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The Role of Financial Incentives in Promoting Electric Vehicle Adoption Among Lower-income Households in California

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The Role of Financial Incentives in Promoting Electric Vehicle Adoption Among Lower-income Households in California

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Abstract

Monetary incentives offered by the state of California have historically played a critical role in driving zero-emission vehicle (ZEV) adoption. Although most ZEV adoption thus far has been by early adopters with relatively high income, some research on the market development of electric vehicles showcases that financial incentives are also significant for relatively lower-income ZEV buyers. Regarding early adopters, a meta-analysis conducted for this study finds that an increase in the ZEV adoption rate by 5% on average is associated with a $1,000 incentive, keeping all else constant. The meta-analysis combines results from 13 studies based on a variety of markets, i.e., the Plug-in Hybrid and Battery Electric Vehicle (PEV) market in California, other states of the United States (US), and other mature EV markets across the globe. As the ZEV market is moving beyond mostly higher-income early adopters toward lower and moderate-income buyers, more adopters may need incentives to purchase ZEVs. The state of California is supporting lower-income buyers in their ZEV purchases through point-of-sale financial incentive programs such as the Clean Vehicle Assistance Program (CVAP). CVAP also provides grants for PEV charging and affordable financing to help income-qualified Californians purchase or lease a new or used ZEV. Since CVAP is a relatively new program, there is less quantitative research on its effectiveness on low- to moderate-income buyers' decisions. The main results in this study are from a quantitative analysis that uses a binary logistic regression model where the dependent variable is a survey question where buyers indicate if they would still purchase a PEV without the CVAP grant. Specifically, program participants respond to the question, "Would you have purchased your clean vehicle if you did not receive a grant through the Clean Vehicle Assistance Program?". This question is from a survey designed by the California Air Resources Board (CARB). The descriptive analysis showcases that the grant offered by CVAP influenced around 86 percent of the recipients from lower-income households to purchase a PEV. The logistic regression model indicates that buyers with the following characteristics are more likely to respond "no" to the above question: older age, not possessing a college degree, lower household income, and being non-male. They are also more likely to respond "no" when purchasing new, less expensive vehicles and when renting rather than owning their own home.

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1. Introduction

Governor Newsom's Executive Order (N-79-20) established a target in the form of a zero-emission vehicle (ZEV) mandate to move to 100 percent ZEV sales by 2035 [1]. This executive order was turned into the Advanced Clean Cars II regulation by the California Air Resources Board (CARB) to help reduce global warming pollution [2]. This regulation is supported by the governor's ZEV budget, which provides financial incentives so that ZEVs can reach Californian buyers from all economic backgrounds, especially low-to-moderate-income buyers. To meet federal air quality standards, the goal is to reduce the light-duty vehicles' (LDVs)' smog-causing pollution by 25% by 2037 and meet the goal of carbon neutrality by 2045 [2].

The ZEV mandate and the Advanced Clean Cars II regulation expect automakers to sell an increasing percentage of new ZEVs beginning the model year 2026. The market share of ZEVs in the LDV sector is expected to be 35% by 2026, followed by 68% in 2030, and finally reach 100% new ZEV sales by 2035 (**Figure 1**) [2].[1]

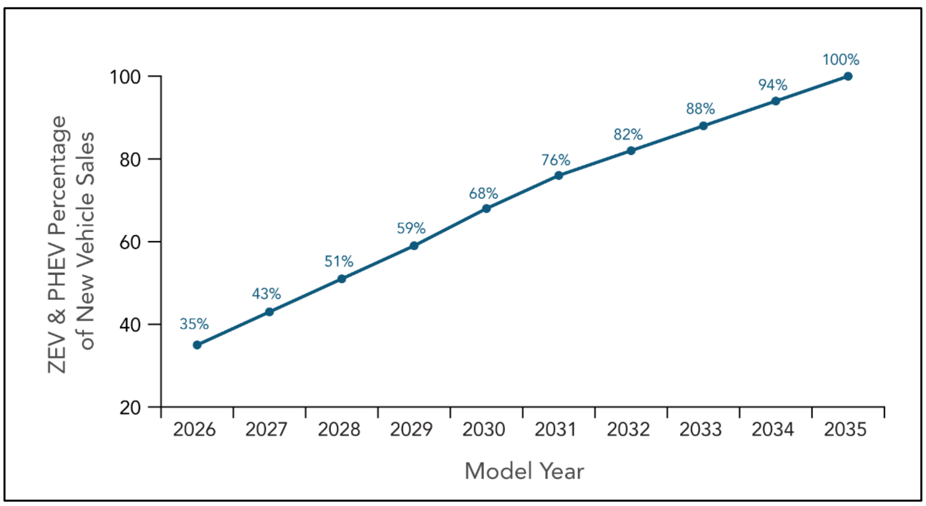


Figure 1: Projected New ZEV and PHEV Sales from 2026 to 2035 [2]

[1] For completeness, note that, although 'ZEV' denotes 'Zero Emission Vehicle,' the ZEV mandate includes complex provisions that allow, e.g., plug-in hybrid electric vehicles (PHEVs) to count toward the mandate requirements in the early years.

Several US states, such as Colorado, Connecticut, Maine, Maryland, Massachusetts, Minnesota, New Jersey, New York, Oregon, Rhode Island, Vermont, and Washington, have followed California's lead in adopting ZEV regulations and Clean Car Standards (**Figure 2**) [3].

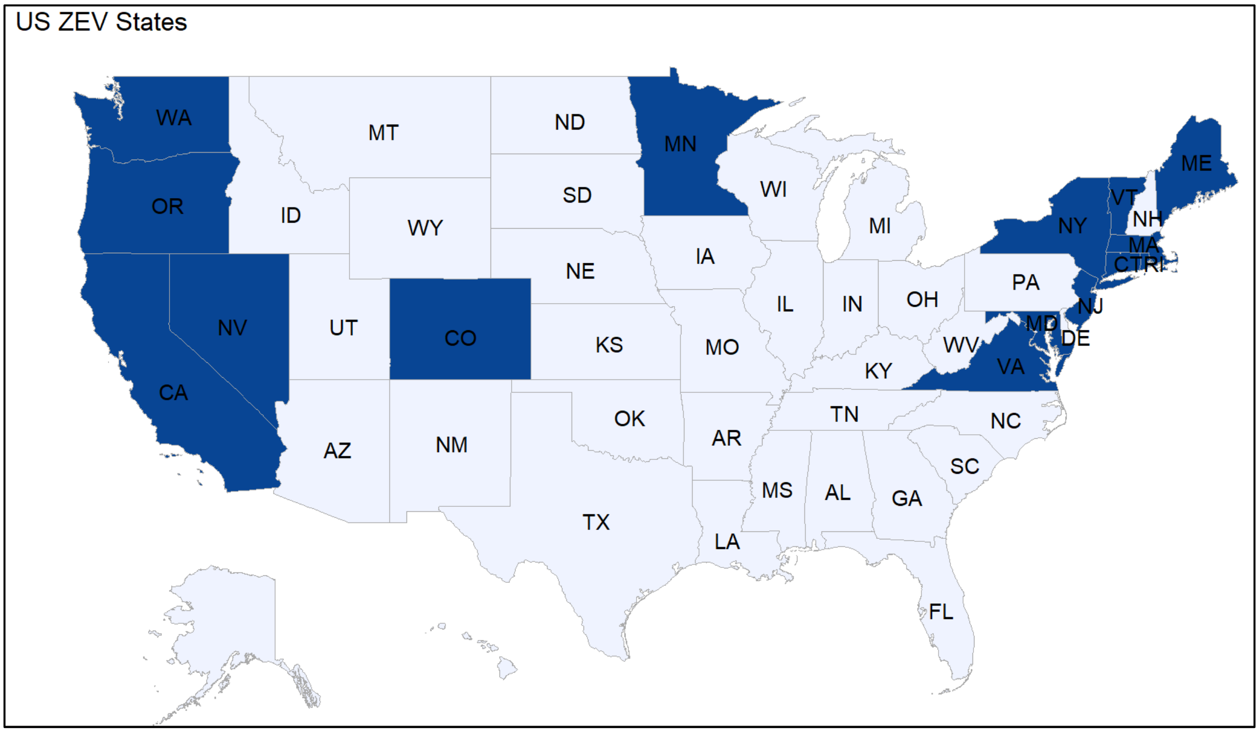


Figure 2: ZEV States in the US (Developed in R language using choroplethr package)

In California, the market share of zero-emission light-duty vehicle (LDV) sales in the year 2023 (up to Q2) was 24.3 percent, with the highest sales belonging to the category of battery electric vehicles (BEVs) with a range greater than 200 miles (**Figure 3**) [4]. The ZEV sales data is fetched from DMV registrations and is updated quarterly. The California Energy Commission (CEC) dashboard showed that the maximum concentration of BEV and PHEV registrations was in Los Angeles County, followed by Orange, San Diego, Santa Clara, and Alameda counties (**Figure 4**) [5].

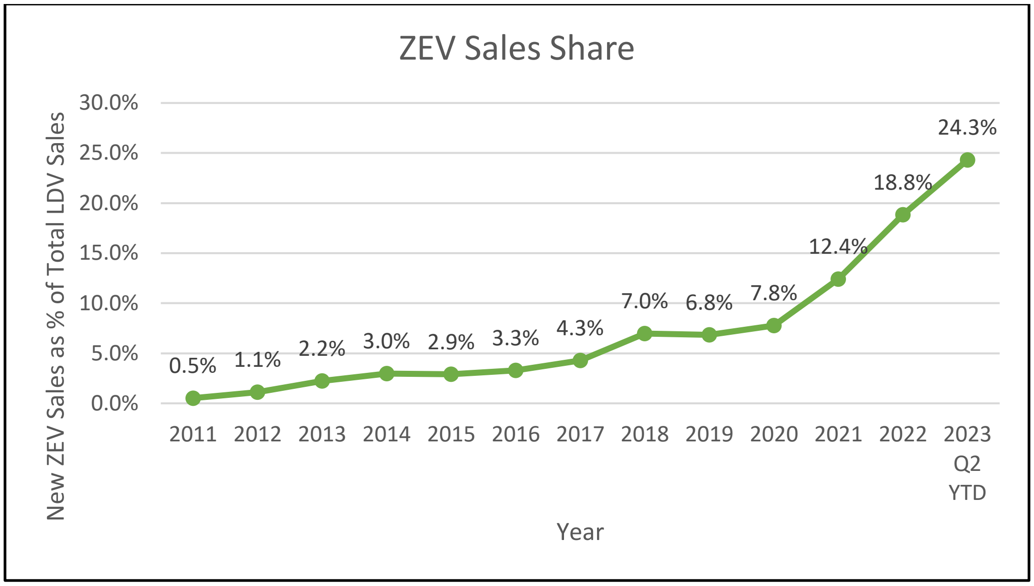


Figure 3: ZEV sales up to 2023 Q2 as a percentage of total LDV vehicle sales [5]

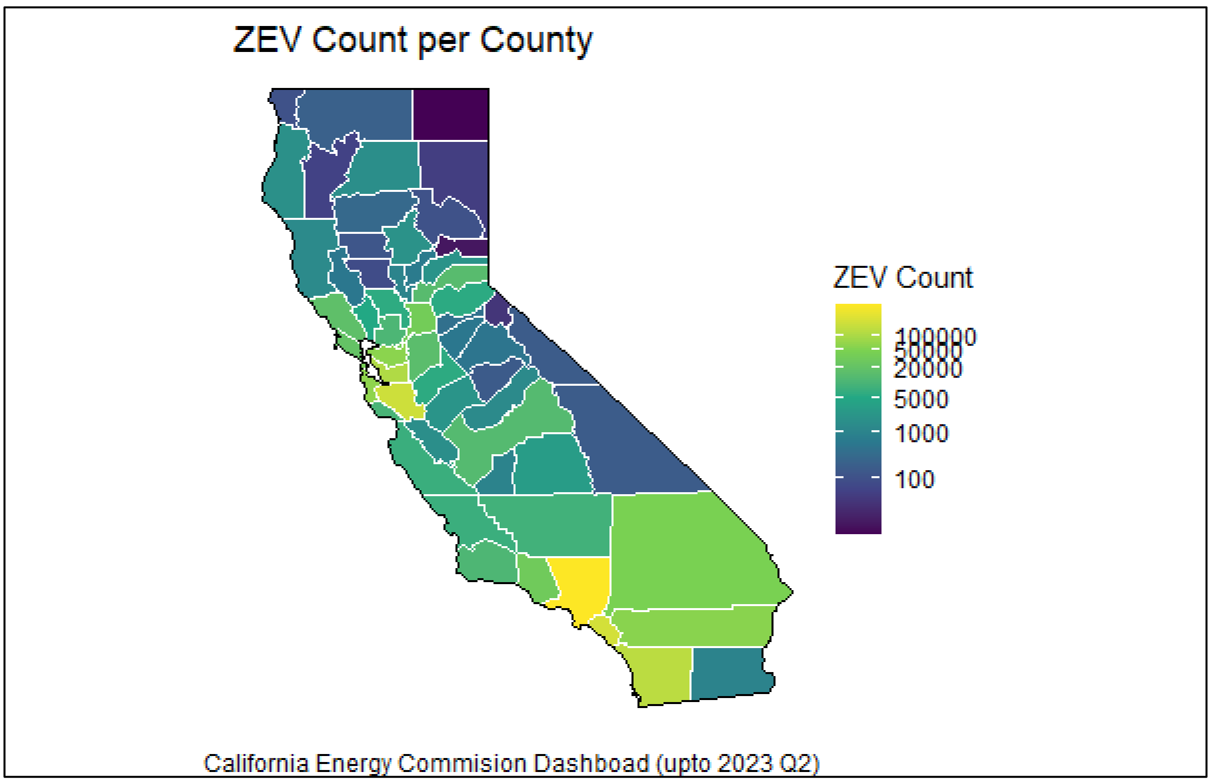


Figure 4: New ZEV Sales and Number of DMV Registrations at the County level [5]

However, the higher upfront purchase price of new ZEVs compared to Internal Combustion Engine Vehicles (ICEVs) could continue to be a barrier to purchasing a vehicle [6]. Hence, evaluating the used vehicle market is essential since it has been found that when the ratio of used over new PEV purchases was measured, the number was higher for lower-income areas [7]. This report also found that California, which has the highest share of PEVs in the US, is the largest *source* of used vehicles for other states. As an indication of this, the California's market share of new PEVs in the U.S. is 54.7%, whereas its share of U.S. used PEV sales is only 33.2%. Turrentine et al., in a 2015 survey-based study, found that the household income was lower for used PEV owners than for new PEV owners but was higher than the average car-owning population of California [8]. Research on ZEV adoption and diffusion has shown that financial incentives are an effective driver of ZEV adoption and are more likely to be considered essential by Californian households with lower income levels [9], [10]. California's lower-income and Disadvantaged Communities (DACs) are investment priorities for the State's cap-and-trade program to curb climate change progress and improve air and life quality [11]. Some other income-eligible incentive programs in California are the Clean Vehicle Rebate Project (CVRP), the Lodi Electric - Zero Emission Vehicle Rebate, the Clean Cars 4 All (CC4A), and the Pacific Gas & Electric (PG&E) - Pre-Owned EV Rebate Plus Program that offers incentives to lower-income and DAC households [12] (See **Appendix 1**).

