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Conference Paper

Access to Zero-Emission Vehicles for Low-Income and Disadvantaged Communities: Evidence from California

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ABSTRACT

This study assesses California's Clean Cars for All (CC4A) program, which seeks to improve access to clean-energy vehicles for low-income residents and reduce emissions. The research examines two questions: (1) How effective is CC4A in reducing greenhouse gas emissions and improving air quality? and (2) What factors influence participants' choice of vehicle type—conventional, hybrid, plug-in hybrid (PHEV), or zero-emission vehicle (ZEV)? Using participant data from the California Air Resources Board (n=3,497) from January 2022 to June 2023, the study applies multinomial logistic regression to identify car choice determinants. Findings indicate that CC4A effectively reduces emissions. Higher-income participants are more likely to choose ZEVs or PHEVs, while larger households tend to select conventional vehicles, likely due to limited ZEV options for larger family needs. Participants in disadvantaged communities show a preference for PHEVs over ZEVs, with notable geographic variation—Bay Area residents prefer ZEVs, whereas Central Valley residents favor PHEVs. Key limitations include data gaps, such as missing participant age and education data, and underrepresented geographic areas. The study concludes that while CC4A promotes clean transportation, further steps could enhance program impact. Recommendations include reducing cost barriers for ZEVs, expanding charging infrastructure in low-income areas, and increasing affordable ZEV options for larger households. These insights support policymakers in improving clean transportation access for underserved communities.

Keywords: Clean Cars for All (CC4A), Greenhouse gas emissions, Zero-emission vehicles (ZEVs), Clean-energy transportation, Emission reduction

Introduction

California, a state renowned for its commitment to environmental sustainability, has been at the forefront of the zero-emission vehicle (ZEV) movement. California's dedication to reducing greenhouse gas emissions and promoting clean energy solutions is exemplified through its stringent emissions standards and pioneering ZEV programs. The Zero Emission Vehicle (ZEV) program, first established in 1990, requires automakers to produce a certain percentage of ZEVs in their fleets (Axsen et al., 2022). This initiative has been a catalyst for innovation in the automotive industry, pushing manufacturers to invest in electric and hydrogen fuel cell technologies.

California leads the nation in the widespread adoption of electric vehicles (EVs). As of December 2022, California led the nation in electric vehicle adoption, with approximately 903,602 registrations for light-duty electric vehicles, constituting around 37% of all registered EVs nationwide (US Department of Energy, 2023). California's leading role in electric vehicle adoption, is reflected in high registration rates and a substantial national share, setting a notable example for the entire nation.

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While the environmental benefits of ZEVs are evident, significant barriers continue to hinder widespread adoption. The main barrier is the high upfront cost, which is particularly challenging for individuals in low-income and disadvantaged communities. To address this issue, programs like Clean Cars for All (CC4A) have been introduced, specifically designed to benefit those with low income and residing in disadvantaged communities. The CC4A provides incentives for low-income families in or near priority populations to adopt clean-energy transportation.

This study aims to examine the effectiveness of the Clean Cars for All program by addressing two key research questions: first, an evaluation of the program's environmental impact and sustainability (how clean is the Clean Cars 4 All program), and second, an exploration of the factors influencing the choice of car types by participants in the program. By examining these aspects, we seek to contribute valuable insights into the success and areas of improvement for initiatives aimed at promoting clean transportation in low-income and disadvantaged communities.

Program description

The Clean Cars 4 All Program, initiated by the California Air Resources Board (CARB), offers incentives to low-income families residing in or near priority populations to access clean-energy transportation. In collaboration with major air districts like South Coast AQMD, San Joaquin Valley APCD, Bay Area AQMD, Sacramento Metropolitan AQMD, and a forthcoming program with San Diego APCD, CARB aims to allocate funds specifically for disadvantaged communities.

Eligible participants must reside in California and have a household income equal to or less than 400% of the Federal Poverty Level. To enroll, individuals should apply through their local air districts and retire a functional vehicle used for less than 8 years. The incentive program encompasses conventional hybrids, plug-in hybrids, battery-electric vehicles, and fuel-cell vehicles.

