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Analysis of the Electric Vehicles Adoption over the United States

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Abstract

Increasing the use of electric vehicles (EVs) has been suggested as a possible method to decrease fuel consumption and greenhouse gas (GHG) emissions in an effort to mitigate the causes of climate change. In this study, the relationship between the market share of electric vehicles and the presence of government incentives, and other influential socio-economic factors were examined. The methodology of this study is based on a cross-sectional/time-series (panel) analysis. The developed model is an aggregated binomial logit share model that estimates the modal split between EV and conventional vehicles for different U.S. states from 2003 to 2011. The results demonstrated that electricity prices were negatively associated with EV use while urban roads and government incentives were positively correlated with states' electric vehicle market share. Sensitivity analysis suggested that of these factors, electricity price affects electric vehicle adoption rate the most. Moreover, the time trend model analysis found that the electric vehicle adoption has been increasing over time, which is consistent with theories about diffusion of new technology.

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1. Introduction

In order to increase the sustainability of transportation systems, it will be necessary to reduce GHG emissions, air pollution and dependence on fossil fuels. The solutions to these problems depend largely on the policies that can reduce U.S. gasoline consumption. Such solutions include driving less, purchasing more fuel-efficient vehicles and using alternative fuel vehicles (e.g. Bagherian et al., 2016; Asgari et al., 2014; Asgari and Jin, 2015; Soltani-Sobh et al., 2015; Talebpour et al., 2015; Soltani-Sobh et al., 2016a).

Electric vehicles (EVs) are one possible innovation to help address energy dependency and environmental concerns. EV adoption is heavily dependent on certain external factors such as stringent emissions regulations, rising

gasoline prices and financial incentives (Eppstein et al., 2011; Nie et al., 2016). Similar to any new technology, there are barriers to adoption, including lack of knowledge, low consumer risk tolerance and high initial production cost (Jaffe and Stavins, 1994; Stoneman et al., 1994; Argote and Epple, 1990).

Social issues are challenging factors that should be considered in the commercial success of EVs. Ozaki and Sevastyanova (2011) determined that consumer acceptance is crucial to the continued success of sustainable transportation. Diamond (2009) summarized some common barriers to the adoption of any new technology as lack of knowledge by potential adopters, high initial costs and low tolerance risk. Hidrue et al. (2011) identified a high level of education, income and environmentalism as consumer characteristics with positive effects on EV adoption. Fuel price has been introduced as an influential predictor of alternative fuel vehicle adoption (Soltani-Sobh et al., 2016; Eppstein et al., 2011). The combination of fuel price and electricity prices makes up the majority of EV operating expenses, and these two factors are positively correlated with the likelihood of EV adoption (Zubaryeva et al., 2012). In some studies, the availability of charging infrastructures was identified as an important criterion in consumer acceptance of alternative fuel vehicles (e.g. Ghamami et al., 2014; Yeh, 2007; Struben and Sterman, 2008; Egbue and Long, 2012).

In order to overcome barriers, different states have established a number of consumer incentives for adopting EVs. Literature reviews on the effect of incentives on adoption of alternative fuel vehicles present conflicting results. Sierzchula et al. (2014) found financial incentives to be significantly and positively correlated to a country's EV market share, whereas Zhang et al. (2014) showed insignificant correlation between financial incentives and an individual's willingness to buy EVs. Thus, analyzing other factors affecting electric vehicles share is imperative.

The purpose of this study is to examine and analyze the significance and strength of state incentives and other significant socioeconomic factors in promoting EV adoption. A cross-sectional time-series analysis was conducted on the number of EV statistics over time. Data from individual states was used to test the relationship between EV adoption and variety of variables. The available EV data are an aggregated number of EVs for different states over time. The developed model is an aggregated binomial logit share model that estimates the modal split between EV and conventional vehicles for different states in the U.S. over time.

2. Methodology

The methodology for this study is based on development of the modal split model between electric vehicles and other fuel type vehicles (mainly conventional vehicles). The annual share of electric vehicles as aggregate data is considered as the dependent variable with a value between 0 and 1.

