21AQP002: MEASURING THE EMISSIONS AND SOCIOECONOMIC BENEFITS OF CARB'S INCENTIVES AND REGULATORY PROGRAMS: THE LIGHT-DUTY VEHICLE SECTOR PROGRAMS

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Executive Summary

- This report aimed to investigate the impact of California Air Resources Board's (CARB) light-duty vehicle incentive programs on zero emission vehicle (ZEV) buyer decisions to purchase a ZEV. The purpose was to estimate an adjustment factor that CARB could use to estimate the impact of their programs.
- This report also seeks to address the California State Auditor (CSA)'s report "Improved Program Measurement Would Help California Work More Strategically to Meet Its Climate Change Goals," published in February 2021.
- We used questionnaire surveys to investigate the impact of the Clean Vehicle Assistance Program (CVAP) and Clean Vehicle Rebate Program (CVRP). Due to limitations in these surveys, we could not accurately estimate the impact of ZEV incentives, mainly due to surveys not accounting for how the incentive programs interact with each other and some survey design limitations.
- Not being able to account for incentive interactions is an issue since PEV buyers can claim multiple incentives, e.g., the CVRP, Clean Cars 4 All (CC4A), the Federal Tax Credit, grant from CVAP, the Clean Fuel Reward, carpool lane access, utility rebates, and other programs. While all of these incentive programs impact PEV buyer decisions, without a survey that includes data on all the existing incentive programs that the buyer is eligible for and includes buyers who purchase ZEV without any incentives, we were unable to estimate a credible adjustment factor.
- We were able to provide preliminary estimates on the impact of CVAP and CVRP in isolation of any other programs using three separate surveys. These surveys have the limitation of not accounting for interactions and other limitations based on the survey design. This includes experimenter demand effects where survey respondents may adjust their answers based on their perceived aim of the question.
- Regardless of these limitations, results show that incentive programs do positively impact PEV buyer decisions; however, one rebate does not result in one buyer choosing a PEV over an internal combustion engine vehicle (ICEV).
- The effect of CVRP and CVAP differs by vehicle type, vehicle manufacturer suggested retail price (MSRP), and demographic attributes. Results show CVAP is overall more influential in purchase decisions than CVRP.
- Overall, we believe the estimated impacts of these CVAP and CVRP, despite the limitations, might provide a more accurate assessment of incentive impacts than considering one incentive as one induced vehicle sale. **Error! Reference source not found.** below shows high level results from survey responses and model outputs for CVRP and CVAP. The range of values in this table could potentially be used by CARB quantification methodologies in place of assuming one incentive results in one ZEV sold for these programs.
- The analysis does not account for how incentives impact those who do not receive them. There may be positive effects; for example, due to anticipating getting an incentive or the symbolic value of incentives showing PEV purchase is a socially desirable decision. There could also be negative impacts; for example, buyers who are ineligible not purchasing a PEV because they cannot receive an incentive when others do, or complicated incentive designs may deter buyers from program participation and choosing a PEV.
- The analysis also cannot account for automaker decision making, vehicle supply, and how this may be influenced by the presence or absence of incentives. For example, a total lack of

incentives may impact automaker decisions on vehicle supply, with automakers potentially preferentially supplying PEVs to markets with incentives. On the other hand, if one PEV buyer does not purchase a PEV due to the absence of incentives, that PEV could be purchased by another buyer (especially when PEV supply is constrained). We are unaware of any data that could be used to account for automaker vehicle supply decisions and how these may or may not be impacted by incentives.

- The challenges in determining the impacts of individual programs are severalfold, and include:
  - The programs interact and have a combined effect on electric vehicle sales. An incentive program alone may be less effective in encouraging electric vehicle sales without vehicle supply regulations, and vice versa. Regulations and incentives serve different purposes and are complementary to each other, making it impossible to disentangle their benefits with the data available to the research team.
  - Given the complexity of consumer decision making and the lack of comprehensive survey data, the UC research team cannot provide an accurate estimate to determine how much of a ZEV sale or lease is due to any particular CARB program accounting for program interactions. The team could provide a preliminary estimate that may be more accurate than assuming one incentive results in one electric vehicle sale.
- Making a credible quantitative determination of the effect of an individual or multiple incentive programs on purchases of ZEVs requires knowledge of all incentives received by each buyer, along with factors effecting consumer decision-making. No existing survey data or vehicle registration data gives a comprehensive view of this.
- The impact of programs will also be affected by supplier decision-making and behavior, which is impossible to measure with the data the research team has access to.
- Due to the existence of various ZEV programs (regulations and incentives) and programs working in concert, the role of any one policy is impossible to disentangle with current data available to the research team.
- The provided estimates for CVRP and CVAP are based on stated responses to survey questions that ask participants to report how they would behave if they did not receive CVAP or CVRP. These questions ask respondents to only consider CVAP and CVRP. As a result, the estimated impacts of these program do not account for participant behaviour considering other incentives they may have received. The estimates may under or overestimate program impacts, depending on how CVAP and CVRP interact with other programs.
- No survey data is available to evaluate CC4A. To evaluate this program, we used a synthetic control method to analyze the impact of the program in the San Joaquin Valley Air Pollution Control District (SJVAPCD) and South Coast Air Quality Management District (SCAQMD) regions. However, due to data limitations, we were unable to propose adjustments for this program, though results do show the program has a positive impact on sales.
- The CC4A program has a positive significant impact on PEV sales in the participating air districts analyzed here (SJVAPCD and SCAQMD). The analysis finds an additional 6% PEV sales per quarter in SJVAPCD post intervention and 55% increase in sales in SCAQMD. These preliminary research results demonstrate positive program impacts, however more data and research are needed to improve these estimates.
- Overall, our recommendation on data collection is to design and administer a revised questionnaire survey to address the limitations of currently available data to obtain a more credible estimate of the impact of CVAP, CVRP, and CC4A programs along with other state

and federal programs. Future improved survey data would need to be continually collected to credibly isolate the GHG emission reductions associated with individual programs.

Finally, it is important to note that CARB uses actual and credible ZEV population data from the Department of Motor Vehicles (DMV) and fuel sales data from the California Department of Tax and Fee Administration (CDTFA) to create emissions inventories of greenhouse gases and criteria air pollutants from on-road vehicles, including the EMission FACtor (EMFAC) inventory model and greenhouse gas emissions inventory. These emissions inventories, instead of the emission reduction estimates for individual regulations and incentive programs, are used to determine whether the State is on track to meet air quality or climate goals.

Table 1: Stated individual responses to incentive programs ("Average survey response") from the surveys we analyzed and the predicted probability of being incentive essential for the whole sample in each survey and at various MSRP or FPL points. This does not account for interaction effects, and combined with the limitations of the available data, these numbers will be over- or underestimates of the incentive impacts.

		Predicted probabilities				
Program	**Average survey response**	**Predicted average**	**<$20,000 MSRP**	**$20,000 to $40,000 MSRP (<$40,000 for CVRP)**	**$40,000 to $60,000 MSRP (>$40,000 for CVAP)**	**>$60,000 MSRP**
CVAP all	0.86	0.86	0.89	0.87	0.83	
CVAP 225% to 400% FLP	0.84	0.84	0.86	0.86	0.82	
CVAP <225% FPL	0.88	0.88	0.90	0.89	0.85	
CVRP all (CSE data)	0.50	0.50		0.54	0.48	0.33
CVRP regular rebate (CSE data)	0.49	0.50		0.53	0.48	0.33
CVRP increased rebate (CSE data)	0.68	0.57		0.59	0.52	0.45
CVRP all (eVMT data)	0.36	0.27		0.31	0.21	0.13

Introduction

California's new Advanced Clean Cars II regulation (ACC II) adopted in August 2022 by the California Air Resources Board (CARB), reinforced the state's already growing zero-emission vehicle (ZEV) market by setting an aggressive target of transitioning to 100 percent ZEV sales by 2035 for the light-duty vehicle (LDV) sector. Achieving this target will help the objective of the ACC II regulations - scale down emissions of light-duty passenger cars, pickup trucks and SUVs starting with the 2026 model year through 2035. Transition to 100% ZEV sales entails increasing sales of battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCEVs).

Recent research has shown that monetary incentives that subsidize ZEV purchase play a key role in enabling adoption of ZEVs, particularly as the diffusion process moves from high-income early adopters who are often single-family homeowners to middle-income households and multi-unit dwelling residents (1). Financial incentives will continue to be important means to reduce the financial barrier, especially as EVs are not likely to reach cost parity with comparable Internal Combustion Engine Vehicles (ICEVs) until barriers such as charger accessibility and cost are addressed, even though the ACC II target requires 100% ZEV sales by 2035 (2).

In California there are multiple state-level as well as local incentive programs for ZEV adopters, and buyers can also claim the federal EV tax credit. The state-level programs administered by the California Air Resource Board include the Clean Vehicle Rebate Project (CVRP), the Clean Vehicle Assistance Program (CVAP), and the Clean Car for All (CC4A) program. An example of a local incentive program would be the Sacramento Municipal Utility District's $1000 cash rebate for charger installation. While the positive impact of financial incentives on EV adoption is unambiguous, as suggested by the findings of multiple research projects over the years (3–7), the extent to which they create new ZEV sales versus being received by those who would have otherwise adopted a ZEV is often questioned by researchers and policymakers and requires further research.

The aim of this project is to develop a better understanding of the benefits of CARB's policy portfolio for the LDV sector in terms of their impact on ZEV sales in the state and thereby the impact on greenhouse gas (GHG) reductions focusing on incentive programs. As the California State Auditor (CSA)'s report "Improved Program Measurement Would Help California Work More Strategically to Meet Its Climate Change Goals," published in February 2021 suggested, CARB has generally not adequately accounted for the effects of its incentive programs on consumer behavior. Specifically, the report mentioned that there is a lack of quantitative estimates of the effect of rebate payments through the multiple incentive programs on consumer decisions to purchase a low emission vehicle than they otherwise would have purchased. Having this information is crucial to making accurate calculations of the GHG reductions of those programs because it would indicate whether the incentive caused the vehicle purchase and therefore contributed to the GHG reductions.

In this report, we evaluate the three main LDV sector programs in CARB's portfolio: the CVRP, the CVAP, and the CC4A and aim to estimate the effect size of these programs, accounting for the impact of these programs on consumer behavior. Using choice models, the CVRP and the CVAP is evaluated by analyzing the impact of changes in MSRP on a consumer's stated decision to purchase a ZEV in the absence of the CVRP or CVAP. The CC4A is evaluated by analyzing its impact on ZEV sales in the air quality management districts that implemented the program using a causal analysis method, the synthetic control model. While the causal model offers a direct estimate of the potential impact of the CC4A program on EV sales, the potential effect size of the CVRP and CVAP program is reported based on the predicted probabilities, as well as the average marginal effect estimates generated by the logistic regression models for various categories of MSRP values and income groups.

The aim of the report was to develop adjustment factors to apply to the estimates of the impacts of these programs (number of ZEV sales) on GHG reduction. In this regard, there are some important insights the analysis here offers. The results of the models firstly show that incentives do not impact purchase decisions for 100% of incentive recipients. Second, the results of the consumer choice model, and the synthetic control model offer a range of values that may be used as adjustment factors, though none of them credibly estimate incentive impacts due to data issues, which we discuss in this report. In terms of a factor used to adjust the impact on GHG reduction, more research is needed to obtain an accurate estimate that considered the interaction effects of programs. This issue is primarily because consumers can stack the CVAP with CVRP along with other incentives including HOV lane access and federal tax credit, but the questions and the survey data analyzed for this study does not capture the impact of incentive stacking or interactions.

As for the CC4A program, the causal impact estimated here can be considered the impact of the program on households who have an older vehicle to replace and are eligible for the CC4A incentive. Even though the method should ideally be able to isolate the impact of the CC4A even when stacked with CVRP, the researchers suggest that the impact of the former program estimated here should be interpreted as another value in the range of factors that can be used to adjust the impact of the incentive programs on ZEV sales and thereby GHG emissions. The adjustment factors are developed based on historical data and depending on how the program evolves (e.g., incentive amounts, incentive eligibility, regional eligibility, vehicle eligibility) the adjustment factors will need to be re-estimated. Moreover, since programs are constantly evolving in response to changes in the ZEV market and complexities like incentive-stacking are not captured in the data collected, it is difficult to estimate a single adjustment based on historical data or develop a predictive adjustment factor.

The report is organized as follows: In Section 2 we briefly summarize the three main LDV sector incentive programs administered by CARB. In section 3, we review the literature related to the importance of incentives on EV adoption behavior, the impact of the CVRP and the other programs on the California EV market, and the literature focusing on the equitable distribution of the incentive payments. Next, in Section 4 we give a description of the survey data and the methods used to analyze the impact of the CVRP on consumer EV adoption decision. Data, method, and findings from the model for CVAP are described in Section 5. We discuss the data, causal model, and the results evaluating the Clean Car for All program in South Coast Air Quality Management District, San Joaquin Air Pollution Management District, and the Bay Area Air Quality Management District in Section 6. Finally, policy implications of the findings (discussion) and the recommendations for future survey data collection is given in Section 7 and Section 8 respectively.

SUmmary of the Three LDV sector incentive programs

California Clean Vehicle Rebate

The California Clean Vehicle Rebate Project (CVRP), launched in 2010, is a rebate project that promotes clean vehicle adoption in California by offering post-purchase rebates for the purchase or lease of new, eligible zero-emission vehicles. Rebate values, the types of vehicles eligible for CVRP, and vehicle eligibility (based on PHEV range and MSRP) have varied over time. As of October 2023, CVRP no longer provides rebated to ZEV buyers.

The Clean Vehicle Assistance Program (CVAP) was launched in 2018 for income-eligible recipients who are residents of the State of California. Eligibility is based on gross annual household income and considers the number of household members. The program is administered by the CARB via the Beneficial State Foundation (BSF). In addition to the grant for vehicles, there is a grant for charging station charge cards, portable EV chargers, or home charger installation and the buyer can apply for it within 90 days of vehicle purchase. The grant funds setting up a level 2 charging station of up to $2000 value or a $1000 prepaid charge credit valid at EVGO public charging stations along with a low-speed portable charging cable (9). The CVAP vehicle grant can be stacked with the CVRP rebate and the California Clean Fuel Reward available to all California residents who purchase or lease an eligible vehicle through a participating dealership when all program criteria are met for each program independently. In this case, "stacking" means to combine multiple grants and rebates to lower the cost of a single vehicle purchase or lease. The CVAP cannot be stacked with the CC4A program.

