Sigma_u) \\ &e \sim N(0, \Sigma_e) \\ &\Sigma_u = \begin{pmatrix} \sigma^2_{u,\,\text{bev}} & \sigma_{u,\,\text{bev\&phev}} \\ \sigma_{u,\,\text{bev\&phev}} & \sigma^2_{u,\,\text{phev}} \end{pmatrix} \\ &\Sigma_e = \begin{pmatrix} \sigma^2_{e,\,\text{bev}} & \sigma_{e,\,\text{bev\&phev}} \\ \sigma_{e,\,\text{bev\&phev}} & \sigma^2_{e,\,\text{phev}} \end{pmatrix} \end{aligned} \tag{2}$$

For Σ_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 Σ_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 β, Σ_u, Σ_e were estimated using Bayesian Markov Chain Monte Carlo (MCMC) sampling technique, as implemented in the MCMCglmm package (*36*) in R.

EV Count Prediction

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 (*37*) 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 the AFDC dataset), relative to current charging infrastructure supply in Virginia, as detailed in the Results section.

Fuel Economy Improvement

To account for uncertainty of future fuel economy improvements, three scenarios of fleet average fuel economy are developed by referencing the historic fuel economy trendline and proposed CAFE standards up to 2025. Specifically, the data used for future fuel economy levels of ICEVs include two parts: (1) U.S. EPA's annual average fuel economy of new light-duty vehicles from 1975 to 2017 (*38*); (2) the fuel economy thresholds from the CAFE standards proposed by the Obama Administration for model year 2018–2025 light-duty vehicles. Finally, VMT in each county in 2016 is collected from Virginia Department of Transportation.

Scenario Analysis

Nine potential 2025 scenarios are developed by combining estimated EV adoption levels and fuel economy improvement levels. For each 2025 scenario, fuel tax revenue in a county is calculated by Equation 3:

$$\begin{aligned}
&TotalRevenue = Revenue_{\mathrm{icev}} + Revenue_{\mathrm{phev}} + Revenue_{\mathrm{bev}}\\
&Revenue_{\mathrm{icev}} = Num_{\mathrm{icev}} \times VMT_{\mathrm{icev}}/mpg_{\mathrm{icev}} \times TaxRate\\
&Revenue_{\mathrm{phev}} = Num_{\mathrm{phev}} \times VMT_{\mathrm{phev}}\\
&\times (1 - UtilityFactor)/mpg_{\mathrm{phev}} \times TaxRate\\
&Revenue_{\mathrm{bev}} = Num_{\mathrm{bev}} \times UseFee_{\mathrm{bev}}
\end{aligned} \tag{3}$$

where,

Num_{icev} refers to the number of ICEVs, calculated by subtracting predicted number of BEVs (Num_{bev}) and number of PHEVs (Num_{phev}) from total vehicle number in the county. According to 2006 to 2016 DMV vehicle registration data, more than 95% counties show less than +/–5% change in total vehicle count. Thus, this paper assumes the total vehicle count in 2025 for each county remains the same as the baseline year 2016, for simplicity.

mpg_{icev}, mpg_{phev} are the fuel economy of ICEV and PHEV, respectively, in 2025.

TaxRate refers to gas tax rate, which is the sum of current state gas tax ($ 0.162/Gal) and federal gas tax ($ 0.184/Gal).

UtilityFactor refers to the fraction of total VMT driven in electric mode 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.

$UseFee_{\mathrm{bev}}$ refers to the annual BEV use fee ($64) which is effective as of 2014 in Virginia. PHEVs currently do not incur an annual fee.