2.1. Macroscopic Logit Model for Cross-Sectional Model

There have been extensive bodies of research on the application of various mathematical, statistical and econometric models in science and engineering (e.g. Pour-Rouholamin and Zhou, 2016a; Pour-Rouholamin and Zhou, 2016b; Jin et al., 2014; Vaziri et al., 2014; Esfahanian et al., 2015; Ahmadi and Merkley, 2009; Hassan-Esfahani et al., 2015; Jalayer and Zhou, 2016; Ghasemi et al., 2016; Baratian-Ghorghi and Zhou, 2015; Zhou et al., 2016). Due to the availability of aggregate dataset, in this study the macroscopic logit market share model was developed to demonstrate the mode choice decisions. The market share model reduces to a utility function, which is a function of a number of independent vehicle type characteristics, and socioeconomic and policy variables that vary by state. The share variation of EVs over states (in addition to their variation over time) help separate and examine the different determinant factors of adoption that vary across states but are correlated in time. On a state level, consumers' preferences for different vehicle type choices are affected by a number of predictor variables. Monetary variables include: risk tolerance for new technologies (labeled as income variable which is considered as effective consumer discount rate for future energy cost), gasoline price (gas price variable), electricity price (Eprice variable) and annual miles travelled (VMT variable, which is related to annual fuel consumption). Non-monetary factors include government incentives (incentive variable) and rates of urban roads (urban variable). As such, the final specification of the utility function for EV in state i at time t can be defined as:

$$U_{Eit} = F(\text{Income}_{it}, \text{Gasprice}_{it}, \text{Eprice}_{it}, \text{VMT}_{it}, \text{Incentive}_{it}, \text{Urban}_{it}) \quad (1)$$

We define P_{Eit} as the share of EVs, and P_{0it} as the share of conventional fuel type vehicles. EV is in state i at

time point t in such a way that $P_{Eit} + P_{0it} = 1$. These fractions can be developed as follows (Bierens, 2003; Gruca and Sudharshan, 1991):

$$P_{Eit} = \frac{e^{U_{Eit}}}{1 + e^{U_{Eit}}} \quad (2)$$

To solve and estimate different coefficients of the utility function, the fraction model was transformed as below:

$$\ln\left(\frac{P_{Eit}}{P_{0it}}\right) = \ln\left(\frac{P_{Eit}}{1-P_{Eit}}\right) = U_{Eit} = \alpha + \beta_1 Income_{it} + \beta_2 Gasprice_{it} + \beta_3 Eprice_{it} + \beta_4 VMT_{it} + \beta_5 Incentive_{it} + \beta_6 Urban_{it} \quad (3)$$

This equation takes a generalized linear form, and its coefficient can be estimated as linear regression via maximum likelihood. Model definition is based on the identifying the effective factors on EV utility improvement and adoption versus conventional vehicle. It is clear that the variables with positive signs encourage the use of EVs, and increasing the value of variables with negative signs increases the use of conventional vehicle.

2.2. Panel Data Regression Model

The panel data regression was chosen for the analysis of EV adoption because this methodology provides various benefits, and overcomes some of the limitations of time-series and cross-section studies (Kennedy, 2003). Panel data can deal with heterogeneity resulting from the variation of some unmeasured explanatory variables that affect the behavior of people in different states. It also overcomes the problem of omitted time-series variables that influence the behavior of people in different states uniformly, but differently in each time period. Panel data alleviates multicollinearity problem by creating more variability through combining the variation across states with variation over time. The equation for a panel data regression is (Washington et al., 2011):

$$Y_{it} = \alpha + X_{it}\beta + u_{it} \quad (4)$$

where i refers to the cross-sectional units (states), t refers to the time periods, α is the constant, X_{it} is the set of explanatory variables, and β is the coefficients of explanatory variables. One-way and two-way error component models for disturbances are specified respectively as follows:

$$u_{it} = \mu_i + v_{it} \quad (5)$$

and

$$u_{it} = \mu_i + \lambda_t + v_{it} \quad (6)$$

where μ_i is the unobserved cross-sectional specific effect, λ_t is the unobserved time effects, and v_{it} is the random disturbances. There are two different approaches to estimate various parameters of the model: fixed effect and random effect. When μ_i and λ_t are assumed to be fixed parameters that need to be estimated, and remainder random disturbances v_{it} are independent and identically distributed such that $v_{it} \sim IID(0, \sigma_v^2)$, the model is called fixed-effect. When μ_i , λ_t and v_{it} are considered random such that $\mu_i \sim IID(0, \sigma_\mu^2)$, $\lambda_t \sim IID(0, \sigma_\lambda^2)$, $v_{it} \sim IID(0, \sigma_v^2)$ and μ_i and λ_t are independent of the v_{it} , the model is called random-effect (Baltagi, 2008).