Given the widespread availability of incentive programs and the high cost of offering incentives, it is essential to observe the consumer's response to these subsidies and quantify the benefits and costs of their implementation. Equitable distribution of financial incentives is a significant aspect that needs attention since post-purchase rebates are not accessible to consumers from the lower-income group due to the higher upfront cost of purchase [13]. Some research has shown that incentives are essential for lower-income buyers; however, this is currently limited to an analysis of summary statistics from the Clean Vehicle Assistance Program (CVAP) [14]. The motivation for our study is to provide a more rigorous, quantitative analysis of the impact of the CVAP using a more complete data set. A logistic regression analysis was developed to investigate of the effect of the CVAP incentive on the adoption of ZEVs by low-to-moderate income Californians (i.e., Californians with household income less than 400% of the Federal poverty line). In addition, for comparison purposes, first a meta-analysis of existing literature on the impact of sales incentives on early adopters was provided. The 13 studies used for the meta-analysis and their characteristics are summarized in **Appendix 2**.

Before proceeding, for context, the institutional details of the CVAP was reviewed. The CVAP grant is given to lower-income buyers who purchase or lease a new or used ZEV in California. The program was funded by California Climate Investments, which utilizes the cap-and-trade dollars to reduce GHG emissions, make the economy more robust, and improve the health and the environment of the residents of disadvantaged communities [15]. As of June 2023, CVAP was discontinued as a stand-alone program, and potential applicants were encouraged to consider other incentive programs for purchasing clean vehicles.

The eligibility of Californian households for CVAP was based on their net annual household income and household size. For a single-member family, the yearly gross income cap was $43,740; for a three-member household, the income cap was $74,580 (eligibility criteria as per 2023 revision). In addition to the vehicle grant, there was a grant of $1,000 for charge cards and portable EV chargers, $2,000 for a home charger, and “affordable financing” that capped interest rates at 8% for participants [16]. The grant is given at the time of purchase; hence, an online application must be completed, and the approval letter should be received before the purchase [16]. The vehicle could be purchased only from approved car dealers. A voluntary consumer survey was administered to recipients of the grant to measure the effect of the monetary incentive. The survey respondents were approved grant recipients that had already chosen their vehicles.

The models were developed to perform analyses for evaluating the influence of the grant on the buyers’ purchase decisions. The dependent variable in the analysis is the buyer’s response to the following survey question: “Would you have purchased your clean vehicle if you did not receive a grant through the Clean Vehicle Assistance Program?”. The analysis considers the effect of socioeconomic and demographic factors, as well as characteristics of purchased vehicles and other features of the CVA program. One specific feature that adds complexity to the analysis is that the grant for the vehicle purchase is supplemented by additional subsidies to support either the purchase of charging equipment or the use of public charging infrastructure. Due to the nature of the data that are available, the analysis has limitations in its ability to make causal inferences. However, it does provide a helpful representation of statistical relationships between the dependent variable and many factors of interest.

2. Literature Review

In this section, literature that analyzed the impact of financial incentives on ZEV purchases, whether the point-of-sale incentive is preferred over post-purchase incentives, the demographics of the ZEV buyers, and the distribution of incentives were reviewed from the equity lens. This section will also review findings from past studies involving meta-analysis of the impact of incentives on PEV adoption. Also, stated preference studies that mention financial incentives as one of the influential factors of PEV adoption will be reviewed to compare how these studies differ from revealed preference studies.

2.1. Impact of Incentives on ZEV purchase

Prior research on purchase incentives, including the federal tax credit and numerous state and local incentives, showed that incentives positively impacted ZEV adoption in California. Recent survey-based studies have found that 30% of all ZEV sales could be attributed to the federal tax credit [17]. Forty percent of ZEV buyers would have changed their purchase decision without the federal tax credits, and this percentage of buyers increased over time [18]. For other programs, such as the MOR-EV rebate, a New York-based rebate program, almost 40% of consumers considered the rebate essential for their purchase [19]. The percentage of participants indicating rebates were necessary for their ZEV purchase was approximately 51% for the CVRP rebates. For the increased rebates for low-income households, 72% were rebate-essential participants [20]. Recent studies using sales/registration data have found that, on average, across all states, a 2.6% increase in sales occurred per $1,000 of incentives offered [21]. BEV registrations increased by 8% per $1,000 incentive offered [22]. The study by Narassimhan and Johnson [23] observed that a 1% increase in incentives relative to vehicle MSRP was associated with a 1.8%

increase in BEV purchases with a tax credit and 2.16% with a rebate. A study by Gallagher and Muehlegger mentioned that a tax incentive of $1,000 was associated with an increase of 5% in hybrid vehicle sales [24]. The authors also found that when the tax incentive was increased by 1% of the vehicle model MSRP, the sales increased by 1.2%. These studies indicated that financial incentives impact ZEV adoption, and this study will attempt to strengthen these findings.

Research has identified differences in incentive impact based on the incentive types, vehicle models and types, and demographics of ZEV buyers. In the United States (US), the federal tax credit is less efficient than some state rebates because lower-income buyers are mostly not eligible for tax filing. The study by DeShazo et al. [25] covered a choice experiment sample size of 1261 new car buyers in California, where 73% of survey respondents indicated that the state rebates were more important than 71% who responded in favor of the federal tax credit. Narassimhan and Johnson [23] found that rebates influenced ZEV adoption more than tax credits because rebates were received closer to the point of purchase compared to the federal tax credit. A recent choice-based US study by Roberson and Helveston [28] found that participants preferred immediate incentives over post-purchase ones. The authors found that immediate incentives were valued at $580, $1,450, and $2,630 more than the exemption on sales tax, tax credits, or tax deductions, respectively. This study evaluated the importance of immediate incentives using a Multinomial Logit (MNL) model in the willingness to pay (WTP) space where the coefficients indicated a preference for immediate discount, valued in US dollars. The four choices in the MNL model were rebate, sales tax, tax credit, and tax deduction. For policy-makers, in addition to monetary incentives, other incentives, such as HOV lane access, can be significant, particularly in states with a high density of traffic in carpool lanes [21] [26] [24]. The study by Jenn et al. has shown that in states with high-density traffic, such as Florida and Georgia, HOV access is a more influential incentive for ZEV adoption than monetary incentives. However, in California, monetary incentives had a higher impact on the adoption rate, even though HOV lane access contributed to a 46% rise in registrations [18]. Past studies have shown that reoccurring non-financial incentives such as access to charging infrastructure, road toll fee waiver, parking incentives, and incentives for license plates have influenced buyers of ZEVs in their purchase decisions, along with monetary incentives [26]. This study will focus on financial incentives and factors that significantly correlate with the positive influence of monetary incentives. Past studies have shown that non-financial and recurring incentives significantly impact purchase decisions more than financial incentives in some states. Hence, it should be noted that the model might have to consider monetary and non-monetary incentives when the study is scaled across a more expansive geography, such as the entire US.

Incentive impacts often vary with the technology type, make, or model of the vehicle, as was shown in the study by Narassimhan and Johnson [23], which found no significant impact of incentives on Tesla adoption and observed a significant relationship between incentives with the adoption of Nissan Leaf BEVs. Jenn et al. [18] found buyers of Tesla BEVs were less likely to report their purchase was dependent on the federal tax credit than buyers of other PEV types. Incentives were less critical for PHEVs with shorter electric driving ranges. The income and deprivation variables also showed that affluent areas were more likely to have higher numbers of household charging points, indicating the adoption of electric vehicles [28]. The study suggested that bridging this equity gap requires further research into what policies could be enacted to mitigate this disparity. As per their study, interest-free loans for a new EV purchase are already available in Scotland, and so are other plans that allow for a more extended repayment period, giving customers a low upfront capital burden along with the cheaper running cost of EVs. This study will attempt to strengthen the findings in past studies, which mention that BEV owners reported that incentives were influential in their purchase decisions and whether the PEV buyers were from lower-income households or were more likely to live in affluent areas.

Incentives for enhancing the public and private charging infrastructure have been deployed in most countries with mature PEV markets [29]. Studies based on the largest PEV market in the world, China, found that incentives play a significant role in enhancing the electric vehicle charging infrastructure (EVCI) [30]. The study observed that construction and operation subsidies for EVCI positively impact their deployment. Also, the incentives should be above a certain threshold to be effective. Self-regulatory market mechanisms alone cannot drive EVCI diffusion [30]. The authors of this study investigated the importance of policy instruments such as incentives for EVCI implementation and enhancement since a well-developed charging infrastructure is closely linked with the growth of the PEV market. This statement is backed by research based in the European PEV market, which recommended that along with offering monetary incentives, it is crucial to implement programs for enhancing charging infrastructure and organize outreach campaigns to spread awareness about EVs [31]. The CVA program, along with grants for vehicle purchase, provides grants for EVSE. Hence, the model will attempt to strengthen the findings of existing studies, which have shown that infrastructure incentives are as essential as vehicle incentives.

2.2. Review of Stated Preference Studies that evaluate the consumer's intent to buy a ZEV

Stated preference survey-based studies based in a mature EV market like China recommended that authorities continue or increase direct financial incentives for EV purchases [32]. Past studies mention behavioral theory frameworks such as the theory of planned behavior and rational choice, the value belief norm framework, and the framework considering the diffusion of innovation based on which the consumers' behavioral outcome, such as EV adoption, can be explained [32]. This study finds that 52 percent of the buyers considered subsidies and a well-developed charging infrastructure critical for their purchase decision. The analysis by Zhang et al. also adopted a stated preference approach to understand the consumers' socioeconomic background, adoption intent, and awareness of the EV market in China [33]. The authors found that prior experience with EVs, environmental awareness, gender, and fuel availability did not impact intent to purchase an EV. The study also found that consumers were more likely to buy an EV when the tax incentives were higher. Potoglou and Kanaroglou, in their research, examined the factors that influence Canadian buyers to choose clean vehicles for their household [34]. They found that the vehicle cost influenced the purchase decision of middle-income buyers more than high-income buyers. "Free parking" and "access to HOV lanes" did not influence EV purchase decisions, whereas the "tax-free purchase'' incentives positively influenced the buyers in their ZEV purchase. Older consumers (45 years of age and above) were less likely to adopt a ZEV, while consumers holding a university degree were more likely to buy a Hybrid vehicle. This study has combined stated preference and revealed preference data to understand consumer behavior based on the buyer's demographics, socio-economic factors, vehicle characteristics, and features of the grant.

The study by Wang et al. investigates the buyer's perception of the impact of incentive policies on BEV purchases, considering the consumers' socioeconomic attributes [35]. This paper focuses on the PEV market in China, where the government has set a target that by 2025, 25 percent of its new vehicle sales will be driven by alternative fuels. The authors found that how buyers perceived monetary incentive policies significantly impacted their purchase decisions. Attitudinal factors such as environmental concern also affected BEV purchase decisions. A recent paper by Nazari et al. looked at EV adoption behavior in the US at the household level with the help of an Integrated choice with latent variables (ICLV) model [36]. They combined latent factors such as attitude, perception, emotions, and symbolism with econometric estimations using the discrete choice model to evaluate EV adoption behavior where the choice was between EVs and ICEVs. With the model that contained four latent constructs and a set of exogenous explanatory variables, the authors developed a framework to evaluate policy effectiveness. In their choice model, the vehicle attributes showed that the buyers were more likely to lease a PEV, mainly a PHEV, as their acquisition cost was lower. The availability of charging infrastructure was another critical determinant of EV adoption behavior.

A stated preference survey-based study in Virginia that examined the preferences of a heterogeneous sample of PEV adopters showed that monetary incentives followed by charging infrastructure deployment were the most influential drivers of PEV adoption [37]. The authors found that the availability of PEVs with improved battery range was ineffective in encouraging PEV adoption. They also mentioned that since a stated survey is based on a hypothetical scenario, the buyer's stated choice behavior may not reflect their actual preferences, mainly because these buyers might not have direct PEV experience. Overall, a review of these stated preference studies will indicate whether past findings are similar to or different from the current sample of CVA participants spanning 2018 to 2022 with respect to the buyer's preference for monetary incentives.

