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Investigating factors affecting electric vehicles adoption: an aggregated panel data analysis over U.S. states

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Abstract
Increasing the usage of electric vehicles has been proposed as a policy to decrease aggregate fuel consumption and greenhouse gas (GHG) emissions in an effort to mitigate the causes of climate change. In order to increase the attraction of electric vehicles for consumers, governments have employed a number of incentives. In this study, the relationship between shares of electric vehicle and the presence of government incentives as well as 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 model was estimated using different panel data methods and the results were compared. 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. According to the sensitivity analysis of electric vehicle adoption rate, state of Vermont has the most sensitivity with respect to electricity price and New Jersey is the most sensitive state with respect to urban roads and incentives. Moreover, the time trend model analysis found that the electric vehicle adoption has been increasing over time, which is consistent with diffusion of new technology theory.

Keywords: Electric vehicles, Public policy, Technology adoption, Panel data modelling

1 Introduction

The United States' dependency on foreign oil has been growing to meet the petroleum demand. Higher dependency results in some national and economical issues. The US transportation sector has always been the major consumer of energy, which uses around 71% of petroleum [1]. High gasoline consumption in the US transportation sector not only raises concerns regarding national energy security, but also poses many questions regarding the environmental impacts of greenhouse gases emissions.

In order to increase the sustainability of transportation system, reduction of GHG emissions, air pollution and dependence on fossil fuels is necessary. Electric vehicles are one possible innovation to help address the energy dependency, and environmental concerns. EV adoption is heavily dependent on some external factors such as stringent emissions regulations, rising gasoline prices, and financial incentives [2], [3], [4]. Factors such as lack of knowledge by potential adopters, low consumer risk tolerance, and high initial production cost are common barriers to any new technology [5], [6], [7].

The technological problems compromise aspects of electric vehicles including short driving range, long recharge time, high battery cost, and heavy curb weight. EV purchase prices, which are heavily dependent on battery costs, have been identified as being the most significant obstacle to widespread EV diffusion [8], [9]. Besides the technological problem, social issues are other challenging factors that should to be considered in order to achieve commercial success of EVs. Ozaki and Sevastyanova (2011) determined that consumer acceptance is crucial to continuing success of sustainable transportation [10]. 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 [11]. Hidrue et al. (2001) identified the level of education, income, and environmentalism as consumer characteristics with positive effect on EV adoption [12]. Fuel price has been introduced as one of the influential predictors of EV diffusion in agent-based models [2], [3]. The combination of fuel price and electricity price as the majority of EV operating expenses are positively correlated to likelihood of EV adoption [13]. In some studies availability of charging infrastructures has been identified as an important criterion in consumer acceptance of alternative fuel vehicles [14], [15], [16], [17]. According to several studies, influential factors on EV adoption rate include: level of urban density, vehicle diversity, local involvement, and public visibility [9], [18], [19], [2], [4].

In order to overcome these barriers, different states have established a number of consumer incentives for adopting EVs. Literature reviews on effect of incentives on adoption of alternative fuel vehicles present conflicting results. While some studies have demonstrated the positive effect of financial incentives on hybrid electric vehicles' (HEV) sales [20], [21], others demonstrated that incentives have no effect on HEV adoption [11]. Sierzchula et al. (2014) found financial incentives to be significantly and positively correlated to country's EV market share [9], whereas Zhang et al. (2013) showed insignificant relation between financial incentives and people's willingness to buy EVs [22]. Thus, besides incentives, analysing other factors affecting electric vehicles share is imperative.

However, little has been done, on the significant factors influencing EV share in the U.S. states. The purpose of this study is to examine and analyse the significance and strength of state incentives and other significant socioeconomic factors in promoting EV adoption. As a primary methodology, cross-sectional time-series analysis of number of EV statistics over time from U.S. states was used to test the relationship between EV adoption and variety of variables. The EV data for a period of 9 years (from 2003 to 2011), for 19 states with no missing data was collected from U.S. Energy Information Administration (EIA). The available EV data are aggregated number of EV 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 of the U.S. over time. In this model, we explicitly incorporated various factors as explanatory variables in order to quantify their effect on EV adoption rates. These explanatory variables include income, vehicle miles travelled (VMT), electricity price, gasoline price, urban area, incentives, and HOV.

