Subsidizing Low- and Middle-Income Adoption of Electric Vehicles: Quasi-Experimental Evidence from California

Erich Muehlegger and David S. Rapson*

September 6, 2022

Abstract

Little is known about electric vehicle (EV) demand by low- and middle-income households. In this paper, we exploit a policy that provides exogenous variation in large EV subsidies targeted at the mass market in California. Using transaction-level data, we estimate three important policy parameters: the rate of subsidy pass-through, the impact of the subsidy on EV adoption, and the elasticity of demand for EVs among low- and middle-income households. Demand for EVs in our sample is price-elastic (-2.1) and buyers capture roughly 73 to 85 percent of the subsidy.

*(Muehlegger) University of California - Davis and NBER. emuehlegger@ucdavis.edu. (Rapson) University of California - Davis. dsrapson@ucdavis.edu. We gratefully acknowledge research funding from the State of California Public Transportation Account and the Road Repair and Accountability Act of 2017 (Senate Bill 1) via the University of California Institute of Transportation Studies. We thank Tom Knox at Valley Clean Air Now and Mei Wang at South Coast Air Quality Management District for sharing their expertise on the pilot programs in San Joaquin Valley and South Coast, respectively; the California Air Resources Board for their support of this project and for funding for acquisition of some of the data used in this analysis; Jim Archsmith, Ben Dawson, Jack Gregory, Tyler Hoppenfeld, Shotaro Nakamura and Reid Taylor for excellent research assistance; and many seminar participants. The views expressed herein are those of the authors and do not necessarily reflect the views of the California Air Resources Board.

1 Introduction

Electrification of the vehicle fleet is seen by many policy-makers as central to reducing greenhouse gas emissions, local air pollution and dependence on oil. Local, state and national governments have set ambitious targets for widespread adoption of electric vehicles (EVs) or phasing out internal combustion engines (ICEs) entirely. National plans to ban ICEs sales include France and UK (by 2040), Norway (by 2025), India (by 2030), and China. Germany has announced plans to put 1 million electric vehicles on the road by 2020. In the U.S., California plans to phase out the sale of new gasoline cars by 2035. To achieve these goals, governments typically pair these targets with generous subsidy programs. The cost of these programs is considerable and presents stark tradeoffs for public funds. Through mid-2020, California spent over $1 billion on the state-wide vehicle subsidies. More recently, the federal government reinstated EV subsidies as part of the Inflation Reduction Act of 2022 – the Congressional Budget Office projects consumer EV subsidies to cost $9 billion over 2022-2031.[1]

Although a long literature estimates the impact of incentives for hybrid, electric or alternative-fuel vehicles,[2] research on past programs may not provide a good guide as to the impact or fiscal costs of meeting these ambitious targets for two reasons. First, past incentives for alternative vehicles rarely offer the quasi-experimental variation necessary for clean causal identification. In virtually all cases, the decision to offer an incentive is endogenously determined. States with populations predisposed to purchase EVs are more likely to offer incentives, confounding estimation of the causal impact of incentives on vehicle adoption. Second, and equally important, the ambitious targets described above require *widespread* adoption of electric vehicles.[3] Yet, past incentive programs typically offered a blanket subsidy to all vehicle buyers, and past adoption correlated strongly with income. As Borenstein and Davis (2016) documents, high-income households were significantly more likely be early adopters of EVs and claimed the vast majority of early federal electric vehicle subsidies.[4] In recognition of the regressive nature of early vehicle subsidies, many current programs (including California's current state-wide incentives and the new incentives included as part of the Inflation Reduction Act of 2022) are means-tested and restricted to less-expensive vehicles, to encourage adoption amongst low-

[1] https://www.cbo.gov/system/files/2022-08/hr5376_IR_Act_8-3-22.pdf

[2] e.g., Chandra et al. (2010), Gallagher and Muehlegger (2011), Beresteanu and Li (2011), Clinton and Steinberg (2017) study effects on adoption, Sallee (2011), Gulati et al. (2017) study pass-through and recent papers, including Li et al. (2017), Li (2017), Springel (2017), study network effects of charging stations.

[3] Mary Nichols, Chair of the California Air Resource Board, noted in Jan 2018 that that the 2030 market share of EVs in California would have to be approximately 40% to meet the 5 million by 2030 goal (Los Angeles Times).

[4] https://energyathaas.wordpress.com/2019/05/13/an-electric-vehicle-in-every-driveway/

and middle-income households. As such, elasticities derived from early adoption may be less relevant for assessing the costs or impacts of recent policies that explicitly target widespread adoption of alternative fuel vehicles. Given the imminence of major policy decisions relating to these targets, there is an urgent need to better understand demand for EVs in the mass market.

In this paper, we study the impacts of the Enhanced Fleet Modernization Program ("EFMP"), a California retire-and-replace subsidy program for EV purchases that addresses both of the challenges above. The design of the EFMP provides clean quasi-experimental variation in the availability of the subsidy to some buyers and not others, allowing for a transparent treatment-to-control comparison. Furthermore, subsidy eligibility is means-tested, directing subsidies specifically towards low- and middle-income buyers, similar to more recent means-tested subsidy programs. This allows the opportunity to estimate the elasticity of demand for EVs for a sub-population that has not, historically, adopted electric vehicles, but will be an important market for meeting ambitious policy targets.

We analyze the universe of electric vehicle sales in California, a state that accounts for 40 percent of EV purchases in the United States and 10 percent of purchases worldwide. Using difference-in-difference, matched diff-in-diff and triple-differenced models that exploit geographic, temporal and subsidy-exposure variation, we retrieve estimates of three policy-relevant parameters: the rate of subsidy pass-through for the program, the impact on EV adoption and the elasticity of demand for EVs among low- to middle-income buyers. Each of these is essential for understanding the effectiveness of public expenditures on demand-side EV subsidies. We find that low- and middle-income buyers capture the majority of the subsidy, consistent with the intentions of program designers. Our estimates indicate a rate of subsidy pass-through of roughly 75 to 85 percent, and in no specification can we reject full pass-through. In addition, low- and middle-income buyers are relatively responsive to the subsidies. In our preferred specifications, the estimated demand elasticity is in a tight range around -2.1, implying that a subsidy that decreases the buy-price of EVs by 10 percent increases demand by 21 percent in this customer segment. While this may seem like a considerable effect, the small baseline quantity implies that even elastic demand translates into a modest number of additional EVs.