Lastly, VMT_{icev}, VMT_{phev} are the post-rebound average ICEV and PHEV's annual VMTs, respectively, in 2025, as calculated in the Equations 4 and 5. The rebound effects of VMT is incorporated here as a result of increased fuel efficiency (and thus decreased fuel cost per mile) in 2025. The ranges of elasticities of VMT with espect to fuel cost are collected from previous literature:

$$VMT_{2025,\,\mathrm{icev}} = VMT_{2016}/(1 + elasticity \times (\frac{FuelCost_{2016} - FuelCost_{2025,\,\mathrm{icev}}}{FuelCost_{2025,\,\mathrm{icev}}})) \tag{4}$$

$$VMT_{2025,\,\mathrm{phev}} = VMT_{2016}/(1 + elasticity \times (\frac{FuelCost_{2016} - FuelCost_{2025,\,\mathrm{phev}}}{FuelCost_{2025,\,\mathrm{phev}}})) \tag{5}$$

where VMT_{2016} and $FuelCost_{2016}$ are the average ICEV's VMT and ICEV's fuel cost in baseline year 2016. Parameters used to calculate fuel cost include current fuel price ($2.60/Gal), electricity price ($ 0.1108/kW-h), and energy efficiency of PHEV on electric mode (31 kW-h/100 mi).

Results

EV Ownership Model

Table 2 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 Σ_u suggests that counties that have more registered BEVs consistently have more registered PHEVs. The correlation coefficient is 0.86 (calculated by $\sigma_{u,\,\mathrm{bev\&phev}}/(\sqrt{\sigma^2_{u,\,\mathrm{bev}}} \times \sqrt{\sigma^2_{u,\,\mathrm{phev}}})$) for BEV and PHEV counts, which demonstrates that correlation between these two

Table 2. Coefficients Estimates for County-Level EV Ownership Model

Predictor variables of model I	Vehicle type	Mean	Lower-95% CI	Upper-95% CI	Marginal effect* (100%)	pMCMC**
Intercept	BEV	–33.168	–41.603	–24.706	na	0.000
	PHEV	–27.149	–34.406	–20.231	na	0.000
Natural logarithm of population density	BEV	0.640	0.327	0.936	2.237	0.000
	PHEV	0.440	0.210	0.674	1.203	0.001
Percent of population over 65 years of age	BEV	0.268	0.139	0.390	3.236	0.000
	PHEV	0.207	0.113	0.313	1.964	0.000
Number of males per 100 females	BEV	0.045	0.021	0.071	0.988	0.000
	PHEV	0.013	–0.012	0.037	0.238	0.308
Percent of population with graduate degree	BEV	0.149	0.095	0.212	1.874	0.000
	PHEV	0.122	0.074	0.162	1.328	0.000
Percent of households with 1 + people <18 years old	BEV	–0.084	–0.152	–0.018	–0.370	0.017
	PHEV	–0.072	–0.121	–0.019	–0.337	0.008
Average household size	BEV	4.555	2.461	6.559	1.972	0.000
	PHEV	3.911	2.310	5.512	1.486	0.000
Average commute time	BEV	0.013	–0.048	0.069	0.115	0.679
	PHEV	0.052	0.009	0.094	0.386	0.021
Percent of workers who use public transit for commute	BEV	–0.138	–0.251	–0.024	–0.390	0.018
	PHEV	–0.102	–0.188	–0.018	–0.317	0.014
Charging port density (#/square mile)	BEV	0.689	0.312	1.123	0.182	0.000
	PHEV	0.587	0.255	0.947	0.142	0.001
Random effects (county effects)						
$\sigma^2_{u,\,\mathrm{bev}}$	na	1.807	0.96	2.807	na	na
$\sigma^2_{u,\,\mathrm{phev}}$	na	0.805	0.3129	1.325	na	na
$\sigma_{u,\,\mathrm{bev\&phev}}$	na	1.042	0.4531	1.684	na	na
Residuals (within-county effects)						
$\sigma^2_{e,\,\mathrm{bev}}$	na	0.4183	0.2682	0.589	na	na
$\sigma^2_{e,\,\mathrm{phev}}$	na	0.3376	0.2025	0.4717	na	na
$\sigma_{e,\,\mathrm{bev\&phev}}$	na	0.3345	0.2053	0.4623	na	na
DIC	na	2815	na	na	na	na
Model validation	na	na	BEV	na	PHEV	na
na	na	na	MAE	RMSE	MAE	RMSE
Model I: Bivariate count model	na	na	2.25	4.45	1.86	3.25
Model II: Bivariate count model with spatial lagged X (binary weight)	na	na	2.28	4.32	1.87	3.32
Model III: Bivariate count model with spatial lagged X (1/distance weight)	na	na	2.22	4.72	1.77	3.14
Model IV: Univariate count model	na	na	2.25	4.75	1.91	3.61

