federal gas tax ($0.184/gallon).

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.

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

Table 1. Summary statistics of model variables at the county level (N = 528)

Variable	Mean	Median	Std Dev	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/sq. mi.)	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 (minutes)	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 (#/sq. mi.)	0.04	0.00	0.22	0.00	3.97

Lastly, VMT_{icev}, VMT_{phev} are the post-rebound average ICEV and PHEV's annual VMTs, respectively, in 2025, as calculated in the equations (4-5). 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 respect to fuel cost are collected from previous literature.

$$VMT_{2025,icev} = VMT_{2016} / (1 + elasticity \times (\frac{Fuel\,Cost_{2016} - Fuel\,Cost_{2025,icev}}{Fuel\,Cost_{2025,icev}})) \quad (4)$$

$$VMT_{2025,phev} = VMT_{2016} / (1 + elasticity \times (\frac{Fuel\,Cost_{2016} - Fuel\,Cost_{2025,phev}}{Fuel\,Cost_{2025,phev}})) \quad (5)$$

Where, VMT_{2016} and $Fuel\,Cost_{2016}$ 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/gallon), electricity price (\$0.1108/kWh), and energy efficiency of PHEV on electric mode (31 kWh/100 mile).

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 $\sigma_{u,bev\&phev} / (\sqrt{\sigma^2_{u,bev}} \times \sqrt{\sigma^2_{u,phev}})$) 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 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 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 (Hidrue et al., 2011; Ziegler, 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. Differently, 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), 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.

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		0.000
	PHEV	-27.149	-34.406	-20.231		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		0.308
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		0.679
	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 (# / sq. mi.)	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)						
$\sigma^2_{u,\ bev}$		1.807	0.96	2.807		
$\sigma^2_{u,\ phev}$		0.805	0.3129	1.325		
$\sigma_{u,\ bev\ \&\ phev}$		1.042	0.4531	1.684		
Residuals (within-county effects)						
$\sigma^2_{e,\ bev}$		0.4183	0.2682	0.589		
$\sigma^2_{e,\ phev}$		0.3376	0.2025	0.4717		
$\sigma_{e,\ bev\ \&\ phev}$		0.3345	0.2053	0.4623		
DIC		2815				
Model Validation			BEV		PHEV	
			MAE	RMSE	MAE	RMSE
Model I: Bivariate count model			2.25	4.45	1.86	3.25
Model II: Bivariate count model with spatial lagged X (binary weight)			2.28	4.32	1.87	3.32
Model III: Bivariate count model with spatial lagged X (1/distance weight)			2.22	4.72	1.77	3.14
Model IV: Univariate count model			2.25	4.75	1.91	3.61

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

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. (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 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 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.

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 eight 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).

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 2, 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 R^2 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 (EVAdoption, 2018).

Figure 4 (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.