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 vehicle as an aggregate data is considered as the dependent variable, with a value between 0 and 1.

2.1 Macroscopic cross-sectional Logit model

Due to the aggregate dataset available, macroscopic logit market share model is developed to demonstrate the mode choice decisions between electric vehicles and conventional vehicles. The market share model reduces to a utility function, which is a function of a number of independent vehicle type characteristics, socioeconomic and

policy variables that are varies over states. The EVs share variations over states (in addition to their variation over time) helps 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 that vary on average by state. The states monetary considerations include the average income per capita, (Income variable, which is considered as effective consumer discount rate for future energy cost saving, and risk tolerance for new technologies) [11], gasoline price (gasprice variable), electricity price (Eprice variable) and annual miles travelled (VMT variable which is related to annual cost of fuel). Non-monetary factors include government incentive (Incentive variable), which increases utility of EV, HOV-lane privilege (HOV variable), which provide a benefit to the consumer via convenience, rate of urban road (Urban variable), which present the rate of urban road with respect to total roads millage in states. The Incentive and HOV variables were considered as two separate dummy variables because they were started at various time points in different states, and their monetary values are not the same; therefore, they may affect EVs share in different ways.
As such, the final specification of the EV utility in state i at time t (U_{Eit}) can be defined as a function of income, gasoline price, electricity price, VMT, urban roads, incentive variable, and HOV variable in state i at time t.
We define P_{Eit} as the share of EV and P_{Cit} as the share of conventional fuel type vehicles in state i at time point t in such a way that $P_{Eit}+P_{Cit}=1$. These fractions can be developed as follows [20], [23]:

$$P_{Eit} = \frac{e^{U_{Eit}}}{1+e^{U_{Eit}}} \tag{2}$$

Then, to solve and estimate different coefficient of the utility function the fraction model can be transformed as below:

$$\ln\left(\frac{P_{Eit}}{P_{Cit}}\right) = \ln\left(\frac{P_{Eit}}{1-P_{Eit}}\right) = U_{Eit} = \alpha + \beta_1 Income_{it} + \beta_2 Gasprice_{it} + \beta_3 Eprice_{it} + \beta_4 VMT_{it} + \beta_5 Urban_{it} + \beta_6 Incentive_{it} + \beta_7 HOV_{it} \tag{3}$$

This equation takes a generalized linear form and its coefficient can be estimated via linear regression. The coefficients of this linear model will be estimated without transforming to log-log model because the left hand side of the utility function in equation (3) is negative[1].
Model definition is based on the identifying the effective factors on EV's utility improvement versus conventional vehicle. It is clear that the variables with positive sign encourage the use of EVs and increasing the value of variable with negative sign increase the use of conventional vehicle. The estimation of the model in this study is accomplished based on the set of panel data over U.S. states.

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 [24]. Panel data can deal with heterogeneity resulted from variation of some unmeasured explanatory variables that affect the behavior of people of 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 [25]:

$$Y_{it} = \alpha + X_{it}\beta + u_{it} \tag{4}$$

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

$$u_{it} = \mu_i + v_{it} \tag{5}$$

and

$$u_{it} = \mu_i + \lambda_t + v_{it} \tag{6}$$

Where μ_i is the unobserved cross-sectional specific effect, λ_t is the unobserved time effect, 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

[1] Due to the negligible EV share with respect to conventional vehicles the fraction in the parentheses is very small, therefore the value of $ln\left(\frac{P_{Eit}}{1-P_{Eit}}\right)$ is negative.

and λ_t are assumed to be fixed parameters that needs to be estimated and remainder random disturbances v_{it} are independent and identically distributed such that $v_{it} = IID(0, \sigma_v^2)$, the model is called fixed effect, and when μ_i and λ_t as well as v_{it} are considered as random such that $\mu_i = IID(0, \sigma_\mu^2)$, $\lambda_t = IID(0, \sigma_\lambda^2)$, $v_{it} = IID(0, \sigma_v^2)$ and μ_i and λ_t are independent of the v_{it}, the model is called random effect [26].