While we are encouraged to offer an estimate of the EV demand elasticity in California that is retrieved using quasi-experimental variation, context is required for those who wish to extrapolate these results. The suitability of these estimates for general use as demand elasticities may differ by setting. Subsidy eligibility under the EFMP is linked to having a car to scrap, and is also driven by targeted marketing efforts by program administrators, particularly in one of the pilot regions. Moreover, the program does not exist in isolation, which is a feature common to all EV elasticity estimates in the literature to date. The presence of large federal and state subsidies for new EVs affects the interpretation of results since many of the new EVs purchased under a given subsidy program (in our case EFMP) were eligible for other state-wide or federal EV subsidies as well. Moreover, the ZEV Mandate – a policy requiring manufacturers to sell a certain proportion of EVs in California and nine other participating states – implicitly subsidizes manufacturers who sell EVs. While our empirical design nets out effects of statewide and federal demand-side subsidies as well as supply-side programs, the extent to which our elasticity estimates (which reflect marginal subsidy changes) apply to ranges of prices on the inframargin is an open question.

Notwithstanding these caveats, this paper makes several new contributions to the state of knowledge about the market for EVs. First, we provide (to our knowledge) the first estimates of the EV demand elasticity that are supported by a treatment-versus-control empirical design that allows key identifying assumptions to be tested directly. Second, ours is (again, to our knowledge) the first paper to examine EV adoption amongst low- and middle-income households that form the bulk of the market and will be central to meeting ambitious EV targets. In many states, levels of adoption are just not reaching levels experienced in California during our study period. Although the market for California has continued to grow since the study period, our results might be particularly relevant to adoption outside of California. Third, our estimates of subsidy pass-through contribute to the literature on the incidence of vehicle incentives. Our results contribute to an important contemporary policy debate that is likely to be repeated in jurisdictions across the globe in coming years.

2 Institutional Details and Data

The Enhanced Fleet Modernization Program is a vehicle incentive program in California that provides subsidies to low- and middle-income households to scrap old vehicles for newer (although in some cases, still used), cleaner and more fuel efficient vehicles. EFMP is distinct from the Clean Vehicle Rebate Project ("CVRP"), the main consumer-facing alternative vehicle incentive program in California that is available state-wide and, until recently, was available to all private buyers of qualified vehicles.

The EFMP was initially designed as a retire-and-replace program along the lines of Cash-For-Clunkers.[5] In April 2015, the California Air Resources Board ("ARB") redesigned the pro-

[5]See Mian and Sufi (2012), Li et al. (2013) for analyses examining the effects of the federal Cash-for-Clunkers pro-

gram to combine features of a retire-and-replace program with an incentive program for the purchase of high fuel economy vehicles and EVs, targeting low- and middle-income consumers in disadvantaged communities ("DACs"). [6] The redesigned program, the focus of this paper, was launched as a pilot in July 2015 in two Air Quality Management Districts ("AQMDs"): the San Joaquin Valley Air Pollution Control District and the South Coast Air Quality Management District.[7] Over the first two years, the pilot program received $72 million in state funding with the expectation to expand the program to other metro areas.[8]

2.1 Subsidy eligibility and generosity

The EFMP pilot program is restricted to participants residing in the two AQMDs and retiring a qualifying vehicle.[9] The program offers two separate subsidies: a base subsidy and a supplementary "plus-up" subsidy.[10] The base subsidy is available to all low- and middle-income households at or below 400% of the federal poverty line ("FPL") households within the pilot AQMDs. Subsidy generosity is progressive, such that households with lower incomes are eligible for more generous incentives. Households below 225% of the FPL are eligible for the most generous base subsidy of $4,500. Households with higher incomes, in the ranges between 225% to 300% and 300% to 400% of the FPL are eligible for base subsidies of $3,500 and $2,500, respectively.

The "plus-up" subsidy is also means-tested. But, the "plus-up" subsidy is targeted specifically at households that reside within a disadvantaged community ("DAC") as determined by the California Environmental Protection Agency ("CalEPA"). At the census-tract-level, CalEPA calculates a CalEnviroScreen ("CES") score that aggregates traditional measures of socio-economic disadvantage (e.g., poverty and unemployment), measures of pollution exposure (e.g., ambient air pollution levels and the presence of clean-up and solid waste sites) and sensitivity to pollution (e.g., child and elderly share of the population).[11] CalEPA classifies all census tracts

gram.

[6]https://www.arb.ca.gov/msprog/aqip/efmp/finalregulationorder2014.pdf

[7]The San Joaquin Valley Air Pollution Control District covers much of California's Central Valley, from Bakersfield in the South to the southern suburbs of Sacramento in the north. The South Coast Air Quality Management District covers Los Angeles, Orange County, Riverside and San Bernardino counties, including roughly half of California's population.

[8]ARB is in negotiation with three new AQMDs (Bay Area AQMD, Sac Metro AQMD, San Diego AQMD) to expand the program.(see. e.g., https://www.arb.ca.gov/board/books/2017/062217/17-6-1pres.pdf). If expanded, ninety percent of "disadvantaged communities" (described further below) in California will be covered by the EFMP.

[9]Vehicles must be: (1) a light-duty vehicle, (2) registered and insured for the two previous years, (3) with relatively high emissions, defined by the AQMD.

[10]Appendix figure A1 illustrates a flowchart for eligiblity.

[11]Appendix figure A2 summarizes the components of the CES score.

in the *top quartile* of the state-wide CES distribution as disadvantaged. To be eligible for the EFMP "plus-up" subsidy, a household must reside in a "disadvantaged zip code", a *zip code that (wholly or partially) contains a disadvantaged census tract*. We adopt the terminology of the EFMP program and refer to these "disadvantaged zip codes" as disadvantaged communities ("DACs").