Clean Cars 4 All (CC4A) started in 2015, an addition to the erstwhile Enhanced Fleet Modernization Program (EFMP) that was launched in 2010, focusing on providing incentives through California Climate Investments to lower-income California drivers to scrap their older, high-polluting car and replace it with a zero- or near-zero emission replacement. In order to receive the CC4A incentive a household must retire a vehicle that is operational, exceeds model year 2000 and newer vehicle model emissions levels, be older than model year 2007, be gasoline or diesel powered, and have a gross vehicle weight rating of 10,000 pounds or less. To be considered operational, a vehicle must be registered with the California DMV for the past two years or have documentation from an insurance company or automotive repair dealer proving two years of vehicle operation in California.[1] Recipients of the incentive have the option of a purchase or lease of a new or used hybrid, plug-in hybrid electric or replacement vehicle, or an alternative mobility option such as an e-bike, voucher for public transit or a combination of clean transportation option. Buyers of plug-in hybrid electric (PHEV) and battery electric vehicles (BEVs) are also eligible for home charger incentives or prepaid charge cards if home charger installation is not an option. To augment the mean-tested feature of the program, CC4A offers additional incentives, the EFMP "Plus-up" to a subset of participants who reside in or near a disadvantaged community census tract. The base EFMP and the EFMP "Plus Up" are jointly operated and is currently administered in five air districts in California: South Coast Air Quality

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[1]https://ww2.arb.ca.gov/sites/default/files/classic/msprog/cc4a/frorev.pdf?_ga=2.260486155.707660979.1560376396-1471894195.1559317486

Management District (AQMD), San Joaquin Valley Air Pollution Control District (APCD), Bay Area AQMD, and the Sacramento Metropolitan AQMD.

Literature Review

In this section, we review the literature on the impact of financial incentives on consumer EV adoption behavior, existing literature on the effect of specifically the CVRP, CVAP, or the CC4A programs on the EV market in California.

Impact of Financial Incentives on EV Adoption Behavior

There is extensive literature on the impact of incentives on the adoption of alternative fuel technology vehicles, mainly BEVs and PHEVs, here on collectively referred to as plug-in electric vehicles (PEVs). Understanding whether incentives create additional PEV sales is important to assess the effective use of public tax dollars and resources. In this case, effectiveness is defined by whether the policy leads to PEV uptake beyond what would have occurred without the intervention. Reviewing the existing literature on effect of financial incentives on adoption of new vehicle technology like PEVs or earlier the conventional hybrid vehicle, in 2017, Hardman et al. found that 32 out of 35 studies in the literature concluded that financial incentives have a positive effect on PEV sales. However, the amount and the structure of the incentive matters in determining its impact on consumer behavior. Jenn et al. (3) studying PEV registrations across 50 states of the US from January 2010 through November 2015 find that $1000 incentive can enable on average a 2.6% increase in PEV sales, implying that a substantial rebate amount is required to influence adoption behavior. Moreover, due to difference in consumer awareness about EVs as well as the incentive program, there can be wide heterogeneity in the impact of financial incentives, 62% increase in PEV registrations in California but 20% in Florida, and 0% in Montana. In terms of incentive structure, there is evidence both from the literature on adoption of conventional hybrid vehicles as well as EVs that point-of-purchase financial incentives have a higher impact on consumer adoption behavior than post-purchase incentives like tax credits (5,10).

Sierzchula et al. (11) focused on quantifying the effect of financial incentives. Considering impact on EV sales at a national level, the authors find low elasticity with a $1000 incentive corresponding to just 0.06% increase in market share. More recently, considering the EV market in Europe from 2010 to 2017, using panel data on PEV sales, Munzel et al. (6) find that financial incentives yield about 5–7% relative sales share increase per 1000 euro. Considering the US market, using fixed effect regression models and synthetic control method, Clinton and Steinberg (7) find that incentives offered as direct purchase rebates generate increased levels of new BEV registrations at a rate of approximately 8% per $1000. Vergis and Chen (12) using simple regression models to understand the factors influencing the market share of PEVs in 2013 showed that a 22% increase in market share can be attributed to purchase incentives. Focusing on the importance of the federal tax incentive, Tal and Nicholas (13) found a 32.5% increase corresponding to the $7,500 incentive). Using similar cohort survey data of PEV buyers between 2010 and 2017, Jenn et al. (4) find that 40% of PEV buyers would not buy PEV without the federal tax credit.

Overall, the quantitative measure of the impact varies considerably across studies based on the incentive program under analysis, the type of sample in the study (whether drawn from the general population, cohort survey or vehicle registration data), time frame, and the geographic scope. Despite these variables, there is a general consensus that incentives play an important role in encouraging the PEV adoption and therefore positively influencing the ZEV market. Moreover, financial incentives will continue to be important in the future as EV diffusion progresses from early adopters to the mass market with a higher share of middle- and lower-income vehicle buyers (4) .

Impact of the CVRP, CVAP, and CC4A Program

The CVRP in California has been running for over a decade and several studies have analyzed the impact of the program. Studying the impact of multiple designs of the CVRP in terms of incentive amount, income, and price caps on PEV sales and market share, Deshazo et al. (14) showed that an average $1,838 in incentives led to approximately a 7% increase in PEV sales and a 0.2% increase in total market share. Analyzing survey data from a group of PHEV drivers in California who purchased a PHEV between 2012 and 2015 and received the CVRP, Johnson and Williams (15) showed that "rebate essentiality" (requiring a rebate to purchase a PEV based) increased when consumers bought lower price vehicles or in other words, cost was a concern. This study looked at a period when there was no income or prices-based eligibility criteria in the CVRP.

Income caps were introduced into the CVRP program in 2016. Income cap implications on the CVRP have been captured in the study by Guo and Kontou (16) where they considered four equal income intervals (less than $50,000, $50,000 - $100,000, $100,000 - $150,000, and over $150,000) and observed that the moderate to high-income group received the greatest share of rebates. Their study was based on CVRP program data from 2010 to 2018. After the income-cap policy implementation in the year 2016 where PHEV and BEV consumers with a gross annual individual income greater than $150,000 were no longer eligible to apply for rebates under CVRP, the share of rebates per capita increased in both lower- and middle-income communities and disadvantaged communities (DACs) at the 95% confidence level based on their empirical analysis. For both PEV types, the rate of adoption was higher during the quarters that preceded the income cap policy implementation date. The rate dropped after the policy was implemented, hinting that higher-income groups predominantly used the rebates before the income cap was introduced. Considering PEV adopters and thereby CVRP recipients from 2016 and 2017, Williams and Anderson (17) found that though the relationship between household income and "rebate essentiality" weakened compared to the 2013-2015 buyers, CVRP recipients who were eligible for increased rebate and residents of disadvantaged communities were more likely to find the rebate essential in their purchase decision. More recently, in a 2020 study, Pallonetti et al. (18) found that approximately 35% of rebated greenhouse gas reductions were associated with standard "Rebate-Essential" participants who were most highly influenced by the CVRP to purchase/lease and approximately 67% of reductions from rebate essential recipients of California's Increased Rebate for Low-Moderate-Income households.

Overall, rebate programs like the CVRP have a positive significant effect on PEV adoption. Examining 376,772 consumers, including 72,552 CVRP survey respondents statistically weighted for representativeness Wiliams and Pallonetti (19) find that "Rebate Essentiality"—the percent of consumers who would not have purchased/leased their EV without the rebate—increased to a high of 57% in the 2016–17 edition of the survey and remained above 50% until 2020. Rebate essentiality decreased from 2019 to 2020 primarily due to Tesla owners and the impact of the

COVID pandemic–31% for Tesla buyers, 47% for PHEVs, 50% for non-Tesla BEVs, 66% for Increased Rebate recipients. Accounting for lag effects in PEV adoption. Narassimhan and Johnson (20) show that 1% increase in tax incentives relative to a vehicle's MSRP is associated with a 1.15% increase in per capita PEV purchases. Their results also suggest that rebates have a higher impact than tax credits and BEV owners may find incentives more important than PHEV drivers due to the price difference between the technologies. Thereby, focusing on BEV owners, the authors find that a 1% increase in incentives relative to vehicle MSRP is associated with a 1.8% increase in BEV purchases with a tax credit and 2.16% with a rebate. E.g., if the California incentive increased from $2500 to $10 000 (i.e. 25% increase for a $30 000 vehicle), it could result in 50% higher adoption (21).

There has been a long-standing equity concern regarding the distribution of financial incentives and the ability to transition to cleaner fuel technology vehicles. In recent years there has been significant research on this topic with researcher analyzing the equity impacts of the CVRP and other mean-tested programs administered by CARB like the EFMP and CC4A. Assessing California's transition to EVs and the distribution of rebates between 2010 and 2020 Hennessy an Syal find that vehicle adoption and rebate use are lower in low-income and Latino-majority ZIP codes and in formerly red-lined neighborhoods. Similar results were also suggested by Rubin et al. analyzing rebate allocation across census tracts in California between 2010 and 2015. These equity concerns initiated an income cap and income-tiered rebate amount part way through the CVRP program. The distribution impact of this change is captured by Guo and Kontou as described earlier. Ju et al. also looked at the distributional impact of the changes in the CVRP program and found that it 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. Additionally, the authors compared the equity impacts of the CVRP changes to the equity -promoting policy design of the EFMP and showed that 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. Their findings indicated 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.

To ensure more equitable distribution of the benefits of the transition to ZEVs and fuel-efficient vehicles, CARB had launched programs like the CVAP and CC4A. We could not find any existing literature on the CVAP but the impact of the CC4A has been analyzed in a couple of studies along with the Ju et al. study. The results of a difference-in difference study by Sheldon and Dua (22) before and after the introduction of the CC4A program called "Replace-your-Ride" (in conjunction with EFMP) in 2015 in the South Coast Air Quality Management District (SCAQMD) suggested that, it was successful in promoting the adoption of clean vehicles - 44% of the PEVs and 78% of the hybrid vehicle purchases made under the program in SCAQMD were additional and would not have occurred without the policy. Also using difference-in-difference and other causal analysis method such as the instrumental variable model to analyze the impact of the CC4A program on PEV demand in the San Joaquin Valley Air Pollution District (SJVAPD) and SCAQMD, Muehlegger and Rapson show that PEV demand for low- and middle-income households is relatively elastic and lowering prices by 10% increases PEV sales by 21 percent for low- and middle-income buyers.

Summarizing the literature review above for this report, the authors would like the reader to note that first, financial incentives, particularly cash rebates encourage EV adoption, and the policy design is important to ensure equitable distribution of the incentive. Second, the quantitative impact of financial incentives on PEV/ZEV sales depend on the geographic scope of the study, the time period, the data sample, as well as the program under analysis. Depending on these factors, the impact can vary between 44% (CC4A in SCAQMD as suggested by the study by Sheldon and Dua) to 2.16% (impact of CVRP in California as suggested by Narassimhan and Johnson (21)). As a result, these estimates give an idea about individual programs in the geographic area of concern and probably for the population studied but they are hard to compare or generalize for the general population of vehicle buyers. Lastly, in these studies the elasticity or marginal effect estimates of the incentives is usually measured for a $1000 increase in rebate amount or a particular percentage change, not accounting for the impact of stacked incentives. Therefore, a policymaker can use the estimates summarized here to get an idea of the impact of individual programs for a particular group of households or specific geographic regions but may not be able to always extrapolate these estimates to the general population or to understand the impact of stacked incentive amount consumers are often eligible for.

The Influence of Clean vehicle rebate project (CVRP) on the decision to adopt an electric vehicle

The objective of this CVRP program analysis is to explore the socio-demographic factors and vehicle characteristics associated with the decision to purchase or lease a PEV in the absence of the CVRP, and to estimate incentive impacts based on currently available data.

Data Description

Two sources of data were used to examine the impact of CVRP on the decision to purchase or lease a PEV in California: 1) survey responses of CVRP recipients from the EV Research Center's survey ("e-VMT survey") and 2) survey responses of CVRP participants from the Center for Sustainable Energy voluntary consumer survey ("CSE survey"). Utilizing multiple datasets enables a more comprehensive and nuanced grasp of underlying trends and patterns, surpassing what can be captured by solely depending on a single dataset**.**

4.1.1 e-VMT Survey

We use a cohort survey of PEV owners in California conducted in 2018 (phase 4 of the survey) and 2019-2020 (phase 5 of the survey). Respondents of the survey are sampled from the pool of CVRP recipients administered by the Center for Sustainable Energy & California Air Resources Board. Altogether, phases 4 & 5 include 7,357 and 7,078 respondents respectively, all of whom have applied for the CVRP rebate following the purchase or lease of a new PEV. 64.3% of the sample are purchasers. Participants report their stated importance of financial and non-financial incentives in the purchase/lease decision, which is used to create a rank order of incentives. The choice alternative question is then asked only to those participants who ranked the CVRP as their number one financial incentive:

"If the CVRP were not available when buying my PEV (or any other plug-in vehicle) I would have chosen:

- *A conventional or hybrid vehicle (non-plug-in vehicle)*
- *Another plug-in vehicle*

- *Not to [purchase/lease] a vehicle at all*
- *The [same] PEV*
- *Other*

Figure 1 shows the distributions of incentive rankings for lessees and purchasers in the data, respectively. These include both financial incentives from the federal government, state, local governments, or utilities, and the non-financial incentive of High Occupancy Vehicle (HOV) lane access. Lessees were not asked to rate the federal tax credit as the credit is received by the dealer and potentially passed onto the buyer in form of lower lease cost. So, there is no distribution of rankings to compare with other incentives. This could explain why 57% of lessees ranked the CVRP as their most important incentive, compared to 12% of purchasers. Lessees also have higher proportion of respondents reporting the HOV lane as their highest ranked non-financial incentive compared to purchasers. Over half of purchasers ranked the federal tax credit as the most important incentive in their decision to purchase PEV, followed by the CVRP, the utility rebate, HOV lane and local rebate.

Table 2 shows the incentive value by ranking for the CVRP compared with the federal tax credit. While the maximum applicable tax credit is greater than the CVRP, participants may place greater importance on the CVRP due to having less uncertainty about the amount of tax credit which they will receive, and possibly receiving the CVRP sooner than the tax credit. Research by Roberson and Helveston (23) also shows consumers value incentives they receive sooner more than those that are received later.

