Title
An equity analysis of clean vehicle rebate programs in California

Journal
Climatic Change, 162(4)

ISSN
0165-0009

Authors
Ju, Y
Cushing, LJ
Morello-Frosch, R

Publication Date
2020-10-01

DOI
10.1007/s10584-020-02836-w

Peer reviewed

Climatic Change (2020) 162:2087–2105
https://doi.org/10.1007/s10584-020-02836-w

An equity analysis of clean vehicle rebate programs in California

Yang Ju[1,2] • Lara J. Cushing[3] • Rachel Morello-Frosch[2,4]

Received: 5 April 2020 / Accepted: 14 August 2020/ Published online: 5 September 2020

Abstract

Rebates incentivize clean vehicle adoption but may raise equity concerns because upfront capital is required for vehicle acquisition, limiting access for low-income households. Since poorer communities typically experience worse air quality than their wealthier counterparts, rebates also may not incentivize clean vehicle acquisitions in more polluted areas where air quality benefits would be greater. We analyzed whether equity-promoting policy design elements changed the associations between rebate allocation rates and census tract characteristics including community disadvantage, household income, education, race and ethnicity, and ambient air pollution in two California rebate programs. We found that the Clean Vehicle Rebate Project issued more rebates per household to advantaged, higher-income, better-educated communities with more White residents and intermediate levels of ambient nitrogen dioxide (NO_2). An income cap and income-tiered rebate amount introduced part way through the program improved distributional equity, but fewer rebates were still issued to lower income, less-educated census tracts with higher percentages of Hispanic and non-Hispanic Black residents. Furthermore, these policy design elements reduced the overall number of rebates that were distributed. In the Enhanced Fleet Modernization Program, which incorporates additional equity-related design elements, rebate allocation rates were positively associated with community disadvantage, lower income and education, and a higher proportion of Hispanics, and were the highest in areas with slightly higher NO_2 levels. These findings indicate that design elements such as an income cap, income-tiered rebate amounts, expanded vehicle eligibility, and increased benefit eligibility in disadvantaged communities, can facilitate distribution of rebates to more socioeconomically diverse populations with higher air pollution burdens.

Keywords Clean vehicle rebate · Social equity · Policy intervention · California

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s10584-020-02836-w) contains supplementary material, which is available to authorized users.

✉ Rachel Morello-Frosch
rmf@berkeley.edu

Extended author information available on the last page of the article

1 Introduction

Clean vehicles including plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and fuel cell electric vehicles (FCEVs) reduce emissions of greenhouse gases (GHGs) and other hazardous co-pollutants from internal combustion engines (Hardman et al. 2017). Government rebates, or monetary refunds after purchase or lease (hereafter referred to as acquisition), are used to promote the adoption of clean vehicles in several US states, including California, in order to meet clean air and climate change mitigation goals (DeShazo 2016). However, rebates require consumers to acquire a vehicle upfront, presenting a barrier for lower-income consumers with limited financial assets or access to credit when compared with point-of-sale incentives such as sales tax exemptions and government purchase discounts (Hardman et al. 2017; Snelling 2018). Rebate programs can be even less accessible to lower-income consumers if the rebate amount does not increase according to income. Wealthier consumers are also more likely to take advantage of rebate programs that lack income or vehicle price caps since these consumers can typically afford higher priced vehicles (DeShazo 2016; Snelling 2018). Such distributional equity issues are found in other policy programs that inadequately address socioeconomic barriers to entry (Zhou and Noonan 2019). Design elements to address these equity challenges are therefore necessary to ensure that socioeconomically disadvantaged consumers can benefit from vehicle rebate programs.

1.1 California's two major clean vehicle rebate programs

Transportation is the largest source of GHG emissions in California and responsible for substantial portions of hazardous air pollutant emissions of nitrogen oxides (NO_x), sulfur oxides (SO_x), carbon monoxide (CO), ozone, and particulate matter (PM) (California Air Resource Board 2018a; Anderson et al. 2018). Clean vehicle rebate programs were established to control emissions from transportation and support emission reduction goals set by California's Global Warming Solutions Act (AB 32) passed in 2006 (Rubin and St-Louis 2016; California Air Resource Board 2018b). The rebate programs are partially funded through proceeds from the state's cap-and-trade program. State law (SB 535) requires that 25% of these proceeds benefit disadvantaged communities, which are defined as having disproportionate pollution burden and population vulnerability using a statewide environmental justice screening tool, CalEnviroScreen (California Environmental Protection Agency 2017). Therefore, equity is also an inherent goal of these rebate programs.

In this study, we analyze the distributional equity of two major clean vehicle rebate programs in California, which differ in design. We emphasize equity (whether benefits accrue to socioeconomically disadvantaged populations that are disproportionately impacted by transportation-related emission of GHG and co-pollutants) over equality (whether benefits are equally shared). The first program is the statewide Clean Vehicle Rebate Project (CVRP), which since 2010 has issued rebates after the acquisition of a new plug-in hybrid electric vehicle (PHEV), battery electric vehicle (BEV), or fuel cell electric vehicle (FCEV). During the first iteration of this program (March 2010 to March 2016), the rebate amount ranged between $1500 and $5000, depending only on vehicle technology. Beginning in April 2016, an income cap was instituted to exclude PHEV and BEV consumers with a gross annual individual income greater than $150,000. The CVRP also started an income-tiered rebate amount by offering an additional $2000 to lower-income consumers with an annual household income below 300% of the Federal Poverty Level (Center for Sustainable Energy 2016). Prior research suggests that income caps and income-tiered rebate amounts can improve the equity and effectiveness of clean vehicle rebate programs in terms of enhancing access for lower-income consumers and incentivizing more clean vehicle adoption (DeShazo 2016; DeShazo et al. 2017; Snelling 2018).

The second clean vehicle rebate program, the Enhanced Fleet Modernization Program (EFMP), was launched in 2015 and sought to address equity concerns by expanding eligible vehicles, setting stricter income caps for participation, and offering higher rebate amounts for lower-income consumers and disadvantaged communities (Pierce and DeShazo 2017; California Air Resource Board 2018b). EFMP includes a Retire and Replace component, which replaces older and higher emitting vehicles with more efficient, new, and used (less than 8 years old) vehicles or other transportation options (e.g., car sharing or public transit). Research suggests that combining retirement with replacement can maximize the net reduction of emissions that could be produced from retired vehicles (DeShazo 2016). A complementary Plus-up component (renamed as Clean Cars 4 All in 2019, however herein we refer to Plus-up to be consistent with prior research) provides an additional rebate amount for consumers living in disadvantaged communities as identified by the California Environmental Protection Agency's (Cal-EPA) CalEnviroScreen (August 2016; Faust et al. 2017). EFMP also includes a vehicle-retirement-only component, but we focused our analysis on the Retire and Replace and the Plus-up components (EFMP hereafter). Compared with CVRP, eligible vehicles in EFMP are likely more affordable due to the inclusion of fuel-efficient internal combustion engine vehicles, non-plug-in hybrid vehicles, and used vehicles. EFMP also sets a stricter income cap limiting participants to those with annual household incomes below 400% of the Federal Poverty Level. Finally, the rebate amount is greater in EFMP: for example, when acquiring a PHEV or BEV, the CVRP rebate amount (new vehicles only) ranges from $1500 to $ 4500, whereas the EFMP rebate amount (both new and used vehicles) ranges between $2500 and $9500. In addition, EFMP can be bundled with CVRP for a new PHEV or BEV, further increasing the rebate amount to a range from $4000 to $14,000 (see Table 1 for the rebate amounts that can be received by lower-income consumers from both programs) (California Air Resource Board 2018b). EFMP covers four air districts, namely South Coast, San Joaquin Valley, Bay Area, and Sacramento, in California by 2020. Among them, we focused on South Coast and San Joaquin Valley air districts that were EFMP's piloting areas and adopted both Retire and Replace and Plus-up components, allowing analysis on a longer timeframe since 2015. We did not include the other two air districts as they started in 2019 and only adopted the Plus-up component. The geography, timeline, and spatial distribution of the rebates that were the focus of our analysis are shown in Fig. S1.