Targeted recipients are divided into different categories and provided with different amounts of subsidies, perks, or face value. Also, the amount that they are qualified to accept is decided by the type of vehicle that they plan to scrap. For scraping conventional and hybrid vehicles less than 8 years, low-income households can receive $7,000, moderate-income households can receive $5,000, while households above moderate-income have no incentive amount. For scraping plug-in hybrids or zero-emission vehicles less than 8 years old, vehicle owners can acquire more subsidies, low-income households are available with $9,500, moderate-income households can get $7,500, and above-moderate-income households can obtain $5,500; besides the fundamental subsidies, they are also eligible to receive perks, for instance, home charger incentives or prepaid charge cards. In addition, participants can also choose to replace their older vehicles with alternative mobility options such as public transportation passes or electric bicycles; no matter which income level they belong to, they are all able to obtain $7,500 face value for vouchers.

Since the Clean Car 4 All Program was implemented in 2019, $436 million has been allocated, $105 million and 13,000 vehicles have been implemented. Over 48% of the total amount provides benefits for disadvantaged communities. Most essentially, the program has resulted in a reduction of 98,700 MTCO2e GHG, 104 tons of NO_x, 17.4 tons of ROG/HC, and 4.17 tons of PM (California Air Resources Board, 2023a).

Material and Methods

This study used the data set of the participant-level data of projects funded by EFMP Scrap and Replace and Clean Cars for All program (California Air Resources Board, 2023b). The data used in the analysis is the participant program from January 2022 through June 30, 2022 (n=3,497). To examine the predictors of the choice of car technology by CC4A participants, we use multinomial logistic regression methods. This model can be used to determine the probability of an independent variable, which is categorical data with more than two classes (James et al., 2023).

The goal of multinomial logistic regression is to model the odds of choice as a function of the covariates and express the results in terms of odds ratios (Hosmer & Lemeshow, 2000). The mathematical function of the model is provided in Equation (Axsen et al., 2022). The dependent variable, car technology, is categorized into three groups (Table 1). First, battery-electric vehicles and fuel-cell electric vehicles were combined into the zero-emission vehicles (ZEV) category. Second, plug-in hybrid vehicles (PHEV) were treated as a separate category. Third, conventional internal combustion engine vehicles and hybrid vehicles were grouped into the ICE/HYBRID category. By collapsing vehicle technologies into these three categories, we achieved relatively equal proportions across groups, ensuring the model's effectiveness. In testing our models, ICE/HYBRID was used as the reference category to interpret the odds ratios more meaningfully.

$$\ln = \left(\frac{P(Y=k)}{P(Y=1)}\right) = \beta_{0\mathrm{k}} + \beta_{1\mathrm{k}}X_1 + \beta_{2\mathrm{k}}X_2 + \ \dots + \beta_{\mathrm{kn}}X_{\mathrm{n}} \quad (1)$$

Where:
$P = (Y = k)$ probability of choosing vehicle type k
$X_1, X_2, \dots, X_{\mathrm{n}}$ Independent variables (e.g., income, household size, geographic location,)
$\beta_{0\mathrm{k}} + \beta_{0\mathrm{k}}, \beta_{1\mathrm{k}}, \dots, \beta_{\mathrm{kn}}$ Model parameters of vehicle type k

Table 1. Vehicle type categorization

Vehicle Types	freq.	%	New Category	freq.	%
BEV	823	23.53	ZEV	890	25.45
FCEV	67	1.92			
PHEV	1,313	37.55	PHEV	1,313	37.55
HYBRID	1,287	36.80	ICE/HYBRID	1,294	37.00
CONVENTIONAL	7	0.20			
Obs.	3,497	100.00		3,497	100.00

The dependent variables in we used in the models are related to socio-economic factors and geographic locations. The dependent variables that are related to socio-economic factors are income tier and household size. The income tier is an ordinal level of measurement which the respondents have an income tier of 225, 300, and 400. Because of they are ordinal in nature, we use the income tier 300 as a reference category. According to the requirements, California Residents whose household income is below 400% of the Federal Poverty Level are eligible to apply the incentive policy. Figure 1. shows that 82.8% of the participants have a household income below 225% of the Federal Poverty Level, 12.0% have a household income between 225% and 300%, and 5.2% have a household income higher than 300%, lower than 400%. For the household size, the variable is in discrete level of measurement. Both income tier and household size variables are used in the three models that we conducted.