Following the program rules, we overlay census tracts and zip codes and classify a zip code as disadvantaged if it contains part or all of a disadvantaged census tract.[12] Figure 1 maps zip code boundaries for the Southern two-thirds of California. Regions in grey are the San Joaquin Valley and South Coast AQMDs, the two AQMDs that participated in the EFMP pilot program during our study period. The zip codes in pink are those that contain a disadvantaged census tracts. Thus, means-tested households in zip codes that are in grey are eligible for the base subsidy, and those in both grey and pink are eligible for the plus-up subsidy. All other households are ineligible.

Figure 2 plots the histogram of the maximum CES score within a zip code for participating AQMDs (right panel) and non-participating AQMDs (left panel). The vertical red line in each plot marks the 75th percentile of state-wide CES score Zip codes to the right of the red line would be classified as disadvantaged communities by the rules of the program.

As with the base subsidy, the plus-up program is means-tested with lower income households eligible for more generous plus-up incentives. Households below the 225% of the FPL are eligible for the most generous plus-up subsidy: $5,000. As household income rises, subsidy generosity declines until a household's income exceeds the 400% of FPL eligiblity threshold. The plus-up subsidy is supplemental to the base subsidy. A household with income below 225% of the FPL residing within a disadvantaged community would be eligible for a total subsidy of $9,500. Table 1 lists the income thresholds and subsidy amounts for both the base and plus-up subsidy.

Roughly half of the population of California resides in the participating AQMDs, of which roughly 80 percent of the population live in zip codes classified as disadvantaged for purposes of the AQMD pilot program. Outside of the pilot regions, a higher fraction of the population lives in non-disadvantaged zip codes, reflective of higher incomes and the fact that the South Coast AQMD and the San Joaquin Valley are locations with relatively poor air quality.

[12] The DAC designations are publicly available at the census-tract-level. `https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-version-20`

2.2 Additional EFMP implementation details

The ARB sets general guidelines for the pilot program which administrators must follow. The AQMDs are responsible for administering the program and determining household eligibility. In addition, the AQMDs must build a network of participating dealerships that agree to a set of consumer protections, including "no-haggle" posted prices, limitations on dealership financing, required information-provision and inspections for used vehicles.

However, the ARB granted each district latitude with respect to implementation, and specifically, marketing, outreach and the application process. In the South Coast AQMD, information about the program is relayed through marketing and participants apply online. After the AQMD assignment determines that an applicant is eligible, the program directs the applicant to contact the list of pre-approved dealerships. In San Joaquin Valley, the program is administered through regular "Tune-in and Tune-up" events on weekends and other direct outreach events throughout the San Joaquin Valley, specifically targeting minority groups. Eligible buyers are then guided through the application process and, if eligible, are directed towards the websites of participating dealerships.

2.3 Rebate and transaction data

In addition to the list of the disadvantaged zip codes, our empirical analysis combines two datasets: (1) program rebate data and (2) transaction-level data on the universe of new and used EVs purchased by California buyers. The EFMP rebate data are publicly available at the transaction-level. For each transaction the data report value of the subsidy, the vehicle purchased and the zip code in which the recipient of the subsidy lives. Our vehicle transaction data was purchased from a major market research firm. For the universe of battery electric vehicles ("BEVs") and plug-in hybrid vehicles ("PHEVs") purchased by buyers in California, we observe the make, model and model-year of the vehicle, the transaction price as reported to the Department of Motor Vehicles, the zip code of the buyer and the dealership that sold the vehicle.

We summarize transaction counts, prices and subsidies in table 2, grouping zip codes by whether they are in or out of the participating pilot regions and whether they are classified as a disadvantaged zip code. Buyers in disadvantaged zip codes purchase less expensive and fewer EVs on a per capita basis, before and after the start of the EFMP pilot. Yet, foreshadowing our empirical results, per capita EV sales rise most quickly in disadvantaged zip codes in the participating AQMDs. Overall, EFMP transactions are a small fraction of total EV sales. In disadvantaged communities during the pilot program, roughly two percent of the transactions received an EFMP subsidy. A smaller fraction of purchases outside of disadvantaged communities received EFMP subsidies, reflective of higher incomes lower eligibility for the base subsidy and ineligibility for the plus-up subsidy.

Consistent with the construction of the disadvantaged community identifier, sociodemographics are different in these communities relative to non-disadvantaged communities. In the first three columns of Table 3, we present population-weighted average demographics for all of California (column 1), disadvantaged communities outside the pilot regions (column 2) and disadvantaged communities outside the pilot regions (column 3). Relative to all of California, households in disadvantaged communities tend to have households incomes that average ten to fifteen thousand dollars lower than the mean household in California, are less likely to have graduated from high school, are more likely to be Hispanic or African American and are more likely to be unemployed. In contrast, column 4 presents average demographics weighting by EV sales over 2014 - 2018. Consistent with the evidence from Borenstein and Davis (2016), the sociodemographics of zip codes of early adopters of EVs suggest these zip codes are a particularly advantaged subset of California, with mean incomes roughly thirty-five thousand dollars higher than the average California household, higher educational attainment and lower rates of unemployment.

3 Pass-Through of the EFMP Subsidy

The features of EFMP program lend themselves to a difference-in-differences specification comparing disadvantaged zip codes in and out of the two participating AQMDs, before and after the start of the pilot program.[13] We can extend this to include an additional difference, by including the non-disadvantaged communities in and out of the participating AQMDs. Using this framework, we estimate three policy parameters of interest: (1) the incidence of the EFMP subsidies and (2) impact of the EFMP incentives on electric vehicle adoption, and (3) the elasticity of demand for alternative fuel vehicles, specifically amongst low- and middle-income customers targeted by the EFMP.