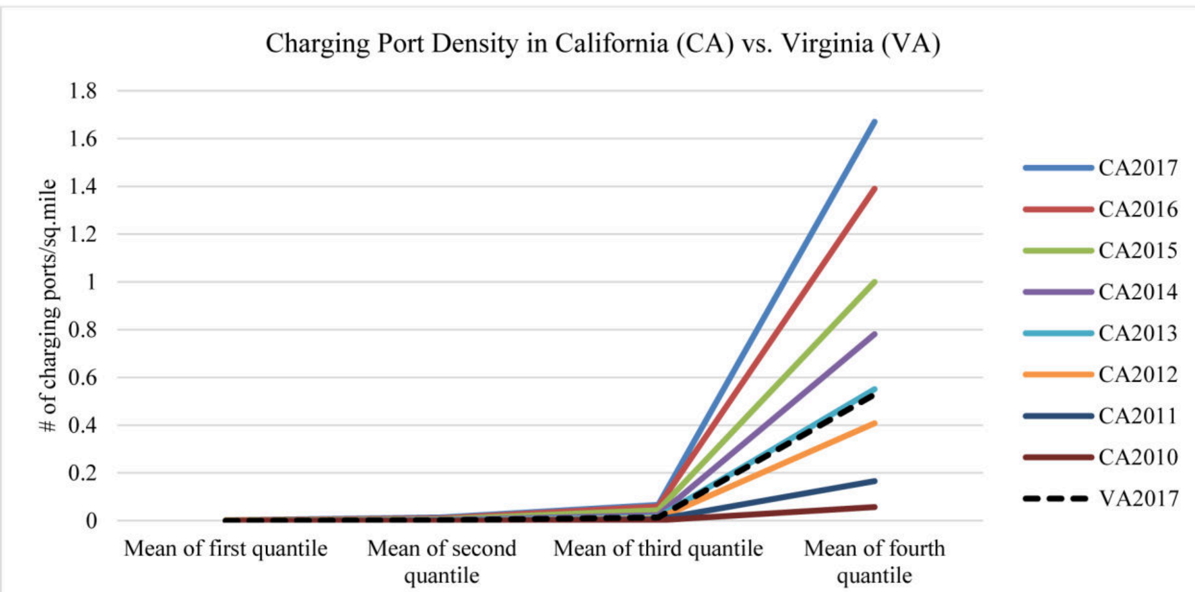

Figure 2. A comparison of charging port density between California and Virginia

Fuel Economy Improvement Levels

Figure 3 shows the fleetwide adjusted[1] fuel economy for light-duty vehicle model year (MY) 1975-2017. Given the volatile nature of fuel economy improvement in the long term, three scenarios of ICEV's 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

[1]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 (EPA, 2018).

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 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 (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.