We employed three models to examine the predictors influencing vehicle type selection in relation to geographic location. In the dataset, geographic-related variables include whether the participant resides in a disadvantaged community, a low-income community, within half a mile of a low-income community, or the specific county where the participant lives. In the first model, we analyzed whether being from a disadvantaged, low-income, or nearby low-income community increased or decreased the likelihood of selecting an electric vehicle (EV) as the chosen vehicle type. These variables were binary, with responses categorized as either "yes" or "no," reflecting the participant's location status. Figure 2. presents the map which is the area that are described by those characteristics.

In Models 2 and 3, we investigated whether geographic location influences the likelihood of selecting specific vehicle types (Table 2). In Model 2, county-level data was grouped into broader regional categories within California. For example, counties such as Alameda, Contra Costa, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma were categorized under the "Bay Area" region. This model analyzed the dataset using regional-level classifications, with the Greater Los

Angeles region serving as the reference category. In Model 3, the analysis was conducted at the county level, maintaining a more granular approach compared to Model 2. Similar to Model 2, Los Angeles County was used as the reference category to evaluate variations in vehicle type selection across different counties.

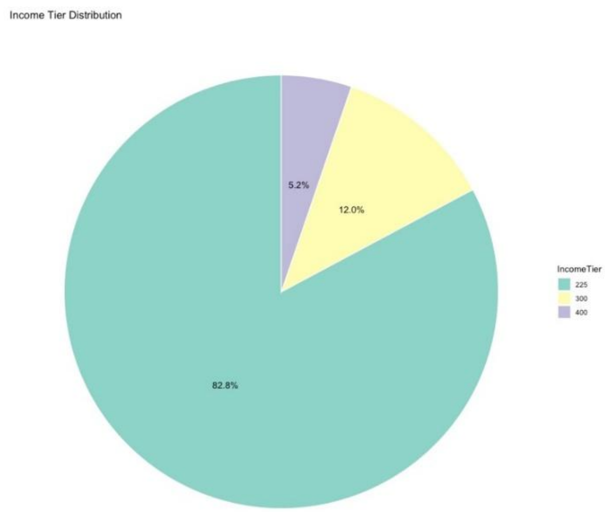
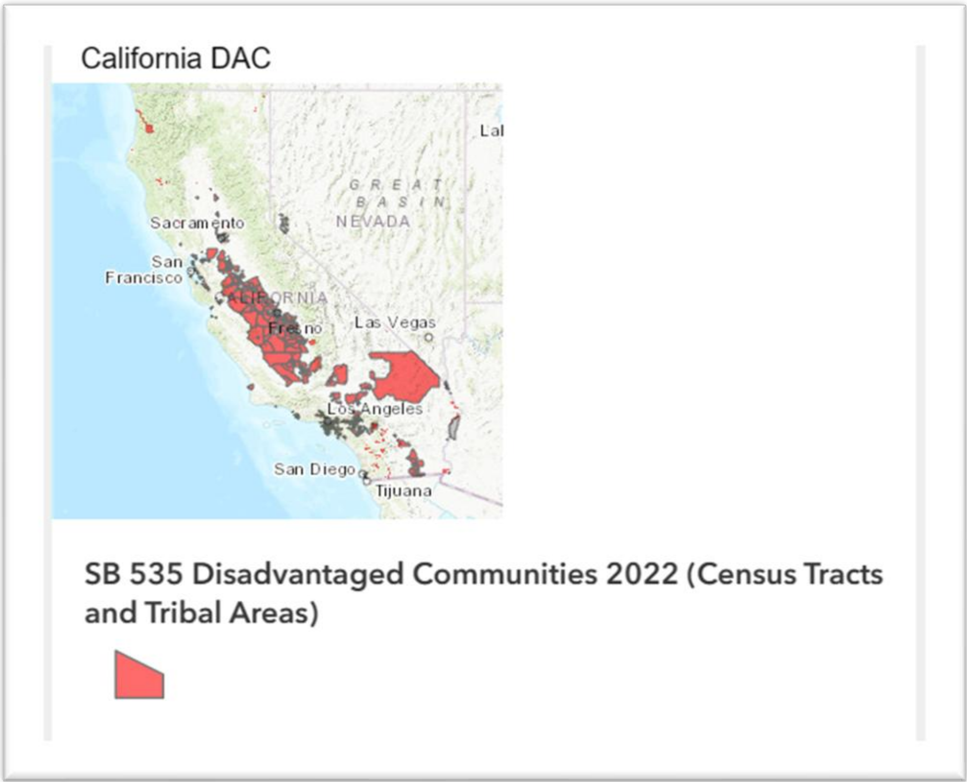