We aggregate our transaction-level data to the zip-quarter, the finest level of temporal and spatial disaggregation for which we have subsidy data, and the geographic level of treatment

[13] While the discontinuous nature of disadvantaged community assignment might suggest a regression discontinuity design is appropriate, the means-testing of the program causes most of the relevant variation to occur well away from the discontinuity. This can be seen in Appendix Figure A4.

assignment.[14] We consider a zip code as treated if the zip code is located in the South Coast or San Joaquin Valley Air Quality Management Districts ("AQMD=1"), contains at least part of one DAC census tract ("DAC=1") and the calendar date is in the third quarter of 2015 or later ("Post=1"). Likewise, for purposes of our analysis, we aggregate the subsidy data to a similar level of aggregation. Although observations in the raw subsidy data are at the individual vehicle level, the subsidy data only include the make, model-year and location of the owner. The subsidy data does not report the VIN, odometer reading or other information that would allow us to match the subsidy and transaction data at the transaction-level.

3.1 Estimating the pass-through of EFMP subsidies

Our first parameter of interest is the pass-through of the EFMP incentives to buyers. Cost efficacy of the program is determined in part by the extent to which the subsidy affects the price paid by the consumer, rather than accruing to dealerships or manufacturers. If we were able to match the transaction data and the subsidy data at the level of each transaction, estimating pass-through would be straightforward. For EFMP-eligible buyer i, purchasing vehicle j at time t, the subsidy-inclusive price paid is given by:

$$P_{ijt} = P_{jt} + \Delta P - S \tag{1}$$

where P_{jt} is the price paid by a buyer of the same vehicle j at the same time t who does *not* receive the subsidy, ΔP is the amount by which the subsidy-exclusive price changes in response to the subsidy, and S is the amount of the subsidy. Pass-through of the subsidy is the fraction of the subsidy reflected in the subsidy-inclusive price paid by the buyer, $(\Delta P - S)/S$.

As discussed above, we aggregate our data to the zip-quarter level, as that is the finest level of aggregation at which the subsidy data can be linked with the transaction data. It is also the geographic level of assignment to treatment. The aggregation requires us to adapt the transaction-level exercise above to reflect two features of our setting. First, only a fraction of the EVs purchased in a particular zip-quarter receive a subsidy. Second, the EFMP subsidies are offered to buyers of both new *and used* EVs and the mix of vehicles purchased differs by zip.[15]

[14] The data on EFMP reports the quarter of purchase and the owner's zip code, but does not provide the Vehicle Identification Number ("VIN") of the purchased vehicle. Thus, we cannot match information on EFMP subsidies to exact transactions in the purchase data. Rather, we observe the mean EFMP subsidy received by EVs purchased by households at the zip-quarter level.

[15] Although the EFMP data does not report the vehicle VIN, the public data does record the model year of the purchased vehicle. Roughly 80 percent of vehicles have models years more than one year less than the calendar year in

Formally, the average subsidy-exclusive price (i.e., the price received by the dealership) in a zip z in quarter t, is given by:

$$\bar{P}_{zt} = \sum_{i \in z} (P_{ijt} + \Delta P) / N_{zt} = \sum_{i \in z} P_{jt} / N_{zt} + \lambda_{zt} \Delta P \tag{2}$$

where N_{zt} is the total number of transactions, and λ_{zt} is the fraction of vehicles subsidized in zip z at time t. Intuitively, the average subsidy-exclusive price in a zip-quarter is a function of the fraction of the subsidy captured by dealers (ΔP), the fraction of vehicles which received a subsidy (λ_{zt}) and the mix of vehicles sold in zip z at time t.

This formulation makes two (modest) assumptions. First, this assumes that the impact of the subsidy on the subsidy-exclusive price ΔP is constant across vehicles j and time periods t. Second, this assumes that the subsidy program is sufficiently small so as to leave the price of the unsubsidized vehicles, P_{jt}, unaffected. In our setting, this is plausible as the pilot program is small relative to the overall market for vehicles in California, although our setting allows this assumption to be tested, which we do in section 4.3.

To derive the analogue to our estimating equation for pass-through from equation (2), we net out the average price of the portfolio of vehicle purchases in zip z and time t[16] and the average per-vehicle subsidy ($\lambda_{zt} S$) from both sides to obtain:

$$\underbrace{\bar{P}_{zt} - \sum_{i \in z} P_{jt} / N_{zt} - \lambda_{zt} S}_{\text{Residual subsidy-inclusive price}} = \lambda_{zt} S \frac{(\Delta P - S)}{S} \tag{4}$$

The left hand side of the expression captures whether buyers on average in zip code z paid more or less, net of subsidies, than buyers that purchased a the same mix of vehicles elsewhere in California.[17] The right hand side of the expression is the product of the average

which they are purchased, suggestive that they are used, rather than new vehicles. In contrast, 87 percent of all EVs in the transaction data would be classified as used by this definition.

[16]In our empirical setting, we observe the model*model-year of the vehicle as well as the odometer reading and whether the vehicle was purchased through a lease. We predict vehicle prices as a function of model*model-year*year-of-purchase fixed effects, odometer reading in miles and a dummy variable reflecting whether or not the vehicles was leased. Formally, denoting transaction, zip, model, model year and year-quarter of purchase as i, z, m, y and t respectively, we regress:

$$P_{izmyt} = \alpha_{myt} + \beta_1 Odometer_i + \beta_2 Lease_i + \xi_i \tag{3}$$

where P_{izmyt} is the transaction price of the vehicle i received by the seller, and α_{myt} captures the average price of a particular make and model-year in a particular quarter and year (e.g., 2015 Nissan Leaf purchased in the first quarter of 2017).