3 Data

In order to develop the model of equation (3), data from various sources had to be merged into one usable data set. 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 State. These states are selected because available data for these 19 states has no missing record over this period of time. The dependent variable in the developed model is the logarithm of annual state EV share, which is defined as 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 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 these 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 considered if states provide incentives on EVs or not (1 or 0). The HOV dummy variable demonstrates whether there is a HOV restriction exemption for EVs on one or more major highways in a state. Table 1 presents the descriptive statistics for selected variables and data sources used in this study.

4 Estimation Results

Table 2 presents the results of regression on developed model[2]. Statistical Software SAS was used in this analysis to estimate the intercept and coefficients of the model. Three different types of effects; between-, fixed- and random-effects were considered to estimate the panel data model. The between-effect regression measures only the impact of the cross-sectional (states) variances on EVs shares. It runs a single multivariate regression on the set of states EV shares against the set of independent variables. All dependent and independent variables in each state's equation are averaged over time. Looking at the between-effect regression results, negative intercept implies that everything else being equal, conventional vehicle is more likely to be chosen.

Average vehicle miles traveled (VMT) per capita was significant with positive coefficient, indicating more EV shares for states with higher VMT per capita . Gasoline price was significant and had positive effect on EV use in different states. Since higher gasoline price increases the conventional vehicles' trip cost, the willingness of EV adoption is more in state with higher gasoline price. Urban roads variable is one of the factors that have positive effect on using EVs. The use of EV in states with more urban roads is higher, because over 75% of U.S. urban commuters travel less than 40 miles per day, which is perfect for the range of today's EVs [27]. The urban road coefficient is positive and strong enough to affect the states' EV shares. Averaged over time, the effect of incentives was significant in encouraging people to adopt EV in different states. The model shows that the HOV exemption privilege is not tempting enough to convince people to adopt EVs instead of conventional vehicles. Most surprising results were the unexpected effects of per-capita income and electricity price on EV shares, which could be due to the lack of information about the impact of time-dependent variables.

[2] Note: In all the estimation results:
*** $p<0.05$, ** $p<0.1$, * $p<0.15$

Table 1: Data description and sources

State	EV share		Income		VMT		Gas price		E price		Urban		Incentive		HOV	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
Alaska	33.22	18.30	41380.30	4750.49	8216.93	2183.69	2.58	0.67	0.60	0.09	0.16	0.010	0.00	0.00	0.00	0.00
Alabama	662.56	301.50	31777.78	2572.34	14842.58	3505.93	2.22	0.57	0.43	0.07	0.24	0.014	0.00	0.00	0.00	0.00
Arizona	3390.11	1272.95	33444.44	2596.20	11268.12	3034.97	2.31	0.49	0.43	0.07	0.39	0.012	0.44	0.53	1.00	0.00
California	27603.33	7165.77	40944.44	3134.53	10196.67	2564.79	2.45	0.57	0.58	0.10	0.53	0.026	0.11	0.33	0.78	0.44
Colorado	197.67	92.87	40400.00	3095.56	11165.57	3113.42	2.30	0.54	0.43	0.07	0.23	0.013	1.00	0.00	0.00	0.00
Florida	744.44	441.02	37355.56	2796.03	12366.67	3272.61	2.21	0.56	0.50	0.09	0.66	0.037	0.00	0.00	1.00	0.00
Georgia	1461.33	940.22	33966.67	1971.04	13722.22	3747.59	2.14	0.56	0.45	0.09	0.32	0.029	1.00	0.00	1.00	0.00
Illinois	168.56	58.12	40233.33	3298.11	9531.11	2342.15	2.29	0.57	0.44	0.08	0.30	0.023	1.00	0.00	0.00	0.00
Massachusetts	2906.00	1128.37	48188.89	4577.24	9628.77	2418.18	2.33	0.56	0.65	0.10	0.78	0.005	0.00	0.00	0.00	0.00
Michigan	2442.78	1321.82	34088.89	1823.76	11516.03	2951.83	2.25	0.55	0.47	0.08	0.31	0.014	0.67	0.50	0.00	0.00
North Carolina	678.78	609.81	33744.44	2500.06	12671.62	3312.93	2.30	0.58	0.42	0.09	0.32	0.047	0.00	0.00	0.00	0.00
New Jersey	502.22	315.84	48244.44	4235.89	9598.46	2418.20	2.24	0.56	0.63	0.10	0.82	0.006	0.67	0.50	0.67	0.50
New York	8502.89	1547.81	45488.89	5140.88	8010.00	2130.53	2.34	0.57	0.74	0.13	0.41	0.039	1.00	0.00	0.00	0.00
Ohio	334.11	163.03	34666.67	2554.41	10931.11	2620.81	2.30	0.57	0.43	0.08	0.37	0.016	0.00	0.00	0.00	0.00
Oklahoma	139.22	189.53	33724.93	3741.04	14837.66	3822.29	2.19	0.57	0.40	0.08	0.15	0.010	0.44	0.53	0.00	0.00
Oregon	1018.78	561.65	34511.11	2553.65	10633.37	2874.82	2.44	0.57	0.34	0.06	0.21	0.022	0.00	0.00	0.00	0.00
Tennessee	262.67	291.96	33488.89	2413.22	13049.53	3307.00	2.23	0.56	0.60	0.09	0.26	0.021	0.00	0.00	0.33	0.50
Vermont	429.22	239.59	37587.68	3603.41	13956.00	3543.08	2.38	0.59	0.43	0.07	0.10	0.003	0.00	0.00	0.00	0.00
Wyoming	39.44	23.40	42797.56	5595.99	19845.97	5047.67	2.25	0.55	0.43	0.07	0.10	0.005	0.00	0.00	0.00	0.00
Sources	U.S. Energy Information Administration, Office of Energy Consumption and Efficiency Statistics provided number of electric vehicle, US Department of Transportation Annual Highway Statistics provided number of registered vehicles		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		US Department of Transportation Annual Highway Statistics (2003-2011)		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)	