1.2 Unanswered questions regarding the distribution of clean vehicle rebates in California

Prior research has shown that CVRP rebates, without an income cap and an income-tiered rebate amount, were disproportionately allocated to wealthier communities with fewer Hispanic and African-American residents (Rubin and St-Louis 2016). While simulation studies and early evidence suggest that the income cap and the income-tiered rebate amount introduced later would likely increase participation of lower-income households (DeShazo et al. 2017; Williams 2018), this hypothesis has yet to be tested with empirical models using actual program data. In addition, it remains unclear whether income-based policy design elements affect rebate distributions based on other community characteristics including education, race

Table 1 Rebate amounts available under California's CVRP and EFMP clean vehicle rebate programs for consumers with annual household incomes below 400% of the federal poverty level

Household income	Program		Internal combustion engine vehicle 20+ MPG	Non-plugin hybrid 20+ MPG	Non-plugin hybrid 35+ MPG	Plug-in hybrid (PHEV)	Battery electric (BEV)	Fuel cell electric (FCEV)
≤ 225% FPL	CVRP					\$1500 + \$2000[a]	\$2500 + \$2000[a]	\$5000 + \$2000[a]
	EFMP	Retire and replace	\$4000	\$4000	\$4500	\$4500	\$4500	
		Plus-up[b]		\$2500	\$2500	\$5000	\$5000	
226–300% FPL	CVRP					\$1500 + \$2000[a]	\$2500 + \$2000[a]	\$5000 + \$2000[a]
	EFMP	Retire and replace			\$3500	\$3500	\$3500	
		Plus-up[b]			\$1500	\$4000	\$4000	
301–400% FPL	CVRP					\$1500	\$2500	\$5000
	EFMP	Retire and replace				\$2500	\$2500	
		Plus-up[b]				\$3000	\$3000	
EFMP bundled with CVRP, new vehicles only			No	No	No	Yes	Yes	No

Note: *CVRP*, Clean Vehicle Rebate Project; *EFMP*, Enhanced Fleet Moderation Program; *FPL*, Federal Poverty Level; *MPG*, miles per gallon; *PHEV*, plug-in hybrid electric vehicle; *BEV*, battery electric vehicle; *FCEV*, fuel cell electric vehicle

[a] Additional \$2000 CVRP rebate issued to lower-income consumers (whose annual household income falls below 300% of the Federal Poverty Level) since 29 March 2016

[b] Plus-up rebates are additional to retire and replace rebates available to consumers living in disadvantaged communities as identified by CalEnviroScreen

and ethnicity, and levels of ambient air pollution. Similarly, the first-year operation of EFMP shows that rebates were largely distributed to consumers in the lowest income bracket of program eligibility and in disadvantaged communities (Pierce and DeShazo 2017), but subsequent work has not confirmed these findings with a more comprehensive set of community characteristics nor compared the distributional patterns with CVRP in areas where both programs overlap. Finally, studies have yet to analyze rebate allocation with respect to ambient air pollution, to understand whether the rebates have been allocated to more polluted communities where benefits from air quality improvements could be greater.

Accordingly, we use publicly available data to evaluate how specific program designs elements in CVRP and EFMP have influenced the associations between rebate allocation and: (1) community disadvantage as defined by CalEnviroScreen; (2) community-level socioeconomic and demographic characteristics; and (3) ambient air pollution of nitrogen dioxide (NO_2) and particulate matter ($PM_{2.5}$). Results from this analysis can inform future iterations of rebate programs, ensuring their benefits are shared across diverse communities and enhancing their potential to improve air quality in the most polluted areas. This study also contributes to broader discussions of distributional equity of climate change mitigation and GHG emission reduction programs and how equity goals can be advanced by policy design elements (Jenkins et al. 2017; Graff et al. 2019; Zhou and Noonan 2019).

2 Materials and methods

We conducted two sets of analyses:

(1) A CVRP-only analysis, which investigated rebate allocations statewide between March 2010 and December 2017 and assessed how patterns of rebate allocation changed after the introduction of an income cap and an income-tiered rebate amount providing an additional $2000 for lower-income consumers in April 2016;
(2) A comparison between CVRP and EFMP, focusing on the South Coast and San Joaquin Valley air districts between July 2015 and December 2017, where and when the two programs overlapped.

2.1 Rebate allocation rate

We used the number of rebates issued to individual applicants per thousand households in a census tract monthly (CVRP-only analysis) or quarterly (CVRP-EFMP comparison) to measure rebate allocation rate. Although individual-level participant data were available, they did not include socioeconomic or demographic characteristics of rebate program participants. To investigate distributional equity regarding socioeconomic and demographic characteristics, we therefore aggregated the individual-level data to the census tract level so that the data could be joined to sociodemographic information from the American Community Survey, a dataset used later in the analysis. In addition, we did not have information on all clean vehicle buyers to construct an individual-level outcome on the likelihood of getting rebates among these buyers.

We downloaded publicly available participant-level data between March 2010 and December 2017 for CVRP (Center for Sustainable Energy 2019) and between July 2015 and December 2017 for EFMP (California Air Resource Board 2019a). For comparability, we restricted these data to rebates assigned to individual applicants who acquired a vehicle, as CVRP included non-individual participants (e.g., businesses) and EFMP had participants funded for alternative options (e.g., public transit passes or car-sharing). While more recent CVRP and EFMP data were available, we chose a shorter time frame based on the availability of the socioeconomic and demographic variables from the American Community Survey. We obtained household counts from a time series of American Community Survey 5-year estimates ending at each year of our analysis (United States Census Bureau 2019). For the CVRP-only analysis, we aggregated the number of rebates by month; for the comparison between the CVRP and EFMP, we aggregated at the quarterly scale at which the EFMP rebates data were reported.

2.2 Community characteristics

Disadvantaged communities were defined by Cal-EPA's CalEnviroScreen 3.0, a census tract-level index combining measures of population vulnerability (including sensitive populations and socioeconomic status) and pollution burden (including exposure to pollutants and proximity to hazardous sites) (August 2016; Faust et al. 2017). Cal-EPA designates census tracts within the top 25th percentile of CalEnviroScreen 3.0 scores, and 22 tracts in the top 5th percentile of pollution burden but without a reliable population vulnerability score (due to missing data or low population) as disadvantaged communities (California Environmental Protection Agency 2017). These disadvantaged communities are prioritized for climate mitigation and adaptation projects, including eligibility for an additional rebate amount from the EFMP Plus-up program (Table 1).

We included the following measures of tract-level socioeconomic and demographic characteristics: median household income, education (percent of the over-25-year-old population with postgraduate degrees), racial/ethnic composition (percent Hispanic, non-Hispanic Black, non-Hispanic Asian/Pacific Islander), home ownership (percent of renter-occupied housing units), the average number of vehicles per household, and population density. We selected these measures to facilitate comparisons with the results of prior equity or clean vehicle studies (Rubin and St-Louis 2016; Narassimhan and Johnson 2018; Zhou and Noonan 2019). These measures were time variant and collected from a time series of American Community Survey 5-year estimates ending at each year of the analysis (United States Census Bureau 2019). We calculated population density by normalizing total population by developed area, rather than total area, of a census tract. Developed areas were calculated based on the percentage of developed impervious surfaces in the National Land Cover Database 2011 (Multi-Resolution Land Characteristics Consortium 2011). Using developed rather than total area better characterizes population density, particularly in rural areas where tracts are large and often contain uninhabited areas (e.g., forest and water bodies). Developed areas have been used to spatially allocate populations within census units (Mennis 2003).