[17]Conditioning on the mix of vehicles is important and follows a similar logic as in Gulati et al. (2017). A change in the unresidualized subsidy-inclusive price can be driven by two factors: (1) the pass-through of the subsidy, and (2) any compositional change in the vehicles purchased as a result of the subsidy. Failing to account for compositional differences can lead to pass-through estimates that mis-represent the split of the subsidy captured by buyers and sellers,

subsidy across all vehicles purchased in zip z and time t, $(\lambda_{zt}S)$, and the pass-through rate of the subsidy onto the buyer, $\frac{(\Delta P - S)}{S}$. Ultimately, our empirical strategy will regress the "residual subsidy-inclusive price" (i.e., the left hand side of 4), on the average subsidy across all vehicles purchased in zip z and time t, $(\lambda_{zt}S)$. The estimated coefficient is the subsidy pass-through rate $\frac{(\Delta P - S)}{S}$.[18]

3.2 Estimation and identification

The features the EFMP pilot program naturally support a difference-in-differences (or triple-differenced) estimation strategy, since we observe data on prices and sales, in and out of the pilot regions, in disadvantaged and non-disadvantaged communities, before and after the start of the pilot program. The difference-in-differences strategy estimates the pass-through of the subsidy by estimating the analog to equation (4), comparing the prices in disadvantaged zip codes, in and out of the pilot regions, before and after the start of the pilot program. Using the residual subsidy-inclusive price (i.e., the left hand side of equation 4) as the dependent variable, we estimate two regression models that capture slightly different measures of pass-through.

First, we regress our dependent variable on the fraction of sales that received an EFMP subsidy in a zip-quarter, λ_{zt}, and a set of fixed effects to capture time-invariant and zip-code invariant unobservables:

$$Y_{zt} = \beta_1 \lambda_{zt} + \nu_t + \gamma_z + \epsilon_{zt} \tag{5}$$

where Y_{zt} is the residual subsidy-inclusive price from (4), ν_t and γ_z are time fixed effects and zip fixed effects. The time fixed effects and zip fixed effects nest the traditional post-period dummy and treatment-region dummy, but allow us to control for unobserved correlation between prices and the take-up of the program at the zip-level. The disadvantaged communities in the pilot region vary substantially by income (e.g., a wealthy zip code might be classified as disadvantaged due to proximity to a pollution point source). Since the EFMP program is means-tested, take-up is not even amongst disadvantaged zip codes with the pilot region. The zip fixed effects control for unobserved drivers of EV purchase prices correlated with zip-level treatment eligibility.

From equation (4), the coefficient β_1 provides an estimate of $(\Delta P - S)$. This captures how

as in Gulati et al. (2017) where subsidized buyers are more likely to purchase vehicle with "add-ons."

[18]Regressing the subsidy-inclusive price on the subsidy is analogous to the standard tax pass-through model from the public finance literature. Regressing the tax-inclusive retail price on the tax rate yields an estimate of the fraction of the tax passed onto consumers. An alternative approach would omit the last term on the left-hand side of equation (4), in which case the coefficient of interest would be interpreted as the fraction of the subsidy captured by dealers.

much less on average, buyers of vehicles who received the EFMP subsidy paid relative to buyers of the same model and vintage who did not receive the EFMP subsidy.[19]

We also estimate the pass-through rate directly, by regressing the residual subsidy-inclusive price on the average subsidy received across all purchases in a zip z and time t, S_{zt}, analogous to $\lambda_{zt}S$ from equation (4).

$$Y_{zt} = \beta_1 S_{zt} + \nu_t + \gamma_z + \epsilon_{zt}. \tag{7}$$

Here, the coefficient β_1 provides an estimate of $(\Delta P - S)/S$, the pass-through rate of the subsidy.

The identifying assumption necessary for interpreting the coefficient, β_1, in equation (5) as an unbiased estimate of the pass-through rate of the subsidy is that the error term, ϵ_{zt}, and the fraction of purchases subsidized, λ_{zt}, are not jointly determined. There are several concerns that might arise. First, if policy is set endogenously to target locations with high demand for electric vehicles, ϵ_{zt} and λ_{zt} might be positively correlated. Yet, the nature of the pilot program suggests that endogenous targeting is unlikely. The roll-out of the pilot program was plausibly exogenous to zip-level demand. Relative to state-wide incentives, the pilot programs were limited in size and scope. The program in South Coast operated largely through its online presence, with a relatively modest amount of targeted marketing, with interested consumers applying on-line. The program in San Joaquin directly marketed to low-income and minority households as part of local "Tune-in, Tune-up" smog testing events. Notably, the "Tune-in, Tune-up" events are pre-announced, rotate between regional population centers in the San Joaquin Valley, and are primarily opportunities for drivers to receive free smog checks. At these events, eligible drivers would also receive information about the EFMP subsidies, if applicable, but the subsidy program itself was not the primary goal of the "Tune in, Tune up" events.[20]

[19] Although we do not do so in the paper, we could alternatively use a "treatment dummy" in lieu of the fraction of vehicles purchased under the EFMP program in a zip-quarter as the explanatory variable of interest. In this case, since take-up is incomplete, the coefficient on the "treatment dummy" is an estimate of the intent-to-treat effect on the average price paid across both eligible and ineligible transactions. Specifically,

$$Y_{zt} = \beta \mathbf{1}_A \mathbf{1}_P + \nu_t + \gamma_z + \epsilon_{zt} \tag{6}$$

where Y_{zt} is the residual subsidy-inclusive price, $\mathbf{1}_A$ and $\mathbf{1}_P$ are indicators for AQMD=1 and Post=1, respectively. Zip code and time fixed effects are conditioned out via γ_z and ν_t, respectively. Here, the coefficient $\hat{\beta}$ reflects an estimate of the intent-to-treat for buyers in disadvantage zip codes in the pilot region. Intuitively, using λ_{zt} as a continuous treatment in place of the treatment dummy in (6) scales up the intent-to-treat estimate β to an estimate of the treatment-on-the-treated, the effect that the subsidy has on the residual subsidy-inclusive price of the vehicles that received the EFMP subsidy.

[20] Since the end of the study period, program officials in the San Joaquin Valley have begun to take online applications. Interested individuals bring their current vehicle to an event, receive a free smog check and, if eligible for the program, receive in-person guidance on how to apply. At the same time, program officials verify applicant eligibility and guide the potential participant through the application process. After the event, officials followed-up with potential applicants to help them complete their application.

