The Interplay of Incentives, Electricity Price, and Demand on Transport Decarbonization: The Case of Electric Vehicles in the U.S.

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The review of this article was arranged by Department Editor Sherwat Elwan Ibrahim.

IEEE DOI 10.1109/EMR.2023.3347147

Abstract**—*****While extant research explores the impact of electric vehicle (EV) incentives on EV market shares, less is known about how such policies and other socioeconomic factors interact that ultimately affect the goal of transportation emission reductions. The study summarized herein employed a sample of 510 state-year CO_2 emissions datasets in the transportation sector spanning a decade (2010–2019) in a multiple linear regression model. Going beyond earlier studies, we find that, while a higher number of EV incentives would significantly contribute to transportation emission reductions, this effect could be dampened by population growth. In addition, we find that, while higher electricity prices may weaken the effectiveness of EV incentives, a high count of EV incentives is more effective in reducing CO_2 emissions than a low count of EV incentives when the electricity price is low. This finding implies that having multiple EV incentives can be effective in reducing transportation carbon emissions even in the face of rising prices of electricity. The study also examines the effectiveness of promoting the density of charging stations and alternative fuel incentives in advancing carbon emission reductions.*

Key words: Electric vehicles, electricity price, emissions, incentives, population growth, transportation.

I. INTRODUCTION

CARBON emissions from the transportation sector have become the largest source of greenhouse gas (GHG) emissions in the United States [1]. According to the U.S. Energy Information Administration (EIA), the U.S. transportation sector had the largest increase in CO_2 emissions of all sectors in 2021 [2]. Carbon emissions from the transportation sector have been increasing continually in recent years, with significant contributions to climate change [3]. Prior research clearly underpins the need for climate change mitigation, since climate change not only causes serious environmental problems in the U.S., but also has detrimental effects on infrastructure systems such as transportation, air, and water, and also contributes to public health problems simultaneously [4], [5], [6]. The rural economy of the U.S. is particularly sensitive to climate change impacts, reflected in such resources categories as agriculture, forestry, water resources, energy, and fisheries [7]. While the drivers of climate change and approaches to adaptation are well documented, the effectiveness of various mitigation policies, and the role of external factors affecting climate mitigation, have received less attention. More intriguing is the influence of these policies on sustainability transitions [8], [9]. The research summarized in this article was directed toward the effectiveness of various climate change mitigation policies and the impacts of related factors.

Some prior research has been devoted to understand the effectiveness of incentives on EV adoption without adequate consideration of the impacts of such policies on actual reductions in carbon emissions [10], [11], [12]. This lack of full consideration of the ultimate goal (carbon emission reductions) has reduced the value of such research in terms of contributing to that goal. Furthermore, some prior research does not consider interactions among the related emission reductions policies and external features [13]. For example, while the inflation reduction act (IRA) provides not only EV incentives but also other clean fuel and renewable energy infrastructure tax credits, most previous work has solely focused on the relationships between EV incentives and EV market shares, largely ignoring the goal of emission reductions and interdependencies between policies and external drivers. Therefore, investigations into the effectiveness of various policies and their interactions with external features are warranted.

A better understanding of how mitigation policy and external drivers, such as population growth or other socioeconomic factors, interact is crucial because the effectiveness of policy implementation involves uncertainty, and thus portends a risk that policy implementation could lead to less than optimal contributions to environmental goals. Similarly, recent studies emphasized the need for effective climate change mitigation to rely on a deep understanding of practical environmental implications and indicated that the external environment plays an important role in the impacts of policy implementation [14], [15]. In our study, we use linear regression to analyze the impacts of external factors on emission reductions.

Population growth is one of the most important factors that contribute to the severe degradation of natural resources [16]. As population grows, energy consumption, ultimately carbon emissions, and other atmospheric pollution also grow. Increased population growth has been demonstrated to increase GHG emissions, particularly CO_2 emissions, through the increase in human daily commute [17]. One study assessed the impact of population growth on CO_2 emissions in California and found a positive relationship [18]. In addition, an increase in population size can lead to a growing demand for residential consumption in housing and transportation, showing that population size is an influential factor of carbon emissions [19]. The study emphasized that a higher population can lead to increased CO_2 emissions. Hence, it is necessary to study the effectiveness of mitigation policies, taking into account population growth. In this study, we consider population influence and its joint effect with the effectiveness of EV incentives by adding an interaction term to our base model and analyzing interaction plots between the population and different levels of EV incentives. Such interactions have been found to be instructive for policymaking [20], [21].

Another influential factor that contributes significantly to carbon emissions is the level of related economic activity. In particular, we study the prices of electricity, which strongly impact the amount of energy consumption, ultimately influencing carbon emissions. A previous study emphasized that residential energy consumption demand is highly price-elastic [22]. This study found that when prices of electricity are low, people are inclined to use electrical appliances. Another study found that the consumer response to higher prices is the dominant effect on electricity usage [23]. As the price of electricity decreases, people shift their preferences from relying on more conventional vehicles to using more EVs. Yet another study found that electricity pricing is an important factor in decarbonizing the transportation sector in California [24]. This study confirmed that, with lower electricity prices, there exists a shift toward EV consumption. Even though consumers are less sensitive to electricity price than to gasoline prices, electricity price still significantly influences consumer commuting preferences. Hence, while the degree to which higher electricity prices dampen the effectiveness of various EV incentives in terms of carbon emission reductions, it is imperative to empirically validate the nature of the interaction between these factors. We consider the effects of electricity price and their joint effect with the effectiveness of EV incentives by adding an interaction term to the basic model and analyzing interaction plots between the electricity price and different levels of EV incentives.

In sum, the effects of different types of policies, such as clean fuel tax credits, electric vehicle rebates, and emphasis on increasing the availability of charging infrastructures, on transportation emissions, are studied to explore the effectiveness of such policies and the interplay between policy and the external environment. This study contributes to prior work in EV policy literature by stressing the implementation effectiveness of policy as influenced by external factors such as population growth and electricity price. We apply a set of empirical panel data from 50 states and D.C. in the U.S. over a period of 10 years, identifying the key factors that have significant negative or positive impacts on transportation carbon emissions through an ordinary least squares (OLS) regression model. Our results show that the number of EV incentives, the number of charging stations, and the number of incentives on alternative fuels have beneficial impacts on transportation carbon emission reductions. We also find that external environmental factors such as higher population and higher electricity price dampen the effect of climate change mitigation actions.