Figure 1. Pie chart of income tier distribution



Source: California Office of Environmental Health Hazard Assessment (California Office of Environmental Health Hazard Assessment (2022)

Figure 2. Maps of disadvantaged communities in California

Table 2. Categorization by area

Region (Model 2.)	freq.	%	County (Model 3.)	freq.	%
Bay Area	1169	33.43	Alameda	437	12.50
			Contra Costa	193	5.52
			Napa	1	0.03
			San Francisco	41	1.17
			San Mateo	40	1.14
			Santa Clara	432	12.35
			Solano	19	0.54
			Sonoma	6	0.17
Central Valley	952	27.22	Fresno	209	5.98
			Kern	131	3.75
			Kings	33	0.94
			Madera	46	1.32
			Merced	97	2.77
			San Joaquin	191	5.46
			Stanislaus	129	3.69
			Tulare	116	3.32
Greater Los Angeles	964	27.57	Los Angeles	639	18.27
			Orange	325	9.29
Inland Empire	126	3.60	Riverside	56	1.60
			San Bernardino	70	2.00
Sacramento Valley	286	8.18	Sacramento	286	8.18
	3497	100.00		3497	100.00

Results and Discussion

Results

Table 3. presents the outcomes of the three models. Holding other variables constant, transitioning from an FPL of 300 to 225 consistently leads to a statistically significant decrease in the log odds of opting for both ZEV and PHEV over ICE/HYBRID vehicles in all models, except for model 1 in the case of PHEV. Conversely, moving from FPL 400 to 300 generally results in an increase in the log odds of choosing ZEV and PHEV over ICE/HYBRID vehicles across the three models, all else being equal. The findings align with expectations, as individuals with higher incomes are more likely to adopt advanced technologies and being from lower income participants decrease the probability of getting PHEV or EV cars.

The other independent variable which is tested in these models are household size. In summary, the negative and statistically significant coefficients for household size across various models suggest that, holding other variables constant, larger household sizes are associated with a decrease in the dependent variable. However, the magnitude of this effect varies across models.

In Model 1, the remaining independent variables assess the likelihood of participants choosing from Disadvantaged Communities (DAC), Low-Income Communities (LIC), and High-Low Communities (HLC). Keeping all other variables constant, individuals from disadvantaged communities exhibit a decrease of 0.49 in the log odds of choosing ZEV over ICE/HYBRID. Conversely, they show an increase of 0.18 in the log odds of choosing PHEV over ICE/HYBRID. Additionally, individuals from low-income communities experience a decrease of 0.22 in the log odds of choosing PHEV. Notably, being from low-income half a mile is not statistically significant in influencing these vehicle choices.

Within Model 2, we explore predictors based on regional categorization, as detailed in Table 2. The reference category for the region is set as Greater Los Angeles. When compared to Greater Los Angeles, being in the Bay Area results in a significant increase of 1.3 in the log odds of choosing ZEV over ICE/HYBRID, with all other variables held constant. Similarly, under constant conditions, being in the Central Valley leads to a notable increase of 0.41 in the log odds of selecting ZEV over PHEV.

In model 3, we investigate predictors at the county level, with Los Angeles County serving as the reference category. When holding other variables constant, a comparison between participants from San Francisco and Los Angeles reveals a decrease of 1.03 in the log odds of acquiring PHEV compared to ICE/HYBRID. However, in the same conditions, there is an increase of 1.32 in the log odds of acquiring ZEV over ICE/HYBRID. Additionally, when holding other variables constant, the transition from participants in Santa Clara to those in Los Angeles results in an increase of 1.5 in the log odds of obtaining ZEV over ICE/HYBRID.

We evaluated the model fit through the Akaike Information Criterion (AIC) scores. Across three models, the AIC scores for models 1, 2, and 3 are 7,329, 6,966, and 6,947, respectively. A lower AIC indicates a better fit, and in this instance, model 3 exhibits the lowest AIC, signifying it as the best fit among the three models.