3. Data

In order to develop the model of the equation (3), data from various sources, presented in Table 1, were merged into one usable data set. The Department of Energy, Energy Efficiency and Renewable Energy Division have recorded the number of EVs in use over different states from 2003 to 2011. The statistical analysis used data from the following states: Arkansas, Alabama, Arizona, California, Colorado, Florida, Georgia, Illinois, Massachusetts, Michigan, North Carolina, New Jersey, New York, Ohio, Oklahoma, Oregon, Tennessee, Vermont and Wyoming.

Table 1. Data description and sources

State	Number of EV		Total Number of Vehicles (Million)		Income (\$)		VMT (Million)		Gasoline Price (\$/gallon)		Electricity price (\$/gallon equivalent)		Urban Area		Incentive	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
Alaska	33	18.30	0.687	0.034	41380	4750	8217	2184	2.58	0.67	0.60	0.09	0.00	0.00	0.00	0.00
Alabama	663	301.50	4.610	0.140	31778	2572	14843	3506	2.22	0.57	0.43	0.07	0.00	0.00	0.00	0.00
Arizona	3390	1272.95	4.223	0.438	33444	2596	11268	3035	2.31	0.49	0.43	0.07	0.44	0.53	1.00	0.00
California	27600	7165.77	32.100	1.790	40944	3135	10197	2565	2.45	0.57	0.58	0.10	0.11	0.33	0.78	0.44
Colorado	198	92.87	2.330	1.111	40400	3096	11166	3113	2.30	0.54	0.43	0.07	1.00	0.00	0.00	0.00
Florida	744	441.02	15.500	0.800	37356	2796	12367	3273	2.21	0.56	0.50	0.09	0.00	0.00	1.00	0.00
Georgia	1460	940.22	8.090	0.396	33967	1971	13722	3748	2.14	0.56	0.45	0.09	1.00	0.00	1.00	0.00
Illinois	169	58.12	9.750	0.393	40233	3298	9531	2342	2.29	0.57	0.44	0.08	1.00	0.00	0.00	0.00
Massachusetts	2910	1128.37	5.410	0.125	48189	4577	9629	2418	2.33	0.56	0.65	0.10	0.00	0.00	0.00	0.00
Michigan	2440	1321.82	8.430	0.498	34089	1824	11516	2952	2.25	0.55	0.47	0.08	0.67	0.50	0.00	0.00
North Carolina	679	609.81	6.150	0.177	33744	2500	12672	3313	2.30	0.58	0.42	0.09	0.00	0.00	0.00	0.00
New Jersey	502	315.84	6.480	0.595	48244	4236	9598	2418	2.24	0.56	0.63	0.10	0.67	0.50	0.67	0.50
New York	8500	1547.81	11.100	0.503	45489	5141	8010	2131	2.34	0.57	0.74	0.13	1.00	0.00	0.00	0.00
Ohio	334	163.03	10.600	0.386	34667	2554	10931	2621	2.30	0.57	0.43	0.08	0.00	0.00	0.00	0.00
Oklahoma	139	189.53	3.320	0.192	33725	3741	14838	3822	2.19	0.57	0.40	0.08	0.44	0.53	0.00	0.00
Oregon	1020	561.65	3.040	0.070	34511	2554	10633	2875	2.44	0.57	0.34	0.06	0.00	0.00	0.00	0.00
Tennessee	263	291.96	5.100	0.163	33489	2413	13050	3307	2.23	0.56	0.60	0.09	0.00	0.00	0.33	0.50
Vermont	429	239.59	0.556	0.034	37588	3603	13956	3543	2.38	0.59	0.43	0.07	0.00	0.00	0.00	0.00
Wyoming	39	23.40	0.665	0.052	42798	5596	19846	5049	2.25	0.55	0.43	0.07	0.00	0.00	0.00	0.00
Sources	U.S. Energy Information Administration, Office of Energy Consumption and Efficiency Statistics		US Department of Transportation Annual Highway Statistics (2003-2011)		US Census Bureau		US Department of Transportation Annual Highway Statistics (2003-2011)		U.S. Energy Information Administration State Energy Data 2012: Prices and Expenditures		U.S. Energy Information Administration State Energy Data 2012: Prices and Expenditures		Incentive data from the Department of Energy, Energy Efficiency and Renewable Energy Division (DOE EERE)		Incentive data from the Department of Energy, Energy Efficiency and Renewable Energy Division (DOE EERE)	