Table 2: Panel data estimation results

Variable	Coefficients (standard error)					
	Between effects	Fixed-one	Fixed-two	Random-one	Random-two	Time trend
Intercept	-66.36*** (20.85)	-12.03*** (1.61)	-13.14*** (4.27)	-10.63*** (1.04)	-10.37*** (1.18)	-10.71*** (1.77)
Income	-3.6E-4*** (1.35E-4)	8.2E-5* (5.2E-5)	4.9E-5 (6.1E-5)	6.2E-5 (4.8E-5)	4.5E-5 (4.7E-5)	5.9E-5 (5.3E-5)
VMT	8.6E-4*** (3.2E-4)	1.1E-5 (2.3E-5)	6.9E-5 (9.7E-5)	8.2E-5 (2.3E-5)	9.2E-6 (2.3E-6)	2.3E-5 (2.4E-5)
Electric price	4.02*** (1.73)	-3.67*** (0.91)	-4.65*** (1.09)	-2.65*** (0.84)	-1.99*** (0.83)	-4.52*** (1.026)
Gasoline price	22.38*** (8.36)	0.076 (0.278)	1.044 (1.32)	0.193 (0.25)	0.2 (0.24)	-0.041 (0.28)
Urban	10.99*** (4.59)	11.1*** (4.19)	8.97** (4.95)	4.28*** (2.11)	3.26** (1.67)	8.51*** (4.42)
HOV	-1.22 (1.12)	-0.392 (0.38)	-0.359 (0.39)	-0.418 (0.367)	-0.412 (0.365)	-0.382 (0.38)
incentive	3.87*** (1.58)	0.52** (0.3)	0.462* (0.31)	0.385 (0.29)	0.314 (0.29)	0.428 (0.31)
Time trend	-	-	-	-	-	0.122 ** (0.07)
R2	0.6	0.775	0.786	0.1	0.07	0.78
Adjusted R2	0.582	0.736	0.734	0.0563	0.029	0.74

Between-effects regression method neglects the effect of time on the cross-sections. Therefore, there is a potential omitted variable bias due to isolating the effect of time on variables.

Between-effects regression results present the relationship between the EV shares and different socioeconomic characteristics and incentive of a particular state without considering the impact of each variable over time. Due to the unreliable effect of income and electricity price on EV shares, the result of this model is not satisfying. In addition, it should be considered that diffusion of new technology changes over time. Therefore, to control the omitted variable bias and to cover time–dependent effects, the fixed-effect regression was run on this model.