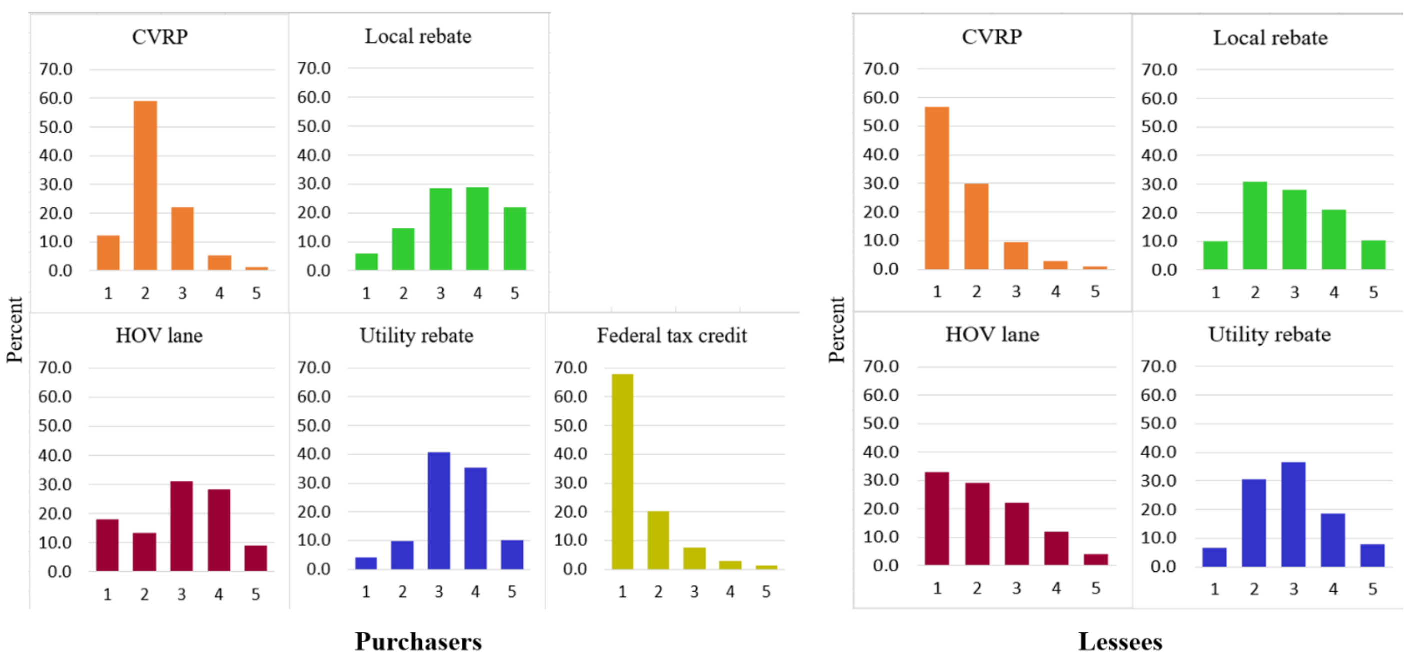

Figure 1: Distribution of incentive rankings by finance method.

Table 2: CVRP and federal tax credit reported incentive values by incentive ranking.

Rank	CVRP ($)	Federal tax credit ($)
1	2,427	6,291
2	2,215	5,661
3	2,046	5,009
4	1,920	4,698
5	1,584	4,552

Figure 2 provides a distribution of the response to the question "*If the CVRP were not available when buying my PEV (or any other plug-in vehicle) I would have chosen*", separated by finance method. There is a larger proportion of lessees choosing the same PEV (no change), or another PEV, compared with purchasers, and a smaller proportion of lessees choosing not to lease a vehicle at all (no vehicle) or choosing a conventional or hybrid vehicle (non-plug-in).

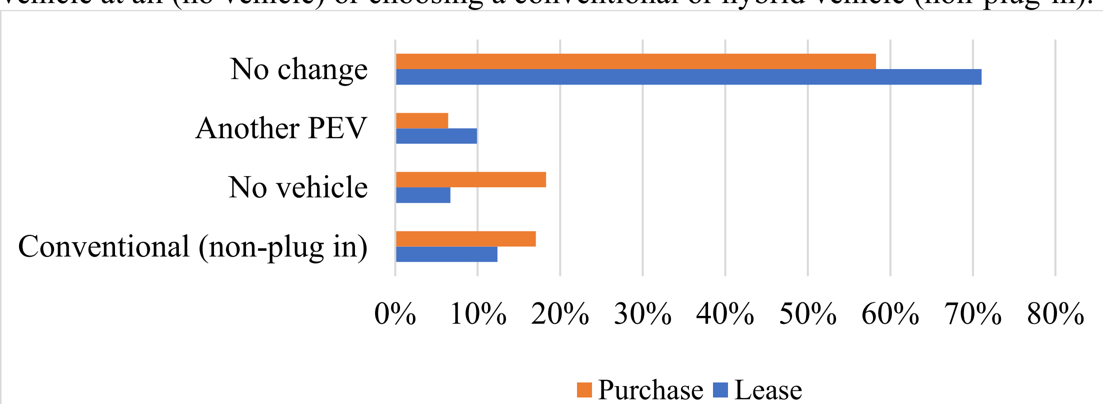

Figure 2: Distribution of choice alternatives by finance type

4.1.2 CSE survey of CVRP Recipients

The Center for Sustainable Energy (CSE) has administered voluntary consumer surveys of CVRP participants since 2013. The survey includes approximately 73,000 individual CVRP participants (i.e., excluding governmental, business, and nonprofit participants) who have purchased or leased plug-in hybrid EVs (PHEVs) or four-wheeled, highway-capable BEVs since September 1, 2012, and were approved for a rebate from October 2013, through June 2020. 57% of the survey participants took the survey for a first and/or only time, whereas the rest of the sample are repeat survey takers (suggesting they purchased multiple EVs and received multiple rebates).

Participants are asked if they would have purchased or leased their PEV without the CVRP, with response options being "yes" or "no". Participants who would not have purchased or leased a PEV without the CVRP are classified as being "rebate essential" (i.e., they reported they would not purchase their PEV without CVRP). **Figure 3** shows the percent of rebate essential participants across various income groups as defined in the program to determine income eligibility Approximately 5% of the sample, or 3,200 observations, received an increased rebate. On average, 50% of the CVRP recipients stated that the CVRP played an essential role in their PEV adoption decision. Compared with those who received a regular rebate, increased rebate recipients have a higher proportion of being rebate essential, at 69%. Similarly, those with an income of $199,000 or less have a higher proportion of rebate essential participants, at 53% compared with 43% for those with an income of $200,000 and above.

These percentages give a baseline estimate of how many EV buyers may not have bought the EV without the rebate, not controlling for factors identified in the literature to be correlated with EV adoption decision. Controlling for vehicle and sociodemographic characteristics, consumer choice models are estimated here to help identify the factors which affect the importance of the CVRP for recipients, such as the incentive amount, vehicle characteristics such as electric range and PEV type, and sociodemographic characteristics such as income and home ownership. Estimating the marginal effect allows the researcher to estimate the change in probability of being CVRP essential for a given change in the discounted MSRP while controlling for all other variables used in the model.

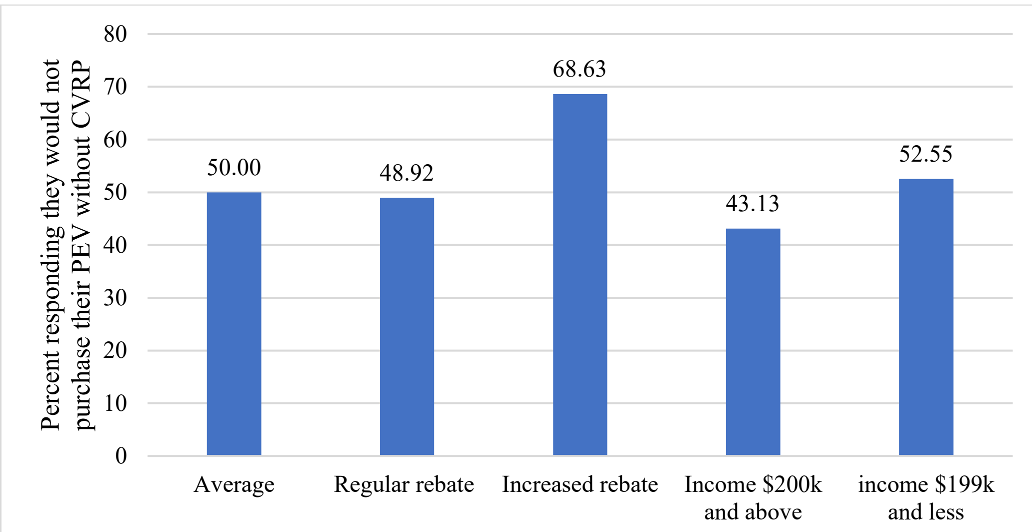

Figure 3: Percent of rebate recipients who reported they would not purchase their PEV without CVRP across various income groups.

In addition to income, rebate essentiality can also vary by the price of the vehicle. So, using the CSE data we explore the distribution of households in different income groups by vehicle price. **Table 3** shows the distribution of MSRP groups by PEV type and income group. BEVs, compared with PHEVs have a higher proportion of MSRPs above $41,000; most PHEVs are between $32,400 and $41,000. There is almost a 16 point decrease in the proportion of households with incomes $199,999 and below purchasing or leasing PEVs above $41,000 compared with the income group $200,000 and above. In other words, households buying lower price PEVs could be more CVRP essential than those buying higher priced PEVs.

Table 3: Distribution of MSRP groups by PEV type and income.

	Average	BEV	PHEV	Income above $200k	Income $199k and below
Below $32,400	22.0	21.0	23.9	16.1	24.2
$32,400 - $41,000	41.9	26.7	71.0	36.3	44.0
More than $41,000	36.1	52.3	5.2	47.6	31.7

Both the eVMT and the CSE data represent a wide variety of PEVs giving researcher the opportunity to control for the main effect of PEV type (BEV versus PHEV), electric range interacted with PEV type, as well as vehicle price, factors that can influence the EV adoption decision as well as rebate essentiality. Ideally, purchasers and lessees should be analyzed separately given the differences in the financing methods and its potential influence on adoption decision, addition to differences in the screening process (lessees were not asked to rank the federal tax credit). However, due to limited data on lessees, the two groups are combined here. Moreover, while there may be endogeneity concerns related to purchasers and lessees' choice of BEV vs PHEV and the importance of incentives in the adoption decision, the powertrain is not differentiated in the estimate of ZEV sales for GHG emissions calculations. **Table 4** shows the distribution of the most popular PEV makes and models for each data set. Tesla is much more prominent in the e-VMT data than in the CSE data, with the Tesla Model 3 accounting for over a third of the e-VMT data, while accounting for less than a fifth of the CSE data.

Table 4: Distribution of PEV makes and models.

Make/Model	CSE data (%)	e-VMT data (%)
Tesla Model 3	19.5	37.2
Tesla Model S	8.3	2.6
Toyota Prius Prime	6.2	7.6
Nissan Leaf	9.6	5.7
Chevrolet Bolt	6.9	14.3
Chevrolet Volt	10.2	5.1
Ford Fusion Energi	3.5	1.9
Honda Clarity PHEV	2.9	4.5

Analysis Methods

e-VMT survey

A multinomial logistic regression model (MNL) is used to model the decision to purchase or lease a PEV in the absence of the CVRP. **Figure 4** shows the alternatives in the choice set. The reference category is "no change" (i.e., "adopting the same PEV"), relative to purchasing another PEV, no vehicle, or a conventional (non-plug-in) vehicle. Equation 1 shows the indirect utility functions for the four alternatives, where all the parameters, calculated as odds ratios, are held constant at one for the reference category, "no change". **Table 5** provides the description and the descriptive statistics of the models' control variables. The model controls for socio-demographic factors including respondent's age, home ownership, income, and number of vehicles per driver, as well as vehicle characteristics including the discounted MSRP (defined in the table below), interaction effect between PEV type and electric range, finance year and finance method (purchase or lease). As mentioned earlier, we combine purchasers and lessees into the same model to maximize the number of observations.

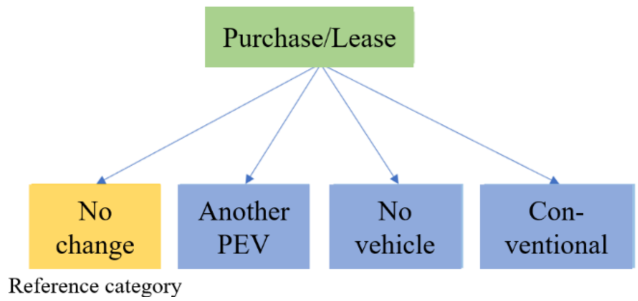

Figure 4: Choice alternatives for the CVRP model.

The utility for alternative "j" for individual "n" is given by:

$$V_{jn} = \beta 0 + \beta_{DiscountedMSRPt} * DiscountedMSRPt + \beta_{BEVdummy} * BEVdummy + \beta_{ElectricRangeBEV} * (PEVtype == \text{“BEV”}) * ElectricRange + \beta_{ElectricRangePHEV} * (PEVtype == \text{“PHEV”}) * ElectricRange + \beta_{2017} * FinanceYear2017Dummy + \beta_{PurchaseDummy} * PurchaseDummy + \beta_{HomeOwnership} * HomeownershipDummy + \beta_{Age} * Agemidpoint + \beta_{IncomeAbove200k} * IncomeDummy + \beta_{NumberOfVehiclesPerDriver} * VehiclesPerDriver + \varepsilon njt$$

Equation 1

Table 5: Variables included in e-VMT model, definition and the descriptive statistics

Variable	**Description**	**Sample average/distribution (standard deviation in parentheses)**
Discounted MSRP	Discount from CVRP subtracted from MSRP (MSRP- Rebate amount reported)	\$38,476 (\$12,925)
PEV type	Dummy, (BEV = 1, PHEV = 0)	BEV: 73.7%
Electric range	Electric range (in miles) interacted with PEV type (BEV or PHEV)	BEVs: 228 (64.06) PHEVs: 36 (14.35)
Finance year	Dummy, (2017 = 1, 2018 & 2019 = 0)	2017: 9.1% 2018: 44.9% 2019: 46.0%
Finance method	Dummy, (Purchase = 1, Lease = 0)	Purchase: 64.3%
Home ownership	Dummy, (Own =1, Rent =0)	Own: 78.7%
Age	Midpoint of age category (years)	47.7 (14.45)
Income above \$200k	Dummy, (Yes = 1, No = 0)	Yes: 24.8%
Number of vehicles per driver	Discrete from 0.2 to 3.	1.1 (0.41)

CSE Survey

A binomial logistic regression model is used to model the decision to purchase or lease a PEV in the absence of the CVRP. The dependent variable (DV) captures whether the participant would have purchased or leased their PEV without the CVRP, with DV = 1 representing rebate essential participants, and DV = 0 representing rebate non-essential participants. Equation 2 shows the utility function for the binomial model, where odds ratios for non-essential rebate participants are held constant at one, therefore parameter estimates estimated for rebate essential participants are relative to non-rebate participants. **Table 6** provides an overview of the model's control variables. The model controls for socio-demographic factors including age, home ownership, income, and male distinction, as well as vehicle characteristics including the discount percent, interaction effect between PEV type and electric range, finance method (purchase or lease), and whether or not the PEV was purchased or leased after the income cap. Additional control variables include whether the participant is a first/and or only time survey taker, as well as their rating of the federal tax credit.