2.3. Demographics of buyers most impacted by incentives

Research into the adoption of ZEVs has primarily gathered information from high-income families, potentially overlooking the needs of other adopters, notably middle-income renters. As per the World Economic Forum, the higher income group comprises household income greater than $156,000, middle-income has income between $52,000-$156,000, and the lower income group has income less than $52,000 with an assumption that the US average household size is 2.6 [38]. High-income consumers may need less policy support to purchase a PEV; they are also likely to have a place to charge their vehicle at home, representing only 3.6% of California households [39] (Hardman et al., 2018). Studies that delve into the demographics of the buyers suggested that the largest cluster (47.9%) consists of higher-income, middle-aged, mostly male, home-owning, highly educated households, with more people in the household [40]. Middle-income renters may need more support with purchase incentives, are less likely to have access to home charging, and may be unable to install a home charger themselves (most middle-income renters live in multi-unit dwellings) [39]. In the study by Lee et al. [40], middle-income renters are the smallest cluster at 2.1% in 2012 and 7.9% in 2017. This showed that this cluster has experienced the fastest growth. But, in the context of the Lee et al. study, it should be remembered that an income cap of $250,000 for single filers, $340,000 for head-of-household filers, or $500,000 for joint filers was introduced in the CVRP program (March 2016) based on which large portion of higher-income buyers were not eligible to apply for the rebate post-March 2016 [41]. These income caps were revised in November 2016 to $150,000 for single filers, $204,000 for head-of-household filers, and $300,000 for joint filers, with an additional cap of $60,000 on the MSRP introduced in December 2019 [42]. In January 2021, the household income requirement for low-to-moderate-income buyers was modified from less than or equal to 300% to less than or equal to 400% of the Federal Poverty Line (FPL), along with a range cap of 30 miles (EPA standard) that was introduced in April 2021[42]. The income cap criteria are relevant to the present study since the CVA program is income-eligibility based, and it is essential to understand and strengthen the observation that targeted incentives reach the intended recipients who would not have purchased the ZEV without financial support.

Past research on the impact of equitable distribution of incentives among lower-income buyers was investigated in this review. Studies showed that most incentives in the US are delivered post-vehicle purchase, and for lower-income car buyers, point-of-sale incentives may make ZEVs more affordable as they reduce their high upfront purchase cost [43]. Income cap implications on the CVRP have been captured in the study by Guo and Kontou [44], where they observed that the moderate to high-income group received the most significant share of rebates. Their analysis was based on CVRP program data from 2010 to 2018. After the income-cap policy implementation in November 2016, where PHEV and BEV consumers with a gross annual individual income greater than $150,000 were no longer eligible to apply rebates under CVRP, the share of rebates per capita increased in both lower- and middle-income communities and DACs. For both PEV types, the adoption rate was higher during the quarter 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. Sheldon and Dua [45] evaluated the impact of the Replace Your Ride (RYR) program that provides income-qualified residents of the South Coast Air Quality Management District (SCAQMD) incentives up to $9,500 to replace their older high-emissions vehicles with newer PEV, electric bike, or an alternative transportation pre-loaded card [46]. Their study employed the difference-in-difference methodology to compare PEV adoption data before and after the introduction of the RYR program. The results suggested that in 2015, RYR was more effective in enabling the adoption of clean vehicles, with evidence that most ZEV purchases made under the program in the South Coast Air Quality Management District (SCAQMD) were additional purchases that would not have occurred without the policy.

The paper by Caulfield et al. [28] looked into data from the Sustainable Energy Authority of Ireland (SEAI). It measured EV adoption based on household charging points installed between 2018 and the beginning of 2020. Within that timeframe, 4611 home chargers were installed, which is close to 99% of new EV registrations in Ireland. This study employed the ordinary least squares linear regression methodology to examine the equity aspect of the EV adoption rate using a national-level affluence indicator. The authors found that affluence was correlated with the concentration of household EV charging points [28]. Their research also showed that areas with higher charging points had higher car ownership, suggesting that the households had multiple EVs. The findings add to the policy debate that EV grants are reaching affluent sections of society with access to home charging facilities and leaving behind marginalized groups towards the transition to an EV. Studies across the globe have shown that incentives for charging infrastructure setup ensure equitable adoption of EVs.

The study by Liu et al. [47] assessed whether monetized credits are accessed equitably and whether they help provide emission reduction benefits across all income groups. At the state level in the US, seven states (Colorado, Georgia, Louisiana, Montana, Oregon, South Carolina, and Utah) have implemented income tax credits where the credits can be redeemed when the individual is filing their state tax returns [48]. The study found that households with higher income and fewer household members in the states of Georgia, South Carolina, and Utah were more likely to receive a higher percentage of income tax credits than families with lower-income buyers with a higher number of members. The authors concluded that ZEV incentives should be designed to nudge buyers from middle- and lower-income households who own old ICEVs and travel extensively during peak hours [47].

A perspective study by Hardman et al. [49] mentioned that if policymakers want to create a more equitable ZEV market, incentives should be structured in a manner that they are higher for lower-income households, offered at the point of purchase, be available on used vehicles, and be available regardless of purchase location (e.g., dealers, private sellers). As per their study, in 2021, to receive the $7,500 Federal Tax Credits, single filers needed to earn at least $66,000, and $91,000 for dual filers. Hence, lower-income households received fewer credits as compared to higher-income households. The authors also found that incentives offered post-purchase and for only new vehicles excluded many lower-income car buyers from the ZEV market. Even charging infrastructure is not equitably distributed, as higher-income communities are more likely to have access to charging facilities than lower-income communities. As part of the study, it was observed that home charging installation is unaffordable for lower-income households and households living in multi-dwelling units. Point-of-sale incentives that reduce the upfront cost of the vehicles will improve their affordability [50]. The CVRP with the income, price, and range cap and the

Clean Cars 4 All (CC4A) that offers incentives for both new and used vehicles focus on equity so that the incentives reach buyers who need them the most instead of higher-income buyers who can afford a ZEV without financial support. This study will investigate the equitable distribution of funds through point-of-sale incentives for new and used vehicles and the charging infrastructure to observe the correlation between lower household income and the preference for an upfront discount.

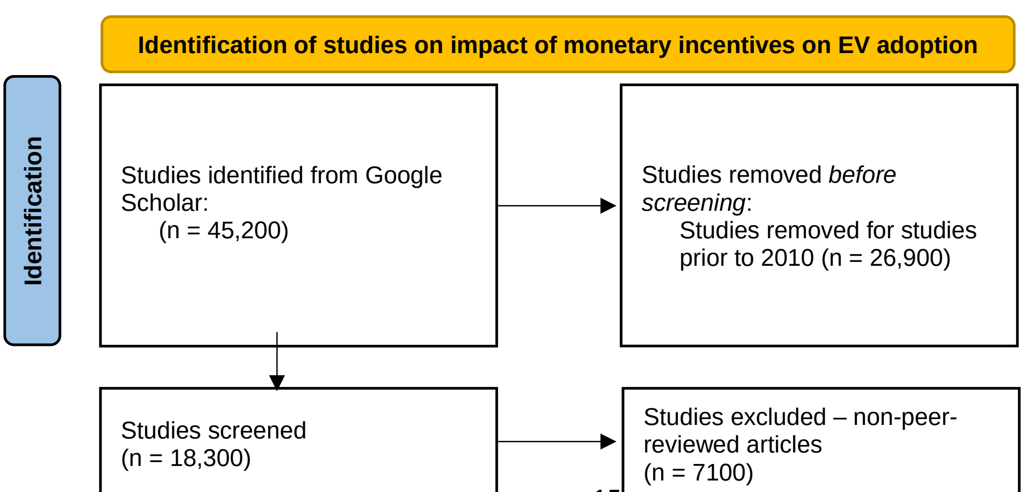
2.4. Meta-analysis or quantification of the impact of incentives on EV adoption

Studies based on a meta-analysis of past literature showed a statistically significant impact of subsidies and other benefits on the behavioral intention of adopting sustainable technologies, including EV adoption [51]. The authors adopted meta-analysis and weight-analysis techniques as they generalized results from different studies with different sample and quantitative methods. Their results evaluated significant variables and quantified their moderating effect. Neves et al., in their paper, mentioned that subsidies are a statistically significant variable and are impactful as they are a concrete strategy that can lead to higher EV adoption. The study by Wang et al. conducted a meta-analysis of 24 existing studies to understand the factors influencing the buyer's willingness to pay for a hydrogen fuel cell vehicle (HFCV) [52]. The authors chose to base their study on HFCVs since they are zero-emission, high efficiency, long-range, large capacity, and refueling is also fast. The analysis found from the combined effect of policy incentives that infrastructure incentives positively and significantly impacted the consumer's intent to buy a HFCV. For HFCVs, monetary incentives such as subsidies, tax credits, and other incentives will encourage the buyer to own a ZEV. The paper by Wang W et al. evaluated the consumer's willingness to pay from a comprehensive and quantitative perspective [52]. They summarized that socio-economic and vehicle characteristics such as household size, vehicle cost, fuel cost, education level, household income, car ownership, driving range, awareness, and policy incentives were positive drivers for the consumer's willingness to own a HFCV. This study will investigate the effect of subsidies on the PEV adoption rate to strengthen the findings of past studies.

Based on past studies, the sample of CVAP recipients will be analyzed with a focus on the socio-economic factors, demographic factors that influence consumer's need for financial incentives, the specific features of the CVA program that influenced buyers to purchase a clean vehicle, and policy implications of a point-of-sale grant. In the policy discussion section, the findings on the CVAP recipients shall be compared with existing research on the recipients of the CVRP program.

3. Meta-Analysis of Existing Literature

The first step in the meta-analysis was to screen the studies from the plethora of literature available on Google Scholar focused on the impact of monetary incentives on PEV adoption. The studies are selected as a mix of inclusion and exclusion criteria and are illustrated in **Figure 5**. The initial search on Google Scholar was conducted using the keywords monetary incentives, electric vehicle adoption, financial incentives, and consumer demand. This research investigated studies in the year range of 2010 to 2023, excluded studies focused on non-financial incentives such as HOV lane access, and considered only peer-reviewed papers. The initial search returned 45,200 studies. After the rejection of 34,253 studies due to the year of publishing being earlier than 2010, non-peer-reviewed papers, and papers that investigated only non-financial impact on PEV adoption, 10,667 studies were shortlisted for final examination. Out of these authors of only 13 studies reported PEV adoption rate expressed as a percentage attributed to a 1,000 USD/EUR/GBP monetary incentive (**Figure 5**).



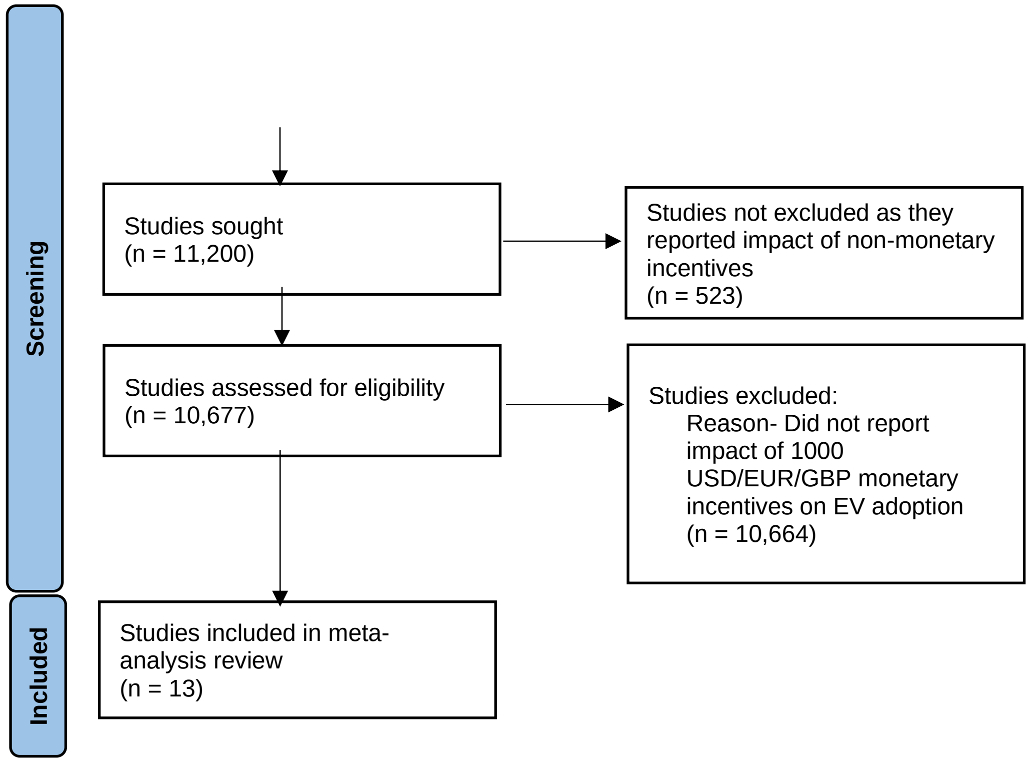


Figure 5: Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA 2020) Flow Diagram for Literature Search [53]

PRISMA 2020 is a tool for transparent reporting of systematic reviews and meta-analyses [53]. It provides a checklist of items that need to be followed in a meta-analysis and a template of a flow diagram that depicts the steps followed. The items covered in this analysis as per the PRISMA 2020 checklist have been listed in Appendix 6

Meta-analysis is a technique frequently used in clinical research and is a subset of the systematic literature review [54]. According to the authors, meta-analyses are conducted to determine the strength of evidence of the effect based on a pool of studies. In this paper, the effect is the PEV adoption rate attributed to monetary incentives on a scale of $1,000. The outcome of the study can strengthen evidence of the presence of the effect, obtain a single summary estimate, and address questions not posed by individual studies [54]. Meta-analysis also typically averages a comparable parameter from each study.

The basic unit of observation in the meta-analysis is the effect size, which is an index of the magnitude of the effect of one variable on another variable (or variables) [55]. In this study, the correlation-based measure of effect size has been used, and it indicates the degree of association among variables [56]. A dataset was prepared based on studies where the authors reported the impact of $ 1,000 financial incentives on the ZEV adoption rate expressed as a percentage (See **Appendix 2** for details). **Figure 6** shows the increase in ZEV adoption rate per $1,000 incentive (effect size) as mentioned by the authors in each study that is part of the dataset (**Appendix 2**). For studies based in Europe, the UK, or Canada, the currency was converted to a scale of $1000 based on the currency conversion rate [57] [58] [59]. For studies that have found the EV adoption rate to correspond to the actual financial incentive amount, the incentive amount was scaled down to $1000, and the corresponding adoption rate was calculated [37].