4.1 Fixed effect models

The one-way fixed-effects regression catches cross-sectional variances by defining unobservable specific effect for each state, while considering the impact and significance of each explanatory variable over time, averaged across all the states [28]. All the variables have proper sign except HOV, which is not significant and it can be ignored. The income per capita is positive and significant, representing the increase of EV shares with income growth over time. Comparing with between-effects model, VMT per capita and gasoline price have lost their significance. According to basics of one-way fixed-effects model, which considers variations of EV shares over time, it can be concluded that variations of VMT per capita and gasoline price are significant over states but not over time.

Electricity price has proper sign; indicating lower utility of EVs in higher electricity price. Urban road is an important factor that has positive effect on EV adoption. Incentive is a significant factor and increases the use of EVs. It demonstrates that establishing incentives encourages people to use EVs over time.

In addition to predefined significant explanatory variables (such as income per capita, electricity price, urban roads, and incentives), there are some unobservable factors that were estimated for each state separately. Impact and magnitude of unobservable factors on each specific state is introduced by state fixed effect [3] as dummy variables. The time-averaged values of income per capita, electricity price, urban roads, and incentives are presented for different states in

[3] States fixed effect: AK=1.891031, AL=0.936412, AZ=1.179288, CA=0.603667, CO= -0.57697, FL= -4.5447, GA= -0.17692, IL= -2.83505, MA= -3.10951, MI= 0.70166, NC= -0.92404, NJ= -6.09443, NY= 1.838628, OH= -2.21032, OK= -1.33355, OR= 1.339569, TN= -1.30497, VT= 5.336568

figure 1-5. Using this figure the impact of unobservable factors can be explained more clearly. For instance, comparing different explanatory variables for two states of Vermont and New Jersey without considering the unobservable factors can mislead the judgment on number of EV use in each state. Vermont has less income, urban roads, incentives and higher electricity prices compared to New Jersey, which could imply considerable more EVs in New Jersey; while this is not true. The positive specific fixed effect for state of Vermont, and negative specific fixed effect for New Jersey State mean that there are some unobservable factors, which encourage Vermont people and discourage New Jersey people to use more EV.

Besides the state specific effects, different time points may affect the share of EV. In some cases natural phenomenon, economy crash or some specific events may shock the market share and would change the share of EVs. In order to investigate these effects, two-way fixed-effects regression was accomplished. The time specific fixed effects are interpreted similar to the state specific fixed effects and intercept of model. It means that their negative signs imply more interest and likelihood of using conventional vehicles over EVs at corresponding time points. The least time fixed effect values are observed in years 2005, 2006 and 2008, respectively[4].

The lower interest of people in adopting EV at 2005 and 2006 would be explained by Hurricane Katrina. However, the Hurricane Katrina increased the gasoline price. Considering the negligible effect of gasoline price on EV shares, increase of gasoline price did not increase the utility of EVs. On the other hand, based on the disruptions on socio and economic conditions resulted by hurricane in 2005, people hardly ever chose to adopt EVs. The 2006 fixed effect is less negative than 2005, indicating that the effect of this phenomena was continued trough 2006 with lower impact. Economic recession in 2008 is another circumstance that had negative impact on people's decision to adopt EVs or not. Due to poor economic condition in 2008, people could not afford higher initial purchase price of EV.

[4] Time point fixed effect: 2003= 0.77, 2004= 0.43, 2005= -0.16, 2006= -0.13, 2007= 0.10, 2008= -0.43, 2009= 0.74, 2010= 0.32.