Second, if the scope of the program is sufficiently large, the program itself might impact the equilibrium price if demand increases. Here, we appeal to the fact that the pilot program was small in scale and equilibrium prices for vehicles are determined based on aggregated demand and supply over are larger region. Even in the disadvantaged communities in the pilot regions, subsidized vehicles are a relatively small fraction of overall electric vehicle sales, and as a result, unlikely to impact equibrium prices.[21]

Finally, we find little evidence that prices are trending differentially in the pilot and non-pilot AQMDs. Figure 3 plots trends in the residual subsidy-inclusive purchase price of electric vehicles (left panel) and the log of EV sales (right panel) in disadvantaged zip codes in and out of the pilot regions over time. In each graph, the red lines and shading corresponds to the means and standard errors for disadvantaged communities in the participating AQMDs; the blue lines and shading plot the analogous values for disadvantaged communities in non-participating AQMDs. In both cases, the pre-trends are statistically indistinguishable. The slight difference in the pre-trends for residual purchase prices as modest in comparison to the value of the EFMP incentives.

3.3 Matched and triple-differenced specifications

Our setting allows for two additional specifications to further address potential concerns with pre-period trends (despite the fact that the pre-trends for residual prices and log-quantities are similar) and omitted variables correlated with the treatment. Although the classification for disadvantaged communities applies identically to both the pilot and non-pilot regions, the histograms of CES scores plotted in Figure 2 indicate that the upper tail of CES scores in participating AQMDs does not overlap with the non-participating AQMD distribution. The highest CES score outside of the participating AQMDs (South Coast and San Joaquin) is 59.9, corresponding to the 75th percentile of CES scores in the participating AQMDs.

As a refinement to the difference-in-difference specification above, we use nearest-neighbor matching to pair disadvantaged zip codes in participating AQMDs with "control" disadvantaged zip codes in non-participating AQMDs. We match based on the pre-period trends in average prices or quantities, following the synthetic control literature (e.g. Abadie and Gardeazabal (2003), Abadie et al. (2010)).[22]

[21] Although we focus on the OLS results when estimating pass-through, we also instrument for the fraction of vehicles subsidized by EFMP using the instrument for the quantity regressions describe in section 4.1. The IV results, presented in the appendix are qualitatively similar to the OLS results, suggesting the subsidies are passed-through to consumer prices to a high degree.

[22] We plot the mean residual purchase price and the mean of log of EV sales (right panel) in the matched sample in

We also examine a triple-differenced specification that leverages the non-disadvantaged communities in both the pilot and non-pilot regions, and includes a full-set of interaction fixed effects, ν_{tA}, ϕ_{tD} and γ_z, capturing shocks common to the pilot region, shocks common to disadvantaged communities and time-invariant zip-level differences. Relative to the unmatched and matched difference-in-difference specifications above, the triple-differenced specification controls for unobservable shocks to EV adoption or prices common to all zip codes within the pilot region. Formally,

$$Y_{zt} = \beta_1 \lambda_{zt} + \theta_{tA} + \eta_{tD} + \gamma_z + \epsilon_{zt} \tag{8}$$

where θ_{tA} and η_{tD} are AQMD and DAC-specific time-fixed and γ_z are zip-level fixed effects. As with the difference-in-differences specification, the triple-differenced specification includes a set of fixed effect that nest the standard triple-differenced interactions between a post-period, AQMD, and DAC dummy variables. The finer fixed effects allow us to control for unobserved correlation between prices and the take-up of the program at the zip-level and unobserved correlation between prices in the pilot regions and the gradual roll-out of the EFMP subsidy.

3.4 Pass-through results

Table 4 presents the pass-through estimates. The first three columns present the difference-in-difference, the matched difference-in-differences and the triple-differenced specifications respectively, using the fraction of subsidized vehicles (λ_{zt}) as the explanatory variable of interest. In this specification, we interpret the coefficient on the fraction of subsidized vehicles as an estimate of the different between the subsidy-inclusive price paid by EFMP recipients relative to non-participating buyers of the same vehicle. We find evidence that consumers likely capture the majority of the subsidy, although confidence intervals include smaller rates of pass-through. Relative to an average base and plus-up subsidy close to \$9,000, our results suggest that buyers pay \$7,000 to \$8,000 less for a vehicle, net of the subsidy, relative to non-participants purchasing the same make, model and model-year elsewhere in California.[23]

Columns (4) through (6) again present the difference-in-difference, the matched difference-in-differences and the triple-differenced specifications, but now use the average subsidy in zip z at time t (i.e., S_{zt} from equation (4)) as the explanatory variable of interest. Here, the coefficient can be interpreted as a direct estimate of the pass-through of the subsidy to the subsidy-inclusive price. Again, the estimates suggest that buyers capture between 73 - 84 percent of the

A5.

[23] After instrumenting, our estimates of the proportion of the subsidy captured by consumers increases slightly, and one cannot reject full pass-through.

subsidy depending on the specification. These estimates are consistent with stated efforts of the program designers who sought to channel most of the subsidy dollars to buyers rather than sellers or upstream market participants. In addition, these pass-through estimates are similar to estimates from previous work examining the pass-through of hybrid vehicles subsidies. Gulati et al. (2017) finds that new hybrid vehicle buyers capture 80 to 90 percent of the value of incentives.[24] But, unlike earlier subsidy programs that were widely available, the EFMP program pilot was limited in scope. Although we find evidence that consumers captured the majority of the benefits of the pilot program, the pass-through of a widely implemented program might differ.

4 Impact of EFMP Subsidies on Sales

In this section we describe our method for retrieving the treatment effect of EFMP subsidies on the quantity of EVs demanded in treated zips (the treatment effect on treated subjects, or "ToT"). The central challenge can be seen by considering a basic difference-in-differences estimate, $\hat{\beta} = (Q_{11} - Q_{10}) - (Q_{01} - Q_{00})$, where in our context a in Q_{ap} equals 1 in treated AQMDs and 0 otherwise, and p equals 1 in the "post" period and 0 in the "pre" period. The intent-to-treat ("ITT") estimate is retrieved under the "parallel trends" assumption, allowing $\hat{\beta} = (Q_{11}|T = 1) - (Q_{11}|T = 0)$. When only a subset of individuals are candidates for treatment, as is the case in our setting, the treatment effect on treated units ("ToT") is retrieved by scaling the ITT estimate by the fraction of treatment-eligible (TE) households in the population: $\frac{N^{TE}}{N}$.