This study has two limitations that might need to be considered. First, the omitted variable bias within the model. The data set contains no personally identifiable information. However, in the context of this study, certain variables of interest such as age, and education attainment could prove instrumental in refining and enhancing the accuracy of the predictive model. Compilations with other data sets which contain such information will be useful for a robust analysis.

The second limitation of the study is that the low cells in model 3. For example, low observation in Napa County which has only one observation might penalize the result. This could elevate the likelihood of a type 1 error or false positive, where a finding appears statistically significant but may not be valid.

Table 3. Multinomial Logistic Regression Results

	Dependent variable:					
	PHEV	ZEV	PHEV	ZEV	PHEV	ZEV
	(1)	(2)	(3)	(4)	(5)	(6)
Income.Tier225	-0.171	-0.437***	-0.217*	-0.287**	-0.210*	-0.276**
	(0.125)	(0.134)	(0.126)	(0.138)	(0.127)	(0.139)
Income.Tier400	3.640***	3.879***	3.728***	3.852***	3.700***	3.833***
	(0.725)	(0.726)	(0.726)	(0.727)	(0.726)	(0.728)
Household.Size	-0.025	-0.136***	-0.057**	-0.101***	-0.062**	-0.104***
	(0.026)	(0.031)	(0.027)	(0.032)	(0.027)	(0.032)
DACYes	0.180**	-0.491***				
	(0.090)	(0.107)				
Low.Income.Community.Yes	-0.225*	-0.229				
	(0.136)	(0.159)				
Low.Income.Half.MileYes	0.122	-0.140				
	(0.116)	(0.143)				

To be continued…

RegionBay Area	-0.302***	1.308***		
	(0.109)	(0.119)		
RegionCentral Valley	0.417***	-0.187		
	(0.100)	(0.150)		
RegionInland Empire	0.610***	0.071		
	(0.209)	(0.317)		
RegionSacramento Valley	0.633***	1.486***		
	(0.169)	(0.184)		
CountyAlameda			-0.529***	1.197***
			(0.161)	(0.163)
CountyContra Costa			0.368*	1.653***
			(0.218)	(0.224)
CountyFresno			0.118	-0.504*
			(0.171)	(0.284)
CountyKern			0.441**	-0.823*
			(0.202)	(0.420)
CountyKings			0.783**	-15.485***
			(0.376)	(0.00000)
CountyMadera			0.641*	-0.161
			(0.332)	(0.574)
CountyMerced			0.707***	0.224
			(0.243)	(0.363)
CountyNapa			-12.289***	-9.864***
			(0.00000)	(0.00000)
CountyOrange			0.169	0.248
			(0.150)	(0.202)
CountyRiverside			0.691**	0.242
			(0.307)	(0.460)
CountySacramento			0.691***	1.572***
			(0.176)	(0.197)
CountySan Bernardino			0.650**	0.087
			(0.278)	(0.428)
CountySan Francisco			-1.037**	1.320***
			(0.524)	(0.365)
CountySan Joaquin			0.559***	0.734***
			(0.188)	(0.238)
CountySan Mateo			0.149	1.839***

To be continued…

					(0.474)	(0.427)
CountySanta Clara					-0.203	1.504***
					(0.161)	(0.166)
CountySolano					-0.456	0.653
					(0.591)	(0.574)
CountySonoma					0.981	2.406**
					(1.229)	(1.164)
CountyStanislaus					0.815***	0.360
					(0.219)	(0.317)
CountyTulare					0.388*	-2.022***
					(0.208)	(0.731)
Constant	0.175	0.647***	0.154	-0.644***	0.104	-0.730***
	(0.150)	(0.160)	(0.151)	(0.176)	(0.158)	(0.189)
Akaike Inf. Crit.	7,329.448	7,329.448	6,966.149	6,966.149	6,947.881	6,947.881
Note:	*p**p***p<0.01					

Discussions

The Clean Cars for All program contributes to the reduction of tailpipe emissions by removing old vehicles from the streets and replacing them with newer, cleaner technologies. It is important to note that while the replacements may not be entirely zero-emission, they represent a significant improvement over previous conditions in terms of environmental impact. Based on the data of the participants, only 25.45% of the participants falls under ZEV category. It is essential to recognize that the program is not explicitly intended to phase out the carbon economy.