These states were selected because the available data have no missing records over this period of time. The dependent variable in the developed model is the logarithm of the annual state EV share, which is defined as the number of EVs in use as a percentage of all registered vehicles in the state for that same time period. The annual number of registered vehicles was obtained from the Federal Highway Administration (FHWA). The incentive variable in this study is a dummy variable that considers statewide tax incentives, rebates and other benefits. In order to convert this data to a monetary value, the price of electric vehicles over time is needed. Based on the data availability on electric vehicles price, this study only considers if states provide incentives on EVs or not (1 or 0).

4. Estimation Results

Statistical Software SAS was used in this analysis to estimate the intercept and coefficients of the model as presented in Table 2. Fixed-effects and random-effects with both one-way and two-way error components are considered as various panel-data models in order to estimate the coefficient of the effective factors of the EV share.

4.1. Fixed Effect Models

The one-way fixed-effects regression catches cross-sectional variances by defining unobservable specific effects for each state, while considering the impact and significance of each explanatory variable over time, averaged across all the states in our data set (Stock and Watson, 2003). The results demonstrate all the variables have the proper sign. The income per capita is positive and significant, representing the increase of EV shares with increased income growth. This can be interpreted as economic situation of society. While the vehicle prices is not available over time, higher income as a surrogate of lower electric vehicles prices leads to more EV shares. Average vehicle miles traveled (VMT) per capita is not significant. Typically due to the “range anxiety” issue, it is generally expected that people and households with high VMT are less likely to buy EVs. Even though driving an EV can save fuel costs due to the relatively lower costs of electricity per mile, saving finances is rarely mentioned as a motivation for purchasing EVs as the high capital cost does not justify the fuel savings. This could be due to the non-linear relationship with VMT and probability for purchasing EV. As VMT increase, consumers are more likely to buy EVs. But the probability of purchasing a vehicle decreases once VMT exceed a level of threshold. Electricity price has a proper sign, indicating lower utilization of EVs in areas with higher electricity prices.

Gasoline price has a positive effect on EV shares. Since higher gasoline prices increase the trip cost of conventional vehicles and decrease the utility of these vehicles, raised gasoline prices leads to higher EV adoption. The significance of the gasoline price variable was not considerable because of the correlation with electricity prices (Pearson Correlation Coefficient is equal to 0.414).

The urban roads variable is one of the factors that has a positive effect on EV use. Over 75% of urban U.S. commuters travel less than 40 miles per day, which is perfect for the range of today’s EVs; thus, it can be interpreted that the willingness of people to adopt EV instead of conventional vehicle is higher in urban areas (National Household Travel Survey, 2009). Referred to the results of the model, the urban road coefficient is positive and strong enough to affect the states’ EV shares. Incentives are a significant factor that increase the use of EVs and demonstrates that establishing them encourages people to use EVs over time.

In addition to predefined significant explanatory, there are some unobservable factors that were estimated for each state separately. The impact and magnitude of unobservable factors on each specific state are introduced by state as fixed-effect dummy variables.

The time-averaged values of number of electric vehicles, income per capita, electricity price, urban roads and incentives are presented for different states in Figure 1. By using these figures, the impact of unobservable factors as presented in Figure 2-a can be explained more clearly. For instance, comparing different explanatory variables for Vermont and New Jersey without considering the unobservable factors can lead to misjudgment of EV use in each state. Vermont has less average income, fewer urban roads, less incentives and higher electricity prices compared to New Jersey, which could imply considerable more EVs in New Jersey; yet this is not true. The positive specific fixed effect for Vermont and negative specific fixed effect for New Jersey mean that there are some unobservable factors, which encouraged residents of Vermont and discouraged residents of New Jersey to use EVs.