We also developed two time-invariant measures: density of electric and hydrogen charging stations, and urbanicity. Locations of currently open electric and hydrogen charging stations were obtained from the National Renewable Energy Laboratory (National Renewable Energy Laboratory 2019). We included public- and private-access stations as both can facilitate clean vehicle adoption (Rubin and St-Louis 2016). As with population density, the density of open charging stations was calculated according to the developed areas within a census tract. We treated the density of these open charging stations as a time-invariant covariate, as only 38% of the stations had their opening date reported. We derived our urbanicity indicator by intersecting the census tract centroids with urban areas from the 2010 Census (United States Census Bureau 2010). Urban represents areas with high population density and/or a large amount of developed area, whereas rural represents the rest of the areas (Ratcliffe et al. 2016).

2.3 Air pollution

We used area-weighted average concentrations of NO_2 and $PM_{2.5}$ between 2010 and 2016 to assess whether more polluted areas received more rebates. We chose NO_2 and $PM_{2.5}$ because mobile sources are significant sources of both of these pollutants (Anderson et al. 2018), which could be reduced locally by uptake of clean vehicles. We acquired NO_2 concentrations from the Berkeley High-Resolution (BEHR) dataset (The Berkeley Satellite Group 2019) and $PM_{2.5}$ concentrations from van Donkelaar et al. (Atmospheric Composition Analysis Group 2019; van Donkelaar et al. 2019). The NO_2 dataset provides daily ambient concentration estimates gridded at $0.05 \times 0.05°$ ($\approx 5.56 \times 5.56$ km) resolution, and we first calculated mean concentration annually between 2010 and 2016 for each grid cell. We then calculated a time-invariant, area-weighted mean NO_2 concentration averaged across 2010 and 2016 for each census tract. The $PM_{2.5}$ dataset provides mean concentrations annually between 2010 and 2016 at $0.01 \times 0.01°$ ($\approx 1.11 \times 1.11$ km) resolution, and a similar procedure was used to calculate a time-invariant, area-weighted mean $PM_{2.5}$ concentration for each census tract. We did not treat NO_2 and $PM_{2.5}$ as time variant, as their respective data sources were 1 year shorter than our time frame of analysis. Consequently, we assumed that the average concentration between 2010 and 2016 was representative of the spatial variations in air pollution in 2017.

After linking census-tract-level rebate allocation rates with the covariates, we omitted 2% of the tract-month observations from the CVRP-only analysis and 7% of the tract-quarter observations from the CVRP-EFMP comparison due to missing data regarding community characteristics.

2.4 Analytical approach

We compared means and correlations to examine whether disadvantaged communities received fewer rebates than non-disadvantaged communities under the CVRP or EFMP, and whether the pattern for CVRP changed after the introduction of an income cap and an income-tiered rebate amount. We conducted the mean comparisons using a permutation *t* test (Millman 2015) and measured the correlations by Spearman rank correlation coefficient to account for non-normality and autocorrelation in the data.

We further conducted a multivariate regression analysis to estimate the associations between tract-level rebate allocation rate and key covariates including tract-level household income, education, racial/ethnic composition, and air pollution levels, while controlling for the density of charging stations, vehicle and home ownership, population density, and urbanicity (model specified as Eq. (1)). Covariates were standardized when applicable to facilitate comparisons between the coefficients and to identify the most influential covariates. We added a quadratic term for air pollution to account for prior research suggesting a non-monotonic relationship between pollution and income (Bechle et al. 2011; Pastor et al. 2016). We also added an interaction term between population density and urbanicity, as previous studies have found the association between population density and participation in similar programs is different between rural and urban areas (Lachapelle 2013). In addition, we included a linear time trend (t) as the number of months (CVRP-only analysis) or quarters (CVRP-EFMP comparison) since the start of the rebate programs to control for the overall secular increase in market penetration of clean vehicles and awareness of the rebate programs.

$$\log Y_{\mathrm{i,j,m,n}} = \beta X_{\mathrm{i,j,n}} + \gamma Z_{\mathrm{i,j}} + \delta t + c_{\mathrm{j}} + d_{\mathrm{m}} + \varepsilon_{\mathrm{i,j,m.n}} \tag{1}$$

where $Y_{\mathrm{i,\,j,\,m,\,n}}$ is the number of rebates received per thousand households in census tract i of county j during month or quarter m in year n, $X_{\mathrm{i,\,j,\,n}}$ represents the covariates varying by census tract, county and year, $Z_{\mathrm{i,\,j}}$ represents the covariates varying by census tract and county, t estimates a linear temporal trend measured as number of months (CVRP-only analysis) or quarters (CVRP-EFMP comparison) since the start of the programs, c_{j} denotes county fixed effects, d_{m} is month or quarter fixed effects, and $\varepsilon_{\mathrm{i,\,j,\,m.\,n}}$ is the error term.

To estimate the combined effect of an income cap and an income-tiered rebate amount implemented in the CVRP in April 2016 statewide, we used an interrupted time series model (Eq. (2)) (Bernal et al. 2017). We selected this model since the income and the income-tiered rebate amount were instituted for the entire state of California at the same time point. The model included a dummy variable ($D_{\mathrm{m,\,n}}$) indicating the presence (coded as 1) or absence (coded as 0) of these newer design elements in the CVRP-only model. We interacted this dummy variable with the linear time trend, socioeconomic and demographic characteristics, and air pollution variables to estimate whether their associations with rebate allocation changed after introducing these two policy design elements.

$$\begin{aligned} \log Y_{\mathrm{i,j,m,n}} = {} & \beta X_{\mathrm{i,j,n}} + \gamma Z_{\mathrm{i,j}} + \delta t + \theta D_{\mathrm{i,j,m,n}} + \rho D_{\mathrm{i,j,m,n}} \times X_{\mathrm{i,j,n}} + \tau D_{\mathrm{i,j,m,n}} \times Z_{\mathrm{i,j}} \\ & + \mu D_{\mathrm{i,j,m,n}} \times t + c_{\mathrm{j}} + d_{\mathrm{m}} + \varepsilon_{\mathrm{i,j,m.n}} \end{aligned} \tag{2}$$

where $D_{\mathrm{i,\,j,\,m,\,n}}$ is a dummy variable indicating the presence (coded as 1) or absence (coded as 0) of equity-promoting policy design elements including an income cap and an income-tiered rebate amount, $D_{\mathrm{i,\,j,\,m,\,n}} \times X_{\mathrm{i,\,j,\,n}}$, $D_{\mathrm{i,\,j,\,m,\,n}} \times Z_{i,\,j}$, $D_{\mathrm{i,\,j,\,m,\,n}} \times t$ are interaction terms between the equity-promoting policy design elements and (1) time-variant socioeconomic and demographic characteristics, (2) time-invariant air pollution, (3) a linear time trend.

We accounted for the fixed effects of time and place to reduce omitted-variable bias. We added d_{m} to reflect monthly (CVRP-only analysis) or quarterly fluctuations (CVRP-EFMP comparison) in vehicle acquisitions. We included c_{j} for unobserved, time-invariant county-level characteristics (e.g., abundance in occupations requiring heavy duty vehicles that are not eligible for rebate programs) in 52 California counties. We did not use tract fixed effects for two reasons: first, although time variant, many of our covariates of interest had limited temporal variability during the study period (shown as limited within-tract variations in Tables S1 and S2), thus applying tract fixed effects can lead to unreliable estimates (Beck and Katz 2001; Plümper and Troeger 2007); second and perhaps more importantly, we were interested in between-tract effects (e.g., if wealthier tracts were associated with higher rebate allocation rates) rather than within-tract effects (e.g., in a given tract, whether an increase in income in time led to higher rebate allocation rates). Adding tract fixed effects means that we would only use within-tract variations to estimate the models, therefore preventing us from estimating between-tract effects.