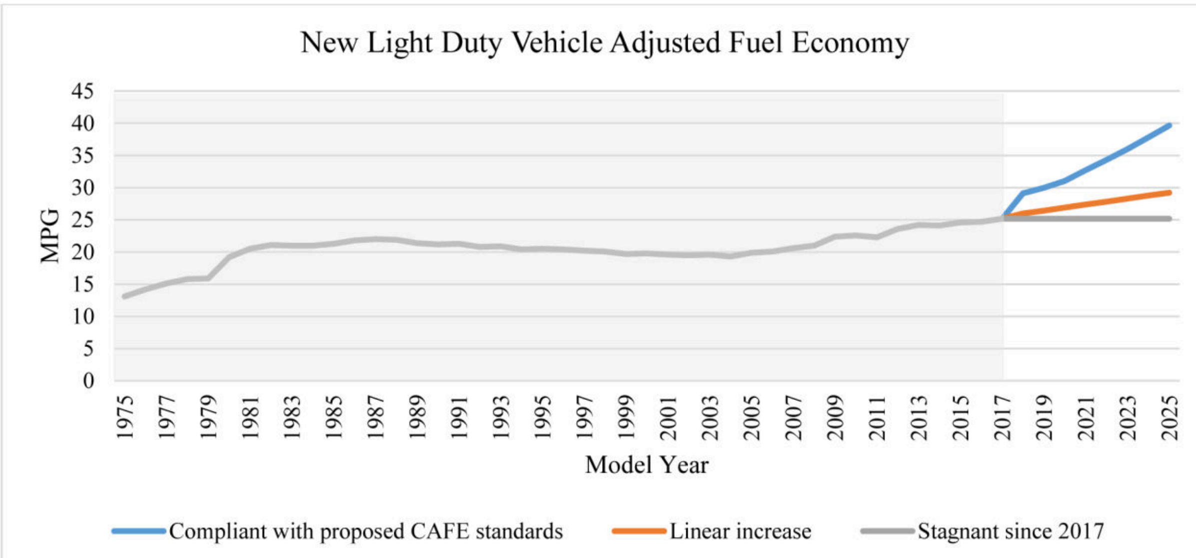

Figure 3. Fuel economy improvement scenarios

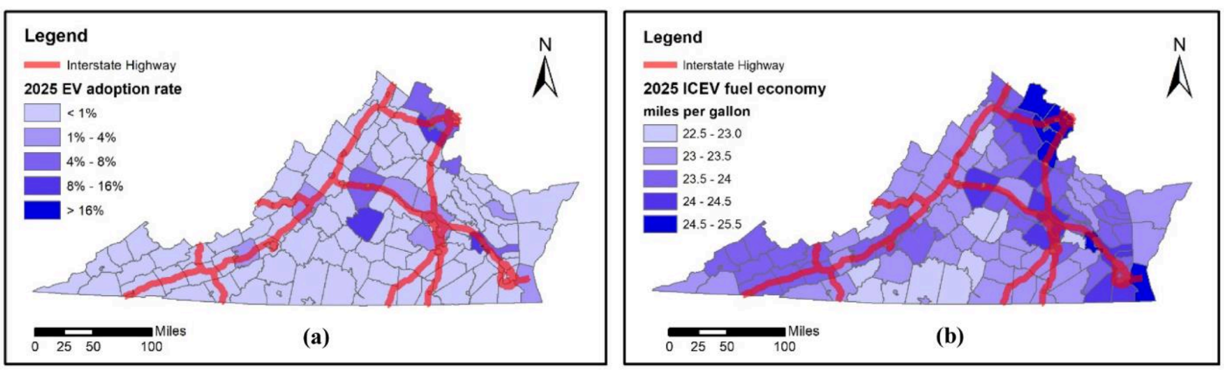

Figure 4. (a) Projected 2025 Virginia EV adoption rates by county; (b) Projected 2025 average ICEV fuel economy by county

Fuel Tax Revenue Impacts Analysis

This section estimates the future fuel tax revenue impacts in 2025. Following the discussions in the prior 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 vary greatly depending on the region and time period. For example, the short-run elasticities have been estimated to be -0.026 (Hymel et al., 2010), -0.026 to -0.047 (Small et al., 2007), -0.12 to -0.17 (Brand, 2009), and -0.15 to -0.2 (Gillingham, 2014). The long-run elasticities have been estimated to be -0.131 (Hymel et al., 2010), -0.121 to -0.22 (Small et al., 2007), -0.21 to -0.3 (Brand, 2009), and -0.24 to -0.34 (Li et al., 2014). This study selects two elasticity thresholds (0 and -0.3) to fully represent the range of rebound effect uncertainty for the 2025 calculations.

Table 3. Definition of Each Scenario

EV Charging Infrastructure / **Fuel Economy**	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

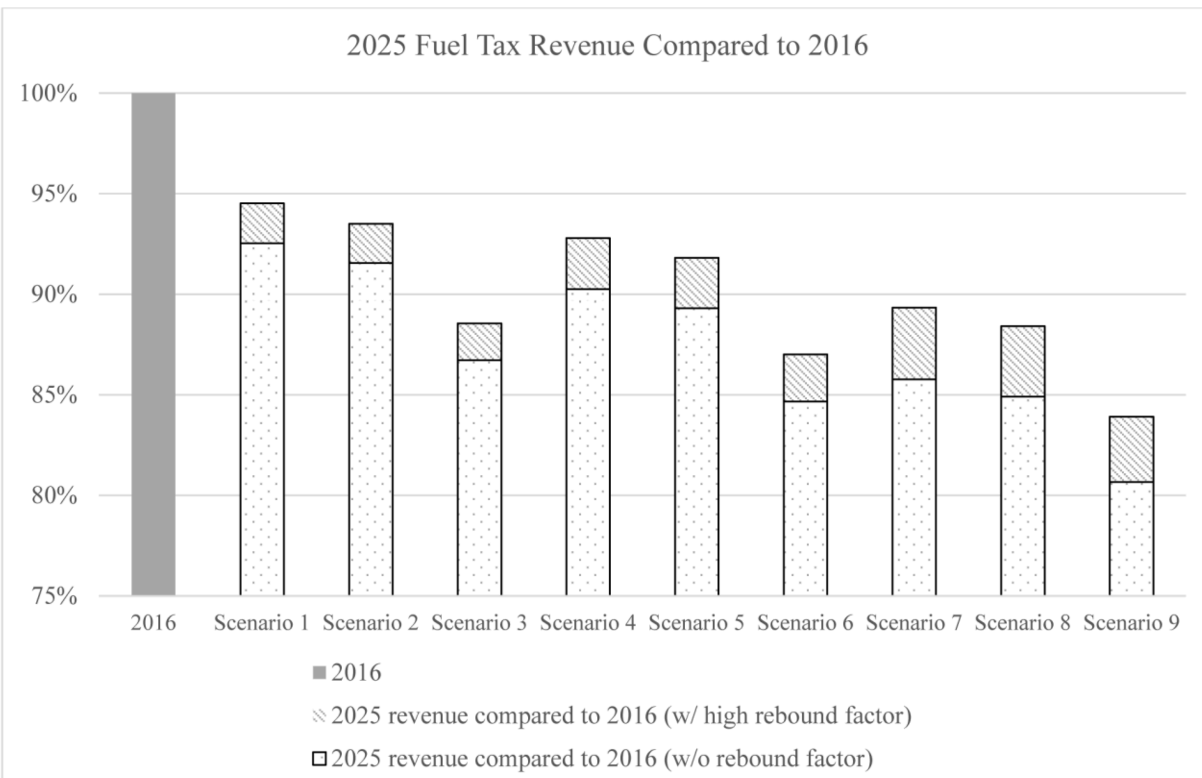

Figure 5. Projected 2025 statewide fuel tax revenue (compared to 2016)