Our study contributes from two perspectives. First, this work contributes to prior work by providing new robust evidence on the extent to which EV policies impact transportation carbon emissions, considering the interactions between EV incentives and external features. Second, our study is the first study that utilizes state-level panel data in the United States to investigate the relationships between policy implementation and transportation carbon emissions.

The rest of this article is outlined as follows. Section II describes three factors and two hypotheses relevant to the effectiveness of emissions reduction policies based on the existing literature. In Section III, we describe the data and methodology for our analysis. Then we present our data analysis results, discussion, and conclusions in Sections IV and V.

II. Theoretical Framework

In this section, we demonstrate the theoretical framework, discussing the conceptual and operational definitions of our studied variables. We also illustrate the pathway of the manner in which we develop and explain the principal factors and hypotheses affecting the implementation of emission reduction policies.

A. The Role of Charging Infrastructures

Due to the limited capacity of batteries, an adequate density of charging stations is extremely important to meet EV user mobility demands [25]. Previous research has examined barriers to EV adoption to show that more than 20% of participants are concerned with the charging infrastructures [26]. With a low density of charging stations or outlets, consumers tend to prefer conventional vehicles to EVs since "range anxiety" is a strong motivating factor for electric car shoppers. Consumers worry about the maximum distance that EVs can travel and whether EVs can successfully bring them to their destinations. Another empirical study demonstrated that charging infrastructure construction is positively correlated with EV adoption rates [27]. The higher density of charging stations shifts the preferences of shoppers toward EVs, as indicated by a higher EV adoption rate. One survey-based study found that free public charging infrastructures can effectively promote the willingness to pay (WTP), ultimately leading to higher EV acquisition rates [11]. Hence, an improvement in the density of charging infrastructures would advance EV adoptions.

Some studies highlight the fact that EVs can efficiently reduce GHG emissions [28]. For example, one study applies an energy system model to analyze the role of EVs in India [29]. The authors found that EVs can efficiently benefit CO_2 mitigation and that a higher EV penetration rate can also improve urban air quality. In another study, a two-stage data-driven framework was developed to show that a higher EV adoption would be beneficial to carbon emissions [30]. The result showed that only a 5–10% increase in EV penetration rate would lead to a 40% reduction in energy consumption and a 25% reduction in GHG emissions. Yet another study explored the actual amount of emission reductions that electric vehicles can provide by designing different scenarios in terms of the location and time that the EV is charged [31]. The analysis demonstrated that the widespread use of workplace charging is expected to reduce emissions associated with electric vehicles. That study also considered the rebound effect of EV adoption dealing with the possibility that more CO_2 emissions could be produced by electricity generation than those that are reduced by EV adoption. The results demonstrated that, while power generation could cause more carbon emissions, a higher EV penetration rate would still lower total carbon emissions. Thus, an increase in the count of charging infrastructure will improve the adoption rate of EVs, ultimately leading to reductions in CO_2 emissions, especially in the transportation sector.

Factor 1: Higher densities of charging stations lead to lower local transportation carbon emissions.

B. The Role of EV Incentives

Electric vehicles are often promoted as a symbol of clean energy and a significant component to reduce transportation sector carbon emissions. Despite these benefits, EV adoption is still confronting some barriers, such as high purchase prices, reliability, and driving distance. To overcome these challenges and improve the adoption rate, the federal government or entities at the state level have experimented with various types of policies to stimulate the desire of consumers to purchase EVs. Such policies include various types of incentives, such as exemptions from registration taxes, free public parking, toll exemptions, and purchase rebates [12]. Most previous studies have estimated EV market share changes due to EV incentives. For example, a regression model was developed to explore the impact of tax rebates on EV market share in Canada [32]. The result of the study found that an implied tax rebate would generate 25% more EV market sales. Similarly, another study investigated the difference in impact on EV adoption among different incentives [33]. The results demonstrated that different incentives play the same role in EV adoption. These studies all show that the implementation of EV incentives can efficiently increase the EV penetration rate. However, the dummy variable, used to represent the implementation of EV incentives in their models, can only capture some aspects of the impact of policy but is not comprehensive. In our study, we operationalize the various levels of EV policy of each state as the count of incentives enacted by the state-level government and posit that has a positive relationship with EV adoption, indicating the higher count of incentives, the higher the emission reductions. Similar approaches have shown that incentives or policies could act to stimulate investments or direct the adoption of new technologies [21], [34], [35].

Moreover, existing literature demonstrates the positive effect of EVs on carbon emission reductions. For example, a study modeled the CO_2 emissions from EV and plug-in hybrid electric vehicles (PHEV) in comparison with conventional vehicles [36]. The results demonstrated that EVs and PHEVs have the advantage to reduce the CO_2 emissions from automotive transport unless the country undertakes a major decarbonization of power generation. This study confirmed that the higher the EV penetration rate, the greater is the gain the carbon emission reductions. Another research effort highlighted the projection of EV penetration rates considering economic factors [37]. It found that a higher level of fleet electrification becomes increasingly important to achieve decarbonization. Therefore, a higher number of incentives that are positively associated with EV market share can increase rates of EV adoption. Since higher usage of EVs can efficiently reduce transportation carbon emissions, we posit that a higher number of EV incentives may result in higher transportation emission reductions.

Factor 2: Higher numbers of EV incentives lead to local transportation carbon emission reductions.

C. The Role of Alternative Fuel Incentives

Alternative fuels in our context indicate that clean fuel is used for transportation, such as hydrogen and biomass [38]. These fuels serve are intended to substitute for more carbon-intensive energy sources, like gasoline, petroleum, and diesel, and contribute to decarbonization in the transportation sector and reductions in air pollution [39]. Unlike EV incentives, alternative fuel incentives do not directly affect EVs. The clean fuels consumed by conventional combustion engines do not emit as much GHG as fossil fuels. Prior research confirms that consuming alternative fuels would emit less GHG than gasoline [40]. For example, one study reviews research from 2015–2020 to analyze the technologies regarding pollution and emissions [41]. The study finds out that alternative fuels, particularly biomass, and biodiesel, are the most capable of reducing carbon emissions. In addition, compared to using fossil fuels, conventional combustion engines rely on clean fuels and can help reduce the significant amount of carbon emissions as well. Similarly, alternative fuel vehicles can also offer considerable benefits to GHG emission reductions.