The utility for alternative "j" for individual "n" is given by:

$$V_{jn} = \beta 0 + \beta_{DiscountedMSRP} * DiscountedMSRP + \beta_{BEVdummy} * BEVdummy + \beta_{ElectricRangeBEV} * (PEVtype == \text{"BEV"}) * ElectricRange + \beta_{ElectricRangePHEV} * (PEVtype == \text{"PHEV"}) * ElectricRange + \beta_{IncomeCapDummy} * IncomeCapDummy + \beta_{PurchaseDummy} * PurchaseDummy + \beta_{HomeOwnership} * HomeownershipDummy + \beta_{MaleDummy} * MaleDummy + \beta_{Age} * Agemidpoint + \beta_{Income} * IncomeMidpoint + \beta_{FederalTaxRating\_low} * FederalTaxCreditRating\_Low + \beta_{FederalTaxRating\_medium} * FederalTaxCreditRating\_Medium + \beta_{RepeatSurveyTaker} * RepeatSurveyTakerDummy + \varepsilon njt$$

Equation 2

Table 6: Variables included in CSE model and description of values.

Variable	Description	Sample average/distribution (standard deviation in parentheses)
Discounted MSRP	Discount from CVRP subtracted from MSRP (MSRP- rebate amount)	\$40,596 (\$17,064)
PEV type	Dummy, (BEV = 1, PHEV = 0)	BEVs: 65.5%
Electric range	Electric range (in miles) interacted with PEV type (BEV or PHEV)	BEVs: 192.4 (92.26) PHEVs: 32.2 (13.43)
Income cap	Dummy (Post income cap = 1, Before income cap = 0)	Post: 61.7%
Finance method	Dummy (Purchase = 1, Lease = 0)	Purchase: 55.4%
Home ownership	Dummy, (Own = 1, Rent = 0)	82.0%
Male distinction	Dummy, (Male = 1, Female = 0)	73.6%
Age mid-point	Midpoint of age category	45.9 (16.96)
Income midpoint	Midpoint of income category	\$164,000 (\$99,802)
Federal tax credit rating	Stated importance of tax credit in PEV acquisition from not applicable/not at all important (1) to extremely important (5)	3.92 (1.29)
Repeat survey taker	Dummy (Repeat = 1, first and/or only survey = 0)	Repeat: 43.2%

Results- e-VMT survey

The results of the e-VMT model are shown in **Table 7**. Results are presented in the form of odds-ratio, which measures the odds of changing adoption behavior when the variable of concern changes by a unit. An odds ratio of less than 1 represents a negative correlation and an odds ratio of more than 1 represents a positive correlation with the probability of choosing one of the alternatives relative to the reference category (no change or purchase the same PEV).

Regarding the main variable of interest capturing the relationship between the price reduction offered by the CVRP and participants' likelihood of adopting the same PEV: for a $1,000 increase in the MSRP, purchasers and lessees are more likely to choose the same PEV, and 0.995, 0.989, and 0.981 times likely to switch to another PEV, no vehicle, or a conventional vehicle, respectively. Regarding finance year, relative to 2017, lessees and purchasers in 2018 and 2019 are more likely to choose another, rather than the same PEV in the absence of the CVRP. Buyers of BEVs are 2.785 times as likely as those of PHEVs to choose no vehicle in the absence of the CVRP. There are also effects for the interaction between PEV type and electric range. Lessees and purchasers are more likely to choose the same PEV, rather than a conventional vehicle, another PEV, or no vehicle at all as the electric range of both BEVs and PHEVs increases. Lastly, purchasers are more likely than lessees to change their adoption decision to another PEV, no vehicle at all, or a conventional vehicle.

In regard to socio-demographics, holding all else constant, homeowners are less likely than renters to switch to another PEV or a conventional vehicle. There is also an income effect: those with an income above $200,000 are more likely than those with an income below that threshold to purchase or lease another PEV rather than the same PEV. Younger lessees and purchasers are also more likely to switch to a conventional or no vehicle at all than to choose the same PEV. Lastly, households with more vehicles available per driver are more likely than those with less vehicles available to not to lease or purchase any vehicle at all.

Table 7: MNL regression results for lessees and purchasers for change in purchase decision in absence of CVRP. The reference group is leasing/purchasing the same PEV. (e-VMT model)

	Another PEV		**No vehicle**		**Conventional**	
Constant	0.279	**	0.168	***	1.588	
Discounted MSRP	0.995		0.989		0.981	**
Finance year 2017	0.258	**	0.490		1.119	
PEV dummy-BEV	0.797		2.785	**	2.114	
Range X BEV	0.990	****	0.989	**	0.993	****
Range X PHEV	0.971	**	0.982	**	0.978	**
Finance method	1.746	**	4.060	****	2.830	****
Home ownership	0.569	**	0.710		0.420	****
Income above $200k	1.710	**				
Age	0.943		0.973	****	0.978	***

	Another PEV		No vehicle		Conventional	
Vehicles per driver	0.309		1.906	***	1.565	
Adjusted Rho squared	**Number of observations**	**Estimated parameters**	**Final log-likelihood**	**AIC**		
0.2974	1,131	33	-1109.11	2260.22		

Statistical significance: 0.0001 '**' 0.001 '***' 0.01 '**' 0.05 '*' 0.1**

Results- CSE survey

The results of the CSE model are shown in **Table 8.** Regarding the variable of interest, for a $1,000 increase in the discounted MSRP, participants are 0.994 times as likely to be rebate essential (i.e., they would not purchase their PEV without incentives). Regarding the income cap, participants who purchased or leased their PEV after the income cap are 1.44 times as likely to be rebate essential compared to those who purchased or leased prior to the income cap. Buyers of BEVs have higher odds than PHEV drivers to be CVRP essential. The interaction effect between PEV type and electric range also yield statistically significant results: as the electric range of both BEVs and PHEVs increases, participants are less likely to be rebate essential. Regarding finance method, results show that lessees are more likely than purchasers to be rebate essential.

There are socio-demographic factors which increase the likelihood of being rebate essential, including, having lower income, being younger, and male. For a $1,000 unit increase in income, participants are 0.999 times as likely to be rebate essential. Lastly, older participants, as well as males are 0.985 times and 1.202 more likely to be rebate essential, respectively.

In regard to the stated importance of the federal tax credit, relative to participants who rated the tax credit as very or extremely important, participants who rated the credit as slightly/moderately important, or as not applicable or not at all important are less likely to be rebate essential.

Table 8: Binary logistic regression results where the dependent variable captures whether participants are rebate essential (rebate essential = 1, non-rebate essential = 0)

Independent Variables	Odds ratio	Significance
Constant- Rebate essential	0.836	***
Discounted MSRP	0.994	****
PEV dummy- BEV	2.915	****
Post-income cap dummy	1.442	****
Range X BEV dummy	0.994	****
Range x PHEV dummy	0.990	****
Purchase dummy	0.866	****
Home ownership dummy	0.993	
Income midpoint (in thousands)	0.999	****
Age mid-point	0.985	****
Male dummy	1.202	****

Independent Variables	Odds ratio	Significance
Federal tax credit rating (relative to very/extremely important):		
Not applicable/not at all important	0.285	****
Slightly to moderately important	0.202	****
Repeat survey dummy	1.023	
Adjusted Rho squared	0.1183	
Number of observations	59,058	
Estimated parameters	14	
Final log-likelihood	-40935.9	
AIC	72289	

Statistical significance: 0.0001 '**' 0.001 '***' 0.01 '**' 0.05 '*' 0.1**

Discussion of the Choice Model Results

The results of the two models reveal useful insights into how adoption behavior may change in the absence of the CVRP. We find that several vehicle characteristics such as the discounted MSRP and PEV type, in addition to socio-demographics such as home ownership and income, are associated with consumers' decision to change their PEV adoption decision in the absence of the CVRP. Findings from both models indicate that the financial incentive supports the adoption of PEVs and encouraged respondents to lease or purchase a PEV. This aligns with results from revealed preference studies such as Jenn et al. (3) which attributes a 2.6% increase of PEV sales in the U.S. for every $1,000 offered as a financial incentive.

The CSE model indicates that lessees are more likely than purchasers to be rebate essential. Previous literature has found that favorable lease terms are associated with consumers deciding to lease, rather than purchase a PEV, demonstrating the effectiveness of discounted lease contracts in driving the PEV lease market (24). The e-VMT model however shows that in the absence of the CVRP, purchasers are more likely than lessees to change their adoption decision.

Results from both models indicate that while buyers of BEVs may be more rebate essential, longer range PEV adopters' decisions are less dependent on incentives than lower range PEVs. This aligns with other findings which have found consumers to prefer higher range BEVs (25). The e-VMT model also reveals that the probability of choosing another, rather than the same PEV increases in 2018 and 2019 compared with 2017. This result could reflect the wider variety of affordable PEVs available on the market in that time span.

The CSE model demonstrates that PEV purchasers and lessees were more likely to be rebate essential after the income cap was enacted in 2016. This could indicate, as prior studies have, that income caps increase the distribution of incentives to those who are rebate essential (16). Results from the CSE model also shows that higher income households are less likely to be rebate essential, which aligns with studies which find that lower income households are more incentive essential (26). The eVMT model also reveals an income effect: in the absence of the CVRP, households with an income above $200,000 are more likely than those below that threshold, to choose another, rather than the same PEV. While this could indicate that higher income households are more flexible in their vehicle purchasing decisions than lower income households, the finding goes against Jenn et al. (4) which found that from 2010- 2017, higher income consumers were less likely to change their adoption decision in the absence of incentives. This difference in results could be a result of the e-VMT model being analyzed with data from later finance years.

Results from the e-VMT model show that in the absence of the CVRP, homeowners are less likely than renters to switch from a PEV to a conventional vehicle. Previous research has identified lack of access to home charging as a barrier to PEV adoption, with renters facing disproportionate barriers compared to home owners in being able to install charging infrastructure in their residential parking spot (27). Jenn et al. (11) found that for PEVs to reach mass penetration in California, middle income renters need to adopt PEV at a higher rate. These findings align with results of the eVMT model, with renters being more incentive essential to overcome barriers related to home charging access.

The findings from both models of older purchasers being less likely to change their PEV purchase decision in the absence of the CVRP varies with stated preference studies which find older age to be negatively correlated with PEV adoption (28). Lastly, the finding of males being more likely to be rebate essential also varies from studies which find being male to be positively associated with PEV adoption (29).

Lastly, the CSE model controls for the stated importance of the federal tax credit. Results show that participants who rate the federal tax credit as being very or extremely important are more likely to be rebate essential, which could indicate that rebate essential participants also rely on other financial incentives for their adoption decision.

Impact of changes in discounted MSRP

The distribution of the response to the question whether the respondents would have purchase/leased the PEV without the CVRP gives a preliminary estimate of the importance of the rebate program: on average 36% (average of purchaser and leases) of the respondents in the eVMT survey data (sample who ranked the CVRP number one) and 50% of the respondents of the CSE survey stated that they found the rebate offered by CVRP essential in their purchase decision. As seen in the CSE data, rebate essentiality is higher for the group eligible for increased rebates (primarily lower-income households) and those in the income bracket of $199,000 and lower.

The output from the choice models is used to estimate the predicted probability of being rebate essential (CSE), or adopting the same PEV (eVMT) for each participant, controlling for all the variables in the model. Here, considering the model specification, we do not use the predicted probabilities to estimate the marginal effect of the rebate itself, but rather the marginal effect of a $1,000 reduction in the discounted MSRP on the probability of being rebate essential (CSE) or adopting the same PEV (eVMT).

Table 9 presents the marginal effect for various categories of respondents defined in terms of household income as well the price range of the PEV bought/leased. We compare participants with household income $199,999 and less to those with income of $200,000 or more (graphical representation of the marginal effect is shown in Error! Reference source not found. **&** Error! Reference source not found.), and for three categories of vehicle MSRP groups.

For the CSE data, for the income group $199,000 and less, all else constant, an additional $1,000 reduction in the discounted MSRP decreases the probability of being “rebate essential” by 0.41%. For the e-VMT data, for the income group $200,000 and more, the probability of “no change or bought the same PEV” increases by 0.29% as MSRP goes up by $1,000.

In regard to the income groups, while the e-VMT data yields a slightly higher marginal effect income for the income group $199,999 and below compared to income group $200,000 and above, the marginal effect for the two income groups is comparable when estimated with the CSE data. Both data sets show that lower and mid-range MSRPs yield a greater change in the probability of being CVRP essential, or adopting the same PEV, than PEVs with MSRP above $41,000.

Table 9: Percent change in the probability of being CVRP essential (CSE) or changing adoption decision (e-VMT) for a $1,000 reduction in MSRP.

Marginal Effect by Respondent Category	**CSE data**	**e-VMT data**
Income $199k or less	0.41	0.32
Income $200k or more	0.42	0.29
MSRP less than $32,400	1.35	1.41
MSRP $32,400 - $41,000	2.55	1.33
MSRP greater than $41,000	0.36	0.21

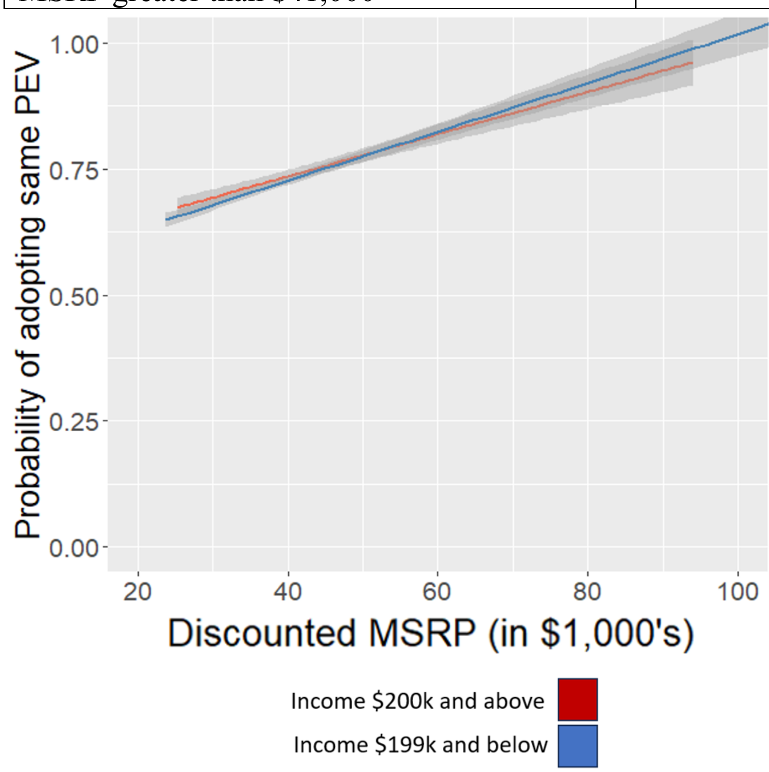

Figure 5: Marginal effect of discounted MSRP on probability of adopting same PEV.