Table 2. Panel data estimation results

Variable	Coefficients (standard error)				
	Fixed-one	Fixed-two	Random-one	Random-two	Time trend
Intercept	-11.72*** (1.58)	-13.12*** (4.27)	-10.38*** (1.27)	-10.18*** (1.18)	-10.39*** (1.77)
Income	7.7E-5* (5.1E-5)	4.2E-5 (6.1E-5)	5.9E-5 (4.8E-5)	4.4E-5 (4.7E-5)	5.4E-5 (5.3E-5)
VMT	9.04E-6 (2.3E-5)	7.1E-5 (9.7E-5)	6.01E-5 (2.3E-5)	7.18E-6 (2.3E-6)	2.2E-5 (2.4E-5)
Electric price	-3.83*** (0.89)	-4.84*** (1.09)	-2.76*** (0.84)	-2.06*** (0.83)	-4.68*** (1.026)
Gasoline price	0.11 (0.276)	1.185 (1.32)	0.213 (0.25)	0.21 (0.24)	-0.088 (0.28)
Urban	10.9*** (4.19)	8.74** (4.95)	3.93** (2.11)	2.88** (1.67)	8.38*** (4.42)
Incentive	0.46** (0.3)	0.404* (0.31)	0.31 (0.29)	0.24 (0.29)	0.365 (0.31)
Time trend	-	-	-	-	0.124 ** (0.07)
R ²	0.77	0.785	0.1	0.07	0.78
Adjusted R ²	0.732	0.735	0.067	0.036	0.742

Note: *** p<0.05, ** p<0.1, * p<0.15

Besides the state specific effects, different time points may affect the share of EVs. In some cases, natural phenomena, economic downturns or other specific events may shock the market share and could change the share of EVs. In order to investigate these effects, a two-way fixed-effects regression was accomplished. The time specific fixed effects are interpreted similarly to the state specific fixed effects and intercept of the model. This means that their negative signs imply more interest and likelihood of using conventional vehicles over EVs at corresponding time points. Presented in Figure 2-b, the least time fixed effect values are observed in years 2005, 2006 and 2008.

Consistent with the study by Diamond (2009), the lower interest of people in adopting EVs in 2005 and 2006 would be explained by Hurricane Katrina. However, Hurricane Katrina increased gasoline prices. Considering the negligible effect of gasoline price on EV shares, increased gasoline price did not increase the utilization of EVs. On the contrary, based on the disruptions of social and economic conditions resulting from Hurricane Katrina in 2005, people rarely chose to adopt EVs. The 2006 fixed effect is less negative than 2005, indicating that the effect of this phenomena continued through 2006, although with a lower impact. The economic recession in 2008 is another circumstance that had a negative impact on whether people decided to adopt EVs. The higher initial price combined with poor economic conditions kept purchases of EVs low in 2008.

4.2. Random-Effect Models

The process of random-effects model is similar to the fixed-effects model in that it postulates a different intercept for each state and/or time, but it crosses different intercepts as having been drawn randomly for possible intercepts. Therefore, these intercepts may be interpreted as random and treated as though they were a part of the error term. The resulting coefficients from one-way and two-way random-effects estimation methods are mostly acceptable in their signs; however, electricity price and urban roads are the only significant variables.

4.3. Trends Over Time

The major factors in adoption of new technology are time, awareness and knowledge. This means that over time, those responsible for innovation or change influence others to switch to EVs. To account for the impact of time trends on EV shares, the one-way fixed-effects estimation method considering a time trend variable was applied. This was chosen because the two-way fixed-effects regression wipes out the effect of time trend because same values were used for each state. The results represent the rational signs for all variables. Electricity price, urban roads and time trend variables are significant factors. The sign and strength of the time trend variable demonstrates the importance and influence of time in convincing people to adopt EVs as a new technology. Note that the adjusted R² of this result is greater than the one without the time trend variable, which can validate the impact of time trend on EV diffusion. In addition to increasing knowledge of new technology over time, the variety of available models of EVs (over time) can encourage and increase the adoption rate of EVs.