Moreover, previous studies suggest that alternative fuel incentives would significantly influence the market share of alternative fuel vehicle adoptions, resulting in reductions in transportation carbon emissions [42], [43]. The results illustrate that a lower price of alternative fuel stimulates the consumers' WTP for clean energy vehicles. Another study also investigates the implication of alternative fuel regulations, using text mining and negative binomial (NB) regression, to show that alternative fuels can help to reduce carbon emissions [44]. However, they also find out that alternative fuel incentives might hinder EV acquisition. In summary, more clean fuels consumed are equivalent to the lower consumption of fossil fuels, which is still conducive to transportation carbon emission reductions eventually. Thus, we posit that alternative fuel incentives would be negatively associated with transportation carbon emissions, indicating that the higher count of alternative fuel incentives, the higher the emission reductions.

Factor 3: Higher numbers of alternative fuel incentives tend to reduce local transportation carbon emissions.

D. Population Growth and the Effect of EV Incentive

The interaction between the impact of EV incentives and population size is captured on different levels of incentives. EV incentives in our study are measured by the number of EV-related policies regardless of type. We posit that, while they contribute to promoting EV adoption, the effectiveness of EV incentives may be dampened by population growth. On the one hand, larger populations may wider variety of consumer behavior types [45]. For example, while the IRA provides consumers a credit of up to US$7,500, consumers need to satisfy several requirements about batteries or other characteristics to redeem the tax credits. As population increases, consumers may have numerous types of preferences for vehicle selections due to different types of cultural backgrounds or personalities [46]. Various purchase preferences may lead consumers to be more willing to purchase conventional vehicles if EVs cannot satisfy their desires or if consumers are not familiar with EVs. Another study investigated transportation structures associated with transportation emissions to show that a higher population would lead to diverse motorization pathways, which could escalate transportation emissions [47].

Other existing efforts also found that population growth is one of the main factors driving transport sector CO_2 emissions growth [48], [49]. For example, one study applied an econometric model to show that an increase in population growth can yield environmental degradation and transportation emissions in Pakistan [50]. Another empirical study confirmed that population size is positively correlated with carbon emissions [51]. Population growth is the most important factor contributing to transportation carbon emissions, which is negatively associated with the impact of EV incentives on emission reductions. In addition, a larger population requires a greater need for transportation, no matter whether these people rely on public transportation or private conventional vehicles. While EV incentives benefit CO_2 emission reductions, population growth offsets such reductions, yielding more CO_2 emissions than would be the case with stable population levels. Hence, we posit that population growth dampens the effect of EV incentives on transportation emissions.

Hypothesis 1: Larger population sizes tend to dampen the effects of carbon emissions reduction incentives.

E. Electricity Price and the Effect of EV Incentive

The interaction between the impact of EV incentives and electricity price is captured on different levels of incentives. Prior work suggests that electricity price would not only influence the spatial distribution of EV owners but also EV adoption rates [52]. For example, one study used questionnaire surveys and structural equation modeling (SEM) to investigate the factors affecting EV adoption in India [53]. They found that, in addition to incentives, such as exemption of road taxes, registration fees, free parking fees, and toll charges, lower electricity tariffs, and higher gasoline prices, may attract more consumers to purchase EVs, since consumers always need to consider the fuel cost of the vehicle in addition to the original purchase cost. The electricity price significantly impacts the willingness of consumers to buy EVs. Similarly, electricity price is considered one part of the operational cost. The level of maintenance cost also significantly affects consumers' WTP [54]. This study also highlighted that people are more willing to purchase vehicles with lower operational costs because compared to the investment cost, the operational cost is a big portion of the total life-cycle cost for a vehicle.

Furthermore, a relatively low electricity price is equivalent to relatively high conventional fuel prices for consumers. Some previous studies confirm that fuel prices are highly associated with commuting behavior [55], [56]. For example, one study used OLS regressions to show that gasoline prices are one of the most important factors to determine commuting modes [57]. With higher fuel costs, people are more willing to use more public transportation tools to save on commuting costs, such as buses or metros, instead of driving private vehicles. Similarly, higher fuel prices may reduce the usage of conventional vehicles, which is reflected by the average fuel consumption [58]. Consumers are less motivated to use or purchase an EV in a low fuel-price period. Conversely, consumers are more willing to purchase EVs when the electricity price is low. Hence, we posit that high electricity prices reduce the effects of EV incentives on transportation emission reductions, indicating that EV incentives is weakened.

Hypothesis 2: Higher electricity prices tend to dampen the effectiveness of carbon emissions reduction incentives.

F. Relationship Between Factors and Hypotheses

This study sheds light on the effectiveness of differing provisions of environmental policy, such as direct and indirect incentives that stimulate people to use more clean energy. Fig. 1 presents an overview of the hypotheses.

In the context of this article, the factors are treated as pseudohypotheses that are often generally known facts, but are required as substrates on which the main hypotheses are based. Thus, the development of charging infrastructures is an important external driver that helps us to reduce transportation carbon emissions (F1). The EV incentives contribute to the reductions of transportation carbon emissions (F2). Alternative fuels, such as clean fuels, are also beneficial to carbon emission reductions (F3). However, as population grows, stable levels of EV incentives are less effective (H1). Similarly, the efficacy of EV incentives is influenced by the fluctuation of electricity price (H2).

III. Methodology

In this section, emphasis is placed on the data collection including sources of data and the regression model. In the regression model, the variables are differentiated as dependent, explanatory, and control. The following sections provide more details.