Note: EV = electric vehicle; BEV = battery electric vehicle; PHEV = plug-in hybrid electric vehicle; MAE = mean average error; RMSE = root mean square error; na = not applicable.
*Marginal effect of one standard deviation increase in predictor variable.
**The posterior probability of the coefficient is not different from zero.

response variables should be considered in the analysis. Similarly, the positive covariance coefficient in Σ_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 because of 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. found that BEV-orientation is strongly urban whereas a PHEV orientation is more moderately urban and is also oriented to suburban areas (*16*). In rural areas where population density is low, residents prefer larger vehicles such as pickups and SUVs (*16*). 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.

Model results predict counties with older populations 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, for example, *9*, *16*, *39*, *40*) which find that young or middle-aged consumers are more likely to show interest in EVs. The authors note that these disaggregate EV studies are mainly based on consumers' SP, which may not fully represent real market behavior. On the other hand, a revealed preference study of EV owners in Maryland (*41*) supports this finding that on average, 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. (*39*), Egbue and Long (8), Ferguson et al. (*16*), and so forth, all individual/household-level studies that 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 whereas income was not (because of high correlation between the two variables). Thus, 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 (*42*), 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 choices when seeking an EV versus 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. (*10*), who 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 them as an addition to their household's car fleet (*43*). 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. report no significant relationship between multi-car households and EV preference (*39*).

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 (as income variables are not included in the final model specification). The EVs' 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 with 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 availability 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, owing 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 (*7–10*) report that males are more likely to be interested in EVs, some studies (*13*, *14*) 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 with 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 shows that such economic benefit contributes to consumers' interest in purchasing or leasing PHEVs (*44*). But for BEVs, the range anxiety, frequently cited in the literature as a key barrier in EV adoption (8), offsets the fuel savings 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 2); (**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. (*29*)), assuming that number of EVs in a county is affected 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 2, 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 because of the modifiable area unit problem (*45*) when aggregating household-based vehicle choice phenomena into county districts, a potential limitation to zone-level count modeling.

2025 EV Ownership Prediction Levels

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 8 years, and a linear trendline is fitted to predict these independent variables through 2025 (with R^2 values ranging from 0.89 to 0.99).

As 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 2, charging port density in Virginia appears to be roughly 4 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

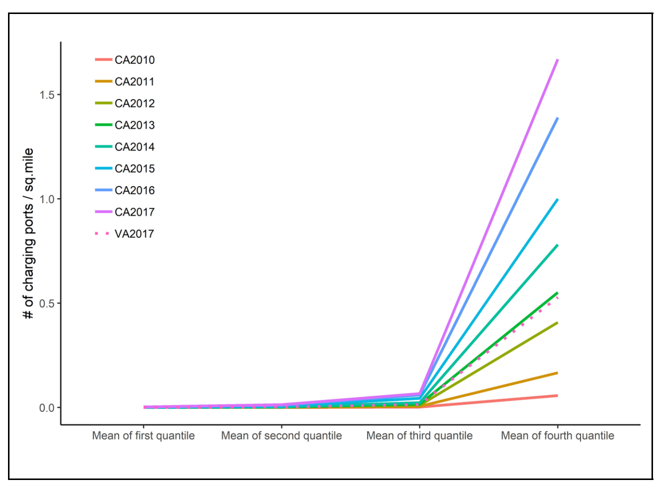

Figure 2. A comparison of charging port density between California and Virginia.