We estimated all models as pooled negative binomial models with cluster-robust standard errors. We chose negative binomial models because the outcome (rebate allocation rate) was a count variable with a mean that did not equal its variance (Tables S1 and S2) (Allison 2009). The pooled estimator identifies coefficients for both time-variant ($X_{\mathrm{i,\,j,\,n}}$) and time-invariant ($Z_{\mathrm{i,\,j}}$) covariates. The estimator also identifies coefficients for the fixed effects (specified as dummy variables), allowing further estimations. We used cluster-robust standard errors to account for heteroscedasticity and the clustering of our observations by census tracts within counties. This tends to produce wider but more accurate confidence intervals and consequently more conservative estimates of statistical significance (Allison 2009; Colin Cameron and Miller 2015).

We used incidence rate ratios (IRR) to interpret the associations between sociodemographic and air pollution covariates and the outcome. IRR is a factor by which the outcome, rebate allocation rate, changes given a 1-unit increase of a covariate, when holding all other covariates constant. An IRR greater or less than 1 indicates a positive or negative association, respectively, between a covariate and rebate allocation rate.

Based on the interrupted time series model (Eq. (2)) in the CVRP-only analysis, we estimated the IRRs for socioeconomic, demographic, and air pollution covariates under two scenarios: (1) if the income cap and income-tiered rebate amount implemented in April 2016 had been implemented throughout the time period of our analysis (March 2010–December 2017); (2) if the income cap and income-tiered rebate amount had never been implemented. The differences in IRRs between the two scenarios reveal how the income cap and income-tiered rebate amount could have changed the association between the outcome and the sociodemographic and air pollution covariates.

3 Results and discussion

3.1 Rebate allocation rates and community disadvantage

Disadvantaged communities (as defined by CalEnviroScreen) had significantly lower CVRP rebate allocation rates compared with their more advantaged counterparts (Fig. 1a). Disadvantaged communities on average received 77% fewer CVRP rebates per thousand households monthly between March 2010 and December 2017 (0.05 (standard deviation (SD) = 0.07) vs. 0.22 (SD = 0.25)). Implementing an income cap and an income-tiered rebate amount providing an additional $2000 for lower-income consumers in April 2016 helped to reduce this relative gap, but the absolute difference widened: before April 2016, disadvantaged communities on average received 78% fewer rebates than non-disadvantaged communities per thousand households monthly (0.04 (SD = 0.05) vs. 0.18 (SD = 0.23)), whereas after April 2016 disadvantaged communities received 70% fewer rebates (0.10 (SD = 0.14) vs. 0.33 (SD = 0.34)) (Fig. 1a).

In the South Coast and San Joaquin Valley air districts between July 2015 and December 2017, the CVRP issued 74% fewer rebates on average to disadvantaged communities (0.29 (SD = 0.36)) vs. non-disadvantaged communities (1.10 (SD = 0.92)) (Fig. 1b). In contrast, during this same period the EFMP on average issued 133% more rebates to disadvantaged communities (0.07 (SD = 0.11)) vs. non-disadvantaged communities (0.03 (SD = 0.07)). In sum, CVRP differentially benefitted non-disadvantaged communities, even after implementing an income cap and an income-tiered rebate amount, whereas EFMP differentially benefitted disadvantaged communities.

CVRP and EFMP rebate allocation rates were also correlated with CalEnviroScreen 3.0 scores (Fig. S2). CVRP rebate allocation rates consistently showed negative correlations with CalEnviroScreen 3.0 scores, even after implementing an income cap and an income-tiered rebate amount. In contrast, EFMP rebate allocation rates were positively correlated with

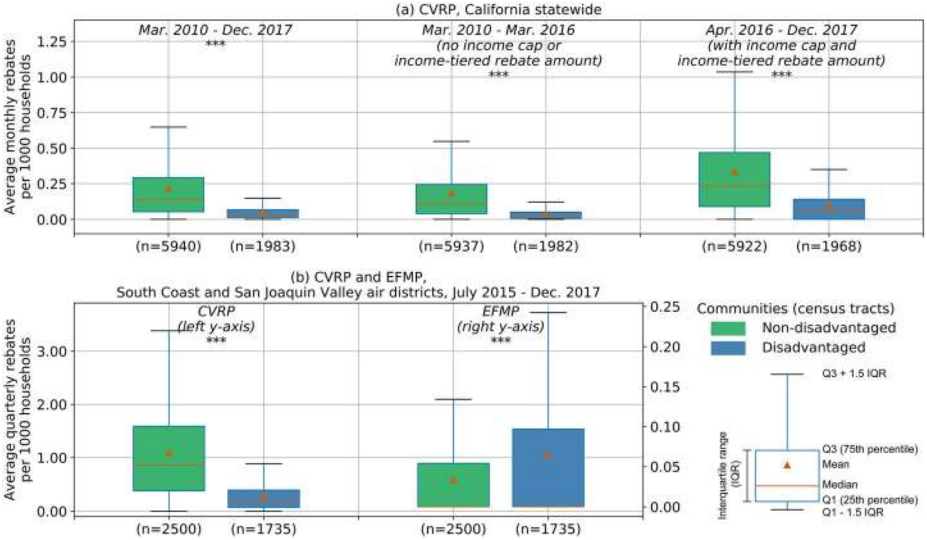

Fig. 1 Rebate allocation rates between non-disadvantaged and disadvantaged communities as defined by CalEnviroScreen. **a** California-wide Clean Vehicle Rebate Project (CVRP) between March 2010 and December 2017 and before and after implementation of an income cap and an income-tiered rebate amount providing an additional \$2000 for lower-income consumers in April 2016. **b** CVRP and Enhanced Fleet Modernization Program (EFMP) in South Coast and San Joaquin Valley air districts between July 2015 and December 2017, when the programs ran concurrently. Rebate allocation rate is the number of rebates received by individual applicants per thousand households monthly (**a**) or quarterly (**b**) in a census tract. About 25% of California census tracts are designated as disadvantaged by CalEnviroScreen 3.0 (August 2016; Faust et al. 2017). ***p value < 0.01, statistically significant differences in mean rebate allocation rates between non-disadvantaged and advantaged communities which was measured by a two-tailed permutation t test (Millman 2015)

CalEnviroScreen 3.0 scores, likely due to the program's expanded vehicle eligibility, stricter income cap, income-tiered rebate amounts, and extra rebate amount offered to disadvantaged communities with high CalEnviroScreen scores. For both programs, rebate allocation correlated more strongly with CalEnviroScreen's population vulnerability score than with its pollution burden score. This pattern likely reflects the rebate program's stronger focus on consumer income rather than pollution burden - a factor only considered in EFMP Plus-up.

3.2 Multivariate models for the statewide CVRP program

Full results from the statewide CVRP-negative binomial models are shown in Table S3. Model 1 (Eq. (1)) estimates the associations between rebate allocation rate, standardized community characteristics, and standardized ambient air pollutant concentrations, after controlling for a linear temporal trend, and county and month fixed effects. Model 2 is an interrupted time series model (Eq. (2)) that additionally estimates the effect of the April 2016 implementation of an income cap and an income-tiered rebate amount. Since both models 1 and 2 produced similar directions of effect for the covariates and because model 2 provides additional estimates for the income cap and the income-tiered rebate amount, we focus on model 2 in the following discussion. We present IRRs from model 2 for the main socioeconomic and demographic covariates in Table 2.