A. Data Collection This study applies empirical data to evaluate the effect of different policies and external environmental features on the carbon emissions from the transportation sector across 10 years, from 2010 to 2019. We collected data from various sources, such as EIA, Office of Energy Efficiency and Renewable Energy (EERE), the US Census Bureau, and the Transportation Energy Data Book (TEDB). The policy data obtained from TEDB indicates the number of incentives in seven major provisions. We do not rely on dummy variables as do some previous studies, since dummy variables cannot accurately reflect the degree to which an ACT can influence emission reductions. Therefore, this study uses the count of incentives to capture the levels of the impacts of policy. Since our analysis unit is the state, the policy data are reflective of state-level policies without taking into account federal policies. The dataset also contains the socio- and macroeconomic features that are highly associated with transportation carbon emissions.

Data for the dependent variable, transportation carbon emissions by state (in millions of tons), were collected from EIA. Explanatory variables we considered include policy data, socioeconomic features, and other control variables. Policy data include various types of incentives, such as for hydrogen, ethanol, natural gas, and EVs. Socioeconomic factors include population size, median household income, electricity price, and gasoline price. Population size represents the size of the state, which has a significant impact on carbon emissions [59], so it is chosen as a control variable. Median household income, electricity price, and gasoline price indicate the citizens' consumption behavior, which may influence commuting behavior, ultimately impacting carbon emissions. We also include the number of charging stations and the number of public vehicles, which capture the impacts of external drivers on transportation emissions. The details of both dependent and independent variables are presented in Table 1.

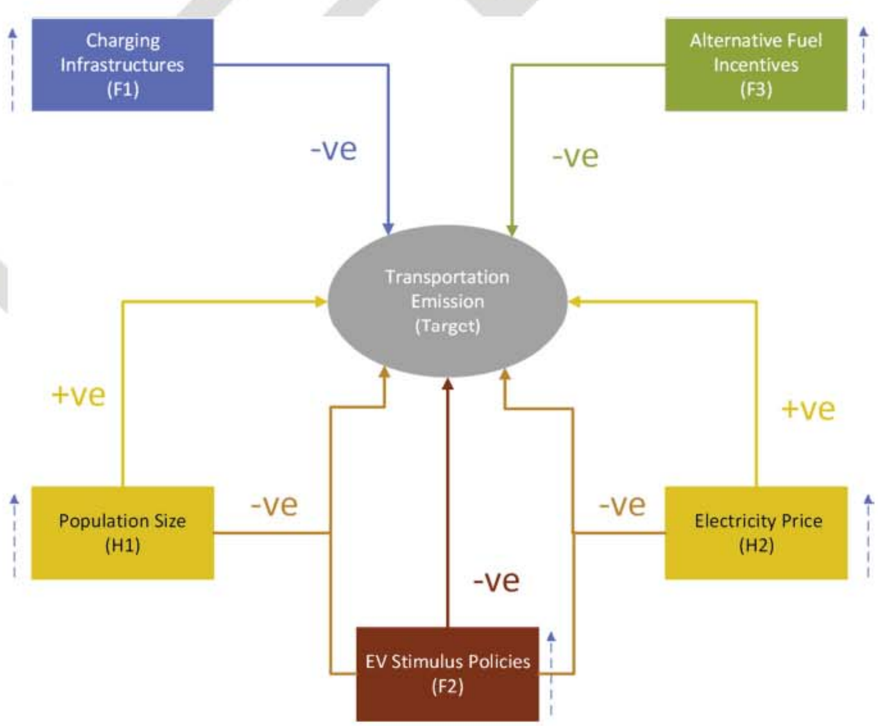

Figure 1. Snapshot of the hypotheses structure.

B. Regression Models The variables from Table 1 are incorporated into an OLS regression model to analyze the effectiveness of different categories of incentives. OLS regression is a type of linear regression method for identifying the unknown parameters in a linear regression model by the principle of least squares, which means minimizing the sum of the squares of the differences between the observed dependent variable in the input dataset and the output of the function of the independent variable. The equation of OLS regression is shown below in

$$\begin{aligned} EM_{i,t} = {} & \beta_1 MHI_{i,t} + \beta_2 EP_{i,t} \\ & + \beta_3 GP_{i,t} + \beta_4 POP_{i,t} \\ & + \beta_5 CS_{i,t} + \beta_6 PVR_{i,t} \\ & + \beta_7 BIO_{i,t} + \beta_8 EV_{i,t} \\ & + \beta_9 NG_{i,t} + \beta_{10} LPG_{i,t} \\ & + \beta_{11} HY_{i,t} + \beta_{12} ET_{i,t} \\ & + \beta_{13} AFC_{i,t} + \beta_{14} EV_{i,t} \\ & * POP_{i,t} + \beta_{15} EV_{i,t} \\ & * EP_{i,t} + \epsilon_{i,t} \end{aligned} \tag{1}$$

where $EM_{i,t}$ represents the amount of carbon emissions for state i at year t. The explanatory variables are $CS_{i,t}$, $EV_{i,t}$, and $HY_{i,t}$, while we control for income, electricity and gas prices, population, count of public vehicle, and other types of incentives. The vector of $\overline{\beta}$ are the coefficients of the independent variables. $EV_{i,t} * POP_{i,t}$ and $EV_{i,t} * EP_{i,t}$ represent the interaction between EV incentives and population, and EV incentives and electricity price for Hypothesis 1 and 2. ϵ is the error term to capture the internal variations.

Model 1 describes and shows the result of testing Factor 1, i.e., evaluating the role of charging infrastructure. The variable, number of charging stations, is included and other variables are used as controls, i.e., median household income, electricity price, gas price, population, number of public vehicles, number of biofuel incentives, number of natural gas incentives, number of LPG incentives, and number of ethanol incentives. Model 2 tests Factor 2, the role of EV incentives on emission reductions, by adding an EV incentives variable to Model 1. In Model 3, alternative fuel incentives variable is included to justify Factor 3. Model 4 sets up the test of the first hypothesis whether population growth dampens the effect of EV incentives (H1) with the inclusion of an interaction term, EV incentives and population, to Model 1. Model 5 separately includes another interaction term, EV incentives and electricity price, to Model 1 to test the second hypothesis on how different levels of electricity price influence the effect of EV incentives on emission reductions (H2).