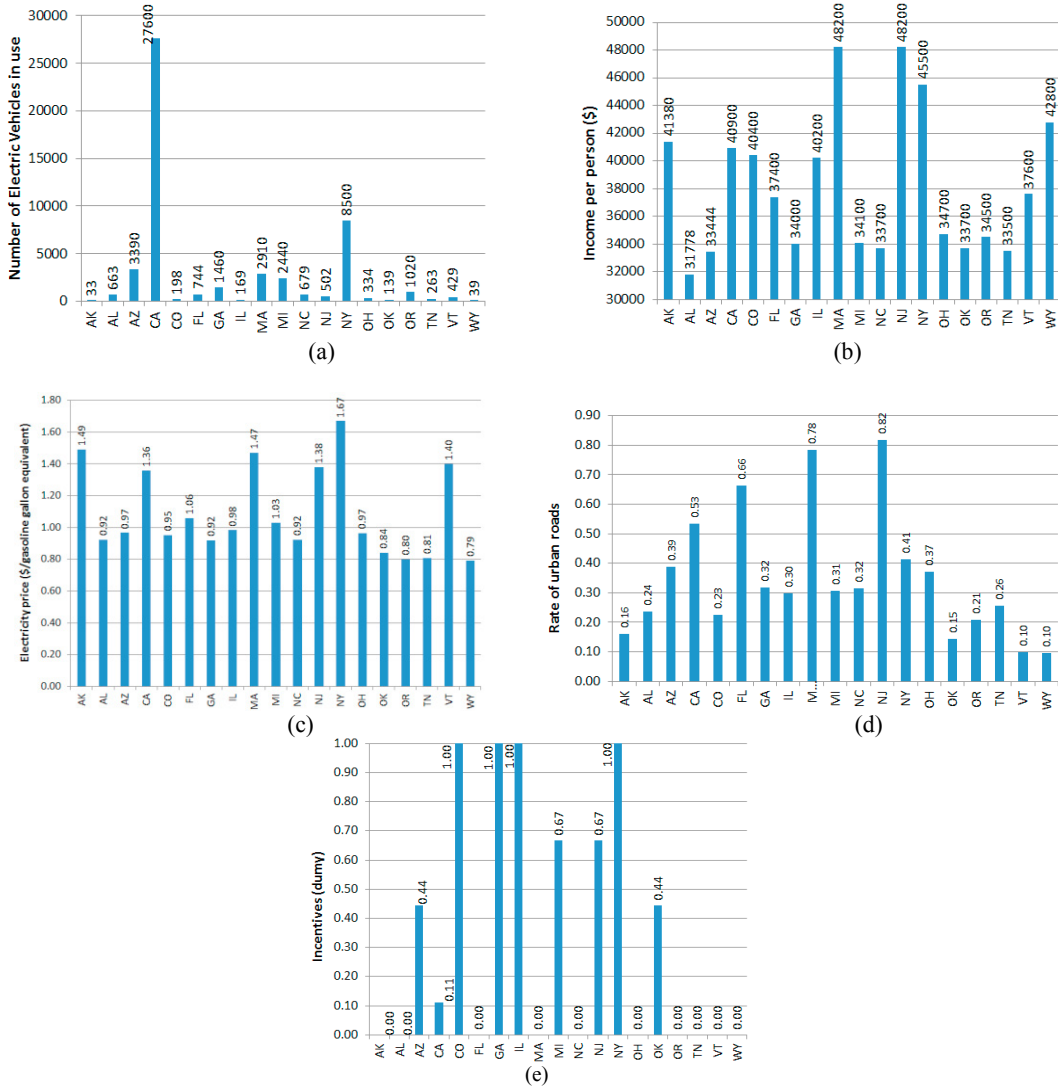


Figure 1- Average value over states for selected variables: a) number of electric vehicles in use, b) income per person, c) electricity price equivalent to a gallon of gas, d) rate of urban roads to all road types, e) existence of the incentive dummy variable