Median household income had a positive and statistically significant association with rebate allocation rate. A 1-standard-deviation increase in tract-level median household income

Table 2 Incidence rate ratios (IRRs) of CVRP rebate allocation statewide, March 2010–December 2017 for socioeconomic and demographic covariates, estimated given: (1) an income cap and income-tiered rebate amount were implemented in April 2016 as actually occurred; (2) an income cap and income-tiered rebate amount either were or were not implemented from the start of the program in March 2010

	(1) Overall[a] (income cap and income-tiered rebate implemented since April 2016)	(2) Conditional (income cap and income-tiered rebate amount either implemented or not throughout the analysis timeframe of March 2010–December 2017)	
		Implemented[b]	Not implemented[b]
Median household income	1.258*** (1.196, 1.323)	1.168*** (1.100, 1.240)	1.285*** (1.223, 1.352)
% over-25 population with postgraduate degrees	1.170*** (1.075, 1.273)	1.104** (1.014, 1.203)	1.189*** (1.092, 1.296)
% Non-Hispanic Black	0.891*** (0.858, 0.925)	0.893*** (0.858, 0.928)	0.891*** (0.857, 0.925)
% Hispanic	0.667*** (0.617, 0.720)	0.674*** (0.614, 0.739)	0.665*** (0.618, 0.716)
% Non-Hispanic Asian/Pacific Islander	1.039 (0.974, 1.108)	1.088** (1.020, 1.160)	1.025 (0.961, 1.094)
n observations (census tract—month)	740,010	740,010	740,010

Note: A coefficient, or incidence rate ratio (IRR), is the factor by which the rebate allocation rate (monthly rebates received per thousand households) changes for a 1-unit increase in the corresponding covariate, when holding other covariates constant; 95% confidence intervals are in parentheses

**p* value < 0.10; ***p* value < 0.05; ****p* value < 0.01—levels of significance

[a] Overall IRR, with the income and the income-tiered rebate amount implemented as they are since April 2016

[b] "If implemented" and "not implemented" represent IRRs conditioned on whether the income cap and the income-tiered rebate amount are implemented throughout the timeframe of the analysis. All IRRs are based on model 2, Table S3 in the Supporting Information

(roughly \$32,407/year) was associated with a 25.8% increase ((1.258–1) × 100% = 25.8%, similar calculations hereafter) in rebate allocation rate (Table 2). This is consistent with consumers needing upfront capital to acquire a new eligible vehicle before receiving the rebate, and that clean vehicles cost more than comparable internal combustion engine vehicles (Potoglou and Kanaroglou 2007; Erdem et al. 2010; Poder and He 2017). A similar phenomenon has been observed in other rebate programs to encourage uptake of environmentally-friendly technologies that require a substantial upfront investment, such as rooftop solar (Soskin and Squires 2013; Briguglio and Formosa 2017).

Education, measured as percent of the over-25-year-old population with postgraduate degrees, had strong positive associations with rebate allocation rate (Table S3). A 1-standard-deviation increase in education level was associated with a 17.0% increase in rebate allocation rate (Table 2). The positive association between education and rebate allocation aligns with a CVRP survey identifying that about 49% of the recipients are from households with postgraduate degrees (Johnson et al. 2017), as well as prior studies showing positive associations between education and clean vehicle adoption (Vergis and Chen 2015; Javid and Nejat 2017).

We found substantial disparities in rebate allocation rates with respect to community racial and ethnic composition. Increases in the percentages of non-Hispanic Black and Hispanic populations were significantly associated with lower rebate allocation rates (with non-Hispanic

White as the reference group) (Table S3). For example, for a 1-standard-deviation increase in tract-level percent of Hispanic residents (roughly 27%) was associated with a decrease by 33.3% in rebate allocation rate (Table 2). In contrast, an increase in the percentage of non-Hispanic Asian/Pacific Islander population was associated with a small and statistically insignificant increase of 3.9% in rebate allocation rate. A similar disparity in CVRP rebate allocation for non-Hispanic Blacks and Hispanics has been previously reported (Rubin and St-Louis 2016). Racial disparities in clean technology access are not unique to CVRP, although the directions of associations are not always consistent. For example, Kwan and colleagues found that across the US, communities with higher percentages of Black and Asian residents have lower rates of residential solar PV installation, whereas installation rates are higher for communities with more Hispanics, controlling for solar radiation (Kwan 2012). The racial/ethnic disparities we observed may result from differences in unmeasured, wealth-related factors (other than median household income and home ownership that we included in our analysis) and other factors affecting vehicle requirements (e.g., occupations requiring heavy duty vehicles or availability of charging stations at work), differential marketing, and language-appropriate outreach about rebate programs in diverse communities.

We observed a pollution-level dependent relationship between ambient air pollutant concentrations and CVRP rebate allocation rates. In less polluted census tracts, an increase in either NO_2 and $PM_{2.5}$ was associated with an increase rebate allocation rates, or an IRR greater than 1 (Fig. 2a, b). However, the IRRs decreased to less than 1 as average NO_2 and $PM_{2.5}$ concentrations continued to increase, indicating negative associations between these air pollutants and rebate allocation rate in more polluted census tracts. At most pollution levels, the IRRs were statistically significant for NO_2 but remained insignificant for $PM_{2.5}$. Therefore, in general, CVRP rebate allocation rates were higher in areas with moderate levels of air pollution, but lower in areas with very high or low air pollution levels, suggesting a possible lost opportunity to improve air quality in the most polluted communities.

The density of electric and hydrogen charging stations showed a statistically insignificant association with rebate allocation rates (Table S3). Prior research has found that access to a charging station is one of the consumer concerns about electric vehicles (Egbue and Long 2012) and can be the most influential factor for nationwide electric vehicle adoption (Sierzchula et al. 2014). The insignificant association we observed may be due to the fact that we only measured these stations by where the rebates were allocated, rather than where actual car charging took place.

The percent of renter-occupied housing units showed a statistically significant negative association with rebate allocation rate, which could be due to renters being less able or willing to install charging facilities at their homes compared with homeowners (Table S3).

There was a negative association between rebate allocation rate and population density, and this association was only statistically significant in urban areas (Table S5). Additionally, urbanicity itself showed a statistically significant negative association with rebate allocation rate (Table S3). A similar trend was observed in an early vehicle retirement program in Quebec, in which the participation rate was higher in low-density metropolitan areas (Lachapelle 2013). Densely populated urban areas may indicate more walkability and availability of alternative modes of transport, including public transit, which reduces the demand for personal vehicles. Furthermore, while in our dataset urbanized areas have higher non-personal charging station densities, these areas may have limited off-street parking for installing personal charging facilities, making operation of PHEVs and BEVs more challenging.

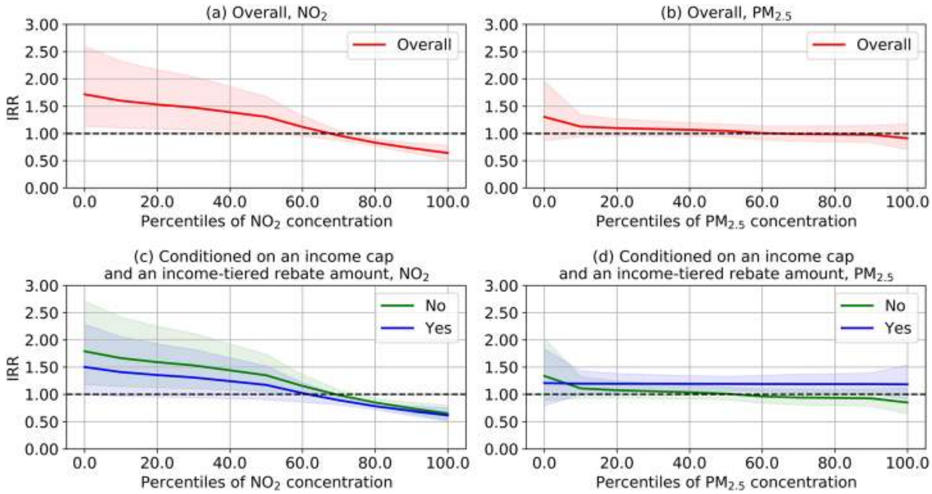

Fig. 2 Incidence rate ratios (IRRs) of CVRP rebate allocation statewide, March 2010–December 2017, for average ambient NO_2 and $PM_{2.5}$ concentrations at different concentrations levels. The IRR is the factor by which the rebate allocation rate (monthly rebates received per thousand households) changed for a 1-standard-deviation increase in average ambient NO_2 or $PM_{2.5}$ concentrations, when holding other covariates constant. **a**, **b** IRRs for NO_2 and $PM_{2.5}$, with an income cap and an income-tiered rebate amount implemented as they were since April 2016. **c**, **d** The IRRs conditioned on whether the income cap and the income-tiered rebate amount had been implemented throughout the timeframe of the analysis. The IRRs are estimated based on model 2, Table S3 in the Supporting information; 95% confidence intervals of the IRRs are shown in shaded areas

The average number of vehicles per household showed a positive and statistically significant association with rebate allocation rate (Table S3). This differs from findings by Rubin et al., in which CVRP rebate allocation rate between 2010 and 2015 was negatively associated with vehicle ownership (Rubin and St-Louis 2016). However, our results align with research suggesting that consumers concerned about battery range tend to view electric vehicles as secondary cars rather than replacements for existing internal combustion engine vehicles (Skippon and Garwood 2011; Tamor and Milačić 2015).