IV. Results

Table 2 shows the correlation matrix of the variables. Carbon emissions strongly correlate with population and the number of public vehicles. Economic factors, such as household median income, electricity price, and gasoline prices, negatively correlate with carbon emissions. In addition, we also calculate the variance inflation factor (VIF) for our selected parameters. A VIF greater than ten signals multicollinearity. We only have one factor, gasoline price, which is slightly greater than 10, which we deemed to be acceptable [60]. Table 3 presents the outcomes of the OLS regression model 1-5, indicating the separate regression models that test Factor 1-3 and Hypothesis 1-2, respectively. We are able to assess the magnitude of the effect based on the sign and statistical significance of the variables' coefficients.

A. Effects of Control Variables

We discuss control variables in Table 3, Model 1, and compare their effects with those in other models. In Table 3, the coefficient of population size ($\beta = 4.415-4.617, p < 0.01$) and the number of public vehicles ($\beta = 0.094 — 0.099, p < 0.01$) are both positive with a p-value close to 0. This finding implies that the population of a state and the number of public vehicles significantly affect the amount of carbon emissions. Similarly, these two factors that are positive and significant in Models 2–5 indicate the

TABLE 1. Variables Summary

Variables	Description	Unit	Source
Dependent	Transportation sector Carbon emissions (EM)	Million Tons	EIA
Independent	Median Household Income (MHI)	thousand \$	US Census Bureau
	Transport Electricity Retail Price (EP)	¢$/kwh$	EIA
	Gas Price (GP)	$\$/MMBtu$	EIA
	Population (POP)	Million	US Census Bureau
	Number of Charging Station (CS)	Count	US DOE
	Public Vehicle Registration (PVR)	Count	TEDB
	Incentives on Biodiesel (BIO)	Count	TEDB
	Incentives on EV (EV)	Count	TEDB
	Incentives on Natural Gas (NG)	Count	TEDB
	Incentives on Liquefied Petroleum Gas (LPG)	Count	TEDB
	Incentives on Alternative Fuel (ALF)	Count	TEDB
	Incentives on Ethanol (ET)	Count	TEDB
	Incentives on Aftermarket Conversions (AFC)	Count	TEDB

TABLE 2. Correlation Analysis

	EP	MHI	EP	GP	POP	CS	BIO	ET	NG	LPG	EV	ALF	AFC	PUB
EP	1.00													
MHI	-0.03	1.00												
EP	-0.02	0.46	1.00											
GP	-0.06	-0.12	0.17	1.00										
POP	0.97	0.01	0.05	-0.03	1.00									
CS	0.44	0.13	0.10	0.03	0.49	1.00								
BIO	0.34	-0.12	-0.13	0.06	0.35	0.21	1.00							
ET	0.31	-0.16	-0.13	0.10	0.32	0.18	0.84	1.00						
NG	0.61	0.04	-0.07	-0.05	0.61	0.42	0.46	0.41	1.00					
LPG	0.52	-0.02	-0.09	-0.04	0.53	0.37	0.53	0.44	0.91	1.00				
EV	0.55	0.37	0.19	0.01	0.62	0.52	0.41	0.33	0.72	0.67	1.00			
ALF	0.55	0.13	0.17	0.10	0.62	0.48	0.53	0.42	0.81	0.80	0.84	1.00		
AFC	0.43	0.10	-0.06	-0.09	0.42	0.31	0.33	0.39	0.66	0.53	0.46	0.47	1.00	
PUB	0.91	-0.01	-0.01	-0.02	0.91	0.56	0.39	0.33	0.62	0.55	0.61	0.63	0.39	1.00

importance of the levels of population and quantities of vehicle in reducing carbon emissions. With a lower level of population or public vehicles, the emissions from the transportation sector are reduced, which confirms the findings of existing literature. The economic factors, such as, income ($\beta = -0.073$––0.015, $p > 0.1$) electricity price ($\beta = -0.145$–0.0778, $p > 0.1$), and gasoline prices ($\beta = -0.792$––0.183, $p > 0.1$) are negatively related to the emissions in the models, except for electricity price in Model 3 (electricity price is insignificant in all 5 models). This might be caused by the implementation of EV and alternative fuel incentives, which leads to a change in the economic environment. However, electricity price does not have significance in any models. For income ($\beta = 0.026$, $p > 0.1$) in Model 2 and 5, the positive coefficient is caused by considering the EV incentives and interaction with electricity price. We also find that the variable, aftermarket conversion ($\beta = 1.011 - 1.198, p < 0.051$), is positive with a low p-value in all five models. This finding implies that the behavior of vehicle or engine modification would significantly influence transportation carbon emissions since people who like conversions always convert their engines to a higher horsepower, which may increase the level of emissions [61]. This result also suggests that policies benefiting engine conversions are not favorable to emission reductions.

B. The Significance of Factors and Hypotheses

Factor 1 predicts that an increase in EV-related infrastructure would reduce transportation emissions. We find that the number of charging stations has a negative coefficient and is significant ($\beta = -0.0024, p < 0.05$) in Model 1, demonstrating Factor 1. This means an increase in charging stations leads to carbon emission reductions from the transportation sector. This result holds true in Models 1–5 by providing a negative regression coefficient and p-values less than 0.05.

Factor 2 states that EV incentives would have a positive impact on transportation carbon emission reductions. As shown in Table 3, the EV incentives have a negative regression coefficient with a low p-value close to 0 ($\beta = -0.53, p < 0.05$). This result demonstrates Factor 2 that more EV-related incentives would reduce transportation carbon emissions. In other words, enacting more EV incentives can effectively reduce transportation carbon emissions, indicating that EV incentives could be effective tools to mitigate the impacts of climate