Figure 6: Marginal effect of discounted MSRP on probability of being CVRP essential.

The Influence of Clean Vehicle Assistance Program (CVAP) on the decision to adopt an electric vehicle

Introduction

The CVAP, launched in the year 2018, is an income-eligibility-based program where the eligibility criteria are based on income and household size (**Table 10** shows 2023 eligibility). Prior to 2023 eligibility was for households up to 400% of the federal poverty line. The CVAP grant applies to low-income buyers who purchase ZEVs or clean vehicles in California. Unlike the CVRP, the CVAP provides a grant that is used at the time of purchase; an online application needs to be completed, and the approval letter received before the purchase (9). CVAP can be stacked with the CVRP if the participant meets the eligibility criteria of both the programs. This section aims to investigate whether recipients of the Clean Vehicle Assistance Program (CVAP) grants would purchase their clean vehicle or ZEV without the grant. We meet that aim using responses to the survey question: "*Would you have purchased your clean vehicle if you did not receive a grant through the Clean Vehicle Assistance Program*?".

Table 10: CVAP 2023 eligibility Criteria based on Gross Annual Income (< 300% of FPL) and Household Size

Household Size (Number of People)	Maximum Gross Annual Income
1	$43,740

2	$59,160
3	$74,580
4	$90,000
5	$105,420
6	$120,840
7	$136,260
8	$151,680

Eligibility Criteria as per 2023 revision

To measure the effect of the monetary incentive a voluntary ownership survey was conducted from 2018 to 2022 for zero-emission vehicles (ZEV) buyers who applied for the CVAP grant and were approved recipients of the grant. The consumer survey covers topics including interest in ZEVs, sources of information used, decision-making process, dealership experience, rebate essentiality (a question asking whether buyers would buy their PEV without the incentive or not), and socioeconomic and demographic characteristics. For this analysis, we use data from surveys administered from 2018 to 2022, focusing only on BEV and PHEV buyers. The analysis here allows us to estimate the impact of the incentive over the last 5 years based on the sample. The distribution of the impact of CVAP on the decision to purchase a ZEV as stated by the survey respondents is shown in **Error! Reference source not found.**. From 2018 to 2022, 86% of the post-purchase survey respondents (provided by CARB) stated that without the incentive they would not have purchased their ZEV.

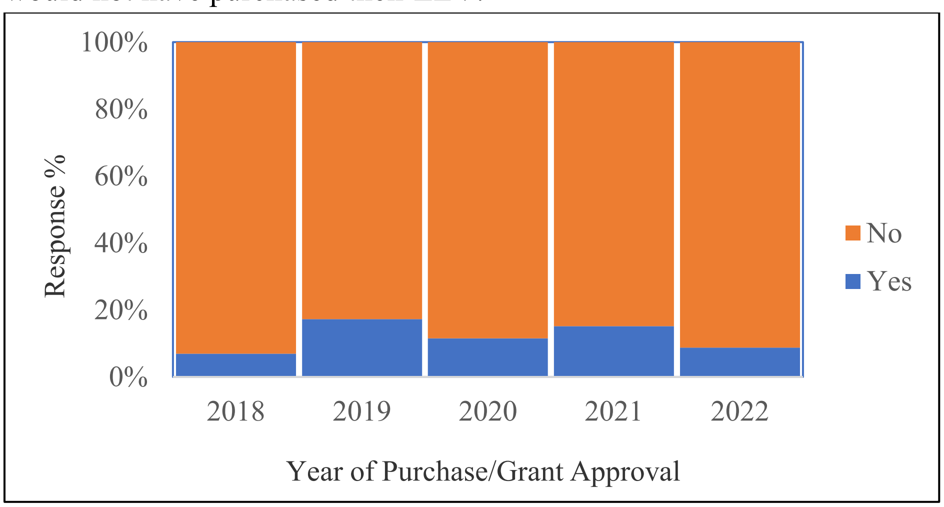

Figure 7: Response Statistics for the Dependent Variable "Would you purchase a clean vehicle without the grant from the CVAP".

Data and Methods

The program offers incentives for both new and used vehicles and we can see that new vehicles comprise 67% of the full sample. Within each response group, the new vehicles' share is higher

(**Error! Reference source not found.**). On investigating the share of leased and purchased vehicles, 86.15 % of the vehicles for which the grant was approved were purchased and 13.85% were leased.

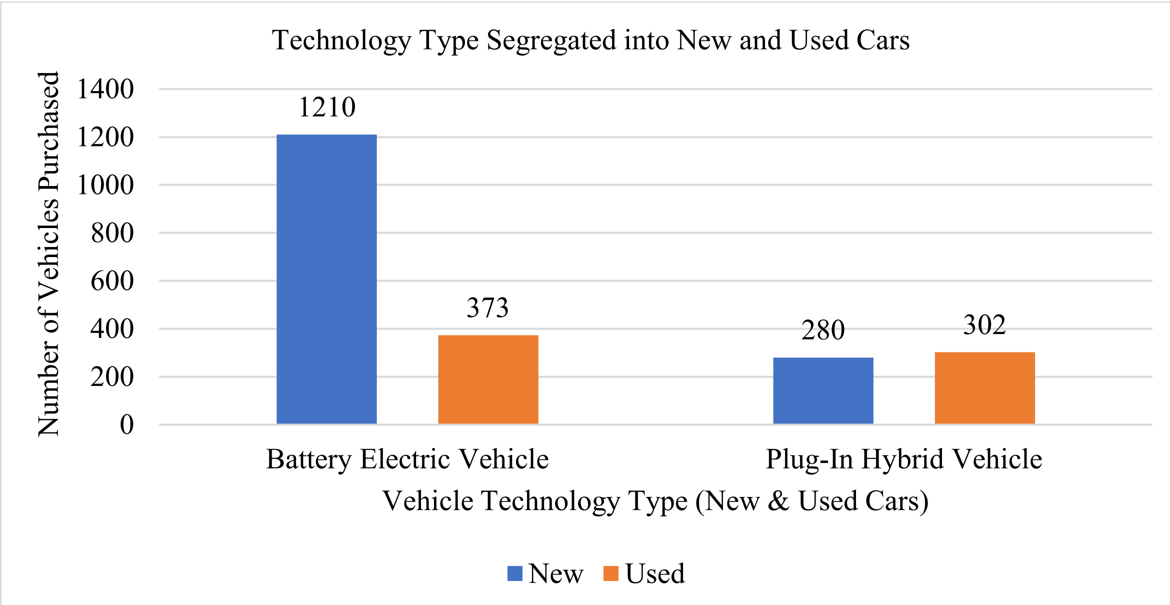

Figure 8: Vehicle Technology Type Segregated into New and Used Vehicles for CVAP recipients.

Table 11 summarizes descriptive statistics of PEV buyers who received the CVAP grant. We present descriptive statistics for the whole survey sample and for response groups who mentioned they would not have purchased their clean vehicle without the CVAP grant (category 1) and those who indicated they would purchase a clean vehicle without the grant (category 0). BEVs are most common in the sample with a 71% share in the full sample, closely followed by the PHEVs which had a share of 25.61% in the full sample. Descriptive statistics show that most rebate recipients live in rented homes (~60%). A possible reason might be that the targeted audience is lower-income households. The mean income of respondents is substantially lower than the state's mean income. Spatially, almost 81% of the recipients of the CVA grant (from the sample of this study) did not reside in disadvantaged communities (DAC) census tracts and almost 41% of the total respondents resided in low-to-moderate income (LMI) census tracts. Whether respondents reside in a DAC is consistent with the definition of DACs in CalEnviroScreen 3.0 (30). Among the rebate recipients for the full sample, it was observed that 58% were male, and the remaining 42% were female/non-binary/undisclosed identity. Education-level descriptive statistics show that approximately 54% of the full sample had a college degree (Bachelor/Postgraduate). The Tesla Model 3 and Model Y are the most common BEVs with an individual share of 22.59% and 19.44%, respectively.

Table 12 shows the age, household size, income, loan amount, and the grant received for charging infrastructure to understand the socio-economic characteristics of the buyers as we consider them to be of importance in the evaluation of the equitable distribution of the grant. We also considered vehicle mpg and the total cost of the vehicle for the vehicle characteristics. The average age of the grant recipients is around 41 and the average household income is $42,337, indicating that the recipients belong to lower-income communities. The median value for the charging infrastructure grant is $2,000 which suggests that most of this grant was given for setting up a home charger.

Table 11: Descriptive statistics of the total sample and responses to the question on rebate impact on buyers' decisions.

Variable	Subset	Will not Purchase without CVAP (1)	Will Purchase without CVAP (0)	Total Sample
#Respondents		1945(86.33%)	308(13.67%)	2253(100%)
Powertrain Technology	Electric	1374(85.88%)	226(14.13%)	1600(71.02%)
	FCEV	4(0.8%)	1(0.2%)	5(0.23%)
	Hybrid	61(87.14%)	9(12.86%)	70(3.11%)
	Plug-In-Hybrid	505(87.52%)	72(12.48%)	577(25.61%)
New/Used Vehicle	New	1292(85.51%)	219(14.49%)	1511(67.07%)
	Used	653(88.01%)	89(11.99%)	742(32.93%)
Leased (Yes/No)	Yes = Leased	278(89.10%)	34(10.9%)	312(13.85%)
	No = Purchased	1667(85.88%)	274(14.12%)	1941(86.15%)
Vehicle Make - Top 6 popular vehicle makes in the full sample	Tesla	814(83.57%)	160(16.43%)	974 (43%)
	Chevrolet	287(87.23%)	42(12.77%)	329(14.6%)
	Toyota	201(90.13%)	22(9.87%)	223(9.89%)
	Nissan	118(90.08%)	14(10.69%)	131(5.81%)
	Ford	104(90.43%)	11(9.57%)	115(5.1%)
	Kia	96(83.48%)	19(16.52%)	115(5.1%)
Vehicle Model - Top 5 popular vehicle models in the full sample	Tesla Model 3	425(83.50%)	84(16.50%)	509(22.59%)
	Tesla Model Y	369(84.25%)	70(15.98%)	438(19.44%)
	Chevy Bolt EV	164(87.23%)	24(12.77%)	188(8.34%)
	Prius Prime	148(90.24%)	16(9.76%)	164(7.3%)
	Nissan Leaf	118(89.39%)	14(10.61%)	132(5.86%)
Home Ownership	Yes = Own	743(85.50%)	126(14.50%)	869(38.57%)
	No = Rent	1192(86.75%)	182(13.25%)	1374(60.99%)
Disadvantaged Community (Yes/No)	Yes	361(85.14%)	63(14.86%)	424(18.82%)
	No	1584(86.60%)	245(13.40%)	1829(81.18%)
Low-to-moderate Income Community (Yes/No)	Yes	802(86.98%)	120(13.02%)	922(40.92%)
	No	1143(85.88%)	188(14.12%)	1331(59.08%)
Gender	Male	1139(87.01%)	170(12.99%)	1309(58.2%)

Variable	Subset	Will not Purchase without CVAP (1)	Will Purchase without CVAP (0)	Total Sample
	Female/ Non-Binary/ Undisclosed	803(85.43%)	137(14.57%)	940(41.8%)
Education level	Bachelor/ Postgraduate Degree	1035(84.63%)	188(15.37%)	1223(54.28%)
	Associate / High School/ No Degree/ No response	910(88.35%)	120(11.65%)	1030(45.72%)

Table 12: Statistical Summary of key variables

Variable	Min	Median	Mean	Std. Dev	Max
Age (years)	17	39	41.46	13.9	87
Household size	1	2	2.364	1.54	12
Annual household income from the previous year's tax returns ($)	0	38709	42337	27350.41	177759
Federal Poverty Line (%)	1	210	207	113	400
Grant amount ($)	1500	5000	4873	467.10	5000
Loan Amount ($)	0	6500	10367	16450.44	91768
Grant for Charging infrastructure ($)	0	2000	1358	901.52	2000
Vehicle mpg (miles per gallon equivalent)	28	120.5	120.1	21.06	142
Total vehicle cost ($)	5753	40713	38053	17050.01	108499

We excluded the data for Fuel Cell Electric vehicles (FCEV) in this study due to the small number of FCEVs (n = 5) in the sample. Conventional hybrids are removed from the sample as they are less in number, and because they are not a ZEV.