Finally, we found a statistically significant and increasing temporal trend in rebate allocation (Table S3), which could be explained by growing market penetration of clean vehicles, likely due partially to the rebate programs themselves. Combined PHEV and BEV sales in the US increased by 446% from 2011 (17,763 vehicles) to 2013 (97,102 vehicles), and incentives such as rebates likely had strong positive influences on this increase (Zhou et al. 2015). A CVRP consumer survey shows that receiving a rebate is the most important deciding factor for purchasing a PHEV or BEV, with 41 and 50% of the respondents indicating they would not have made a purchase without the rebate (Johnson et al. 2017). We also hypothesize that the temporal increase in rebate allocation may be partially due to a growing awareness of CVRP over time.

3.3 Effects of an income cap and an income-tiered rebate amount on CVRP

Implementing an income cap and an income-tiered rebate amount lessened but did not eliminate disparities in rebate allocation under the CVRP with respect to income, education, race and ethnicity, and air pollution. Even if these policy design elements had been implemented throughout the timeframe of our analysis (March 2010–December 2017), we estimated that rebates would still more frequently be allocated to higher-income and better-educated communities and less frequently allocated to communities of color (column "Implemented" in Table 2). However, the income cap and income-tiered rebate amount attenuated the association between rebate allocation rate and median household income, with the IRRs decreasing from 1.285 to 1.168 (a 10% decline). The implementation of an income cap and income-tiered rebate amount was also associated with weaker associations (IRR closer to 1) between rebate allocation rates and covariates including education, and the percentages of non-Hispanic Black and Hispanic residents (Table 2).

The income cap and income-tiered rebate amount also changed the associations between rebate allocation rate and ambient air pollution. These policy design elements slightly attenuated the IRRs of NO_2 and shifted its tipping point (where the IRR dropped below 1), suggesting greater rebate allocation in less polluted census tracts (Fig. 2c). In contrast, the IRRs of $PM_{2.5}$ remained greater than 1 as the $PM_{2.5}$ level increased (Fig. 2d), suggesting that more rebates would have been allocated to communities with greater $PM_{2.5}$ had the income cap and income-tiered rebate amount been implemented sooner.

Our analysis also suggests that the income cap and income-tiered rebate amount were associated with a decrease of 0.095 (95% confidence interval, (0.067, 1.222)) rebates per thousand households monthly if implemented throughout the analysis. If these policy design elements were never implemented, a census tract was expected to receive 0.319 (0.223, 0.415) rebates per thousand households monthly. If these policy design elements were implemented throughout, the rebate allocation rate would be 0.224 (0.142, 0.307) rebates per thousand households monthly. This reduction might indicate that the exclusion of high-income consumers by the income cap was not entirely offset by an increase in low-income consumers attracted by the income-tiered rebate amount. But this finding, along with the effects of the income cap andincome-tiered rebate amount discussed earlier, should be cautiously interpreted as they could be confounded by other time-varying factors such as saturation in the clean vehicle market. The reduction in rebate allocation rates indicates that additional measures, such as greater increases in rebate amounts for lower income consumers, may be needed to reduce the income gap in rebate allocation while ensuring similar levels of clean vehicle adoption facilitated by rebate programs.

3.4 Comparison between CVRP and EFMP

Full model results (based on Eq. (1)) for CVRP and EFMP rebate allocation rates in the South Coast and San Joaquin Valley air districts between July 2015 and December 2017 are in Table S4. We present IRRs for the main socioeconomic and demographic covariates in Table 3. For CVRP, rebate allocation follows the statewide pattern: the IRRs for the two air districts were similar to those from the statewide model ("Overall" column in Table 2).

In contrast, EFMP presents a different pattern: median household income and education had negative associations with EFMP rebate allocation rate, and the percentage of Hispanics was positively associated with rebate allocation rate (Table 3). Furthermore, there was a statistically insignificant, yet positive association between non-Hispanic Blacks and EFMP rebate allocation rate, differing from the negative association in CVRP (Table 3). These different distributional patterns between CVRP and EFMP are likely due to their different designs: while CVRP had an income cap and offered an additional $2000 to lower-income consumers during the study period, EFMP set a stricter income cap, offered higher rebate

Table 3 Incidence rate ratios (IRRs) of CVRP and EFMP rebate allocation in the South Coast and San Joaquin Valley air districts between July 2015 and December 2017 for socioeconomic and demographic covariates

	CVRP	EFMP
Median household income	1.236*** (1.091, 1.400)	0.680*** (0.508, 0.910)
% Over-25 population with postgraduate degrees	1.096*** (1.027, 1.171)	0.827*** (0.758, 0.902)
% Non-Hispanic Black	0.905*** (0.867, 0.943)	1.019 (0.934, 1.112)
% Hispanic	0.654*** (0.584, 0.732)	1.324* (0.959, 1.829)
% non-Hispanic Asian/Pacific Islander	1.053** (1.004, 1.104)	1.470*** (1.314, 1.645)
Number of observations (census tract—month)	42,260	42,260

Note: A coefficient, or incidence rate ratio (IRR), is the factor by which the rebate allocation rate (quarterly rebates received per thousand households) changes for a 1-unit increase in the corresponding covariate, when holding other covariates constant. The IRRs are based on models 3 and 4, Table S4 in the Supporting Information; 95% confidence intervals are in parenthesis

CVRP, Clean Vehicle Rebate Project; *EFMP*, Enhanced Fleet Modernization Program retire and replace and Plus-up components

*p value < 0.10; **p value < 0.05; ***p value < 0.01—levels of significance

amounts to lower-income consumers, expanded vehicle eligibility, gave an additional rebate amount to consumers living in socioeconomically and environmentally disadvantaged communities, and could be combined with CVRP when purchasing new PHEVs and BEVs to substantially increase the total rebate amount (Table 1).

For both CVRP and EFMP, the IRRs for NO_2 dropped below 1 as NO_2 concentration increased (Fig. 3a), such that the highest rebate allocation rates were associated with census tracts with moderate NO_2 concentrations. In addition, compared with CVRP, we found that EFMP rebates were likely allocated to census tracts with higher levels of NO_2, as the tipping point (where IRR dropped below 1) was in areas with higher NO_2 concentration. This pattern could be due to the fact that the EFMP, particularly its Plus-up component, attracted more consumers in lower-income and disadvantaged communities with higher pollution burden.

We found more attenuated patterns for $PM_{2.5}$ in CVRP such that rebate allocation rates did not differ much across pollutant levels. In EFMP, the IRR for $PM_{2.5}$ remained slightly larger than 1 across pollutant levels. However, the IRRs for $PM_{2.5}$ in CVRP and EFMP both were close to 1 and statistically insignificant (Fig. 3b).