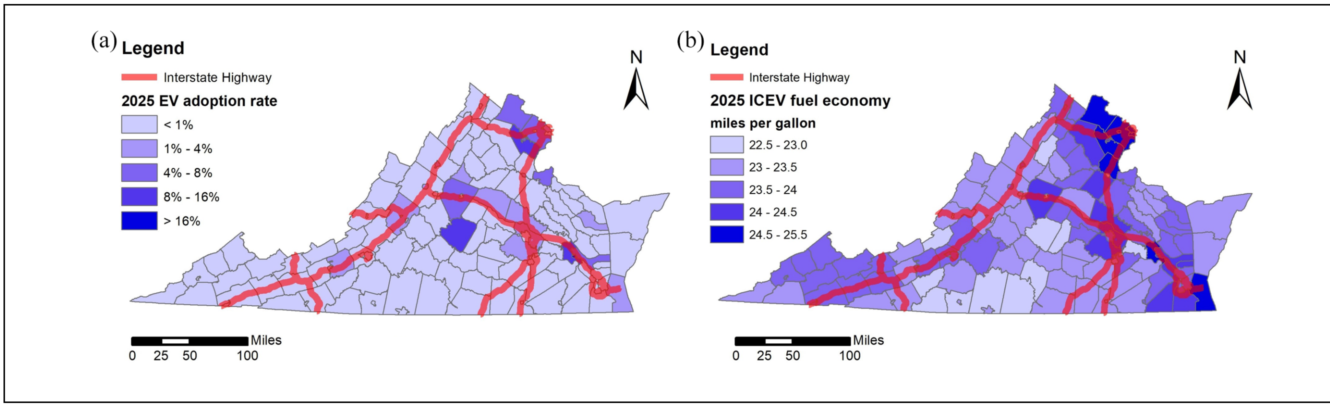

Figure 3. (*a*) Projected 2025 Virginia EV adoption rates by county; (*b*) projected 2025 average ICEV fuel economy by county.

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 R^2 values ranging from 0.98 to 0.99).

After inputting all the predictor variables into the EV ownership model, the total numbers 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 (*46*).

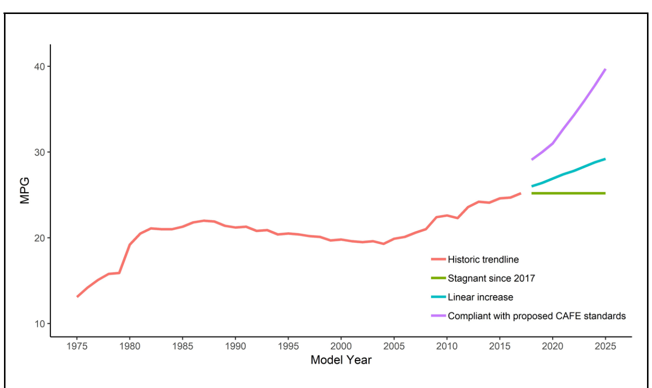

Figure 4. New light-duty vehicle adjusted fuel economy improvement scenarios.

Figure 3*a* 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.

Fuel Economy Improvement Levels

Figure 4 shows the fleetwide adjusted fuel economy for light-duty vehicle model year (MY) 1975–2017. (Adjusted fuel economy values reflect real-world performance and are not comparable to automaker standards compliance levels. Adjusted fuel economy values are about 20% lower, on average, than unadjusted fuel economy values that form the fuel economy standard compliance [*38*].) Given the volatile nature of fuel economy improvement in the long term, three scenarios of ICEV fuel economy are developed. The first conservative scenario assumes the fuel economy will remain stagnant from MY 2017 to 2025. The second (most likely) scenario assumes the fuel economy follows the historic growth rate since MY2005. The last aggressive scenario assumes the fuel economy will be in compliance with the proposed CAFE standards for MY 2017–MY 2025 released in August 2012 by U.S. 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

Table 3. Definition of Each Scenario

Fuel economy \ EV charging infrastructure	Growth stagnant (stays at Virginia 2017 levels)	Follows likely growth rate (matches California 2021 levels)	Follows aggressive growth rate (matches California 2025 levels)
Stagnant since 2017	Scenario 1	Scenario 2	Scenario 3
Linear increase based on historical trend	Scenario 4	Scenario 5	Scenario 6
Compliant with proposed CAFE standards	Scenario 7	Scenario 8	Scenario 9

Note: EV = electric vehicle; CAFE = corporate average fuel economy.