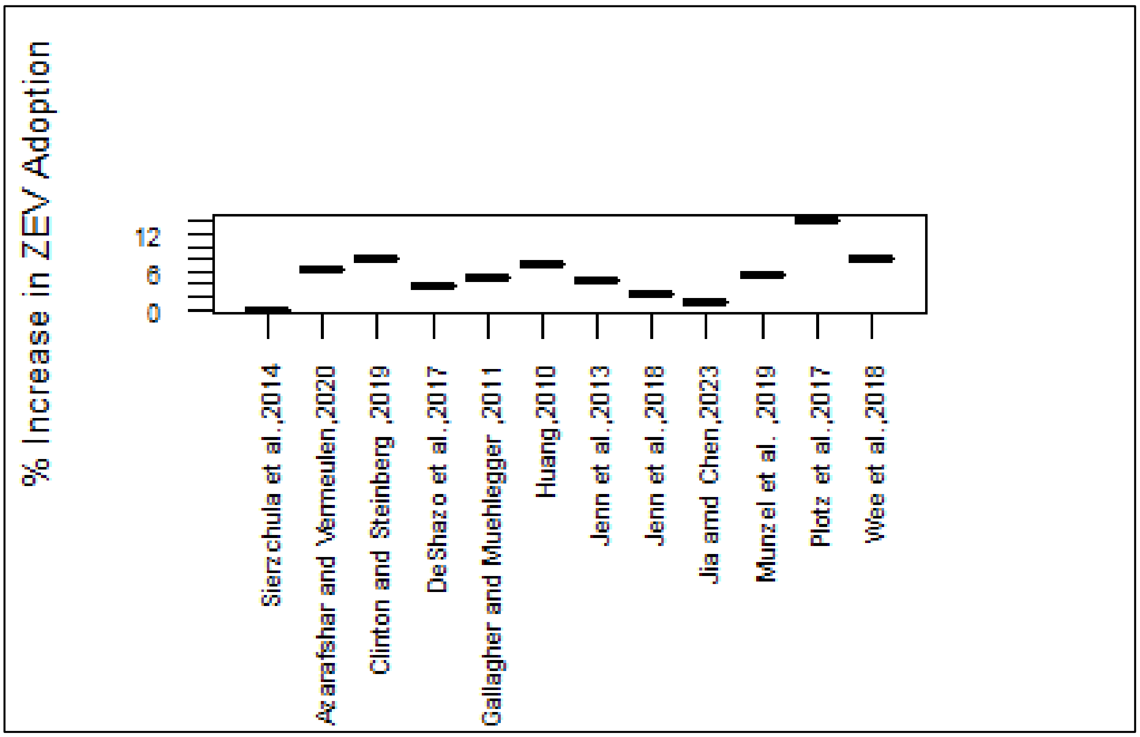


Figure 6: The Increase in ZEV Adoption Rate for $1,000 Financial Incentives on EVs

3.1. Meta-Analysis Model Specification

The meta-analysis was conducted using the random effects model due to significant heterogeneity in the reviewed literature for evaluating the impact of incentives on ZEV adoption. The random effects model assumes that the studies' underlying effects vary [60]. The paper by Song et al. also mentioned that the confidence interval of the overall effect estimate may be wider in a random effects model than in a fixed effect model [60]. Moreover, the assumption of normal distribution allowed the calculation of confidence and prediction intervals. The random effect model in this study is based on the average PEV adoption rate that is reported by the authors of the studies included in the literature pool (**Appendix 2**). In this analysis, the effects from the studies (EV adoption rate) are linearly correlated to the response ($1,000 incentives), so Fisher's Z-transformation was used to generate a normal distribution from Pearson's correlation coefficient. The effect underlying the i^{th} study of K studies will be represented by θ_i. It is assumed that these effects are drawn from some unspecified distribution $f(\Phi)$, with parameters Φ, such that $E[\theta_i]=\mu$ and $var(\theta_i) = \tau^2$ [61]. τ^2 represents heterogeneity in the sample, essential for measuring the extent of inconsistency.

Special Considerations in random-effects meta-analysis are:

i. Diversity and bias – While considering the heterogeneity of effect sizes, it is vital to distinguish the effect of diversity (diversity of population, intervention, exposure, outcome) and publication bias (based on design and quality of study) [61]. A random effects meta-regression analysis can summarize the risk of bias, but publication bias is difficult to measure, primarily if the studies are conducted in different locations and timelines.

ii. Biases and minor study effects –The study size is an influential and relevant covariate for a random-effects meta-analysis. The study size (or study precision) may lead to an asymmetric funnel plot if a set of studies skew the net effect and may reflect publication bias. In many cases, publication bias demonstrates a correlation between study size and essential covariates such as study quality [62].

As the meta-analyses have been conducted on a moderate number of studies, the following was considered:

- A visual plot, such as the forest plot, as a preliminary inspection of heterogeneity
- Heterogeneity in a meta-analysis using random effects
- Random-effects meta-analyses interpreted with due consideration of the whole distribution of effects, ideally by presenting a 95% confidence interval and

- Statistical tests that address important questions of whether an effect exists anywhere and whether it has a consistent direction across studies.

The random effects model considers the sample size and the estimate reported by the author's on PEV adoption rate for every $1,000 of incentives. The "robumeta" and "metafor" R Studio packages have been used for the meta-analysis, forest plot, and the funnel plot. The random effect has been presented in the result section (**Figure 7**) at a 95% confidence interval using the forest plot. If the interval contains zero, the relationship is not statistically significant; the effect is statistically significantly correlated. The Q-value, the I^2- value, and the H-value were evaluated to measure heterogeneity. The Q-value indicates the heterogeneity by rejecting the null hypothesis on the homogeneity of the "effects" showcased by the studies being considered in the analysis. The Q-value is based on the chi-squared (χ^2) distribution with degrees of freedom df(Q) of K – 1.

Equation 1 gives the definition of Q value:

$$Q = \sum \omega i(Ti - T)^2 \qquad (1)$$

Where:

Ti = The effect size selected from the i^{th} study

T = The mean value of all the effect sizes mentioned in the literature that is part of the meta-analysis

ω_i = The size of the overall weight given to the i^{th} study that is part of the meta-analysis

A large Q - value gives a small p – value. In determining the heterogeneity of the studies included in the meta-analysis a small p-value indicates statistically significant heterogeneity in the studies and that there is less possibility that the observed variation in the studies is by chance [60].

The I^2 statistics, derived from the Q - value, varies between 0 to 100 and indicates the percentage of variance in the studies included in the meta-analysis, indicating the heterogeneity of the studies. The I^2 statistic can be found by **Equation 2** [63]:

$$I^2 = \left[\frac{Q-df(Q)}{Q}\right] * 100\ \% \quad (2)$$

Where:

Q = Q- value from **Equation 1**

df(Q) = K – 1 where K is the number of studies included in the meta-analysis

The I^2 levels are categorized as low, medium, and high levels of heterogeneity based on the thresholds 25%, 50%, and 75%, respectively [63].

The H - value can be defined as follows (**Equation 3**) [52]:

$$H = \sqrt{\frac{Q}{K-1}} \quad (3)$$

Where:

Q = Q- value from **Equation 1**

K = the number of studies included in the meta-analysis

When H > 1.5, there is heterogeneity among the literature included in the meta-analysis, and when H < 1.2, there is homogeneity among the literature included in the meta-analysis [52].

3.2. Result of Meta-Analysis of Literature

The Random Effects Model for the meta-analysis captures the heterogeneity of 84.9% based on the effect of incentives on the increase in EV adoption being captured from the studies and is significant at the 95% confidence interval using meta-regression. The overall correlation coefficient of the random effects model shows a 5% increase in ZEV adoption for a $1,000 incentive (**Figure 7**). At a 95% confidence interval, the ZEV adoption rate lies in the range of 4% to 6 % on average (**Figure 7**). The forest plot reports effect estimate and confidence interval by a block at the point estimate as reported by the authors of the studies.

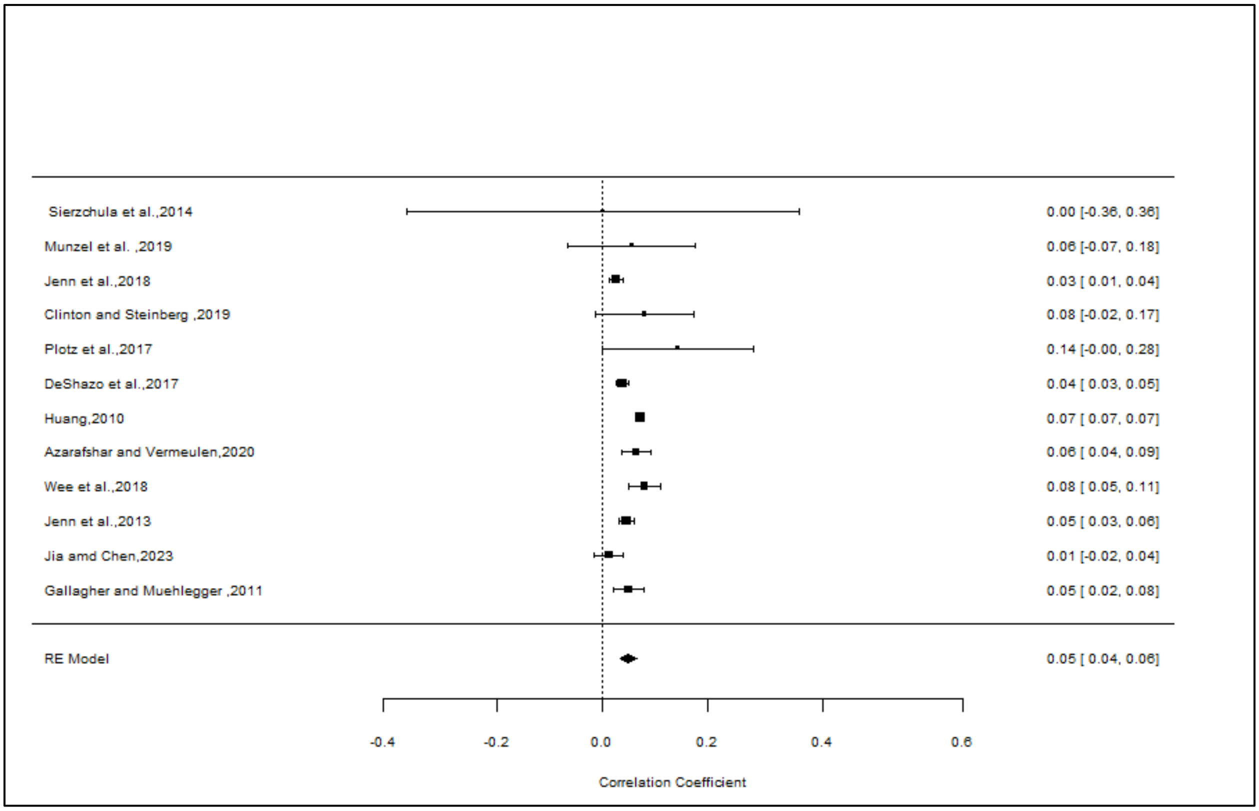


Figure 7: Forest Plot for the Effect of $1,000 Incentives on ZEV Adoption

The funnel plot (**Figure 8**) attempts to capture publication bias-based or small study bias evaluation in the meta-analysis. The funnel plot used Standard Error (SE) as the vertical axis. The studies with larger sample sizes have smaller SE and, hence, are placed at the top of the graph with the axis inverted (standard error 0 at the top) [64]. The asymmetry in the plot shows that the mixed effects meta-regression model with standard error predictor is not impacted by any single or group of studies within the dataset of the analysis. Fisher's z transformation is a normalizing transformation for the Pearson correlation of bivariate normal samples of size N. Pearson's correlation coefficient measures the linear association between two variables.

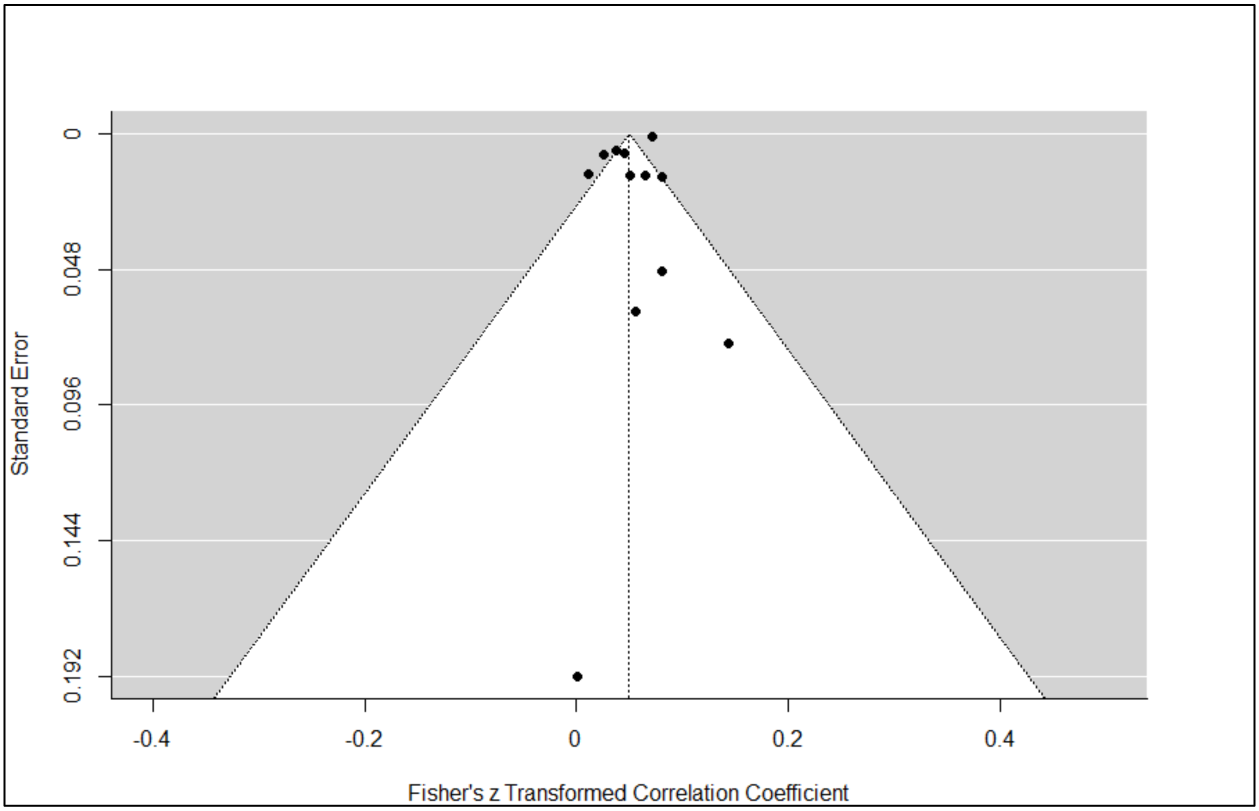


Figure 8: Funnel Plot for Visualization of Study Bias

The results (**Table 1)** show that the buyer's response to the $1,000 monetary incentive is heterogeneous in the ZEV market worldwide. The caveat that needs to be mentioned is that the pool of studies adopts varied methodologies to arrive at results reported by the authors. This study did not consider the correlation of age, gender, education level, and income and looked at the correlation of monetary incentives with PEV adoption in isolation, considering all else constant. The heterogeneity can be attributed to the variety of locations, awareness of new technology, interest level of buyers of new technology, and timeline of studies, to name a few plausible reasons.