In our setting, $\frac{N^{TE}}{N}$ is unobservable. Households within treated zips are eligible to receive the EFMP subsidy only if they pass a means test and have a car available to be scrapped. We proceed by estimating the effect of the EFMP subsidy program on quantity of EVs purchased by using high and low scaling factors which, together, bound $\frac{N^{TE}}{N}$. Before describing these scaling factors in detail, it is helpful to keep in mind the estimating equation. Equation 9 is the quantity analog of equation 5 above.

$$Y_{zt} = \beta_1 T_{zt}^{\omega} + \nu_t + \gamma_z + \epsilon_{zt} \tag{9}$$

[24]Gulati et al. (2017) further finds that subsidy-eligible buyers are more likely to choose vehicle options that increase the purchase price of the vehicle, and thus pay a higher purchase price, unadjusted for options. In our case, we do not observe the options purchased by customers. However, EFMP buyers are substantially more likely to purchase used EVs, where the set of potential options is more limited. Moreover, unobserved options would tend to bias our estimates towards zero, suggesting, if anything our results understate the fraction of the subsidy captured by consumers.

The dependent variable, Y_{zt}, is the inverse hyperbolic sine of EV quantity in zip z at time t. T^{ω}_{zt}, the treatment variable, is a weighted average subsidy amount per EV sold under EFMP, which will be based on the high and low scaling factors ($\omega \in \{high, low\}$) which we will describe next. Estimates of β_1 are "lower" and "upper" bounds of the treatment effect, respectively. (Note that the higher the scaling factor, the less it will scale up the ITT estimator to retrieve the ToT.) Controls are ν_t and γ_z: time fixed effects and zip fixed effects.

The average subsidy amount per EV purchased under EFMP is:

$$T^{\omega}_{zt} = \alpha^{\omega}_{zt} * S_{zt} \tag{10}$$

where S_{zt} is the sum of EFMP subsidies applied to EV purchases in zip z in quarter t, and α^{ω}_{z} is the high or low scaling factor used to calculate the mean subsidy amount. *The high scaling factor (α^{high}_{zt}) is the fraction of households under 400 percent of the poverty line.* This is time-invariant, reflecting Census data we use to obtain the fraction of households in each of the three subsidy-eligible income bands. As such, $\alpha^{high}_{zt} = \alpha^{high}_{z}$. Note that α^{high} overestimates true treatment eligibility ($\alpha^{high}_{z} > \frac{N^{TE}}{N}$) because only a subset of these households have scrap-eligible cars.

To place bounds on our estimates, we introduce the "low" scaling factor: α^{low}_{zt} *is the fraction of EV buyers in each zip-quarter that purchase EVs under the EFMP program.*

$$\alpha^{low}_{zt} = \frac{q^{EFMP}_{zt}}{q^{EV}_{zt}} \tag{11}$$

This factor underestimates the true treatment eligibility ($\alpha^{low}_{zt} < \frac{N^{TE}}{N}$) so long as $Pr(EV_t|eligible) < Pr(EV_t)$, which is empirically true. Low-income (treatment-eligible) households purchase EVs at a lower rate than the population average.

Together, these high and low scaling factors yield two treatment variables that allow us to assess the lower and upper bounds on the effect of subsidies on EV purchases:

$$T^{high}_{zt} = \alpha^{high}_{z} * S_{zt} \tag{12}$$

and

$$T^{low}_{zt} = \alpha^{low}_{zt} * S_{zt} \tag{13}$$

4.1 Identification and results

There is an identification challenge when using the lower-bound scaling factor, α_{zt}^{low}, since quantity of EVs transacted now appears on both the left- and right-hand sides of the regression. To address this endogeneity, we turn to an instrumental variables approach. We instrument for T_{zt}^{low}, the average EFMP subsidy amount, using the zip-level average eligible subsidy based on the representation in population in each of the relevant eligibility bands. Specifically,

$$W_z = \sum_{l} \alpha_{z,r} * S_r \tag{14}$$

where $r \in \{225, 300, 400\}$ denotes the three ranges of household income (as a percent of the federal poverty line) that relate to different subsidy levels. To account for potential nonlinearities in the relationship between eligibility and take-up, we use both W_z and $(W_z)^2$ in our main IV specifications. The exclusion assumption is that, conditional on zip and quarter-of-sample fixed effects, there is no correlation between pre-period and post-period EV demand. By construction, the denominator of the instrument is constant for each zip code and hence, uncorrelated with idiosyncratic shocks to log quantities in the *post-treatment* period.

We attempt to falsify the main assumption by running a two stage test. The intuition for the test stems from the need for the instrument to be uncorrelated with Q_{zt} after conditioning out zip and quarter-of-sample fixed effects. Recall that instrument is comprised of zip-level EV demand in the pre-treatment period, interacted with average EFMP subsidy levels that are a function of population demographics and EFMP program design. In stage one of the test, we regress the instrument on zip-level pre-period quantity, $\alpha_{z,225} * 5000$, $\alpha_{z,400} * 4000$, $\alpha_{z,300} * 3000$ and time fixed-effects. Stage two regresses the fitted residual from stage 1 on demeaned Y_{zt}. A high R^2 in the second stage reflects a high level of correlation between the IV and Q_{zt}, which leads to a rejection of the identifying assumption. We find an R^2 of 0.000036.

Additionally, we wish to reject the possibility that our exclusion assumption is contaminated by zip-level autocorrelation in unobservable determinants of EV demand. This concern arises from the presence of autocorrelation in zip-level EV demand which, empirically, attenuates substantially after two quarters. We thus construct the alternative version of the instrument excluding the two quarters preceding treatment when calculating pre-period EV demand. Results from this robustness check are nearly identical to those using the preferred IV. This should not be surprising given the evidence presented in the preceding paragraph.