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 3*b* for the most likely fuel economy improvement scenario. It is worth noting the similarity between the 2025 fuel economy spatial distribution and the predicted distribution of EVs.

Fuel Tax Revenue Impacts Analysis

This section estimates the future fuel tax revenue impacts in 2025. Following the discussions in the previous sections, nine scenarios were designed based on three charging infrastructure investment levels and three future fuel economy improvement levels. Table 3 shows the definition of these nine scenarios.

The rebound effects of VMT with respect to fuel cost is considered for each scenario. In the U.S., the elasticity of VMT with respect to fuel cost varies greatly depending on the region and time period. For example, the short-run elasticities have been estimated to be −0.026 (*47*), −0.026 to −0.047 (*48*), −0.12 to −0.17 (*49*), and −0.15 to −0.2 (*50*). The long-run elasticities have been estimated to be −0.131 (*47*), −0.121 to −0.22 (*48*), −0.21 to −0.3 (*49*), and −0.24 to −0.34 (*51*). This study selects two elasticity thresholds (0 and −0.3) to fully represent the range of rebound effect uncertainty for the 2025 calculations.

Statewide Fuel Tax Revenue Loss. Figure 5 shows the estimated statewide 2025 fuel tax revenue compared with 2016, with and without taking rebound effects into consideration. As seen in Figure 5, ignoring rebound effects (elasticity = 0), the scenarios show 7% to 19% fuel tax revenue loss in 2025 compared with 2016. When considering a relatively high rebound effect (elasticity = −0.3), 2025 fuel tax revenue is projected to decrease 5% to 16% compared with 2016 revenue. The total amount of fuel tax revenue loss ranges from \$ 0.11 to \$ 0.27 billion (elasticity = 0) and from \$ 0.08 to \$ 0.23 billion (elasticity = −0.3).

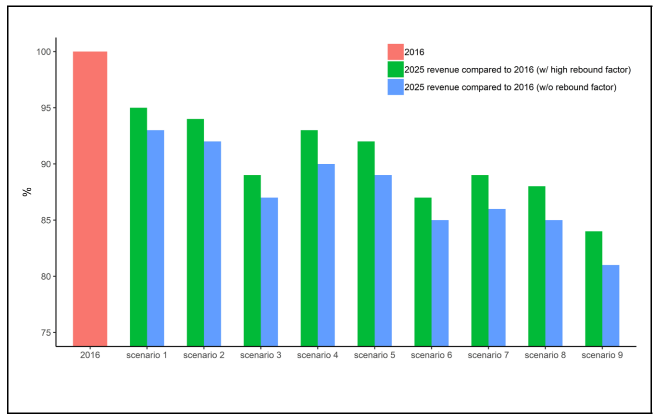

Figure 5. Projected 2025 statewide fuel tax revenue (compared with 2016).

To make up the fuel tax revenue shortfall, gas tax rate would need to increase to \$ 0.363 to \$ 0.379/Gal from the current rate of \$ 0.346/Gal. The proposed fuel tax rates are calculated based on necessary increases to maintain the same fuel tax per ICEV as 2016 levels, including the consideration of rebound effects. For the most likely scenario (Scenario 5), a \$ 0.368/Gal gas tax is needed, which is a 6.4% increase from current gas tax rate.

Currently, Virginia imposes a \$64 annual use fee for BEVs. Given an ICEV contributes \$218 gas tax annually in the baseline year 2016, an additional \$154 use fee for BEVs is needed to maintain the same fuel tax revenue level per vehicle in 2016. Different from BEVs, PHEVs contribute to fuel tax revenue as they can be powered by gasoline. Assuming a utility factor of 0.76 (that of the 2017 Chevrolet Volt), a PHEV, on average, contributes about \$28 fuel tax annually. Virginia imposes no use fees for PHEVs currently, and a \$190 use fee would be needed to maintain the same tax revenue per vehicle level as 2016.