Table 1: Measures for the Meta-Analysis Showing that Response to $1,000 Incentives is Heterogeneous

Test Statistics	Value
τ^2 (estimated amount of total heterogeneity)	0.0004 (SE = 0.0003)
I^2 (total heterogeneity / total variability)	84.9%
H-value (total variability / sampling variability)	2.57
Q-value	99.45
p-value	<0.0001 ***

*** Statistically significant at a 5% significance level

4. Methods and Data

The quantitative analysis in the following sections will focus on the adopter's behavior toward an income eligibility-based grant program. This section will discuss the data, model specification, estimation, and validation in detail. The results will be discussed in **Section 5**.

4.1. Binary Logistic Regression on CVAP Adoption Data

4.1.1. Data

The research is based on the consumer survey data provided by the California Air Resources Board (CARB). It covers topics including interest in ZEVs, sources of information used, decision-making process, dealership experience, the importance of the grant in their purchase decision, socioeconomic, and demographic characteristics. For this study, the data was combined from two sources: the data collected from the online application forms submitted by the CVAP recipients and the survey conducted by the Center for Sustainability (CSE) on consumer experience and preferences. The data is from surveys administered from 2018 to 2022, focusing only on BEV and Plug-in Hybrid Electric Vehicles (PHEV) buyers. The dataset is a combination of revealed preference (RP) and stated preference (SP) data, where the socio-economic, vehicle, and program characteristics are RP data. In contrast, the dependent variable is a hypothetical question: "Would you have purchased your clean vehicle if you did not receive a grant through the Clean Vehicle Assistance Program?", hence SP data (**Appendix 3a**).

The trend for the impact of CVAP on the decision to purchase a ZEV is shown in **Figure 9** from 2018 to 2022. **Figure 9** suggests that most respondents would not have bought their ZEV without the grant (Yes = almost 14%, No = almost 86%). **Table 2Table 2** summarizes descriptive statistics of ZEV buyers who received the CVAP grant. The descriptive statistics have been presented for the whole survey sample, 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 buy a clean vehicle without the grant (category 0).

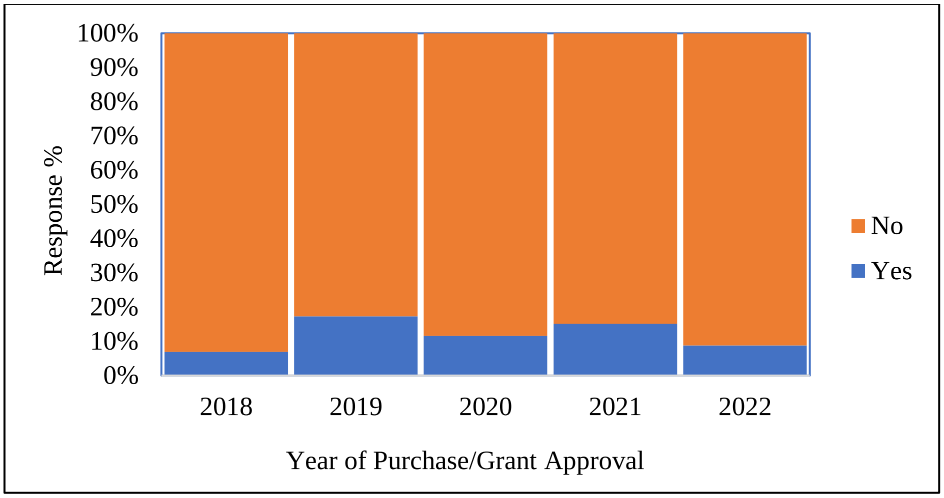


Figure 9: Response Statistics for the Dependent Variable "Would you purchase a clean vehicle without the grant from the CVAP?"

Figure 10 shows that the grants are mainly concentrated in 9 out of 58 counties in California, namely Sacramento, Alameda, Santa Clara, Fresno, San Bernardino, Los Angeles, Orange, Riverside, and San Diego.

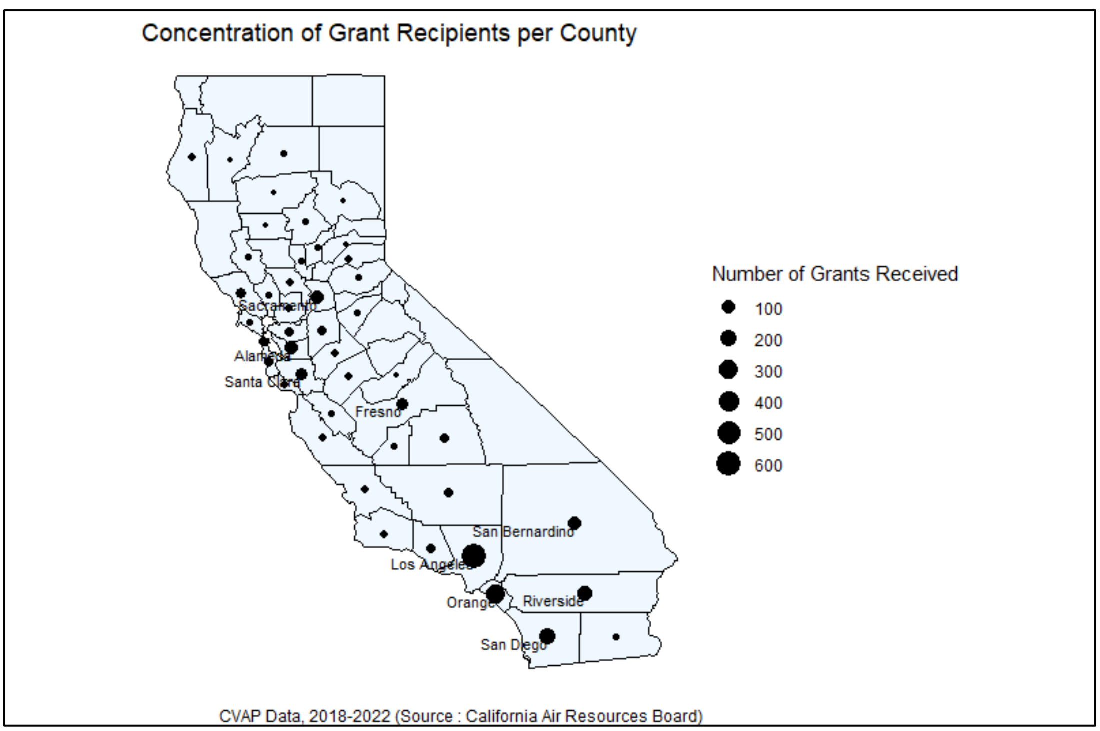


Figure 10: Concentration of Grant Recipient per County

Table 2 shows that BEVs are most common in the sample, with a 71% share, followed by PHEVs, which had a share of 25.61% in the entire sample. New vehicles comprise 67% of the total percentage of the whole sample. New vehicle share is higher for BEVs within each vehicle technology type, but for PHEVs, used vehicles are more common (**Figure 11**). On investigating the percentage of leased and purchased vehicles, 86.15 % of the vehicles for which the grant was approved were purchased, and 13.85% were leased.

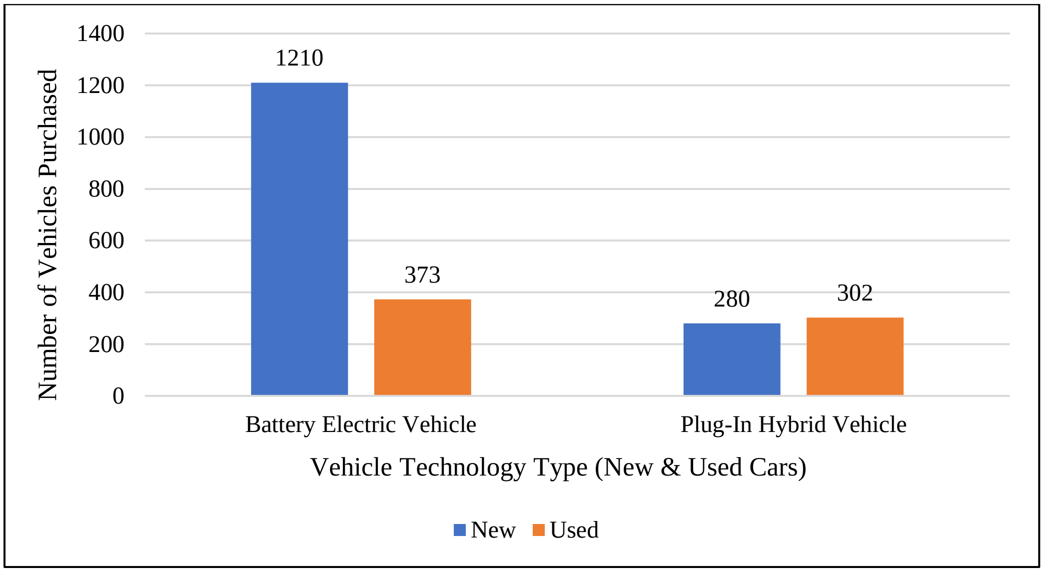


Figure 11: Vehicle Technology Type of Survey Respondents Segregated into New and Used Vehicles

Figure 12 shows homeownership and the charging grant category that the consumer received. It can be observed that homeowners mostly received grants for home EV chargers, indicating that they could set up charging equipment at their residences. Renters mostly applied for the charge card and portable EV charger.

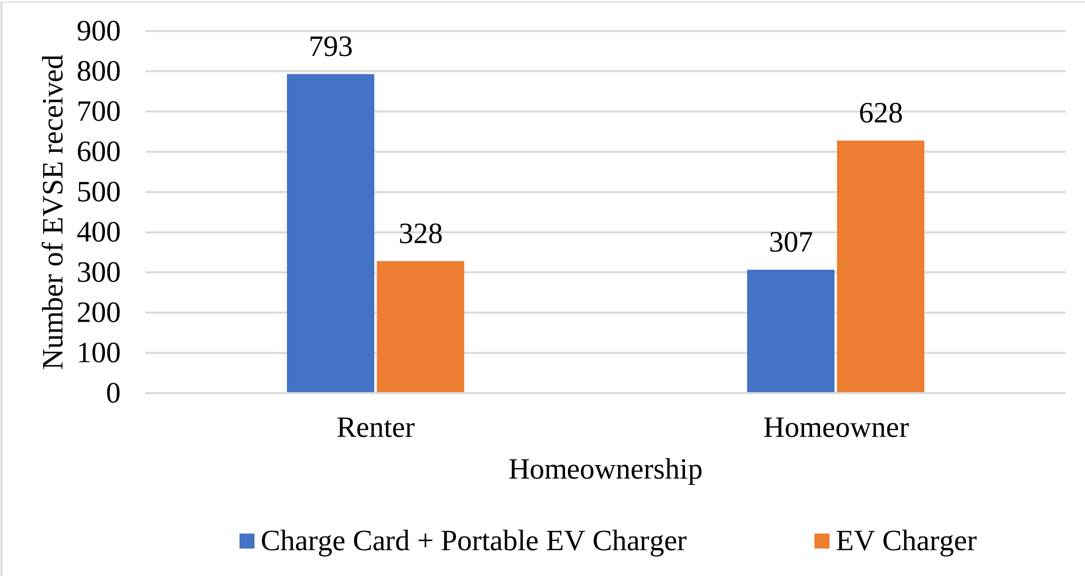


Figure 12: Homeownership & EVSE

Figure 13 shows that buyers whose household income was between 225% to 400% of the Federal Poverty Line (FPL) (relatively away from the poverty line) purchased more expensive vehicles, such as the Tesla Model 3 and Model Y, more than buyers whose income was closer to the FPL (<225% of FPL). Whereas less expensive vehicles such as the Chevrolet Bolt EV, Toyota Prius Prime, Nissan Leaf, Chevrolet PHEV, and others were purchased more by consumers whose income was closer to the FPL (< 225% of FPL).