Regarding analysis method, we developed three binary logistic choice models to examine the influence of the socioeconomic characteristics of the decision maker (buyer), vehicle characteristics, and the CVAP features on the dependent/response variable. Model 1 captures the correlation of exogenous demographic characteristics and socioeconomic factors with the response variable. Model 2 adds vehicle-specific and CVAP -specific characteristics to the first model such as vehicle technology, new or used vehicle, the vehicle selling price (MSRP – grant amount), whether the buyer received a home EV charger or charge-card or nothing, and interaction terms of BEV technology with gender and BEV technology with new vehicles. Model 2 analyzes how the vehicle and program-specific features are correlated to the response variable. In Model 3 we replace the vehicle selling price (MSRP – grant amount) in Model 2 with discount percent, which is the ratio of grant amount over MSRP, expressed as a percentage. The detailed model specifications are given in Equation 3,4 and 5 below.

a) Model 1: Equation with demographics and socio-economic factors as explanatory variables:

$$Vnj = \beta 0 + \beta 1 * Age + \beta 2 * Male + \beta 3 * CollegeDegree + \beta 4 * Homeownership + \beta 5 * DAC + \beta 6 * FPL\% + \varepsilon nj$$

(Equation 3)

b) Model 2: Equation with vehicle selling price (MSRP – grant amount) as an explanatory variable in addition to the demographics and socioeconomic characteristics as explanatory variables. The utility for alternative "j" for individual "n" is given by:

$$Vnj = \beta 0 + \beta 1 * Age + \beta 2 * Male + \beta 3 * CollegeDegree + \beta 4 * Homeownership + \beta 5 * DAC + \beta 6 * FPL\% + \beta 7 * BEV + \beta 8 * NewVehicle + \beta 9 * VehicleSellingPrice + \beta 10 * ChargerRecipient + \beta 11 * Male * BEV + \beta 12 * BEV * NewVehicle + \varepsilon nj$$

(Equation 4)

c) Model 3: Equation with discount percent as an explanatory variable in addition to the demographics and socio-economic factors as explanatory variables. The utility for alternative "j" for individual "n" is given by:

$$Vnj = \beta 0 + \beta 1 * Age + \beta 2 * Male + \beta 3 * CollegeDegree + \beta 4 * Homeownership + \beta 5 * DAC + \beta 6 * FPL\% + \beta 7 * BEV + \beta 8 * NewVehicle + \beta 9 * DiscountPercent + \beta 10 * ChargerRecipient + \beta 11 * Male * BEV + \beta 12 * BEV * NewVehicle + \varepsilon nj$$

(Equation 5)

We used the Apollo choice modeling package in R to run the models. The response variable is a binary variable indicating whether consumers "Would not have purchased the clean vehicle without the CVAP grant" (coded as 1) or "Would have purchased the clean vehicle without the CVAP grant" (coded as 0), based on survey responses to the question, "Would you purchase a Clean Vehicle without the Grant through the Clean Vehicle Assistance Program?".

The explanatory variables in the model include:

- Vehicle attributes like technology type, the interaction of the BEV technology type with gender, the interaction of the BEV technology type with new vehicles, new or used vehicles, and the cost/MSRP of the vehicle.
- Socio-demographic characteristics,
- Socio-economic characteristics,
- Census tract characteristics like disadvantaged community (DAC), and

- CVAP-specific variables such as the charging equipment grant.

We investigate the effect of home ownership (own/rent) as the program offers a grant for setting up home charging infrastructure along with the grant for the vehicle. The program is income and household size eligibility based so we included the percentage of the Federal poverty line (FPL) in the model. We also include a variable for whether respondents reside in disadvantaged communities (31);. We would like to understand how the reported recipients from disadvantaged communities are correlated to the response variable and whether there is statistical significance.

After data cleaning, the sample size of the model is 2150 unique survey responses. Correlation tests were conducted to address multicollinearity within the independent variables and to maximize the overall model's log-likelihood estimation: the independent variable for the DAC indicator was correlated to the indicator for LMI buyers, hence we removed the variable for LMI and retained only the DAC indicator variable. The percentage FPL, household size, and log-transformed income were found to be correlated with each other, so we dropped the income and household size variables from the model.

Results- CVAP

We estimated the binary logistic choice model's response variable that answered the question of whether the buyer would purchase the clean vehicle without the CVAP grant (Yes = 0, No = 1) Equation 1, Equation 2, and Equation 3 indicate the explanatory variables for Models 1, 2, and 3, respectively. For model validation, we report the maximized log-likelihood estimate (see **Table 12**) along with the adjusted rho-square, AIC, and BIC values that indicate the model's goodness of fit. We also report and the likelihood estimates and t-ratio of the explanatory variables of Model 1, Model 2, and Model 3. It is important to note that if a decision maker in this model responds "Yes" (0 in the binary response) the grant reportedly did not impact their decision to buy the vehicle. If the decision maker responds "No" (1 in the binary response) the buyer would not have purchased their PEV without the grant meaning the grant impacted their decision to buy a PEV. Key findings from the model (Table 13) show the following:

Model 1: The age of the buyer, gender, college degree, and the percentage below the Federal Poverty Line are statistically significantly correlated to the response variable at 5% significance level. Homeownership is statistically significantly correlated to the response variable at 10% significance level.

Model 2: The age of the buyer, gender, college degree, the percentage of the Federal Poverty Line, opting for a home charger or an Evgo charge card, and the interaction term of gender with the technology of vehicle (BEV) are statistically significantly correlated to the response variable at 5% significance level. Homeownership, purchase of a new vehicle, and MSRP of the vehicle is statistically significantly correlated to the response variable at a 10% significance level.

Model 3: The age of the buyer, gender, college degree, the percentage of the Federal Poverty Line, opting for a home charger or an Evgo charge card, and the interaction term of gender with the technology of vehicle are statistically significantly correlated to the response variable at 5% significance level. Homeownership is statistically significantly correlated to the response variable at a 10% significance level. The discount percent which is a function of grant and MSRP is not significantly correlated to the response variable in this model. Independent variables such as vehicle technology type as the main effect, its interaction with the purchase of new vehicles, and buyers staying in DACs are not statistically significant (Models 2 and 3). The dummy variable for new or used vehicles and discount percent is not significant in Model 3.

The outcome of our models suggests that when the age of PEV buyers is higher, they are more likely to respond that they would not have bought their PEV without the grant. Non-male (Female/Binary/Undisclosed) buyers were more likely to respond that they would not purchase their PEV without the grant. Buyers without a college degree (associate degree and below) were more likely to respond that they would not purchase their PEV without the grant. The negative correlation of homeownership with the response suggests that renters were more likely to respond that they would not have purchased their PEV without the grant. The negative correlation of FPL% with the response indicates that as the percentage of FPL increases (buyers with higher income, and/or fewer people in the household) buyers were less likely to respond that they would not have purchased their PEV without the grant.

Buyers who received the EVgo charge cards or home EV chargers were more likely to respond that they would not have purchased their PEV without the grant, suggesting these charging-related incentives are influential in the decision to purchase a PEV. When buyers purchased less expensive vehicles, they were more likely to respond that they would not have purchased without the grant as observed directly in Model 2. In Models 2 and 3 we can observe from the interaction term of gender with vehicle technology that male BEV owners were more likely to respond that they would not have purchased their ZEV without the grant.

Table 12: Estimation results for whether the buyer will purchase without the CVAP grant (Yes = 0, No = 1)

Characteristics/Attributes	**Model 1 with Demographic & Socioeconomic Variables**		**Model 2 with MSRP - Grant**		**Model 3 with Discount %**	
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Constant	2.1779	7.9175	2.4327	6.6012	2.1342	4.8485
Socioeconomic and Demographic Characteristics						
Age	0.0107**	2.0671	0.0097**	1.8859	0.0100**	1.9525
Gender (Male =1, non-Male = 0)	-0.2259**	-1.7297	-0.6889**	-2.4108	-0.6732**	-2.3578
College Degree (Bachelor Degree and above = 1, Associate degree and below = 0)	-0.2701**	-2.0835	-0.2627**	-2.0185	-0.2697**	-2.0731

Characteristics/Attributes	Model 1 with Demographic & Socioeconomic Variables		Model 2 with MSRP - Grant		Model 3 with Discount %	
Homeownership (Own = 1, Rent = 0)	-0.2095*	-1.4471	-0.1998*	-1.3613	-0.2065*	-1.4103
Disadvantaged Communities (DAC) (1 - Yes, 0 - No)	-0.1600	-1.0002	-0.1795	-1.1176	-0.1747	-1.0915
% of Federal Poverty Line	-0.1685**	-2.8254	-0.1332**	-2.1084	-0.1507**	-2.3752
Vehicle Characteristics						
Technology Type (BEV = 1, PHEV = 0)			-0.2310	-0.6930	-0.2489	-0.6957
New or Used Vehicle (New = 1, Used = 0)			0.4504*	1.6088	0.2518	0.8804
Vehicle Selling Price (MSRP – Grant Amount)			-0.00001**	-2.4680		
BEV * Gender of Buyer			0.5550**	1.7299	0.5477**	1.7094
BEV * New vehicle buyer			-0.2420	-0.7239	-0.4173	-1.1592
CVAP Characteristics						
Discount Percentage (Grant Amount/Vehicle Cost)					0.3134	0.3162
Opted for Grant for EVgo Charge Card/ Home EV Charger (Yes = 1, No = 0)			0.3497**	2.4541	0.3681**	2.5934
Goodness-of-fit Test Results						
Log-likelihood(final)	-847.32		-838.13		-840.77	
Number of parameters	7		13		13	
Number of Observations(N)	2150		2150		2150	
Adjusted Rho-Squared	0.4267		0.4289		0.4271	
AIC	1708.63		1702.27		1707.54	
BIC	1748.34		1776.02		1781.29	

Statistical significance: <0.05 '**' <0.1 '*'

Discussion of the Choice Model Results

Overall, most recipients considered the grant instrumental in their purchase decision. In contrast to CVRP survey data where around 51% of respondents indicated they would not purchase a PEV (2016-2017 survey of CVRP recipients) without a rebate (35), around 86% for the CVAP sample indicated they would not purchase their PEV without the grant. A study on New York State's Drive Clean Rebate examined consumers who would not have purchased/leased their ZEV without the rebate (32) and showed that additional financial incentives; besides the grant for the vehicle itself were considered crucial in the buyer's response which suggests that the respondent would not have bought the clean vehicle without the grant and the rebate. Our result that receiving a charging grant is positively correlated with respondents indicating they would not have purchased the vehicle without the CVAP grant agree with that result.

Research on the impact of CVRP rebates shows that being "rebate essential" (considering the grant instrumental in the decision to buy a ZEV) is associated with younger male buyers having a lower income (33). This agrees with the results of our model where buyers whose household income was farther away from the FPL were less likely to respond that they would not have purchased their ZEV without the CVAP grant. The result however diverges from the CVRP study with respect to age and gender of the buyer as being older and non-male is correlated with reporting CVAP as more influential in our study. We find no relationship between residing in a DAC and the importance of CVAP. This may mean CVAP is important for low-income ZEV buyers regardless of whether they live in a DAC or not.

Impact of changes in discounted vehicle selling price

The model results reported above allows us to understand the influence of the vehicle price reduction. The marginal effect estimates here give the change in probability of responding in favor of the grant by changing the vehicle selling price.

The average marginal effect of the vehicle selling price (MSRP – Grant) on the response variable (**Error! Reference source not found.**) shows that a $10,000 reduction in the vehicle selling price (MSRP-Grant) is associated with approximately 2% increase in the probability that the buyer would not have purchased the ZEV without the grant (FPL< 225% and FPL between 225% and 400%). But the probability of responding in favor of the grant is higher for buyers whose household income is less than 225% of the FPL (lower-income households).

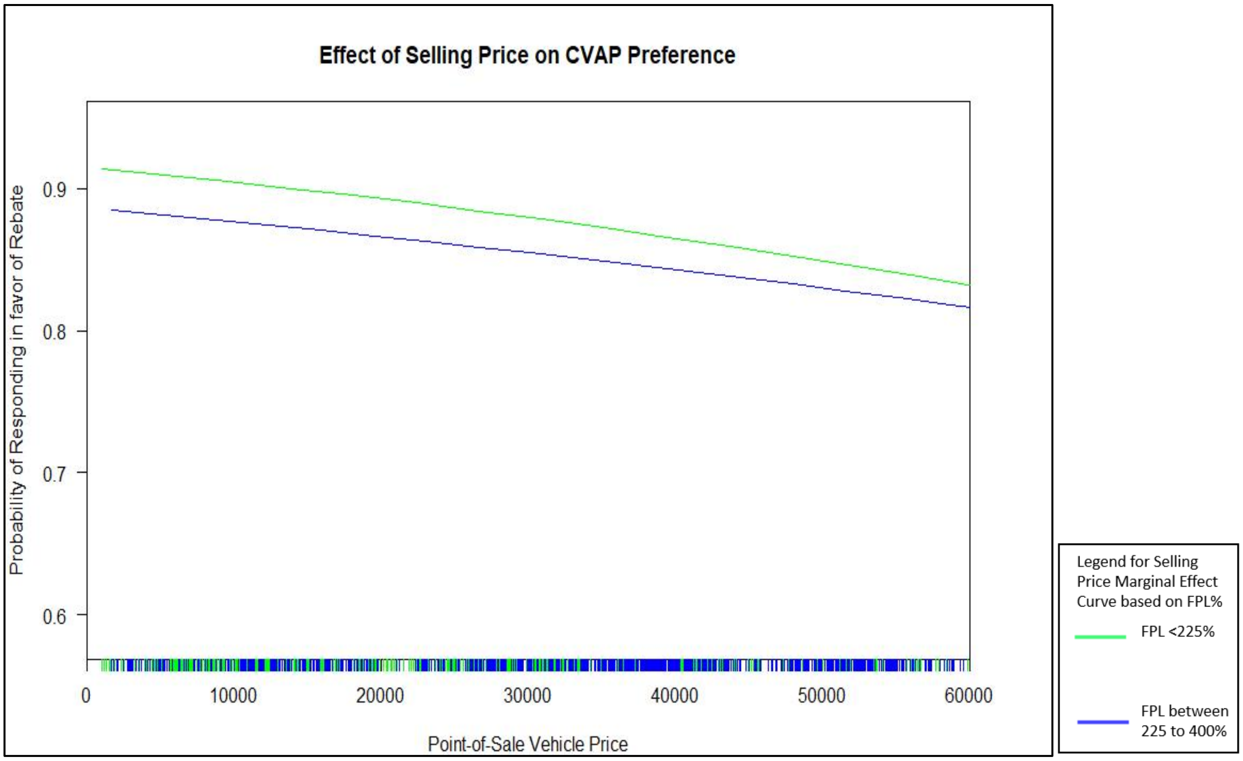

Figure 9: The average marginal effect of vehicle selling price (MSRP – Grant Amount) on the response variable.

Summing up the analysis presented above, assuming the response to the stated question CVAP grant essentiality is independent of other factors that may have influenced the decision to adopt an EV (like PEV type or socioeconomic factors), the descriptive analysis of the question on CVAP importance suggested that on average 86% of respondents report they would not have purchased their PEV without the CVAP incentive. The average predicted probability from the model indicates the probability of a respondent indicating they would not purchase their PEV without a rebate is 0.827.

As with the CVRP, here we estimate the marginal effect of the reduction in vehicle selling price offered by the CVAP grant. Among low-income consumers, the marginal effect estimates suggest that the importance of the grant reduces when households purchase vehicles with high MSRP, showing how the importance of the program can change for households depending on the price of the vehicle bought if the grant amount is changed in the future.

The Influence of CLEAN CAR FOR ALL PROGRAM (CC4A) on the PEV market

As California transitions to 100% of new vehicles sales being zero-emission vehicles by 2035, it is critical to understand how financial incentives impact EV sales in low-income neighborhoods and disadvantaged communities, where the price barrier can be stronger when transitioning from ICEVs to EVs. The objective of this analysis of the CC4A program is to explore the impact this mean-tested program has on EV adoption in low-income neighborhoods where it has been implemented. Our aim is to investigate the effect of this program in absence of any available survey data on program impacts.