TABLE 3. Regression Results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Median Household Income	-0.073	0.026	-0.015	-0.015	0.026
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Electricity Price	-0.145	-0.156	0.0778	-0.164	-0.156
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Gasoline Price	-0.792**	-0.30	-0.192	-0.183	-0.300
	(0.27)	(0.28)	(0.27)	(0.28)	(0.26)
Population	4.415***	4.591***	4.579***	4.617***	4.591***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)
Public vehicles	0.095***	0.094***	0.098***	0.0995***	0.094***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Biofuel	-0.431*	-0.292	-0.0391	-0.319*	-0.292
	(0.19)	(0.19)	(0.19)	(0.19)	(0.18)
Natural Gas	-0.084	0.237	0.49*	0.354	0.237
	(0.24)	(0.24)	(0.24)	(0.24)	(0.23)
LPG	-0.010	0.158	0.657*	-0.069	0.158
	(0.31)	(0.30)	(0.32)	(0.32)	(0.30)
Ethanol	0.141	0.170	0.010	0.149	0.170
	(0.19)	(0.18)	(0.18)	(0.18)	(0.18)
AF-Conversions	1.198***	1.075**	1.011**	1.069**	1.075**
	(0.35)	(0.34)	(0.34)	(0.34)	(0.33)
Charging Stations	-0.0024***	-0.0019***	-0.00184***	-0.001***	-0.00196***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
EV		-0.5317***	-0.1955**	-0.3231*	-0.5311**
		(0.086)	(0.099)	(0.123)	(0.26)
Alternative Fuel			-1.421***		
			(0.23)		
EV * POP				-0.0077**	
				(0.003)	
EV * EP					-0.000002
					(0.014)
R^2	0.955	0.958	0.964	0.958	0.962
N	510	510	510	510	510

Standard Errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

change. This result stays consistent in other models. These findings thus illustrate the impact of Factor 2.

Factor 3 predicts that policies on alternative fuel reduce transportation emissions. For Model 3, we add an explanatory variable, compared with Model 2, representing the number of alternative fuel incentives. The regression result reflects a negative coefficient and *p*-value close to 0 ($\beta = -1.421, p < 0.05$). This finding implies that the effect of clean fuel incentives would significantly influence transportation carbon emissions, demonstrating Factor 3. Compared with the results from Model 2, we obtain one interesting finding, that is the coefficient of EV incentives becomes higher but still negative. This result shows that an increase in the count of EV incentives would result in emission reductions, which implies the impact of EV incentives on emission reductions is weakened by the implementation of alternative fuel incentives. This is because people might choose to use alternative fuel vehicles instead of EVs.

Hypothesis 1 indicates that population growth dampens the effect of EV incentives. We add an interaction term, EV incentives, and population, based on Model 2 to develop Model 4. The coefficient of the interaction term is negative and significant ($\beta = -0.0077, p < 0.05$). We also compare the value of EV incentives in Model 2 with that in Model 4 ($\beta = -0.323, p < 0.05$). The coefficient of EV incentives in Model 4 is greater without considering population interaction, indicating that an increase in the count of EV incentives would result in less emission reductions. This result implies considering the interplay between EV incentives and the population would lead to a weakened effect of EV incentives on emissions reductions. This observation demonstrates Hypothesis 1.

Moreover, we graphed the interaction effect, as shown in Fig. 2. According to the figure below, for both high-count and low-count incentives lines, populations are positively related to transportation emissions. In other words, regardless of the count of incentives, as the population grows, transportation emissions increase.

These two lines intersect with each other at the moderate population level. When the population size is low, the high count incentives line is above the low-count line, indicating that more count of incentives can reduce more carbon emissions. In contrast, the high-count line goes above the lower count line. This result shows that the effect of EV incentives is dampened by the population growth. In other words, a higher

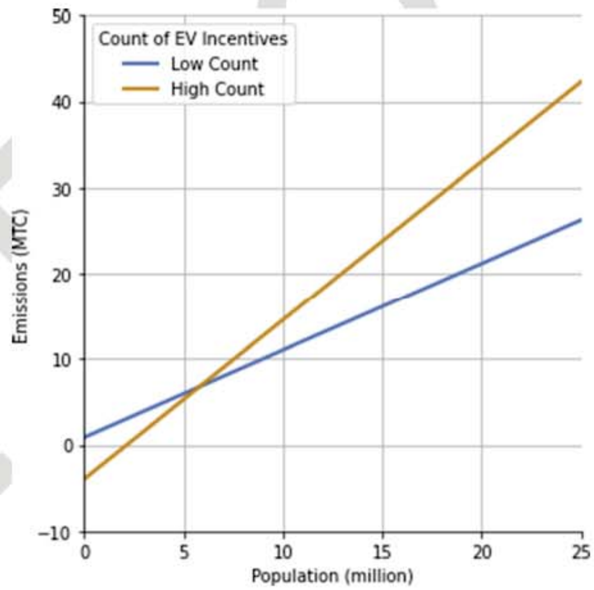

Figure 2. Interaction effect between the count of EV incentives and the population growth.

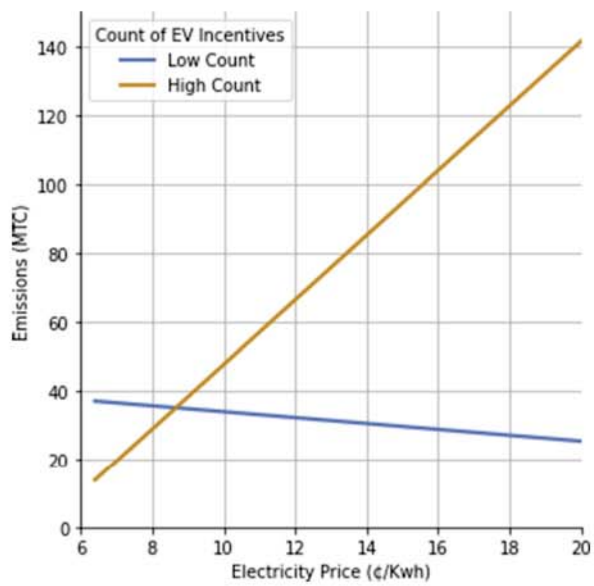

Figure 3. Interaction effect between the count of EV incentives and the Electricity Price.

count of incentives does not reduce carbon emissions as it is supposed to. This result also demonstrates Hypothesis 1.