Spatial Distribution of Fuel Tax Revenue Contribution per Vehicle. Based on the scenario analysis of the revenue loss for each county, a spatial heat map in Figure 6 shows the

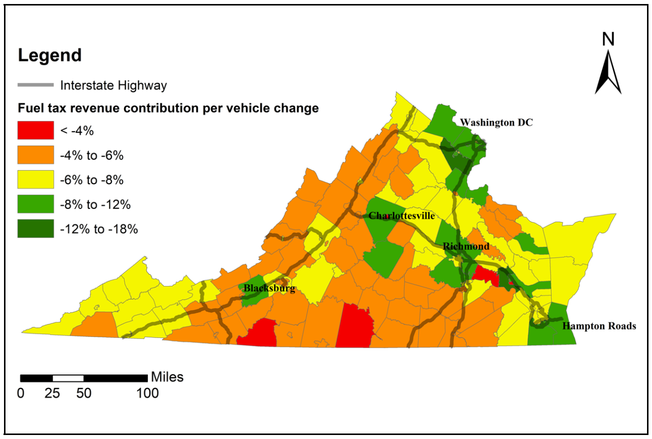

Figure 6. Heat map of fuel tax revenue contribution per vehicle change (from 2016 to 2025).

county-level average fuel tax revenue contribution per vehicle change from 2016 to 2025 in Scenario 5 (incorporating full rebound effects). Figure 6 indicates that almost half of the counties will see more than 6% fuel tax revenue contribution (per vehicle) decrease, with the highest decrease in James City County (where the average vehicle's fuel tax contribution will decrease 18% from 2016 to 2025). Furthermore, the change in fuel tax revenue contribution (per vehicle) shows spatial heterogeneity. The counties with larger decreases (green counties on the heat map) are more concentrated in dense metropolitan regions such as Washington DC, Richmond, Hampton Roads, and so forth. As also noted in the EV predictions discussion, these regions are also located along Virginia's major transportation corridors. In 2016, FHWA designated I-64, I-66, I-81, I-85, and I-95 in Virginia as EV Corridors (*52*). It is expected that future EV charging infrastructure investments will be mainly located along these corridors, further encouraging EV adoption. Thus, such regions' already significant fuel tax revenue contribution (per vehicle) decrease may actually be underestimated here.

Next, the fuel tax revenue contribution per vehicle difference between urban and rural areas is examined. The U.S. Census Bureau identifies all urban and rural areas and records the corresponding urban and rural population. Among the 132 counties in Virginia, 19 counties belong to a Census-defined urban area, and 29 counties fall into a Census-defined rural area. However, the remaining 84 counties include both Census-defined urban areas and rural areas. Thus, this study simply categorizes the 132 counties into two categories: (1) counties with more than 50% urban population are classified as urban; (2) counties with more than 50% rural population are classified as rural. On average, a vehicle in a rural county in 2016 pays $230 gas tax annually, 22% higher than a vehicle in an urban county. Under Scenario 5, such fuel tax revenue contribution (per vehicle) gap is predicted to increase to 28% in 2025. Such results point to the likely increasing geographic inequity of gas tax between urban and rural areas as EV adoption and fleet fuel economy increase.

Conclusion

This paper integrates a county-level EV ownership model to a statewide fuel tax revenue impacts evaluation, using Virginia as a case study. First, using panel vehicle registration data in 132 counties from 2012 to 2016, a bivariate EV count model is developed to predict BEV and PHEV counts in each county in Virginia in 2025. The model demonstrates a high correlation between BEV and PHEV counts, as counties that have more registered BEVs consistently have more PHEVs. Most covariates show consistent effects across both BEV and PHEV counts. For example, greater population density, percent of population over 65 years of age, percent of population with graduate degree, and average household size are predicted to increase both BEV and PHEV counts in a county, whereas higher percent of households with one or more people under 18 are predicted to decrease EV counts. However, two predictor variables show mixed effects across BEV and PHEV adoption. Greater percent of males in a county is associated with higher BEV counts, but not PHEV counts. In contrast, counties with higher average commute time are associated with higher PHEV counts, but not BEV counts.