Data and Methodology

The impact of the CC4A program is analyzed using vehicle registration data from the California Department of Motor Vehicles (DMV). In California, every vehicle must be registered annually and when a vehicle is transferred to a different owner it needs to be registered under the new owner as soon as possible. We use vehicle registration records from the DMV for the period January-2011 to December-2020 to obtain counts of BEVs, PHEVs, and vehicles of other fuel types in the state. The registration database for the period mentioned earlier is built using DMV data snapshots for the years 2015, 2016, 2017, 2018, 2019, and 2020; a data snapshot gives all the vehicles registered until October 1st of the year being considered. Each record in the DMV data that researchers had access to include a 10-digit vehicle identification number (VIN) that uniquely identified the vehicle, the last odometer reading date, and the date for the last 8 transaction, i.e., when the vehicles changed ownership when the vehicle was last sold (last transaction), and other vehicle purchase/transfer related information. The database had information of the census tract of the vehicle. Basic vehicle attributes (e.g., make, model, body type, fuel type, etc.) are obtained using a VIN decoder purchased from DataOne Software. Results from the VIN decoder is used in combination with the DMV data to obtain vehicle counts for different fuel technology types at the census tract level.

For the impact analysis we first construct a census tract level panel data of total vehicle registrations (new and used) and total PEV registrations by splitting the years for which DMV data are available into quarters, i.e., we have 40 quarters of vehicle registration records, starting with quarter 1 of 2011. Vehicle registration is allocated to a quarter based on the odometer reading date or the last transaction date, whichever is the latest, assuming the latest date is when the last vehicle buyer (or in other words the current owner) took ownership of the title and registered the vehicle. Since the CC4A program applies to both new and used EVs, we do not differentiate between the registrations based on the new/used criteria. The final dataset has total number of vehicles and total number of PEVs at the census tract level registered each quarter (quarter 1 to quarter 40) for the period January 2011 – December 2020. For each census tract, vehicles and EVs registered prior to January 2011 is clubbed together under quarter 0.

The CC4A program was first introduced as an extension to the Enhanced Fleet Modernization Program in July 2015 in the San Joaquin Valley Air Pollution Control District (SJVAPCD) where it is referred to as the Drive Clean Program and in the South Coast Air Quality Management District (SCAQMD) where the program is called Replace your Ride. The program was later adopted by the Bay Area Air Quality Management District (BAAQMD) in September 2019 and the Sacramento Metropolitan AQMD in July 2020. In this project, considering the time period of the DMV data we have access to and the fact that all census tracts in the Bay Area AQMD may not have been eligible for the CC4A program, we restrict our analysis here to the Drive Clean Program and Replace your Ride. As mentioned in the study by Rapson and Muehlegger on the impact of the CC4A program on EV sales and incentive pass through (31), the program design offers a unique opportunity to estimate causal impact of the program using causal analysis methods like the difference-in-difference or instrument variable regression, or synthetic control method as done here; the financial incentives under these programs are restricted to residents of the AQMD that has adopted the program. So AQMDs with the CC4A program form the treatment group while all the other AQMDs are in the control group for the causal analysis model used here- synthetic control method (SCM).

Both Rapson and Muehlegger and the study by Sheldon and Dua use difference-in-difference method to analyze the impact of the CC4A program (31), (20). In both cases the authors had individual transaction level data that allowed them to check for pre-treatment parallel trends and other factors for a robust choice of control units required to isolate and estimate the causal impact of the program on the treatment group. Aggregate quarterly vehicle registration data at the census tract level does not offer the same flexibility – there are multiple factors that can impact vehicle registration in a treatment census tract or one of those in the control group for the assumption of parallel pre-treatment trends to fail. More conventional matching methods like propensity score matching does not require pre-treatment conditions to be met, but the robustness of the causal impact analysis depends on availability of data on observable characteristics to build an appropriate control group for the treatment unit. Considering the data constraints present, i.e., we have vehicle registration data at the census tract instead of individual vehicle transaction data and the limited number of observable characteristics for conventional matching methods, synthetic control method (SCM) is deemed appropriate for the analysis here. Synthetic control method is generally applied when a few aggregate units, AQMDs here, are exposed to an intervention and the remaining untreated units form the donor pool for the control group (the potential donor pool includes 33 AQMDs, with SJVAPCD and SCAQMD excluded). EV buyers in the AQMDs in the donor pool were eligible for the CVRP, federal tax credit and all other major incentives except the EFMP and CC4A. Therefore, the difference in PEV registration in the post-treatment period should represent the impact of the CC4A. Unlike comparative studies that can also be used in these scenarios, synthetic control method formalizes the choice of control group using a data driven method, it is a weighted average of the available control units in the donor pool (32). Overall, the idea behind synthetic control method is that a combination of units often provides a better comparison for the treated unit than a single untreated unit, as may happen in the case of AQMDs (33).

The Drive Clean and the Replace your Ride Program is analyzed separately using SCM. The treatment effect (impact of the CC4A program in the treats AQMD) for the two programs are estimated as below (**Equation 6**).

$$\hat{\delta}_{it} = Y_{it} - \hat{Y}_{it}^{N} = Y_{it} - \sum_{j=1}^{K} w_j Y_{jt}$$

Equation 6

where, i=treated unit, j=1, …., K include units in the donor pool for synthetic control group (AQMDs other than SJVAPCD and SCAQMD), $t > T_0$ is the period post-treatment (quarter 4 of 2015 and later), and Y_{it} is the potential outcome of the treated unit (SJVAPCD or SCAQMD) post intervention.

$\hat{Y}_{it}$ i is the synthetic control representing how PEV sales would have evolved in the treated AQMDs in the absence of the CC4A program. It is estimated using the pre-treatment outcome of the values of, i.e., PEV registration in the quarters before the third quarter of 2015, total vehicle registrations in the quarters before the third quarter of 2015 along with other predictors including population density, unemployment rate, and share of population with college education. Even though the other predictors also play a role in determining the synthetic control, the credibility of a synthetic control estimator depends on the ability to track PEV sales (outcome variables) in the pre-intervention period for the treated and untreated AQMDs (34). For analysis here we start from quarter 1 of 2011 because the PEV sales were very few before 2011 across California.

We use quarterly DMV vehicle and PEV registration data for the period quarter 1 of 2011 to quarter 2 of 2015 to create the control group that for the synthetic control analysis, a method that allows to estimate the causal impact of any intervention that impacts a few aggregated units. Here, in the SCM analysis, the treatment group is the AQMD where the CC4A program is in place while the control group includes AQMDs without the program. The treatment period is quarter 2 2015 for SJVAPCD and quarter 2 of 2015 for SCAQMD. The pre-intervention period (quarter 1 of 2011- quarter 2 of 2015) PEV sales in AQMDs outside of SJVAPCD and SCAQMD are used as predictors of post-intervention outcomes/PEV sales, assuming that the pre-intervention sales are unaffected by the CC4A program. In other words, the synthetic control group is estimated using the pre-intervention sales of AQMDs without CC4A for the period under study. This is meant to reproduce the PEV sales trend the treated unit (SJVAPCD or SCAQMD) would have in the absence of the treatment (CC4A). The pre-intervention period (quarter 1 of 2011- quarter 2 of 2015) is chosen, since the number of EV sales before quarter 1 of 2011 was negligible across all AQMDs with Tesla Roadster being the only EV in the market before 2011. The causal impact in the subsequent periods post intervention estimated by considering the difference in sales in the treated unit post intervention and the estimated sales of the synthetic control group. The analysis therefore is of PEV sales in the census tracts of the treated AQMDs post-intervention (introduction of the CC4A program) in comparison to what sales would have been in absence of the program (non-CC4A regions). Details of the data requirements and model feasibility can be found in the paper by Abadie, A[2].

Results of the Synthetic Control Analysis

Drive Clean Program (SJVAPCD)

The synthetic control group for the SJVAPCD included the Bay Area AQMD, the Sacramento AQMD, and the San Diego AQMD. In other words, the assumption here is the PEV sales trend in SJVAPCD prior to CC4A is best reproduced by a combination of these three AQMDs. The main treatment effect of the Drive Clean program is captured in **Figure 10**: the difference in PEV registrations per quarter between SJVAPCD and its synthetic version post launch of CC4A in July 2015. **Figure 10** suggests that there is a quarter lag in the impact of the program but after that the program had a positive impact on PEV registrations with the difference improving over the quarters in the post-intervention period. Specifically, after the CC4A program, with a lag, registration go up by 240 PEVs between Q4 of 2015 and Q3 of 2016 (6%).

[2] Abadie, A. (2021) Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects, Journal of Economic Literature 2021, 59(2), 391–425 https://doi.org/10.1257/jel.20191450

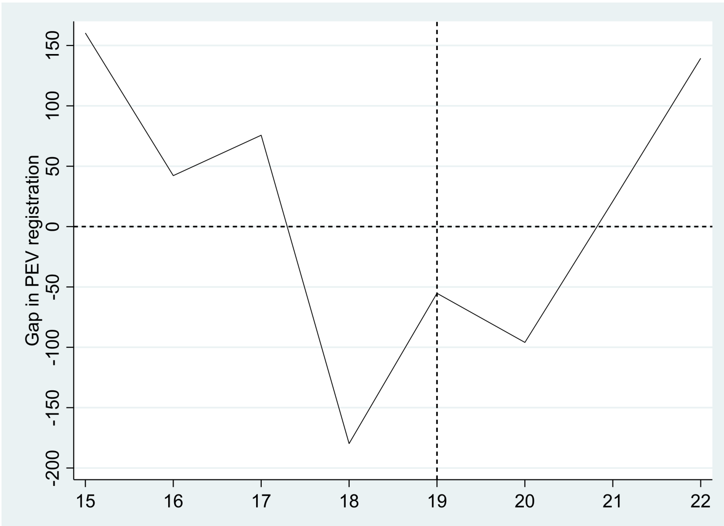

Figure 10: PEV sales gap (in number of PEVs sold) between SJVAPCD and synthetic SJVAPCD from Q3 2014 (15) to Q2 2016 (23).

Replace your Ride (SCAQMD)

The synthetic control group for the SCAQMD included only the Bay Area AQMD. In other words, the PEV sales trend in SCAQMD prior to CC4A is best reproduced by the Bay Area AQMD. The main treatment effect of the Replace your Ride program is captured in Figure 11: the difference in PEV registrations per quarter between SCAQMD and its synthetic version post launch of CC4A in July 2015. **Figure 11** suggests that PEV registrations increased after the launch of CC4A but goes down after a couple of quarters. Specifically, after the CC4A program was introduced (July 2015), registrations go up by approximately 7000 EVs between Q3 of 2015 and Q1 of 2016. However, it falls after Q1 2016. From Q3 2015 to Q3 2016, the effective increase was 55%.

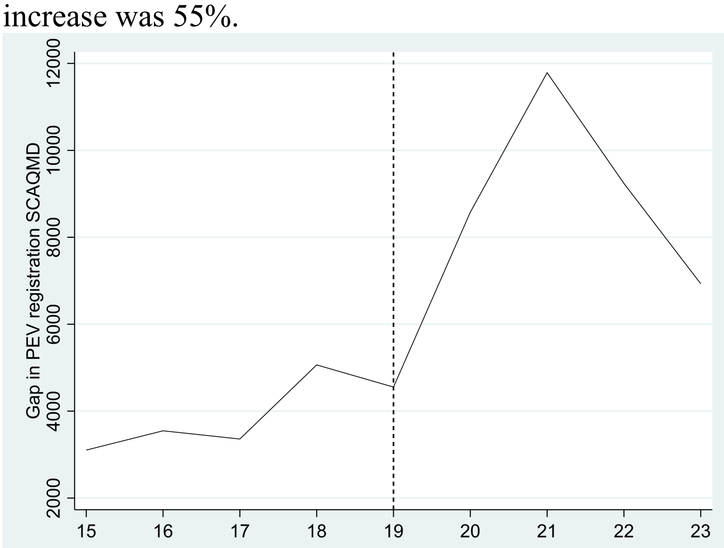

Figure 11: PEV sales gap (in number of PEVs sold) between SCAQMD and synthetic SCAQMD from Q3 2014 (15) to Q3 2016 (23).

Discussion of CC4A Results

The study by Rapson and Muehlegger found that a subsidy that decreases the buy-price of EVs by 10% increases demand by 21% for customers eligible for the CC4A. Analyzing the Replace your Ride program, Sheldon and Dua found that the PEV sales in the AQMD went up by 44% after the launch of the program. Here, the results of the SCM for the SJVAPCD and the SCAQMD suggest that the CC4A program has a positive impact on PEV sales in the area where it is administered. Moreover, we find that the quantitative estimate of the impact is comparable for the SCAQMD area to the impact estimated in the study by Sheldon and Dua. Considering the scope of the research objective here, the main takeaway here is that the CC4A has a positive impact for the eligible customer segment: low-income households and those residing in the census tracts designated as disadvantaged communities in the AQMDs administering the program. This implies that the estimate of contribution of incentive programs on PEV sales in AQMDs with CC4A program needs to account for not only the impact of CVRP on PEV sales, but also the positive effect of the increased price reduction offered by CC4A on EV sales.

The CC4A analysis presented here is part of ongoing research. P-value and falsification tests are required to determine the robustness of the causal impact estimates[3]. Nevertheless, there are some limitations with the analysis and results presented here. While the DMV data of vehicle registration allows estimation of impact of a program like CC4A for the AQMDs with the program at an aggregate level using the SCM method, it is limited in terms of the information that can be used to analyze the impact of other sociodemographic or economic factors on PEV sales. The DMV data does not have vehicle transaction price that can allow researchers to better identify PEVs that may or may not have been eligible for the CC4A or the CVRP or both. In other words, the vehicle registration data is not adequate to disentangle the impact all incentives or understand how different PEV adopters may be impacted. In the years before CC4A was introduced, the causal estimates using difference in difference as previously used in the literature or the SCM (as done here) gave the impact of the introduction of the CC4A, and the price reduction offered by the program. A data source that allows researchers to identify the incentive amount received or the types of rebates received is required to identify and correctly estimate the impact of the different incentive programs including the CC4A. Lastly, DMV data or any other publicly available data source does not have records of the disruptions or delays in program implementation or gaps in funding for the participating AQMDs that may have an impact on PEV sales. Therefore, the analysis here does not account for these issues, for example on buyers who did not purchase a PEV due to these problems. It is required to have this information to credibly estimate the impact of the program at an aggregate level, as done by SCM.