While the significant upfront cost remains the most formidable obstacle, another issue is the insufficient public charging infrastructure, which continues to be a concern for individuals transitioning to electric vehicles (EVs), particularly those in low-income and disadvantaged communities. A prior study (Ledna et al., 2022) suggests that both subsidies for vehicle purchases and investments in public charging infrastructure can effectively expedite EV adoption.

The insights derived from this study offer valuable guidance for regions and counties with a lower likelihood of both ZEV and PHEV adoptions. Public charging infrastructure, serving as an alternative to home charging, is only necessary in certain densely populated areas (Funke et al., 2019). By strategically increasing charging infrastructure in low-income and disadvantaged communities, as well as in regions and counties with a lower likelihood of ZEV and PHEV adoption, accessibility to charging points can be improved, potentially overcoming a critical barrier to widespread EV adoption.

Another challenge is the disparity between homeowners and renters concerning in EV adoption. Homeowners are three times more likely to own an electric vehicle (EV) than renters (Davis, 2019). Because the number of renters in the U.S. reaches 36% of 122.8 million households in 2019 (Desilver, 2021). ZEV adoption in low-income and disadvantaged communities poses a significant barrier, particularly if most residents are renters rather than homeowners. The main barrier in ZEV adoption might be due to the impracticality of charging their vehicles. Landlords may be unwilling to upgrade their properties to accommodate level 2 (240 volt) charger, which is essential for EV users.

The study's findings reveal that an increase in household size is linked to a decrease in the likelihood of acquiring both PHEV and ZEV. This correlation may be attributed to the limited availability of 7-seater ZEV options in the market, particularly relevant for participants with families. For instance, a family of three may find a 5-seater vehicle sufficient, but larger families of 4 or 5, even if they fit into a standard car, express a desire for a 7-seater vehicle to accommodate additional space.

Supply-side policies can incentivize people to acquire EVs. Supply-side polices can be both supportive and restrictive (Paul & Moe, 2023). Supportive supply-side measures can include expanding the tax credits available for EV purchases. Currently, the tax credit for EVs is up to $7,500 for a new car and $4,500 for a pre-owned car (US Department of Energy, 2024). Expanding these tax credits can be achieved in three ways. First, by increasing the total incentive amounts beyond the current limits. Increasing the total tax credit means that it should be more than $7,500 for a new car. Second, by broadening the eligibility criteria for participants, such as raising the income limits for those who can qualify for the credits. Third, by expanding the range of vehicles eligible for the tax credits. Only vehicles with final assembly in North America which qualify to acquire the maximum tax credit. This limits the options available to consumers. Another policy option is to increase the EV population not only with the U.S.-made EVs, but with imports from other EV producers. However, EVs imported from China is subjected to 100% tariffs (The White House, 2024). In an environmental economics perspective, importing EVs from China is a sound argument in because China has a comparative advantage in producing affordable EVs, and the U.S. can reduce their direct emission caused by vehicles on the road. Unfortunately, this approach faces political challenges, as policymakers often accuse China of engaging in unfair trade practices.

Conclusion

The Clean Cars for All program represents a promising approach to addressing environmental sustainability and transportation equity in California. By providing incentives for low-income and disadvantaged communities to adopt cleaner vehicle technologies, the program demonstrates a nuanced strategy for reducing greenhouse gas emissions while supporting vulnerable populations. The study reveals critical insights into the barriers and opportunities for zero-emission vehicle (ZEV) and plug-in hybrid electric vehicle (PHEV) adoption.

The research highlights several key challenges that must be addressed to enhance the program's effectiveness. These include the significant upfront costs of clean vehicles, insufficient charging infrastructure in low-income areas, and limited ZEV options for larger households. Geographic variations in vehicle preferences, such as the differences between Bay Area and Central Valley residents, underscore the need for tailored, localized approaches to clean transportation initiatives. Furthermore, the disparities between homeowners and renters in EV adoption point to the importance of comprehensive policy interventions that go beyond direct vehicle subsidies.

Moving forward, policymakers should consider a multi-faceted approach to accelerate clean transportation adoption. This could include expanding tax credits, increasing the range of eligible vehicles, investing in public charging infrastructure in disadvantaged communities, and incentivizing manufacturers to develop more diverse ZEV options, particularly for larger families. By addressing these challenges, California can continue to lead the way in reducing transportation-related emissions while ensuring that the benefits of clean energy technologies are accessible to all communities, regardless of income level or geographic location.

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