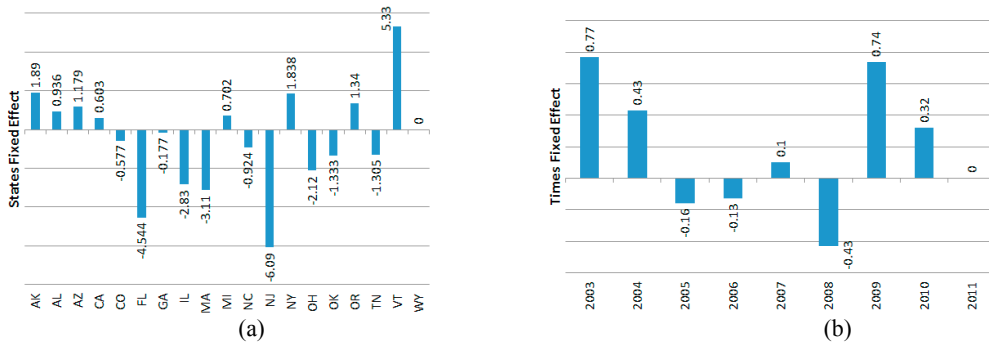


Figure 2- Value of fixed effect, a) states, b) times

A sensitivity analysis was conducted in order to test the base model's overall robustness and the sensitivity of different variables. The one-way fixed-effects model is considered a base model to present the impacts of different explanatory variables. Sensitivity analysis was conducted as the variations of the model's goodness of fit (explanatory power) with the removal of any individual explanatory variable from base model. Results from Models 1-4 are presented in Table 3. Removing the electricity prices variable from the base analysis in Model 1 resulted in decreasing the adjusted R^2 from 0.732 to 0.705. Taking out the variable of urban roads and incentive in Model 2 and Model 3 reduced the adjusted R^2 to 0.726 and 0.734 respectively. Considering the results of the sensitivity analysis, it is possible to conclude that the significance order of electricity prices, urban roads and incentives is declining. Despite the significant effects of these three factors on EV shares, eliminating these factors does not decrease the explanatory power significantly (adjusted R^2 equal to 0.702). This shows that state specific fixed effects explain the majority of EV share variation. Thus, in order to analyze the sensitivity of different states' EV shares with respect to electricity price, urban roads and incentives, the variation of state specific fixed effect on models 1-3 was analyzed.

However, coefficients of developed base model are based on the various states data over time. The impacts of various explanatory variables on each individual state are unknown. In order to analyze the sensitivity of each state EV share with respect to electricity prices, urban roads and incentives, the effect of removing one of the explanatory variables on states' fixed-effect factors were investigated. When a variable remove from the model, it is considered an unobservable variable, which influences the model through the fixed effect. Removing a variable that has a positive correlation with a state's EV share increases the state's fixed-effect factor and vice versa. Table 4 describes the order of states' sensitivity with respect to proposed explanatory variables.

According to the base model results, it is expected that electricity price would be a deterrent factor, which thereby reduces the use of EVs. The negative values Model 1 in Table 4 demonstrates discouraging impacts of electricity prices in various states. Vermont is the most sensitive state with respect to electricity prices. Georgia's sensitivity to electricity price is the lowest and the encouragement impact of this factor on EV adoption is negligible; however, the results imply that the electricity prices do not have negative effect on EV adoption rate in Illinois, Massachusetts, Florida, and New Jersey.

6. Summary and discussion

In the United States, demand for travel has been consistently increasing for several decades as a result of population and economic growth (Heaslip et al., 2014, Soltani-Sobh et al., 2016b). Higher travel demand results in more oil consumption, creating an increased dependency on foreign oil in the past decade. At the same time, emissions from the transportation sector have contributed the major share of air pollution and caused significant concerns regarding air quality and public health. In order to address concerns regarding oil dependency and air quality, increasing the use of electric vehicles is helpful. Hence, the motivation of this study is to draw connections among the market share of EVs, government incentives and different socio-economic factors.

Table 3. Sensitivity analysis models 1-4

Variable	Coefficients (standard error)			
	Model 1 (Electricity prices)	Model 2 (Urban roads)	Model 3 (Incentives)	Model 4 (All three)
Intercept	-10.42*** (1.64)	-11.67*** (4.27)	-11.76*** (1.59)	-10.52*** (1.64)
Income	2E-5* (4.8E-5)	9.1E-5** (5.2E-5)	7.3E-5 (5.2E-5)	-5.25E-6 (4.7E-5)
VMT	2.7E-5 (2.4E-5)	4.24E-7 (2.3E-5)	6.13E-6 (2.3E-5)	1.8E-5 (2.3E-5)
Electric price	-	-3.41*** (0.9)	-3.51*** (0.88)	-
Gasoline price	0.087 (0.292)	0.238 (0.27)	0.159 (0.276)	0.19 (0.28)
Urban	7.84** (4.36)	-	10.17** (4.18)	-
Incentive	0.167 (0.3)	0.36* (0.3)	-	-
Time trend	-	-	-	-
R^2	0.745	0.763	0.77	0.739
Adjusted R^2	0.705	0.726	0.734	0.702