Hypothesis 2 states that higher electricity prices dampen the effect of EV incentives on emission reductions. In Model 5, we test our hypothesis by interacting the EV incentives with electricity price, indicated by adding another interaction term to Model 3. The coefficient of the interaction term is negative but insignificant ($\beta = -0.000002, p > 0.1$). Comparing the value of the coefficient of EV incentives between the two models, the coefficient of EV incentives in Model 5 is higher than the one in Model 2. This finding implies an increase in the count of EV incentives would result in less emission reductions. This result also indicates a high count of EV incentives does not maintain the same level of carbon emission reductions, considering the effect of higher electricity prices. This result supports this hypothesis, indicating that higher electricity prices would lead to more conventional vehicle usage, ultimately increasing transportation emissions.

In addition, according to the interaction plot shown in Fig. 3, the low count line has a negative slope. It shows that the electricity price is negatively, but very slightly, related to carbon emissions. Even as the electricity price increases from \$0.06/kWh to \$0.20/kWh in 3, the amount of emissions barely changes. This finding also demonstrates Factor 2 indirectly, showing that a low count of incentives is not effectively beneficial to emission reductions. Conversely, the high count line has a positive slope. The higher the electricity price, the higher the carbon emissions. When the electricity price is low, high-count incentives reduce more emissions than low-count incentives. When electricity price increases, the impacts of low count of incentives one carbon emissions are not sensitive to high electricity price, but the high-count incentives do not reduce emissions as they perform when electricity price is low. This finding implies that as the electricity price increases, the effect of EV incentives is dampened, demonstrating Hypothesis 2. These results provide information to policy makers that increasing the amount of EV incentives is most effective in reducing emissions when electricity is relatively cheap for consumers.

C. Robustness Test

We estimate several robustness tests as presented in Table 4 for Models 1–5. First, we re-estimate each model using only the subsample chosen randomly from the whole dataset [62].

TABLE 4. Robustness Test Results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Median Household Income	-0.103 (0.06)	0.015 (0.07)	-0.048 (0.07)	-0.040 (0.07)	0.015 (0.06)
Electricity Price	-0.141 (0.16)	-0.266 (0.15)	0.086 (0.15)	-0.176 (0.24)	-0.284 (0.15)
Gasoline Price	-0.654* (0.34)	-0.05 (0.35)	-0.081 (0.35)	-0.088 (0.35)	-0.144 (0.33)
Population	4.290*** (0.17)	4.781*** (0.17)	4.471*** (0.17)	4.477*** (0.17)	4.479*** (0.16)
Public vehicles	0.115*** (0.01)	0.112*** (0.01)	0.112*** (0.01)	0.116*** (0.01)	0.111*** (0.01)
Bio-fuel	-0.569** (0.24)	-0.424 (0.24)	-0.132 (0.24)	-0.422** (0.24)	-0.361 (0.23)
Natural Gas	-0.405 (0.29)	0.749 (0.30)	0.293 (0.30)	0.076 (0.30)	-0.033 (0.29)
LPG	-0.334 (0.39)	0.383 (0.37)	0.969*** (0.39)	-0.202 (0.39)	0.456 (0.37)
Ethanol	-0.037 (0.23)	0.116 (0.23)	0.144 (0.23)	0.276 (0.23)	0.129 (0.22)
AF-Conversions	1.832*** (0.43)	1.607*** (0.42)	1.501*** (0.42)	1.604*** (0.42)	1.624*** (0.40)
Charging Stations	-0.0027*** (0.0004)	-0.0022*** (0.0004)	-0.002*** (0.0004)	-0.002*** (0.0004)	-0.0022*** (0.0004)
EV		-0.483*** (0.086)	-0.093 (0.120)	-0.292** (0.104)	-0.680** (0.337)
Alternative Fuel			-1.607*** (0.28)		
EV * POP				-0.0066** (0.004)	
EV * EP					0.01 (0.017)
R^2	0.957	0.961	0.964	0.962	0.961
N	375	375	375	375	375

Standard Errors in parentheses; $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The results presented in Model 1 and Model 2 are consistent with those in the main model, showing that all coefficients remain in the same direction and significance. In Model 3, all the results are consistent with the outcomes from the main model. In Model 4, the results are mostly consistent with those in the main model. Only the *p*-value of biofuel incentives becomes lower, so it still remains significant. Besides, the *p*-value of EV incentives becomes smaller, which indicates the significance level of EV increases. Similarly, in Model 5, only the coefficient of incentives for natural gas changes from negative to slightly negative. This might be caused by the random selection of samples. Overall, only the coefficients of incentives for natural gas are slightly sensitive to the sample size, but their insignificance remains consistent through all models. This finding indicates that this predictor does not seem to influence the transportation emissions in our sample.

V. Discussion

In this section, we discuss our findings and their implications. The interpretation of results is presented based on the order of factors and hypotheses. We also provide some insights and recommendations for policy-making.

The density of charging stations, as an important factor in improving the adoption of EVs, has a significant impact on transportation CO_2 emissions. Increasing the number of charging stations properly addresses the consumer concerns about the distance an electric vehicle (EV) can travel on a single charge, called "range anxiety." This is one of the biggest barriers that prevent consumers from purchasing EVs, since consumers worry about the maximum distance an EV can travel and fear getting stranded. Consequently, our results demonstrate a significant negative relationship between the density of charging stations and CO_2 emissions.

Alternative fuels or clean fuels, such as hydrogen, are important components in efforts to mitigate climate change. Clean fuels do not affect the adoption of EVs directly, but they do contribute to emission reductions in that their usage leads to less GHG emissions than fossil fuels. Providing tax credits for alternative fuels can motivate consumers to use more clean energy and rely less on conventional vehicles, ultimately leading to reductions in carbon emissions. Our results show that the number of alternative fuel incentives has a negative relationship with CO_2 emissions and is statistically significant. However, policymakers should realize that the effectiveness of EV incentives, as shown in Model 3, is reduced. This indicates that the impact of EV incentives on mitigating CO_2 emissions might be dampened in the face of alternative fuel incentives since consumers then would be willing to use alternative fuel vehicles instead of EVs. The mitigation impacts of EV incentives on transportation emissions can be dampened by population growth as we have shown. While the interaction between EV incentives and population affects emission reductions, the positive impact of EV incentives on emission reductions is dampened by population growth. The higher the population, the higher the need for transportation, resulting in higher carbon emissions. Therefore, policymakers are encouraged to adjust policy enactments in correlation with population growth.