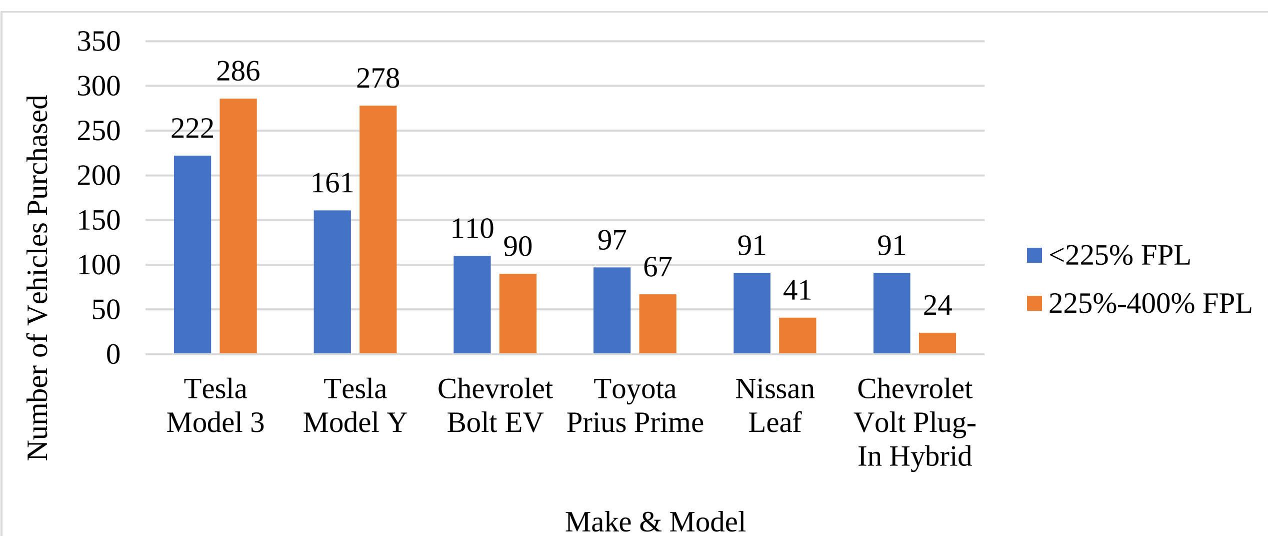


Figure 13: Make and Model Purchased by Buyers for both New and Used Cars

Table 2 shows that most rebate recipients live in rented homes (~60%), and the remaining own residences. A possible reason for the higher proportion of renters compared to prior studies might be that the targeted audience is lower-income households. Spatially, almost 81% of the grant recipients did not reside in disadvantaged communities (DAC) census tracts (as per the definition in CalEnviroScreen 3.0 [65]), and almost 59% of respondents did not live in low-to-moderate income (LMI) households. CalEnviroScreen 3.0 assigns scores to census tracts based on pollution burden and population characteristics, where 1-10% are the lowest scores and 91-100% are the highest scores [66]. Pollution burden comprises exposure to ozone and PM 2.5 concentration, lead exposure, diesel emissions, drinking water contamination, use of pesticides, and traffic density along with environmental effects caused by solid and hazardous waste, groundwater threat, and impaired water bodies [67]. Population characteristics considered in the scoring model comprise exposure to asthma, cardiovascular diseases, and low birth weight of infants, along with socioeconomic factors such as education level, housing-burdened low-income households, poverty, and unemployment [67]. The census tracts which are assigned the top 25% of the scores have been identified as SB535 DACs 2022 (Census tracts and Tribal Areas) [68]. It is important to note that the census tract definition of CalEnviroScreen 4.0 has not been referred to in this study since the survey uses the CalEnviroScreen 3.0 definition.

The lower-income category is defined as households earning less than 80% of the local area median family income, and the moderate-income category is defined as these households earning between 80% and 120% of the local median family income [69]. Among rebate recipients 58% were male, and the remaining 42% were female/non-binary/undisclosed identity. Education-level descriptive statistics show that almost 55% of the total sample had a college degree (Bachelor/Postgraduate), but among those who mentioned that the grant influenced their purchase decision, almost 88% did not have a college degree. The Tesla Model 3 and Model Y are the most common ZEVs, with individual shares of 22.59% and 19.44%, respectively.

Table 3 shows the statistical distribution of the continuous variables, mainly the demographics and socioeconomic characteristics (including age, household size, income, %FPL), loan amount, and whether respondents received a grant for charging infrastructure. Other variables, such as the vehicle mpg equivalent and the cost of the vehicle for the vehicle characteristics, have also been included in **Table 3**. From the table, it can be observed that 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 households. 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 2: Socioeconomic, Demographic, and CVAP 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	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%)

Variable	Subset	Will not Purchase without CVAP (1)	Will Purchase without CVAP (0)	Total Sample
in the full sample	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%)
	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 3: Statistical Summary of Numeric and Continuous 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

4.1.2. Model Specification

Three binary logistic choice models were developed to examine the effect of the decision maker's (buyer's) socioeconomic characteristics, vehicle characteristics, and program-specific features on the dependent/response variable. The selected explanatory variables will assist in evaluating the effectiveness of the financial incentive policy. The models were based on the random utility maximization behavioral framework where the decision maker can determine competing options based on the preference or utility for each option, and the buyers choose the alternative with the highest utility. As mentioned in the paper by Brownstone et al. [70] SP survey experiments observe consumer preferences under hypothetical circumstances, which might lead them to respond to questions that they do not comprehend correctly or are comprehended by each decision maker differently. According to the authors, such a scenario might arise if the “product,” which in this paper is the incentive program, is new or if the buyers lack awareness about the program. Sometimes, respondents strategically report their “politically correct” choice in SP experiments to showcase their support for policies that support “zero-pollution” vehicles. On the other hand, there are inherent multicollinearity issues associated with RP data since, in real market scenarios, the attributes/explanatory variables under consideration, e.g., new/used vehicles and vehicle cost, might be collinear or even have less variation in the sample [70]. The models combined RP and SP data to utilize the advantage of both categories of data and mitigate the inherent disadvantages associated with the same [70].

In this study, Model 1 captures the correlation of exogenous demographic characteristics and socioeconomic factors with the response variable. Model 2 adds endogenous variables to the first model, such as vehicle technology, new or used vehicle, the vehicle selling price at point-of-sale (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. The independent variables such as technology type, new/used vehicles, and vehicle selling price influence the importance of incentives on the PEV purchase decision of the buyer (dependent variable). But, in the opposite direction, the incentive program influences the decision with respect to technology type, whether the vehicle is new/used, or the cost of the vehicle, hence introducing endogeneity. Model 2 analyzes how the vehicle and program-specific features are correlated to the response variable. Model 3 will replace the vehicle selling price at point-of-sale in Model 2 with discount percent, the ratio of grant amount over MSRP, expressed as a percentage. The Apollo choice modeling package in R was used to run the models.

The response variable is a binary variable indicating whether consumers responded "No" (coded as 1) or "Yes" (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?" (**Appendix 3a**)

Fuel Cell Electric vehicles (FCEVs) have been excluded from this study due to their small number in the sample (n=5). Conventional hybrids are removed from the sample because they are less in number and are not ZEV. Moreover, from 2023 onwards, the grant will not be offered for hybrid vehicles [71]. Home ownership was included as the program provides a grant for setting up home charging infrastructure along with the grant for the vehicle [72]. The program is federal poverty line eligibility-based (which considers income and household size), so the Federal poverty line (FPL) percentage was included in the model. Also, a variable for whether respondents reside in disadvantaged communities [72] was added to investigate any relationship between living in a DAC and the response variable. After data cleaning, the sample size of the model (N) is 2150 unique survey responses. Correlation tests were conducted to address multicollinearity among the independent variables.

The explanatory variables in the models 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.
- Demographic characteristics,

- Socioeconomic characteristics,
- Census tract characteristics like disadvantaged community (DAC) and
- CVAP-specific variables such as the grant for vehicle and the charging equipment grant.

The utility function of the choice model is defined by **Equation 4. Equation 5, 6, and 7** indicate the explanatory variables for Models 1, 2, and 3, respectively.

1. A decision maker (n) faces a "j" alternative. The utility decision maker "n" obtains from alternative "j" (U_{nj}) is divided into two parts; (a) observed parameters by the researcher (V_{nj}) and (b) the unknown random error (ε_{nj}) which is independently, identically distributed (iid) value that follows Gumbel distribution. The variance of the Gumbel distribution is $\pi^2/6$.

$$Unj = Vnj + \varepsilon nj \;\forall\; j \tag{4}$$

2. Equation with demographics and socio-economic factors as explanatory variables:

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

3. 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:

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

4. 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:

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

The likelihood ratio test compares a model with only generic attributes (having the same weight or meaning in both alternatives) with a model having a combination of generic and specific attributes. Specific attributes have a different meaning in each alternative and hence can take a zero value in any of the alternatives [73]. A likelihood ratio test of Model 1 over Model 2 and Model 1 over Model 3 was conducted. The likelihood ratio test attempts to reject the null hypothesis that Model 1 and Model 2 are indistinguishable. Also, the same test is applied to Model 1 and Model 3 to reject the null hypothesis that the two models are indistinguishable:

a) $H_{O:}$ The log-likelihood estimates of Model 1 and Model 2 are the same

   $H_{A:}$ The log-likelihood estimate of Model 1 and Model 2 is not the same

b) $H_{O:}$ The log-likelihood estimates of Model 1 and Model 3 are the same

   $H_{A:}$ The log-likelihood estimate of Model 1 and Model 3 is not the same

Marginal effect analysis has been done to observe how a change in the vehicle selling price at the point of sale (MSRP – Grant amount) affects the probability of responding to whether the buyer would not have purchased without the grant.

4.1.3. Model Estimation and Validation

The binary logistic choice model's response variable was the answer to the question of whether the buyer would purchase the clean vehicle without the CVAP grant (Yes = 0, No = 1). For model validation, the overall maximized log-likelihood estimate (see **Table 4**) along with the adjusted rho-square, AIC, and BIC values that indicate the model's goodness of fit has been reported. Also, reported and analyzed the likelihood estimates and robust t-ratio of the explanatory variables of both Model 1, Model 2, and Model 3. The p-value of the explanatory variables has been calculated based on the one-tailed t-statistics.

The log-likelihood estimate takes the mathematical form (**Equation 8**):

$$LL(\beta) = \sum_{n=1}^{N} \ln Pn(\beta)/N \tag{8}$$

Where:

N = sample size

Pn(β) = probability of the observed outcome of decision maker "n"

β = K * 1 vector of parameters/attributes

The maximum log-likelihood can be found by selecting the β such that the likelihood function does not increase any further.

The AIC and BIC values are calculated as per **Equations 9 and 10** as follows:

$$AIC = -2LL(\hat{\beta}) + 2K \tag{9}$$

$$BIC = -2LL(\hat{\beta}) + K\ln(N) \tag{10}$$

Where:

N – Choice set size and

K – number of parameters

The BIC value penalizes the models as the number of attributes/parameters increases.

5. Results

If a respondent in this model responds "Yes" (0 in the binary response), the buyer would have purchased their ZEV without the grant. If a survey taker responds "No" (1 in the binary response) the buyer would not have purchased their ZEV without the grant.

Key findings from the models (**Table 4**) show the following:

Model 1: The age of the buyer, gender, college degree, and the percentage of the Federal Poverty Line are statistically significantly correlated to the response variable at a 5% significance level. Homeownership is statistically significantly correlated to the response variable at a 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, the vehicle selling price (MSRP-Grant amount), and the interaction term of gender with the technology of vehicle are statistically significantly correlated to the response variable at 5% significance level. Homeownership and purchase of a new vehicle are 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 ratio of grant over MSRP is not significantly correlated to the response variable in this model.

The independent variables such as vehicle technology type as the main effect and 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. Since the program is designed for lower-income buyers and the year 2023 onwards was proposed to be only for buyers living in DACs, it was important to see the effect of the variable that mentioned whether the buyer was from DAC or not (Yes = 1, No =0). This is a policy-specific explanatory variable and current practice recommends the inclusion of a relevant policy-type variable with a correct sign even if it fails the significance test. The reason according to the authors of [73] is that the estimated coefficient is the best possible approximation for the real value and lack of significance might be an outcome of lack of sufficient data points.

The estimation of the model is given in terms of log-odds and can be interpreted as follows:

Negative correlation: For continuous variables, as the value increases, the buyer is less likely to respond that he/she/they would not have purchased their PEV without the grant. For dummy variables, the category marked as one is less likely to respond in favor of the grant.

Positive correlation: For continuous variables, as the value increases, the buyer is more likely to respond that he/she/they would not have purchased their PEV without the grant. For dummy variables, the category marked as one is more likely to respond in favor of the grant.

Based on the above-mentioned details, the outcome of our models suggests that when the age of ZEV buyers is higher, they are more likely to respond that they would not have bought their ZEV without the grant. Non-Male (Female/Binary/Undisclosed) buyers were more likely to respond that they would not purchase their ZEV without the grant. Buyers without a college degree (Associate degree and below) were more likely to respond that they would not purchase their ZEV 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 ZEV 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 ZEV 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 ZEV without the grant, suggesting these charging-related incentives are influential in the decision to purchase a ZEV. 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 it can be observed 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 4: Binary Logistic Regression 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 Vehicle Selling Price (MSRP - Grant)		Model 3 with Discount %	
	Estimate	**t-ratio**	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
Constant	2.1779	7.9175	5.7202	2.5073	2.1342	4.8485
Socioeconomic and Demographic Characteristics						
Age	0.0107**	2.0671	0.0097**	1.8978	0.0100**	1.9525
Gender (Male =1, non-Male = 0)	-0.2259**	-1.7297	-0.6872**	-2.4030	-0.6732**	-2.3578
College Degree (Bachelors Degree and above = 1, Associate degree and below = 0)	-0.2701**	-2.0835	-0.2683**	-2.0624	-0.2697**	-2.0731
Homeownership (Own = 1, Rent = 0)	-0.2095*	-1.4471	-0.2028*	-1.3844	-0.2065*	-1.4103
Disadvantaged Communities (DAC) (1 - Yes, 0 - No)	-0.1600	-1.0002	-0.1804	-1.1236	-0.1747	-1.0915
% of Federal Poverty Line	-0.1685**	-2.8254	-0.1405**	-2.2183	-0.1507**	-2.3752
Vehicle Characteristics						
Technology Type (BEV = 1, PHEV = 0)			-0.2947	-0.8762	-0.2489	-0.6957
New or Used Vehicle (New = 1, Used = 0)			0.4275*	1.4583	0.2518	0.8804

Vehicle Selling Price (MSRP – Grant Amount)			-0.00001**	-2.4680		
BEV * Gender of Buyer			0.5580**	1.7395	0.5477**	1.7094
BEV * New vehicle buyer			-0.2718	-0.7937	-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)			0.3605**	2.5447	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 '*'

From the likelihood ratio tests, the following can be observed:

a) Model 1 vs. Model 2 - The likelihood ratio test gives p-value = 0.017 (< 0.05). So, the null hypothesis that the log-likelihood estimate of Model 2 is the same as the log-likelihood estimate of Model 1 at a 5% significance level can be rejected. Model 2 is a better model with maximized log-likelihood value, hence the impact of vehicle and CVAP characteristics on the value of the response variable needs to be included in the model.