[3] These test results and further improvements of the model specification will be part of a peer-reviewed paper by the researchers.

Policy Implications

This research explored the impact of the CVRP, CVAP, and the CC4A program on PEV purchase or leasing decision using stated choice data of PEV owners in California from multiple data sources and DMV data. Our findings indicate that the absence of several financial incentives will have a negative impact on the purchase decisions of some PEV buyers in California. The findings demonstrate that without financial incentives, both purchasers and lessees are more likely not to purchase or lease a PEV under the CVRP and CVAP program. **Table** summarizes some results from the analysis for CVAP and CVRP. Note the table does not include values for CC4A because we were unable to obtain satisfactory estimates for that program given the limited data we have access to.

Results from the CVRP analysis show, within the sample, an average predicted probability a buyer would not choose their PEV without CVRP is between 0.27 and 0.50, holding all other variables in the models constant. These numbers show the predicted probability of CVRP recipients reporting they would not have chosen their PEV without the CVRP (CSE sample) or they would change their adoption decision without CVRP (eVMT sample). An alternative way to state this is that without CVRP, somewhere around 27% and 50% of CVRP recipients would not purchase the PEV they received CVRP for. Rebate essentiality is also higher for increased rebate recipients, and buyers of lower MSRP PEVs. In other words, from the perspective of the scope of this project, if currently every CVRP rebate is considered equivalent to an EV sale[4], then it needs to be scaled down by the income group being considered and then by the price range of the vehicle using the predicted probabilities. However, as we note below, we believe these numbers may not be an accurate estimate of incentive impacts given various limitations.

Results from the CVAP analysis show, within the sample, an average predicted probability of 0.86 for respondents choosing the response they would not have chosen their PEV holding all else constant. This shows for this program a higher percent of incentive recipients purchase was self reportedly dependent on the incentive. Using the number from this analysis 86% of CVAP recipients would not have purchased their PEV without CVAP. However, as we note below, we believe these numbers may not be an accurate estimate of incentive impacts given various limitations.

Even considering the limitations, in terms of translating the impact of financial incentives like the CVRP on EV purchase decisions, the analysis here suggests that one CVRP, CVAP, or CC4A incentive does not translate to one PEV sale. The analysis shows significant difference in incentive impacts on buyer decisions based on demographics, and the results suggest that a scaling factor should be adjusted based on income group of recipients and the price of PEVs. Lower income recipients of CVRP were more dependent on incentives than high income buyers ($200,000 and higher). Moreover, as the analysis of CVAP and CVRP suggests, the recipients of the CVAP grant found the incentive important in their adoption decision (often stacked with the CVRP) and the CC4A had a strong positive impact on PEV registrations in the eligible areas. In other words, the scaling factor should account for these additional incentives, e.g., account for effect of stacked incentives in determining the scaling factor for the eligible customers.

[4] Table A-7 in /https://ww2.arb.ca.gov/sites/default/files/2022-10/fy2022_23_funding_plan_appendix_a.pdf

The preliminary analysis of CC4A requires additional data and has limitations, however the results also show this program had a positive impact on PEV sales. More work is needed to better estimate the effect of this program to give an accurate adjustment factor. We outline limitations of the analysis and data needs below.

Overall, we were unable to credibly estimate the combined and interaction effects of California incentive programs due to limitations of existing data. As a result, we cannot provide an accurate adjustment factor to estimate emissions and socioeconomic benefits of California incentive programs. Results do show a positive impact of programs on buyer decisions to purchase an electric vehicle, however not all recipients of rebates or incentives purchase decisions were dependent on incentives. This means that one incentive does not necessarily convert to one additional PEV buyer choosing a PEV rather than a gasoline vehicle, but it is more than zero and may be close to the values reported here. But it should be noted how different the values can be based on the method chosen, for example the range for CVRP is between 27% and 49% depending on the survey used. The range of values in Table 13 could be used by CARB in place of assuming one incentive results in one PEV sale assuming policymakers understand the limitations of the methods used to estimate these values with the available data.

Table 13: Stated individual responses to incentive programs ("Average survey response") from the surveys we analyzed and the predicted probability of not purchasing a PEV in the absence of the incentive for the whole sample in each survey and at various MSRP points. This does not account for interaction effects or the limitations of data and the numbers will be over or underestimates of incentive impacts. These are also subject to the independence of irrelevant alternatives (IIA) assumption. Empty cells are due to a lack of data.

		Predicted probabilities from choice models				
Program	**Average survey response**	**Predicted average**	**<$20,000 MSRP**	**$20,000 to $40,000 MSRP (<$40,000 for CVRP)**	**$40,000 to $60,000 MSRP (>$40,000 for CVAP)**	**>$60,000 MSRP**
CVAP all	0.86	0.86	0.89	0.87	0.83	
CVAP 225% to 400% FLP	0.84	0.84	0.86	0.86	0.82	
CVAP <225% FPL	0.88	0.88	0.90	0.89	0.85	
CVRP all (CSE data)	0.50	0.50		0.54	0.48	0.33
CVRP regular rebate (CSE data)	0.49	0.50		0.53	0.48	0.33
CVRP increased rebate (CSE data)	0.68	0.57		0.59	0.52	0.45

CVRP all (eVMT data)	0.36	0.27		0.31	0.21	0.13

LIMITATIONS OF CURRENT SURVEY DATA

Across the surveys that we analyzed, we were not able to credibly estimate the impact of all incentive programs due to limitations in the available data and the methods used.

The UC Davis eVMT survey has limitations since only respondents who ranked CVRP as the most important incentive to them were asked about their purchase decisions in absence of CVRP, this may overestimate incentive impact. Additionally, while purchasers were asked to rank the federal tax credit, lessees were not, therefore there is a higher proportion of lessees ranking the CVRP as their most important incentive. Second the survey does not ask about the impact of other incentives on the decision to purchase a PEV, which means we cannot account for incentive interactions which could increase or decrease the impact of CVRP. The question also depends on direct questioning methodology which can elicit bias responses from survey takers, including because survey takers deduce the purpose of the survey question. However, the survey does allow respondents to choose from more than one option which may give a more accurate estimate of behavior in absence of incentives compared to a binary response. While the eVMT survey captures participants' reported change in adoption behavior, participants choosing to adopt another PEV were not asked which PEV they would choose, or why, presenting a limitation in interpreting the results for this alternative.

The CVAP and CVRP (CSE) survey ask a similar question and have similar limitations as one another. Both surveys ask a binary question (yes or no answer) and do not ask respondents about their decision in the absence of CVRP or CVAP except for whether buyers would purchase the PEV or not. This may overlook buyers choosing a different PEV in absence of the incentive, not buying any vehicle, choosing a conventional vehicle or anything else. The survey also uses a direct questioning approach to understand incentive impacts, this may be more likely to induce experimenter demand effects, with participants able to deduce the purpose of the research question and being more likely to answer with a response desirable to them. This may overestimate incentive impacts. The UC Davis eVMT also suffers from this since it is also a direct question, but because the question is worded differently, and survey takers have more answer options the purpose of the question may be slightly less obvious to survey takers. The acquiesce and social desirability biases could also explain the differences in the descriptive statistics, with 50% of CSE participants identifying their PEV purchase as being CVRP essential, compared with 35.5% of eVMT participants changing their adoption decision in the absence of the CVRP, a lower percent even though only those who report this as the most important incentive were asked the question.

The CVAP survey has some additional limitations due various aspects of the program not being captured in the survey question. The CVAP survey only measures the impact of one component of the program and does not consider the impact of charging incentives or the provision of vehicle financing. Further the response question "Would you have purchased your clean vehicle if you did not receive a grant through the Clean Vehicle Assistance Program?" could be interpreted differently by survey respondents who may or may not consider other program attributes (e.g., charging grants) in their response, whereas the question may intend to only ask about the impact of the CVAP grant. This means we cannot confidently assume the question only measures the impact of the grant. The survey also does not include any additional question on the impact of the charging incentive or loan aspect of the program and how that may impact purchase decision (along with other PEV incentives).

The above limitations mean we cannot account for how CVAP and CVRP interact with each other and other programs including the federal tax credit, the clean fuel reward, clean cars for all, carpool lane access, and other incentives available to ZEV buyers. This means that with existing survey data, we cannot credibly estimate the impact of these incentives on the decision to purchase a ZEV. The estimates provided for each program may under or overestimate incentive impacts on buyer decisions. Finally, incentives may impact buyers who do not receive incentives. This could be positive effects because buyers expected to receive one when buying their PEV or the presence of them having a positive impact on PEV perceptions, or negative impacts due to buyers not purchasing a PEV because they will not receive an incentive.

Even when data is available to account for all incentives and how they interact, any analysis may struggle to account for automaker decision making, vehicle supply, and how this may be influenced by the presence or absence of incentives. For example, a total lack of incentives may impact automaker decisions on vehicle supply, with automakers potentially preferentially supplying PEVs to markets with incentives. We are unaware of any data that could be used to account for automaker vehicle supply decisions and how these may or may not be impacted by incentives. The same is true for how automakers decide to supply vehicles to market with PEV supporting/requiring regulations such as the ZEV regulation.

Despite the limitations that we presented, these preliminary results can be used to inform future program design. Furthermore, to be able to capture some of the data necessary to develop a more robust estimate of consumer behavior impacts from each incentive program, we recommend several considerations for CARB to incorporate into future surveys, as outlined in the following section.

RecomMendations for future surveys

Here we discuss recommendations for survey methods to evaluate incentive impacts. An updated survey design could help address some of the limitations discussed in the previous section. Note that additional experimental design work would be needed to properly design a procedure to measure the combined and interaction effects of all incentive programs which is beyond the scope of the discussion here. It is also likely that other survey designs than the ones mentioned here could alternatively be used.

First, any survey should be a survey for all program participants and nonparticipants (i.e., the sample would be all PEV buyers) administered after PEV purchase. The survey should record information on participation in all incentives and programs including California, local, federal, and other programs. The survey should also record information on all program aspects influential in decision making (e.g., including charging grants).

Any survey sample should be a random sample and the sample size required would depend on the nature of the survey question chosen but would likely only need to be a small percent of all PEV buyers. A survey question should ask about the impact of all incentives on the decision to purchase a PEV and not just individual incentives and be designed in such a way that it accounts for interaction effects. This would include non-California programs since they significantly impact PEV purchase decisions. This could be achieved through a survey experiment, choice experiment, or conjoint experiment.

In a choice experiment respondents would be shown a choice of a conventional vehicle, a plug-in electric vehicle, no vehicle, and any other relevant choices. One of the choice experiment attributes for the plug-in electric vehicle could be different incentives (e.g., including CVRP, CVAP, the federal tax credit, HOV lane access etc.) and these attributes would be varied among respondents. Respondents would choose between a conventional vehicle and their PEV but with different incentives scenarios. Most choice experiments are analyzed using discrete choice models.

In a survey experiment, respondents could be shown scenarios where they receive all incentives, only some incentives, or no incentives and asked whether they may purchase their PEV in the scenarios. If respondents only received a small number of incentives (e.g., CVRP and CVAP) a within subject design could be used to ask how respondents would behave in every possible scenario (CVRP and CVAP, only CVRP, only CVAP, or no incentives). If respondents received many incentives, for example 4 incentives, the survey would not be able to ask about all combinations since there would be 16 possible combinations of incentives and therefore 16 possible questions. Further, if programs have more than one attribute, the design would be further complicated assuming program attributes need to be tested. In this case, each incentive combination would have to be randomly distributed among the survey sample (i.e., a between subject design). Survey experiments are typically analyzed by regression methods, the specification of which varies depends on the answer scale used which can be anything from binary to a continuous scale. Any survey should also account for all program attributes in the event programs include more than one incentive type or multiple incentives.

Any survey should also record demographic, built environment, and attitudinal questions that are known to correlate to incentive impacts and may be important controls (e.g., control variables in a choice model) in any analysis of incentive impacts. In addition to providing specific recommendations for surveying PEV buyers, we suggest a comprehensive approach to data collection. This entails implementing a continuous survey that encompasses all new car buyers, including both internal combustion engines and plug-in vehicles, in urban, rural, disadvantaged, and other diverse communities (since all of these groups are likely impacted by incentives). By conducting this survey continuously (e.g., every three to six months), we can effectively analyze the impacts of policy changes across various regions and over time, as well as the effects of fluctuations in prices and external factors such as gas prices.

We believe that maintaining an ongoing, broad data collection effort is important to addressing key questions regarding the effects of policy adjustments and shifts in supply and demand. Looking ahead to the rollout of the advanced clean car initiative in 2026, and other changes (e.g., the recent expiration of CVRP), we anticipate a substantial impact on buyer decision making due to changes in incentives and future alterations in supply dynamics. Consequently, gathering data both before and after these supply regulation changes may help understand the impact of the introduction of that regulation. Moreover, as the secondary market for zero-emission vehicles (ZEVs) continues to grow, understanding how incentives influence not only the initial buyers but also the secondary market and ownership patterns of ZEVs becomes increasingly important. This necessitates a proactive approach to studying the evolving landscape of ZEV ownership and its relationship with incentives.

Limitations and Recommendations for Synthetic Control Methods

Our takeaway from the CC4A analysis is that CC4A has a positive impact on PEV sales. However, the analysis is limited by the available data for program evaluation. There are limitations with the available data that lead us to conclude that any further analysis would be unlikely to yield results that the researchers would confidently propose as adjustment factors. The DMV data used allowed for estimation of the impact of a program like CC4A on AQMDs overall. However, the data cannot be used to analyze the impact of other sociodemographic or economic factors on PEV sales. The DMV data does not have vehicle transaction data (e.g., including price, model, etc.) that would allow researchers to identify PEVs that may or may not have been eligible for the CC4A or the CVRP or both. The vehicle registration data is not adequate to disentangle the impact of incentives or understand how different PEV adopters may be impacted (e.g., by demographics). A data source that allows researchers to identify the incentive amount received by PEV buyers, all types of incentives received (including amounts), attributes of the PEV, and the attributes of PEV buyers would be required to identify and correctly estimate the impact of the different incentive programs including CC4A. Finally, DMV data or any other publicly available data source does not allow us to understand disruptions or delays in program implementation or gaps in funding for the participating AQMDs that may have an impact on PEV sales. Therefore, the analysis here does not account for the impact of these issues on buyers who did not purchase a PEV due to these problems or buyers who purchased a PEV anyway given uncertainties and complexities of the program. More data including the information outlined above are required to credibly estimate the impact of the program at an aggregate level via SCM, while such data does not exist to our knowledge.

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