Note: *** $p < 0.05$, ** $p < 0.1$, * $p < 0.15$

Table 4. States' sensitivity analysis results

Based Model		Model 1 (Electricity prices)		Model 2 (Urban roads)		Model 3 (Incentives)		Model 4 (All three)	
State	Fixed factor	State	Fixed factor	State	Fixed factor	State	Fixed factor	State	Fixed factor
NJ	-6.09	VT	-2.60	NJ	7.65	NJ	0.76	NJ	6.77
VT	5.34	AK	-2.28	MA	7.17	IL	0.60	MA	5.60
FL	-4.54	NY	-1.61	FL	6.17	CO	0.55	FL	5.11
MA	-3.11	AL	-1.00	CA	4.51	NY	0.53	CA	2.84
IL	-2.84	MI	-0.75	AZ	3.22	GA	0.48	AZ	2.36
OH	-2.21	OK	-0.68	NY	3.12	MA	0.43	GA	2.08
AK	1.89	CA	-0.60	OH	3.00	MI	0.39	IL	1.96
NY	1.84	NC	-0.55	GA	2.56	FL	0.25	OH	1.89
OR	1.34	OH	-0.42	NC	2.42	AZ	0.22	NC	1.33
OK	-1.33	OR	-0.29	MI	2.33	OK	0.19	CO	1.26
TN	-1.30	TN	-0.24	IL	2.21	CA	0.13	MI	1.23
AZ	1.18	AZ	-0.13	TN	1.81	OH	0.12	TN	1.12
AL	0.94	CO	-0.04	AL	1.59	NC	0.08	NY	1.12
NC	-0.92	GA	-0.03	CO	1.42	TN	0.01	OR	0.66
MI	0.70	IL	0.06	OR	1.24	AL	0.01	AL	0.29
CA	0.60	MA	0.15	OK	0.65	OR	0.00	OK	-0.03
CO	-0.58	FL	0.53	AK	0.30	AK	-0.22	AK	-1.89
GA	-0.18	NJ	0.91	VT	-0.22	VT	-0.24	VT	-2.56

In this research, a macroscopic binomial logit market share model was conducted to investigate the transportation modal choice between EV and conventional vehicles. In the proposed model, the mode choice decision was assumed to be a function of income, VMT, gasoline price, electricity price, urban roads and incentive.

The results demonstrate that electricity prices, urban roads and incentives are effective factors on commuters' vehicle fuel type decision. Decreasing electricity prices increases use, while increasing urban roads and incentives increases use and the overall percentage of EVs. Considering sensitivity analysis, electricity price is most influential among these three factors. In addition, a sensitivity analysis of different states' EVs share with respect to these three factors expressed that Vermont has the highest sensitivity to electricity prices, and New Jersey is most sensitive with respect to urban roads and incentives.

Moreover, it was presented that the low EVs share in 2005 and 2006 was due to Hurricane Katrina, and the low share in 2008 was the result of an economic recession. As a result of these events, commuters chose EVs less often in these years. The time trend model results demonstrated that time has impacted and is increasing the use of EVs. It is based on the effect of time on new technology diffusion. Over time, knowledge about new technology increases; thus, people are more ready to accept new technology.

Incentives were considered as a dummy variable, because most incentives are based on the vehicle price, which is unavailable as data over time. In order to have more accurate results, it is suggested to accomplish the modeling on data with monetary incentive values. Another suggestion for future work is incorporating the amount of EVs' infrastructure into model development. Construction of more charging stations will increase the possible operation range of EV, which will increase utility of EVs and will encourage commuters to adopt EVs. This variable was not used in this study due to the lack of data history on EV infrastructure over time for various states.

The results of the study can be a policy guide on how to incentivize the further adoption of electric vehicles and to understand the regional differences in EV adoption. In other words, it can be used as a policy instruction for various states to implement the best policy to increase the number of electric vehicles. States with high sensitivity to electricity prices are willing to decrease electricity prices, while state which are sensitive to incentives would investigate on providing financial advantageous for EV adopters.

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