Our findings also imply that the positive impact of EV incentives on emission reductions is reduced by higher electricity prices. Electricity price is one of the major factors that affect consumers' preferences when choosing between EVs and conventional vehicles. Consumers are also more willing to purchase EVs when the electricity price is low or gasoline prices are high. Therefore, the guidance for policymaking is to enact EV incentives with the knowledge of the dampening effect of higher electricity prices.

VI. Conclusion

This article sheds light on how climate change mitigation policies and socioeconomic factors interact to influence emissions in the transportation sector. While prior research has explored the impact of EV incentives on EV market shares, less is known about the mixed outcome related to whether an EV incentive can ultimately achieve the goal of emission reductions. We link the policies' effectiveness to the ultimate goal of carbon emission reductions directly.

First, according to the outcomes from Model 1, we find that the number of charging infrastructures has a mitigation impact on transportation emissions. A reason for this finding is that building more charging stations would mitigate EV consumers' concerns, improving their willingness to buy an EV. As more EVs are adopted, less GHG is emitted due to the reduced usage of conventional vehicles. This finding suggests to policymakers that developing charging infrastructures can significantly reduce transportation carbon emissions. Besides initiating more EV incentives, building more charging stations is also a necessary step to mitigate carbon emissions from the transportation sector.

Second, we find that alternative fuel incentives are negatively related to transportation emissions. This result suggests a higher count of incentives for clean fuel can lower the carbon emissions from the transportation sector. The reason for this finding is that alternative fuels are clean fuels, that have low or zero emissions when combusting in vehicle engines. In addition, alternative fuel incentives also promote alternative fuel vehicle adoption, which can reduce transportation emissions compared to conventional vehicles. Even though the implementation of alternative fuel incentives may dampen the effectiveness of EV incentives, they both still contribute to reductions in transportation emissions, if combining these two types of policies.

Third, the results indicate that EV incentives have a beneficial impact on transportation emission reductions. This finding implies that a higher number of EV incentives would effectively reduce transportation emissions. However, based on the results from Model 4, the effect is dampened by population growth. Due to the qualified vehicle limitations under EV incentives, a larger variety of options on vehicle purchase negatively influences the adoption of EVs, that is unfavorable to emission reductions. Furthermore, population growth itself always has a positive and significant relationship with transportation emissions. Hence, population growth dampens the positive impact of EV incentives on emission reductions. This suggests that with a low population size, a high count of incentives can effectively reduce carbon emissions. However, in a larger population environment, the effectiveness of EV incentives is reduced.

Similarly, high electricity prices tend to reduce the positive influence of EV incentives on emission reductions as well. This finding is because higher electricity prices tend to shift consumers' preferences toward conventional vehicles. High electricity prices increase the operational cost of using an EV, which reduces the adoption of EVs since consumers might feel the energy cost of EVs is too high to afford. Moreover, the interaction effects also suggest that effective incentives need to combine with the low level of electricity prices. To be more specific, high-count incentives coupled with low electricity prices can be effective tools to reduce transportation carbon emissions.

Furthermore, the effectiveness of such CO_2 reduction policies, in terms of cost, is still of crucial importance that must be factored into consideration. This is because transportation policies promoting EVs generally tend to come with cost implications either to the individual consumer or the government [63]. Some contemporary studies show that by 2030, the cost of CO_2 abatement of EVs would have significantly increased to approximately \$200 per ton [64], [65]. This cost implication has been examined relative to the effectiveness of the policy as a function of the cost per unit CO_2 reduction in a metric referred to as "policy effectiveness index" [66]. This index is the ratio of the relative reduction in CO_2 emissions to the value of the incentive. There is no doubt that there are ample opportunities for research to further shed lights on the relative cost effectiveness of the policies and/or incentives as electrified mobility continues to rise.

Moreover, it is worth noting that prior research has examined the influence of incentives using different approaches. For instance, some studies assessed the effects of electric vehicle incentives, such as rebates, subsidies, income tax credits, excise tax credits, or sales tax exemptions, by quantifying their monetary value [11], [67]. Other studies treat incentives as a binary variable where the variable is taken as 1 if incentive is present or as 0 if incentive is absent (**12,** [43], [68]). In addition, as done in this study, some use the count of different incentives [8], [21]. This research examines the effects of EV incentives using the count approach based on the number of EV-related incentives. This option was adopted in this article because of the diverse characteristics of these incentives for two main reasons. First, some local governments offer EV incentives through tax credits for EV consumers, while others implement policies that indirectly support EV adoption, such as providing production or investment tax credits for EV charging stations. Second, this model employs panel data spanning a decade, therefore, the effects of monetary incentives vary depending on time and the prevailing economic conditions. Thus, determining a suitable reference point for the actual incentive amounts is challenging. While the count of incentives approach in this article did not account for the relative dollar amounts of the incentives, it does not diminish the aim of investigating the influence of such incentives given that there is time value of money differences, and the count is proportional to the magnitude of the incentives.

Our study obviously has practical implications for policymakers: Our findings imply that any incentives for EVs and alternative fuels could significantly contribute to transportation emission reductions. An increase in the amount of these incentives can lead to greater CO_2 emission reductions. However, the positive impact of such EV incentives on the reductions in CO_2 emissions can be dampened by population growth and high electricity prices. In addition, the development of clean energy infrastructure, such as constructing more charging stations, could also effectively reduce transportation emissions, since the primary concern of consumers, range anxiety, is properly addressed by increasing the charging density. This is consistent with the extant literature that demonstrates how policy could impact investments in clean technologies or provide accessories for the implementation of such technologies [35], [69], [70]. Finally, besides focusing on the policies surrounding EVs, alternative fuel incentives can also be an effective tool to mitigate transportation emissions. Overall, our findings suggest that, while EV incentives foster climate change mitigation in the U.S. transportation sector, the dampening effects of external drivers need to be considered in the implementation of such policies.

Acknowledgments

This work was partially supported by the U.S. National Science Foundation (NSF) under Grant 1847077. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF.

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