The EV ownership model predicts a 0.6–10% statewide EV adoption rate in 2025 depending on future charging infrastructure investment, with a 2.4% adoption rate under the most likely scenario. Such a large range across predictions demonstrates the importance of charging infrastructure investment in promoting EV adoption. These three EV adoption rates are combined with three levels of future fuel economy improvement to develop nine scenarios to evaluate fuel tax revenue impacts in 2025.

Model results anticipate 2025 statewide fuel tax revenue to decrease 7–19% compared with 2016. When incorporating a high VMT rebound effect resulting from increased fuel efficiency, the fuel tax revenue loss is slightly relieved: a 5–16% decrease from 2016. To make up the 5–16% fuel tax revenue loss, increasing the gas tax rate and imposing EV use fee are two potential measures. To maintain 2016 fuel tax revenue levels, models estimate the gas tax rate would need to increase to $ 0.363–$ 0.379 per gallon from the current rate of $ 0.346 per gallon, and a $218 BEV annual use fee (compared with the current $64 BEV annual use fee), and a $190 PHEV use fee (compared with the current $ 0 PHEV annual use fee) would be required. These calculations are purely based on fuel tax revenue, and do not consider the greater external costs associated with ICEV use compared with EV use (e.g., emissions, noise, etc.).

In addition to the statewide fuel tax revenue impacts, this paper also examines spatial distribution of fuel tax revenue contribution per vehicle. Though per vehicle fuel tax revenue contribution is predicted to decline in all counties, the decrease is more significant in urban areas than in rural areas. Urban areas are predicted to have higher EV adoption rates and better average fuel economy among ICEVs, resulting in an overall greater fuel tax revenue contribution decrease. For the most likely scenario, an average light-duty vehicle in rural areas in 2025 would pay 28% more in fuel taxes compared with its urban counterpart (compared with a 22% difference in 2016).

Many other regions face the same questions regarding sustainable transportation funding in the vehicle electrification era. The methodology framework proposed in this study can provide a reference for other regions to conduct similar analyses on future fuel tax revenue impacts. However, there are several limitations with this study. First, fuel price is not included in the EV ownership model's set of covariates. As a result of the county-annual analysis unit in this study, annually averaged fuel price offsets the volatile nature of short-run price fluctuations. Second, the EV ownership model is developed using data from 2012 to 2016 in which 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 2025. Third, the average vehicle age in Virginia saw an increase from 9 to 11 years old from 2006 to 2014, and then stayed relatively stable at 11 years since 2014. For simplicity, this study assumes the vehicle age distribution in each county remains the same as in 2016. Future work should examine the specific vehicle age distribution pattern at each county to yield more accurate predictions. Lastly, although the scope of this paper focuses on fuel tax revenue, the authors note that transportation funding comes from many other sources (vehicle registration fees, vehicle property taxes, local option transportation taxes, etc.), though these sources are not directly related to EV adoption. Though this paper discusses several measures to fill the predicted shortfall in fuel tax revenue, they do not address more complicated issues with transportation financing: an increase in gas tax rate needs to constantly adjust to future fuel economy improvement, whereas a flat EV use fee fails to capture vehicle use intensity. Alternative transportation financing mechanisms such as VMT-based fees may be more appropriate solutions to capture use intensity for both ICEVs and EVs, but the fee structure associated with such a policy is beyond the scope of this paper.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: WJ, TDC, ZJ; data collection: WJ, ZJ; analysis and interpretation of results: WJ, ZJ, TDC, RP; draft manuscript preparation: WJ, TDC. All authors reviewed the results and approved the final version of the manuscript.

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