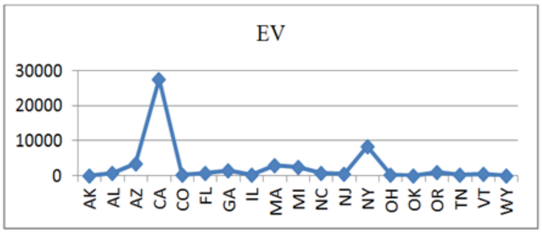

Figure 1: Average number of EV over time

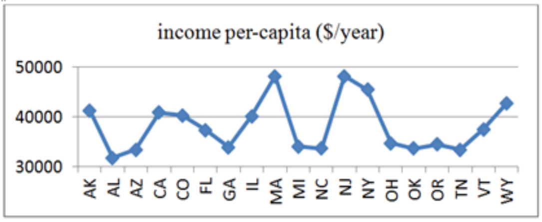

Figure 2: Average income over time

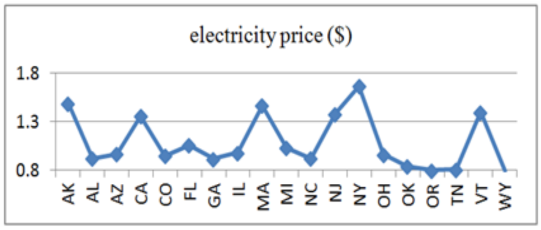

Figure 3: Average electricity price over time

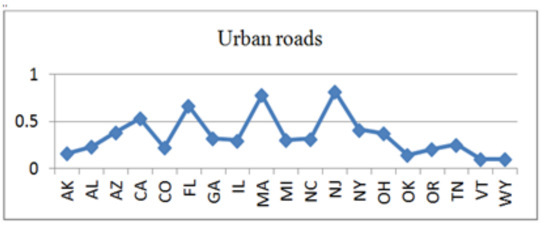

Figure 4:- Average of urban road over time

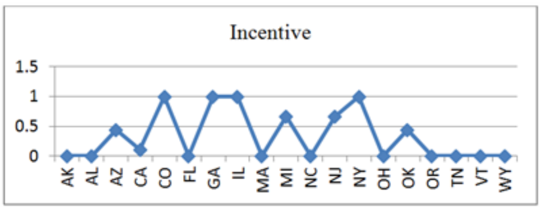

Figure 5: Average of incentives over time

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 interpret different intercepts as random and treated as though they were a part of the error term. The coefficients resulted from one-way and two-way random-effects estimation methods are mostly acceptable in sign; however, the electricity price and urban roads are the only significant variables in both methods.

4.3 Trends over time

People awareness and knowledge on new technology has been growing over time. It means that over time the innovators influence imitators to switch to EVs. To catch the impact of time trends on EV shares, the one-way fixed-effects estimation method, considering a time trend variable, was applied. 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 sign for all variables except HOV (same as other regression methods). 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 R^2 of this result is more than the one without time trend variable, which can validate the impact of time trend on EV diffusion.

In addition to increasing the knowledge of individuals about new technology over time, the variety of available models of EVs (over time) can encourage and increase the adoption rate of EVs.

5 Sensitivity analysis

Sensitivity analysis was conducted in order to test the base model's overall robustness and sensitivity of different variables (specifically electricity price, urban roads, and incentives). The one-way fixed-effects model is considered as a base model to present the impacts of different explanatory variables. Sensitivity analysis was conducted as the variations of model's goodness of fit (explanatory power) with the removal of any individual explanatory variable from base model. The model's number is identified based on the individual variable(s) in which explored through sensitivity analysis e.g., electricity prices in Model 1.

Model 1-4's results 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 0.736 to 0.709. Taking out the variable of urban roads and incentive in Model 2 and Model 3 reduced the adjusted R^2 to 0.725 and 0.733, 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 effect of these three factors on EV shares, eliminating of these factors does not decrease the explanatory power significantly (adjusted R^2 equal to 0.704). This shows that states specific fixed effects explain the most part of EVs 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 U.S. states data over time. Impact of various explanatory variables on each individual state is 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 factor were investigated. When a variable remove from the model, it is considered as unobservable variable, which influence the model through the fixed effect.

Removing the variable which has positive correlation with state EV share, increases the state' fixed effect factor, and vise 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 be a deterrent factor, which reduces the utility of EVs. The negative value in column associated with electricity price in Table 4 (Model 1) demonstrates discouraging impact of electricity price in various states. State of Vermont is most sensitive state with respect to electricity prices. This effect is decreasing over states in order in such a way that state of Georgia sensitivity with respect to electricity price is lowest and the encouragement impact of this factor on EV adoption is negligible, however; the results imply that the electricity price does not have negative effect on EV adoption rate in States of Illinois, Massachusetts, Florida and New Jersey. Considering Model 2 in table 4, it could be concluded that the sensitivity of EV share with respect to urban roads variable in New Jersey State is the most, and in the Arkansas State is the least. This conclusion is based on the increasing the fixed effect factor in various states resulted by removing urban roads variable. In contrast, urban roads variable does not have positive effect on state of Vermont EV share.