Statewide Fuel Tax Revenue Loss

Figure 5 shows the estimated statewide 2025 fuel tax revenue compared to 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 to 2016.

When considering a relatively high rebound effect (elasticity = -0.3), 2025 fuel tax revenue is projected to decrease 5% to 16% compared to 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).

To make up the fuel tax revenue shortfall, gas tax rate would need to increase to $0.363 to $0.379/gallon from the current rate of $0.346/gallon. 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/gallon 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.

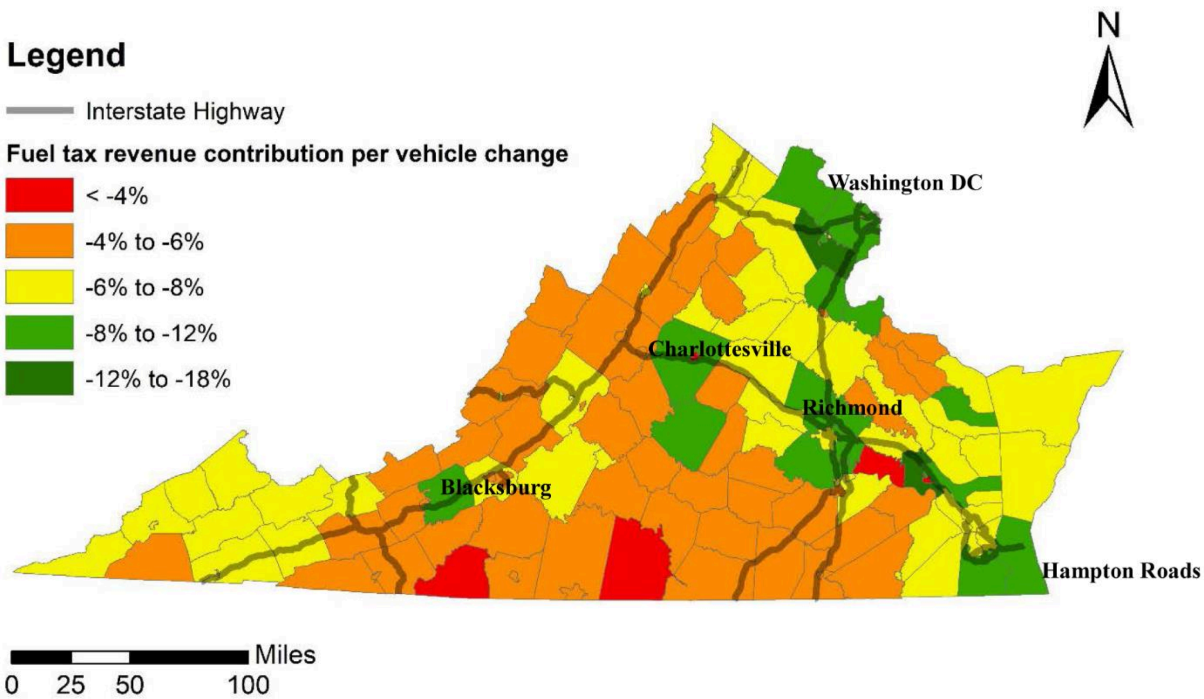

Figure 6. Heat map of fuel tax revenue contribution per vehicle change (from 2016 to 2025)

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 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, etc. 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 (FHWA, 2018). 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, while 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 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, while 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 are 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% to 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% to 19% compared to 2016. When incorporating a high VMT rebound effect resulting from increased fuel efficiency, the fuel tax revenue loss is slightly relieved: a 5% to 16% decrease from 2016. To make up the 5% to 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 to $0.379 per gallon from the current rate of $0.346 per gallon,