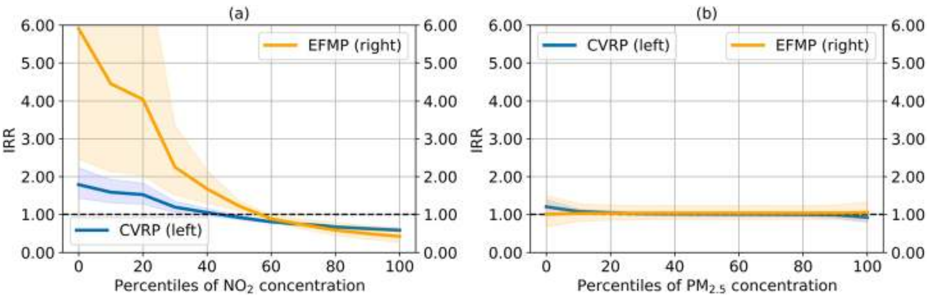

Fig. 3 Incidence rate ratios (IRRs) of CVRP and EFMP rate allocation in South Coast and San Joaquin Valley air districts, July 2015–December 2017, for average ambient NO_2 and $PM_{2.5}$ concentrations at different concentration levels. IRR is the factor by which the rebate allocation rate (quarterly rebates received per thousand households) changes for a 1-standard-deviation increase in average ambient NO_2 or $PM_{2.5}$ concentrations, when holding other covariates constant. The IRRs are estimated based on Model 3 and 4, Table S4 in the Supporting information; 95% confidence intervals of the IRRs are shown in filled areas

Another difference between EFMP and CVRP is that, while there was a positive but statistically insignificant association between charging station density and rebate allocation rate for CVRP, the association was negative and statistically significant for EFMP. This negative association could be explained by the fact that EFMP included internal combustion engine and non-plug-in hybrid vehicles that do not require charging stations. However, we should interpret these associations with caution due to the fact that tract-level charging station density may not be a good proxy for where vehicles get charged.

While both CVRP and EFMP showed positive associations between rebate allocation rates and vehicle ownership, the interpretations might differ. Since CVRP does not require vehicle retirement, households with any number of vehicles can participate. However, the EFMP requirement of retiring vehicles means that households must have at least one vehicle to qualify for the program.

3.5 Limitations and future research directions

Future studies should explore other strategies for reducing disparities in the distribution of clean vehicle rebates, use individual-level socioeconomic and demographic data (when available), and measure the distribution of associated environmental benefits and costs (e.g., changes in air quality). For example, on January 30, 2018, the CVRP began preapproving rebate applications in San Diego County in order to remove the barrier facing low-income households of the upfront capital required to purchase vehicles (Center for Sustainable Energy 2017). The CVRP also proposed to restrict vehicle eligibility (e.g., higher all-electric range and a cap for vehicle price) and participant eligibility (e.g., one rebate per person and a 3-month application window after purchase) for fiscal year 2019–2020 (California Air Resource Board 2019b). Research could evaluate how these interventions affect rebate allocation patterns by income, race/ethnicity, and other factors. If participant-level socioeconomic data become available, future studies can specify multi-level models that integrate individual- and area-level information to validate the associations we observed at the census tract level in our analysis.

While this study used allocation rate of clean vehicle rebates as the main outcome, we did not investigate potential benefits from the program to disadvantaged communities in the form of reductions in transportation-related emissions of GHGs and co-pollutants resulting from increased use of clean vehicles. Since communities of color and low income in California tend to live in closer proximity to traffic (Gunier et al. 2003; Cushing et al. 2015), clean vehicle rebate programs may help reduce exposures to transportation-related pollutants in disadvantaged communities. On the other hand, power plant air pollutant emissions may increase if electric vehicle adoption results in increased electricity demand, which could disproportionally impact disadvantaged communities (Carley et al. 2018).

4 Conclusions

Results of our analysis suggest that California's CVRP disproportionately benefits higher-income neighborhoods with higher levels of educational attainment and fewer residents of color. Introducing an income cap and an income-tiered rebate amount providing an additional $2000 for lower income consumers reduced, but did not fully close, the gaps in CVRP rebate allocation with respect to income, education, and race/ethnicity. Additionally, we found that the income cap might exclude more potential participants than the ones attracted by the income-tiered rebate amount, causing a reduction in the total number of rebates that were distributed.

In contrast, the design of the EFMP, including expanded vehicle eligibility of used fuel-efficient vehicles, inclusion of non-plug-in hybrids and lower-emission internal combustion engine vehicles, stricter income caps, more progressive rebate amount increments for lower-income households, and an additional rebate amount in disadvantaged communities, appear to have a stronger effect on extending participation to racially and ethnically diverse communities with lower incomes, higher average ambient NO_2 concentrations, and more community disadvantage. Although we were unable to distinguish which of these design elements had the greatest impact, our analysis suggests that implementation of equity-related designs beyond an income cap and income-tiered rebate amounts are needed to make rebate programs more accessible to those who could benefit the most.

Funding This work was funded by the California Office of Environmental Health Hazard Assessment (https://oehha.ca.gov/; Contract #16-E0012-2).

References

Allison P (2009) Fixed effects regression models. SAGE Publications, Inc., 2455 Teller Road, Thousand Oaks California 91320 United States of America

Anderson CM, Kissel KA, Field CB, Mach KJ (2018) Climate change mitigation, air pollution, and environmental justice in California. Environ Sci Technol 52:10829–10838. https://doi.org/10.1021/acs.est.8b00908

Atmospheric Composition Analysis Group (2019) Surface PM 2.5 North American Regional Estimates. http://fizz.phys.dal.ca/~atmos/martin/?page_id=140#V4.NA.02. Accessed 8 Feb 2019

August L (2016) CalEnviroScreen 3.0. In: OEHHA. https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-30. Accessed 11 Feb 2019

Bechle MJ, Millet DB, Marshall JD (2011) Effects of Income and Urban Form on Urban NO : Global Evidence from Satellites. Environ Sci Technol 45 (11):4914–4919

Beck N, Katz JN (2001) Throwing out the baby with the bath water: a comment on Green, Kim, and Yoon. Int Organ 55:487–495

Bernal JL, Cummins S, Gasparrini A (2017) Interrupted time series regression for the evaluation of public health interventions: a tutorial. Int J Epidemiol 46:348–355. https://doi.org/10.1093/ije/dyw098

Briguglio M, Formosa G (2017) When households go solar: determinants of uptake of a photovoltaic scheme and policy insights. Energy Policy 108:154–162. https://doi.org/10.1016/j.enpol.2017.05.039

California Air Resource Board (2018a) California greenhouse gas emissions for 2000 to 2016. California Air Resource Board

California Air Resource Board (2018b) Enhanced fleet modernization program. https://www.arb.ca.gov/msprog/aqip/efmp/efmp.htm. Accessed 15 Jan 2019

California Air Resource Board (2019a) EFMP retire and replace participant-level data. https://www.arb.ca.gov/msprog/aqip/efmp/stats/participant_data_q3_2018.xlsx. Accessed 11 Feb 2019

California Air Resource Board (2019b) Proposed fiscal year 2019–20 funding plan for clean transportation incentives

California Environmental Protection Agency (2017) Designation of disadvantaged communities pursuant to Senate Bill 525 (de León)

Carley S, Evans TP, Graff M, Konisky DM (2018) A framework for evaluating geographic disparities in energy transition vulnerability. Nat Energy 3:621–627. https://doi.org/10.1038/s41560-018-0142-z

Center for Sustainable Energy (2016) Income eligibility. In: Clean Veh. Rebate Proj. https://cleanvehiclerebate.org/eng/income-eligibility. Accessed 14 Jan 2019

Center for Sustainable Energy (2017) Preapproval for CVRP rebates. In: Clean Veh. Rebate Proj. https://cleanvehiclerebate.org/eng/rebatenow. Accessed 18 Mar 2019

Center for Sustainable Energy (2019) California Air Resources Board Clean Vehicle Rebate Project, Rebate Statistics. https://cleanvehiclerebate.org/eng/rebate-statistics. Accessed 21 Jan 2019