Comparison of states fixed effect of base model with Model 3 (incentive variable excluded model) revealed that the encouragement impact of incentives on EV adoption rate in New Jersey and Oregon States are highest and lowest, respectively. Providing incentives does not have any positive effect on stimulating consumer to adopt EV in state of Arkansas and Vermont.

Table 3: Sensitivity analysis Models 1-4

Variable	**Coefficients (standard error)**			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Intercept	-11.03*** (1.6755)	-11.96*** (1.64)	-11.97*** (4.27)	-10.78 (0.64)
Income	-8.63E-6 (49E-6)	9.5E-5 (5.2E-5)	7.6E-5 (5.2E-5)	-
VMT	3E-5*** (24E-6)	2.3E-6 (2.3E-5)	7.22E-6 (2.3E-5)	1.8E-5 (2.3E-5)
Electric price	-	-3.26*** (0.91)	-3.37*** (0.9)	-
Gasoline price	0.029 (0.292)	0.207 (0.279)	0.14 (0.27)	0.21 (0.13)
Urban	8.25*** (4.346)	-	10.16*** (4.18)	-
HOV	-0.665* (0.4)	-0.36 (0.39)	-0.25 (0.38)	-0.53 (0.38)
incentive	0.296 (0.315)	0.42 (0.3)	-	-
R^2	0.7503	0.7645	0.77	0.7431
Adjusted R^2	0.709	0.725	0.733	0.704

Table 4: States' sensitivity analysis results

Base Model		Model 1 (electricity prices)		Model 2 (Urban roads)		Model 3 (Incentives)		Model 4 (all three)	
State	Fixed factor	State	Fixed factor change	State	Fixed factor change	State	Fixed factor change	State	Fixed factor change
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

6 Summary and Discussion

Demand for travel has been persistently increasing for several decades as a result of population and economic growth (Bosworth et al. 2014). Higher travel demand results in more oil consumption, which has increased the U.S. dependency on foreign oil during past decade. Moreover, at the same time, emissions from transportation sector have contributed to a large 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 as green vehicle is helpful. Hence, the motivation of this study is to draw connection among EVs share, government incentives, and different socio-economic factors.

In this research, a macroscopic binomial logit market share model was conducted to investigate transportation modal choice between EV and conventional vehicles. In proposed model, the mode choice decision was assumed to be a function of income, vehicle miles traveled, gasoline price, electricity price, urban roads, presents of incentive, and HOV lane privilege. The model was estimated using different panel data methods over data for 19 U.S. states from 2003 to 2011.

Results demonstrated that electricity prices, urban roads, and incentives are effective factors on commuters' vehicle fuel type choice decision. Decreasing electricity price increases the EVs share, while increasing urban roads and providing incentives increase utility and share of EVs. Considering sensitivity analysis, electricity price is most influential among these three factors. In addition, sensitivity analysis of different states EVs share with respect to these three factors expressed that Vermont State has highest sensitivity of electricity price, and New Jersey is most sensitive state with respect to urban roads and incentives.

Moreover, this study investigated the effect of different time points and time trend on EV share. Lower EVs share at 2005, 2006 was due to Hurricane Katrina, and at 2008 as result of economic recession. After these phenomena commuters roughly chose EVs due to the disrupted socio and economic conditions. Time trend model's result demonstrated that the EVs share has been increasing over time. It is based on the effect of time on new technology diffusion. Over time people knowledge about new technology has been increasing, and it makes their mind ready to accept new technology.

In this study, incentives were considered as a dummy variable, because most of the incentives are based on the vehicle price, which is unavailable 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 number of EVs' infrastructures in model development. Construction of more charging stations will increase the EV's range, which will increase utility of EVs and will encourage commuters to adopt EVs.

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