   The difference in Log-likelihood - 9.19

   Likelihood ratio test-value - 18.38

   Degrees of freedom – 6

   Likelihood ratio test p-value - 0.0054

b) Model 1 vs. Model 3 - The likelihood ratio test gives p-value = 0.0415 (< 0.05). So, the null hypothesis that the log-likelihood estimate of Model 3 is the same as the log-likelihood estimate of Model 1 at a 5% significance level can be rejected. Model 3 is a better model with maximized log-likelihood value, hence the impact of vehicle technology, discount percent, and CVAP on the value of the response variable needs to be included in the model.

Difference in Log-likelihood - 6.55

Likelihood ratio test-value - 13.1

Degrees of freedom – 6

Likelihood ratio test p-value - 0.042

The goodness-of-fit parameters such as overall loglikehood, the adjusted rho-squared value, AIC, and BIC values of Model 2 are better than Model 3, indicating that the model with vehicle selling price (MSRP-Grant) fits better than the model with discount percent as one of the explanatory variables.

6. Discussion

The model results (see **Table 4**) show the influence of the CVAP grant in isolation of other incentives, such as the CVRP or Federal tax credits that may impact PEV purchase. The average marginal effect estimates of the vehicle selling price (MSRP-grant) were estimated keeping all else constant in the model (Model 2 specifications) to observe the effect of the grant on the response variable. **Figure 14** shows that a $10,000 reduction in MSRP is associated with approximately a 2% increase in the probability that the buyer would not have purchased their PEV without the grant (FPL < 225% and FPL between 225% and 400%). However, 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).

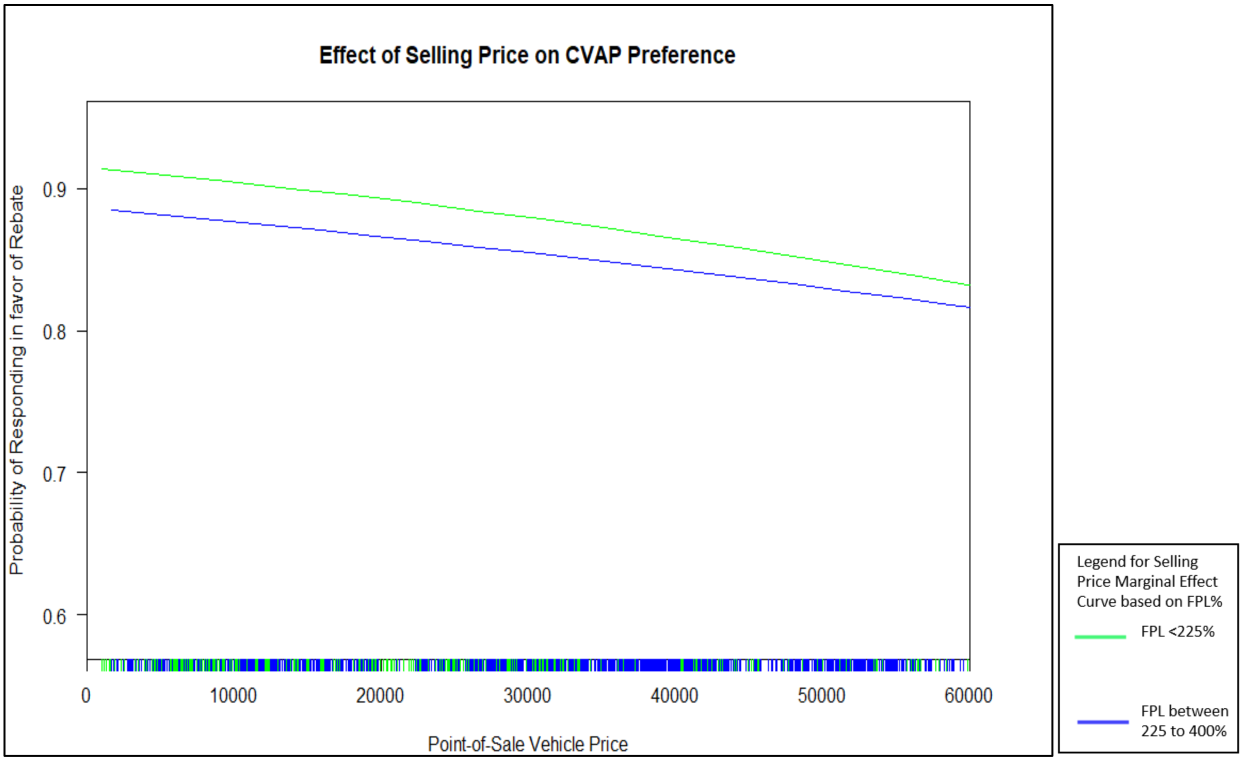


Figure 14: The average marginal effect of the vehicle selling price (MSRP – Grant Amount) on the response variable

Overall, most recipients considered the grant instrumental in their purchase decision. In contrast to CVRP, where around 51% of respondents indicated they would not purchase a ZEV (2016-2017 survey of CVRP recipients) without a rebate [20], around 86% of the CVAP sample indicated they would not purchase their ZEV without a grant. The insights from this study are reciprocated by a study on the European PEV market, which mentions that direct purchase rebates have shown a significant positive impact on adoption in the mature global EV market [74]. The author observes that one-time point-of-sale subsidies at the national and local levels and the national tax breaks on vehicle registration have led to high EV market shares in Amsterdam, Oslo, and The Hague. Whereas the EV market share has evolved slowly in Spain and Belgium (Brussels and Madrid mainly) as they have not addressed cost barriers on car purchases. In a recent stated preference study based in China, the largest EV market, 52 % of the respondents chose purchase subsidies and more charging stations as essential determinants of their behavioral outcome of ZEV adoption [32]. This agrees with the result of our study, which shows that buyers who opted for charging station grants considered the CVAP influential in their purchase decision.

A similar study on New York State's Drive Clean Rebate examined consumers who would not have purchased/leased their ZEV without the rebate [19]. The result of that study shows that additional financial incentives, besides the grant for the vehicle itself, were considered crucial in the buyer's response, which stated that they would not have bought the clean vehicle without the grant. This study's observations 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 [10]. 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 [10] as being older and non-male is correlated with reporting CVAP as more influential in the research. However, some studies have found that females have more positive attitudes towards EVs and towards policies that are targeted towards supporting their adoption [75]. In this study, 60 to 80% of respondents mentioned that the incentive policies were instrumental in making their EV purchase decision. There is no statistically significant correlation between residing in a DAC and the importance of CVAP. This may mean CVAP is essential for low-income ZEV buyers regardless of whether they live in a DAC.

The meta-analysis of past literature highlights the positive impact of financial incentives on the PEV adoption rate. As per the analysis, a $1,000 incentive is correlated to a 5% increase in PEV adoption rate on average at a 95% confidence interval. The adoption rate varies between 4% to 6%. However, the 84.9% heterogeneity in the effect size of the random effects model suggests that the impact of financial incentive significantly differs from region to region and depends on the point of time the effect of incentive has been measured. For example, the study by Chandra et al. shows that a $1,000 incentive correlates to 26% of hybrid vehicle adoption [76], which is much higher than the result of the random effects model. This study investigated vehicle sale and lease data from 1989 to 2006 in Canada, coinciding with the introduction of hybrid technology. So, the high adoption rate of this study can be attributed to interest in new technology. The study appears as an anomaly/outlier in the data set (appears as a red dot) based on the statistical test of influence such as the cook's distance, tau-square, covariance, and students t-test (**Appendix 5**). Hence, this study was removed from the final dataset for the meta-analysis as it contributed to study bias.

The insights from the CVAP sample show that a median incentive of $5,000 (see **Table 3**) influence almost 86% buyers to adopt a PEV. When scaled down to an incentive of $1,000, the adoption rate due to the CVA grant is almost 17% which is much higher when compared to the results of the meta-analysis (Section 4.2) which shows an increase in ZEV adoption rate of 5% for a $1,000 of incentive. But there are limitations that need to be documented to showcase some inherent differences in the insight derived from the CVAP sample and the result of the meta-analysis. Firstly, the CVAP is focused on lower-income buyers of California, whereas the meta-analysis investigated studies across varied geographies, timelines and focuses on higher-income buyers. Secondly, it is also essential to mention that covariates such as age, gender, education level, and household income effects were not considered in the meta-analysis and is a potential limitation for the result of the analysis. The scope of the meta-analysis was to investigate the correlation of incentives with PEV adoption rate (%) keeping all else constant.

7. Conclusion

Past literature has shown that policy incentives, including the federal tax credit and numerous state and local incentives, have stimulated BEV adoption in California [76]. Meta-analysis of existing literature conducted in this study shows that monetary incentives drive the PEV adoption rate from the consumer end. Results from the choice model developed as part of this study show that CVAP may be more efficient than the Clean Vehicle Rebate Program (CVRP) regarding the buyer's response to the incentive [10]. This could be because the program is designed for lower-income communities and DACs, or it is delivered at the point of purchase, or it provides larger incentives, or it provides charging incentives, or a combination of these factors.

It was found that non-male and older buyers had higher odds of responding that the CVAP grant was influential in their decision to purchase a PEV. Buyers without a college degree had higher odds of responding that they would not have bought their PEV without the grant. Buyers from households with a higher percentage above the FPL % (households income between 225 to 400% of the federal poverty line) also had higher odds of responding that they would not have purchased their PEV without the grant. This indicated that buyers from lower-income households considered the grant more influential for their purchase. Renters had higher odds of responding that they would not have bought a PEV without the grant compared to homeowners and so did buyers of new, less expensive vehicles and those receiving any charging incentives. Looking at the interaction term of gender with technology type, it was observed that male buyers had higher odds of responding that they would not have bought their BEVs without the grant.

7.1. Policy Implications and Factors that Nudge the Consumers toward EV Adoption

The percentage of buyers influenced by the grant suggests that almost 86 percent of buyers considered the grant important for their purchase. This percentage is much higher than other incentive programs in the US and California. Since few buyers would purchase a ZEV without the CVAP grant, it may not be easy to further increase the efficiency of CVAP without also impacting those who would not have bought a ZEV without CVAP. While CVAP is influential in adopters' decisions, less than 5,000 grants have been distributed [15], compared to over 500,000 CVRP rebates [77]. Given the efficiency of CVAP, increasing the availability of rebates may positively impact ZEV adoption in lower-income communities, by lower-income households, and in DACs. Recent changes to CVAP mean low-income households not living in DACs will no longer be eligible for incentives. The results of this study show no difference in incentive impacts between DACs and non-DACs, which will likely impact ZEV purchases by low-income households living outside of DACs. This study found that not only a majority of buyers mentioned that they would not have purchased their ZEV without the grant, but the grant for charging equipment/station was also influential in their purchase decision. This serves as a guidance to policy makers that buyers from lower-income communities need financial support not only for their vehicle purchase but also for the supporting infrastructure.

Research on financial incentives has shown that policies are an effective catalyst for ZEV adoption. Still, there are pressing concerns over the sustainability of the funding as BEV adoption shows a rise. Hardman and Sperling [78] shared that as the market depends on EV adoption incentives, a phase-out would lead to market shrinkage. According to the authors, the late adopters or the imitators of EV technology are not yet ready to purchase their ZEVs without financial incentives. The result of the meta-analysis strengthens the thoughts of the authors by showcasing that even without considering impact of demographics and household income 5% PEV adoption was correlated to $1,000 incentives on average. To achieve the electrification goals, this finding intends to guide policymakers on the influence of incentives on PEV adoption.

Several market analysts have forecasted that the cost of BEVs will reduce with technological innovations like lower-cost lithium-ion batteries or the light-weighting of vehicles. Yet the significant point here is that it is up to the automaker's strategic decision whether to pass on the cost savings to the consumer or to increase their profit margin. It is also up to the policymakers to devise alternative policies that support BEV adoption once large-scale subsidies are phased out since BEVs are desirable for decarbonizing transportation [76]. Policymakers can reduce the negative impacts of incentive policy phase-out by highlighting the ZEV's environmental benefits and increasing charging infrastructure to handle range anxiety concerns [79]. States with value-based taxes (e.g., sales, property, or ad valorem taxes) may consider reducing the tax rates or taxable value of BEVs. Some policy scholars further suggested that standardized vehicle TCO labels may help alleviate the perception of high BEV costs and "nudge" consumers toward BEVs [76].

Besides designing a sustainable incentive structure, automakers, lithium (a key component of PEV batteries) exporting countries, PEV charging infrastructure firms, and electric utility companies should collaborate to deploy every policy tool available to increase PEV adoption. The policies should drive the market development until it reaches a self-sustainable stage.

7.2. Limitations and Future Work

The CVAP can be stacked with CVRP, HOV lane access, the US federal tax credit, and several other local or utility incentives. Based on the current questionnaire survey, the combined and interaction effects of all incentives received by buyers cannot be measured. Results from this study show the CVAP may be more efficient than the CVRP in terms of the buyer's response to the incentive [10]; however, it is difficult to account for the impact of CVAP in combination with other incentive programs. Therefore, it is not known whether receiving another incentive increases, reduces, or results in no change in the impact of CVAP on the decision to purchase a ZEV. A possible limitation of the survey question may be that 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 (charging incentives and lower APR loans) in their response. In contrast, the question may intend to only ask about the overall impact of the CVAP grant. Hence, there is an inherent limitation in isolating the effects of the vehicle grant and the impacts of other program features, such as the charging incentives or the provision of vehicle financing at a lower interest rate. In the future, it would be interesting to observe how the buyers rank each aspect of the CVAP incentive: the vehicle, loan, and charging station grants. From 2023 onwards, the eligibility criteria for the CVAP have combined income eligibility of 300% of FPL and DAC residents. So, in future years, observing the diffusion of clean vehicles in DACs and by low-income households not in DACs may be possible.

The scope of the meta-analysis in this study was limited to investigation of the correlation of incentives with PEV adoption rate (%). In a future scope of work effect of demographics and socioeconomic factors such as age, gender, education level, and household income could be observed in the meta-analysis. A limitation that needs to be mentioned here is that there is always the risk of exclusion of relevant studies from the pool of literature.