Colin Cameron A, Miller DL (2015) A practitioner's guide to cluster-robust inference. J Hum Resour 50:317–372. https://doi.org/10.3368/jhr.50.2.317
Cushing L, Faust J, August LM et al (2015) Racial/ethnic disparities in cumulative environmental health impacts in California: evidence from a statewide environmental justice screening tool (CalEnviroScreen 1.1). Am J Public Health 105:2341–2348. https://doi.org/10.2105/AJPH.2015.302643
DeShazo JR (2016) Improving incentives for clean vehicle purchases in the United States: challenges and opportunities. Rev Environ Econ Policy 10:149–165. https://doi.org/10.1093/reep/rev022
DeShazo JR, Sheldon TL, Carson RT (2017) Designing policy incentives for cleaner technologies: lessons from California's plug-in electric vehicle rebate program. J Environ Econ Manag 84:18–43. https://doi.org/10.1016/j.jeem.2017.01.002
Egbue O, Long S (2012) Barriers to widespread adoption of electric vehicles: an analysis of consumer attitudes and perceptions. Energy Policy 48:717–729. https://doi.org/10.1016/j.enpol.2012.06.009
Erdem C, Şentürk İ, Şimşek T (2010) Identifying the factors affecting the willingness to pay for fuel-efficient vehicles in Turkey: a case of hybrids. Energy Policy 38:3038–3043. https://doi.org/10.1016/j.enpol.2010.01.043
Faust J, August L, Bangia K, et al (2017) CalEnviroScreen3. Office of Environmental Health Hazard Assessment
Graff M, Carley S, Pirog M (2019) A review of the environmental policy literature from 2014 to 2017 with a closer look at the energy justice field. Policy Stud J 47:S17–S44. https://doi.org/10.1111/psj.12316
Gunier RB, Hertz A, Von Behren J, Reynolds P (2003) Traffic density in California: socioeconomic and ethnic differences among potentially exposed children. J Expo Anal Environ Epidemiol 13:240–246. https://doi.org/10.1038/sj.jea.7500276
Hardman S, Chandan A, Tal G, Turrentine T (2017) The effectiveness of financial purchase incentives for battery electric vehicles – a review of the evidence. Renew Sust Energ Rev 80:1100–1111. https://doi.org/10.1016/j.rser.2017.05.255
Javid RJ, Nejat A (2017) A comprehensive model of regional electric vehicle adoption and penetration. Transp Policy 54:30–42. https://doi.org/10.1016/j.tranpol.2016.11.003
Jenkins K, McCauley D, Forman A (2017) Energy justice: a policy approach. Energy Policy 105:631–634. https://doi.org/10.1016/j.enpol.2017.01.052
Johnson C, Williams B, Hsu C, Anderson JW (2017) The clean vehicle rebate project: summary documentation of the electric vehicle consumer survey, 2013–2015 edition. Center for Sustainable Energy, San Diego
Kwan CL (2012) Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States. Energy Policy 47:332–344. https://doi.org/10.1016/j.enpol.2012.04.074
Lachapelle U (2013) Participation and incentive choice of participants in an early vehicle retirement program in Quebec, Canada. Transp Res Rec J Transp Res Board 2375:8–17. https://doi.org/10.3141/2375-02
Mennis J (2003) Generating surface models of population using dasymetric mapping. Prof Geogr 55:31–42. https://doi.org/10.1111/0033-0124.10042
Millman KJ (2015) Permute—a python package for permutation tests and confidence sets. University of California, Berkeley
Multi-Resolution Land Characteristics Consortium (2011) NLCD 2011 Percent Developed Imperviousness (CONUS). https://prd-tnm.s3.amazonaws.com/StagedProducts/NLCD2011/Urban_Imperviousness/CONUS/nlcd_2011_impervious_2011_edition_2014_10_10.zip. Accessed 25 Jan 2019
Narassimhan E, Johnson C (2018) The role of demand-side incentives and charging infrastructure on plug-in electric vehicle adoption: analysis of US states. Environ Res Lett 13:074032. https://doi.org/10.1088/1748-9326/aad0f8
National Renewable Energy Laboratory (2019) Alternative fuel stations. https://developer.nrel.gov/docs/transportation/alt-fuel-stations-v1/. Accessed 7 Feb 2019
Pastor M, Morello-Frosch R, Sadd JL (2016) The Air Is Always Cleaner on the Other Side: Race, Space, and Ambient Air Toxics Exposures in California. J Urban Aff 27(2):127–148
Pierce G, DeShazo JR (2017) Design and implementation of the enhanced fleet modernization plus-up pilot program. UCLA Luskin Center for Innovation
Plümper T, Troeger VE (2007) Efficient estimation of time-invariant and rarely changing variables in finite sample panel analyses with unit fixed effects. Polit Anal 15:124–139. https://doi.org/10.1093/pan/mpm002
Poder TG, He J (2017) Willingness to pay for a cleaner car: the case of car pollution in Quebec and France. Energy 130:48–54. https://doi.org/10.1016/j.energy.2017.04.107
Potoglou D, Kanaroglou PS (2007) Household demand and willingness to pay for clean vehicles. Transp Res Part Transp Environ 12:264–274. https://doi.org/10.1016/j.trd.2007.03.001
Ratcliffe M, Burd C, Holder K, Fields A (2016) Defining rural at the U.S. Census Bureau. 8
Rubin D, St-Louis E (2016) Evaluating the economic and social implications of participation in clean vehicle rebate programs. Transp Res Rec J Transp Res Board 2598:67–74. https://doi.org/10.3141/2598-08

Sierzchula W, Bakker S, Maat K, van Wee B (2014) The influence of financial incentives and other socio-economic factors on electric vehicle adoption. Energy Policy 68:183–194. https://doi.org/10.1016/j.enpol.2014.01.043
Skippon S, Garwood M (2011) Responses to battery electric vehicles: UK consumer attitudes and attributions of symbolic meaning following direct experience to reduce psychological distance. Transp Res Part Transp Environ 16:525–531. https://doi.org/10.1016/j.trd.2011.05.005
Snelling A (2018) Evaluation of state plug-in electric vehicle purchase incentive programs: what drives vehicle uptake?
Soskin M, Squires H (2013) Homeowner willingness to pay for rooftop solar electricity generation. Environ Econ 4:10
Tamor MA, Milačić M (2015) Electric vehicles in multi-vehicle households. Transp Res Part C Emerg Technol 56:52–60. https://doi.org/10.1016/j.trc.2015.02.023
The Berkeley Satellite Group (2019) The Berkeley high-resolution NO_2 product. http://behr.cchem.berkeley.edu/TheBEHRProduct.aspx. Accessed 8 Feb 2019
United States Census Bureau (2010) 2010 census urban and rural classification and urban area criteria. https://www.census.gov/geo/reference/ua/urban-rural-2010.html. Accessed 7 Feb 2019
United States Census Bureau (2019) American community survey. https://www.census.gov/developers/?#. Accessed 25 Jan 2019
van Donkelaar A, Martin RV, Li C, Burnett RT (2019) Regional estimates of chemical composition of fine particulate matter using a combined geoscience-statistical method with information from satellites, models, and monitors. Environ Sci Technol. https://doi.org/10.1021/acs.est.8b06392
Vergis S, Chen B (2015) Comparison of plug-in electric vehicle adoption in the United States: a state by state approach. Res Transp Econ 52:56–64. https://doi.org/10.1016/j.retrec.2015.10.003
Williams B (2018) CVRP: data and analysis update
Zhou S, Noonan DS (2019) Justice implications of clean energy policies and programs in the United States: a theoretical and empirical exploration. Sustainability 11:1–20
Zhou Y, Wang M, Hao H et al (2015) Plug-in electric vehicle market penetration and incentives: a global review. Mitig Adapt Strateg Glob Change 20:777–795. https://doi.org/10.1007/s11027-014-9611-2

Affiliations

Yang Ju[1,2] • **Lara J. Cushing**[3] • **Rachel Morello-Frosch**[2,4]

1 Institute of Urban and Regional Development, University of California, Berkeley, Berkeley, CA, USA

2 Department of Environmental Science, Policy and Management, University of California, Berkeley, Berkeley, CA, USA

3 Department of Environmental Health Sciences, Fielding School of Public Health, University of California, Los Angeles, Los Angeles, CA, USA

4 School of Public Health, University of California, Berkeley, Berkeley, CA, USA