Finally, future scope includes exploration on how consumer awareness of vehicle technology and available incentives drive adoption. Public outreach initiatives might increase the effectiveness of the monetary incentives, educate consumers on the new technology, eliminate incorrect notions of the technology, and highlight the benefits of the technology [21]. The study by Hardman et al. [80] measures the extent to which buyers have already considered vehicle purchase and understand the relationship between consideration and measures of knowledge, awareness, and engagement in Sacramento, California, where ZEV policies originate.

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Appendix

1. California's income eligibility based financial incentive programs for ZEV purchase.

Incentive Program	Utility/ Air District/ Statewide	Type of Incentive	When is it Given?	State/Federal funded	Maximum Incentive Amount (USD)	Is there a MSRP Cap?	Is there Vehicle Range Cap?
Clean Vehicle Rebate Project	Statewide	Rebate	Post Purchase	State	FCEVs – 4,500 BEVs – 2,000 PHEVs – 1,000	Yes	Yes
Clean Cars for All	Bay Area AQMD and Sacramento Metro AQMD	Rebate	Point of Sale	State	9,500	Yes	Yes
Alameda Municipal Power (AMP) - Income-Qualified Used BEV Rebate	AMP residential customers	Rebate	Post Purchase	State	6,000	Yes	No
Lodi Electric - Zero Emission Vehicle Rebate (Income Qualified)	City of Lodi	Rebate for Vehicle/EV Charger	Post Purchase	State	4,000	NA	NA
Los Angeles Department of Water and Power (LADWP) -	LADWP Electric Service Recipients Only	Used EV Rebates	Post Purchase	State	2,500	No	No

Used EV Rebate Adder							
Pacific Gas & Electric (PG&E) - Pre-Owned EV Rebate Plus	Active PG&E residential electric customer	Used EV Rebates	Post Purchase	State	4,000	No	No
Replace Your Ride	South Coast AQMD	Rebate	Point of Sale	State	9,500 (May go up to 12,000 in future)	No	No
Federal Tax Credit	Nationwide Program	Credits at the time of annual tax filing	Post Purchase	Federal	7,500	No	No

2. Studies that measure the impact of $1,000 financial incentives on the ZEV adoption rate (%)

Paper Name	Authors	Year	Methodology	Data Collection	Location of Study	Sample Size	Effect size
The influence of financial incentives and other socio-economic factors on electric vehicle adoption [81]	Sierzchula et al.	2014	Ordinary least squares (OLS) regression	Sales Share during 2012	Worldwide	30	0.06
How large is the effect of financial incentives on electric vehicle sales? – A global review and European analysis [57]	Munzel et al.	2019	Panel data regression	Registration of new vehicles (2010-2017)	Europe	256	5.56
Effectiveness of electric vehicle incentives in the United States [21]	Jenn et al.	2018	FE panel data regression	Absolute sales data	US	18644	2.6
Providing the Spark: Impact of Financial Incentives on Battery Electric Vehicle Adoption [22]	Clinton and Steinberg	2019	Difference-in-differences and synthetic controls methods	Vehicle registration data in the United States	US	425	8

What are the effects of incentives on plugin electric vehicle sales in Europe? [58]	Plotz et al.	2017	Panel Regression	PEV Sales Share	Europe	185	14.3
Designing policy incentives for cleaner technologies: Lessons from California's plug-in electric vehicle rebate program [25]	DeShazo et al.	2017	Choice Model	Stated Preference Survey	California, US	28959	3.8
Do Public Subsidies Sell Green Cars? Evidence from the U.S. “Cash for Clunkers” Program [82]	Huang	2010	Ordinary least squares (OLS)	Absolute sales data	US	677081	7.2
Electric vehicle incentive policies in Canadian provinces [59]	Azarafshar and Vermeulen	2020	Generalized lineal Model (GLM) regression	Absolute sales data (2012-2016)	Canada	4718	6.5
Do electric vehicle incentives matter? Evidence from the 50 U.S. states [83]	Wee et al.	2018	Multi-level FE regression	Absolute sales data	US	4287	8
The impact of federal incentives on the adoption of hybrid electric vehicles in the United States [84]	Jenn et al.	2013	FE panel data regression	Absolute sales data	US	20787	4.6
Investigating heterogeneous preferences for plug-in electric vehicles: Policy implications from different choice models [37]	Jia and Chen	2023	Mixed Logit Model (MXL) and a combination of LC-MXL Model (LC- Latent Class)	Stated Preference Choice Survey Data (2018)	Virginia, US	5022	1.2
Giving green to get green? Incentives and consumer	Gallagher and Muehlegger	2011	FE panel data regression	Sales per capita	US	4630	5

adoption of hybrid vehicle technology [24]							

3. Survey Questionnaire from the Stated Preference Survey Experiment:

a. Would you have purchased your clean vehicle if you did not receive a grant through the Clean Vehicle Assistance Program?

Option Title	**Reporting Value**
Yes	1
No	0

b. What is your age?

Option Title	**Reporting Value**
16-20	1
21-29	2
30-39	3
40-49	4
50-59	5
60-69	6
70-79	7
80+	8
Prefer not to answer	-77

c. How do you prefer to describe your gender?

Option Title	**Reporting Value**
Female	1
Male	2
Non-binary/third gender	3
Prefer to self-describe:	-99

Prefer to self-describe:	6
Prefer not to say	-77

d. What is the highest level of education you have completed?

Option Title	**Reporting Value**
Some high school but no diploma	1
High school graduate or equivalent	2
Some college, no degree	3
Associate degree	4
Bachelor's degree	5
Postgraduate degree	6
Prefer not to answer	-77

4. Model Estimates

a. Only demographics

Variables	**Estimate**	**Std.err.**	**t-ratio(0)**	**Rob.std.err.**	**Rob.t-ratio (0)**
asc1	2.177939	0.272607	7.989313	0.27508	7.917481
asc0	0	NA	NA	NA	NA
b_age	0.010657	0.005248	2.030669	0.005156	2.067071
b_male	-0.22588	0.130405	-1.73213	0.130586	-1.72973
b_college_degree	-0.27006	0.129398	-2.08707	0.129619	-2.0835
b_home_owner	-0.20954	0.1438	-1.45717	0.144802	-1.44709
b_dac	-0.16002	0.158353	-1.01052	0.159992	-1.00017
b_fpl	-0.1685	0.057608	-2.92494	0.059637	-2.8254

b. Demographics + vehicle characteristics + CVAP characteristics including MSRP

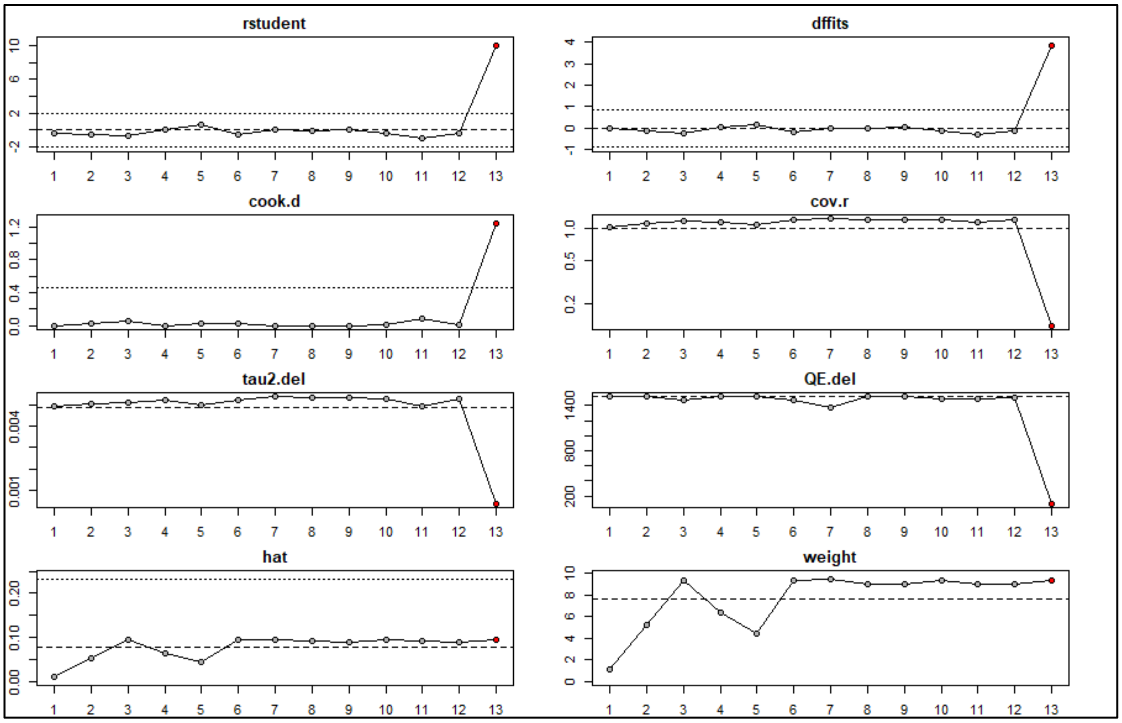
Variables	**Estimate**	**Std.err.**	**t-ratio(0)**	**Rob.std.err.**	**Rob.t-ratio(0)**
asc1	5.720208	2.198751	2.601571	2.281423	2.507298
asc0	0	NA	NA	NA	NA
b_age	0.009732	0.005243	1.856144	0.005128	1.897846
b_male	-0.68716	0.282594	-2.4316	0.28596	-2.40298
b_college_degree	-0.26829	0.129987	-2.06399	0.130084	-2.06245
b_home_owner	-0.20282	0.144903	-1.39966	0.146499	-1.38442

b_dac	-0.18035	0.159827	-1.12842	0.160513	-1.1236
b_fpl	-0.14049	0.061302	-2.29186	0.063333	-2.21835
b_bev	-0.29466	0.32687	-0.90147	0.336284	-0.87623
b_new_veh	0.427505	0.291147	1.468347	0.29315	1.458315
b_msrp	-0.35525	0.219939	-1.61522	0.227176	-1.56376
b_charger	0.360539	0.139354	2.587218	0.141685	2.544651
b_male_bev_interact	0.557953	0.318591	1.751312	0.320757	1.739486
b_bev_new_veh_interact	-0.27182	0.340362	-0.79863	0.342476	-0.7937

c. Demographics + vehicle characteristics + CVAP characteristics including discount percentage

Variables	Estimate	Std.err.	t-ratio(0)	Rob.std.err.	Rob.t-ratio(0)
asc1	2.13424	0.421075	5.068555	0.440183	4.848531
asc0	0	NA	NA	NA	NA
b_age	0.009982	0.00523	1.908539	0.005113	1.952475
b_male	-0.67318	0.282429	-2.38355	0.285514	-2.35779
b_college_degree	-0.26975	0.129947	-2.07584	0.130117	-2.07314
b_home_owner	-0.20652	0.144834	-1.42593	0.146443	-1.41026
b_dac	-0.17474	0.159747	-1.09387	0.160088	-1.09153
b_fpl	-0.15067	0.061246	-2.46016	0.063438	-2.37515
b_bev	-0.24893	0.341138	-0.72972	0.357805	-0.69573
b_new_veh	0.251795	0.279719	0.900171	0.286008	0.880375
b_discount_percent	0.313362	0.854666	0.366648	0.990997	0.316209
b_charger	0.368129	0.13925	2.64366	0.141947	2.593438
b_male_bev_interact	0.547655	0.31846	1.719696	0.320373	1.709429
b_bev_new_veh_interact	-0.41732	0.346402	-1.20473	0.360021	-1.15916

5. Test of influence of a study on the overall impact of effect size (publication/study bias)



6. **PRISMA Checklist Items for the Meta-Analysis**

Section and Topic	Item #	Checklist item	Location where item is reported (Heading & Page No.)
TITLE			
Title	1	Identify the report as a systematic review.	It's a Meta-Analysis Study.
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Abstract (Page iii)
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Section 1 (Page 6)
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Section 1 (Page 6)
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Section 3 (Page 15-16)
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Section 3 (Page 15)

Section and Topic	Item #	Checklist item	Location where item is reported (Heading & Page No.)
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Section 3 **Figure 5** (Page 15-16)
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	Section 3 **Figure 5** (Page 15-17)
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Section 3 **Figure 5** (Pages 15-17)
Data items	10	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Section 3 (Pages 15-17)
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Sections 3.1 and 3.2 (Pages 18 - 23)
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	Section 3.2 (Page 23)
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	Section 3 (Pages 15-16)
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics or data conversions.	Section 3 (Pages 15-16)
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Section 3 **Figure 6** (Page 18) and Appendix 2 (Page 54)
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify	Sections 3.1 and 3.2 (Pages 18 - 23)

Section and Topic	Item #	Checklist item	Location where item is reported (Heading & Page No.)
		the presence and extent of statistical heterogeneity, and software package(s) used.	
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	Section 3.2 (Pages 21-23)
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	NA
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	Section 3.2 **Figure 8** (Pages 22-23)
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Section 3.2 **Figure 7** (Pages 21-22)
RESULTS			
Study selection	16	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Section 3 **Figure 5** (Page 16)
Study characteristics	17	Cite each included study and present its characteristics.	Appendix 2 (Page 54)
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Section 3.2 **Figure 8** (Pages 22-23)
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Sections 3.1 and 3.2 (Pages 18 - 23)
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Section 3.2 **Figure 8** (Pages 22-23)
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Section 3.2 (Pages 21-23)
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Section 6 (Pages 42-43)
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	NA

Section and Topic	Item #	Checklist item	Location where item is reported (Heading & Page No.)
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	NA
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Section 3.2 **Figure 7** (Pages 21-22)
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Section 6 (Pages 42-43)
	23b	Discuss any limitations of the evidence included in the review.	Section 6 (Page 43) Section 7.2 (Page 46)
	23c	Discuss any limitations of the review processes used.	Section 7.2 (Page 46)
	23d	Discuss implications of the results for practice, policy, and future research.	Section 7.1 (Page 45)