Table 5 shows the effect of the EFMP subsidies on the quantity of EVs transacted. As with the price regressions, we present OLS estimates in columns 1 through 3, for the difference-in-differences, matched difference-in-differences and triple differenced specifications respectively, and IV results in columns 4 through 6. To reiterate, we regress the inverse hyperbolic sine of quantity on T^h_{zt} and interpret the estimated coefficient as the percentage change in EV sales resulting from EFMP program exposure moving from zero to 100 percent eligibility. Columns 1 and 2 suggest that zip codes in which all buyers were eligible for the program would experience mean lower-bound increases of between 1.6 to 2.8 percent in the quantity of new EVs purchased relative to zip codes with zero program eligibility. The triple-differenced estimator in column three is slightly lower (1.1 percent) but indistinguishable from zero. The upper-bound estimates in columns 4-6 show larger responses to the subsidies – between 12 to 15 percent treatment effects per $1,000 subsidy. The consistency within these upper-bound estimates reflects the robustness of identifying assumptions. As reported in the table, the instruments are sufficiently strong. First-stage f-statistics and the Sargan-Hansen p-values reflect strong first-stage power.[25]

To place these results in broader context, recall that table 2 reports that just over 1,300 EVs were purchased under the EFMP program in our sample. Despite the large magnitude of subsidies (up to a combined base and plus up subsidy of $9,500 in subsidies on an average EV transaction price of roughly $26,000) only 2 percent of EVs purchased in qualifying zip codes are purchased through the program. The relatively low level of uptake is likely due to a combination of factors. These may include low intrinsic demand for EVs among the subsidy-eligible population, less than full pass-through of the subsidy to buyers, the fact that EVs tend to be substantially more expensive than alternatives during the sample period, the potential concentration of subsidy-eligible buyers in multi-unit dwellings without access to overnight charging infrastructure, and the requirement that eligibility is conditional on having a suitable "clunker" to trade in at the time of EV purchase. However, table 5 shows that the *relative* change in EV demand stimulated by the presence of the subsidy is proportionately high.

4.2 Elasticity of demand for electric vehicles

The elasticity of demand for EVs in this setting is of particular interest, as estimates on the broader population of early adopters primarily reflects the price sensitivity of high-income households. In contrast, the EFMP program specifically targets low and middle-income households that form the bulk of the population and potentially play an important role in wide-scale

[25]Point estimates obtained using only the linear IV, W_z, are nearly identical, with first-stage F-statistics in the 18 to 24 range.

adoption of EVs. We approach this in two ways. First, we can use the estimates from tables 4 and 5 to back out the elasticity of demand of EFMP-eligible buyers as:

$$\varepsilon^{P}_{Q_E} = \frac{\beta^{PT}}{\beta^{Q}} P_E. \tag{15}$$

where β^{PT} is the fraction of the subsidy captured by buyers and β^{Q} is an estimate of the impact of a $1,000 subsidy on demand for EVs.[26] Alternatively, we can estimate the elasticity directly by regressing (inverse hyperbolic sine of) quantity on the percent premium or discount at which EVs were sold in the zip-quarter. Formally, we estimate:

$$IHS(Q_{zt}) = \beta \, \%Premium_{zt} + \nu_t + \gamma_z + \epsilon_{zt} \tag{16}$$

where $\%Premium$ is calculated as residual subsidy-inclusive price in zip z and time t normalized by mean price of EVs in our data. Since the residual subsidy-inclusive price is plausibly a function of the number of EVs sold, we once again will deploy the IV described in Section 4.1.

Table 6 presents elasticity estimates obtained from Equation 15 using the "upper-" and "lower-"bound estimates from Table 5 for β^{Q} and β^{PT} estimates from Table 4. These place the upper and lower bounds of the elasticity at -2.8 to -3.8 and -0.3 to -0.9, respectively. The middle row of Table 6 ("Direct Estimate (IV)") presents our preferred estimates of the demand elasticity, which arise from estimating Equation 16. These all vary in a tight range between -2.1 to -2.2.

Collectively, these estimates are roughly in line with, but slightly higher in absolute magnitude than, recent estimates in the literature for the elasticity of early EV adopters.[27] Our range includes all estimates in the literature, with our preferred estimates ("Direct Estimate (IV)") in the upper half of the range in the literature. This suggests that low- and middle-income buyers may be more price elastic than higher-income earlier adopters.

4.3 Price effect on non-participants

An implicit assumption in the analysis above is that the EFMP subsidies do not affect the price paid by ineligible buyers through, for example, a shock to aggregate electric vehicle demand. If the EFMP subsidy increases the prices paid by ineligible buyers, $\frac{dP_{jt}(\lambda_{zt})}{d\lambda_{zt}} > 0$, the pass-through specification in equation (7) would tend to overestimate fraction of the subsidy captured by

[26] See appendix section A.3 for the derivation.
[27] Li et al. (2017) uses gasoline prices as an IV and estimates a demand elasticity of -1.3. Springel (2017) and Li (2017) both use BLP IVs to retrieve estimates of -1.0 to -1.5 (Springel) and -2.7 (Li), respectively.

program participants.

As noted in section 3.2, two features of our setting suggest the program is unlikely to affect aggregate prices and significantly bias our pass-through estimates. The fraction of buyers who receive the EFMP is small — in "treated" zips, two percent of vehicles on average receive an EFMP subsidy. Thus, the impact of the program on the prices paid by non-participants is likely to be modest. Second, our level of analysis is at the zip-quarter level despite the fact that zip codes themselves are not isolated markets. Rather, these zip codes are part of large metro areas across which people purchase vehicles. Vehicles commonly flow between metro areas in response to local supply and demand conditions so as to arbitrage away local price premia. Thus, we consider it unlikely that the small fraction of buyers who receive EFMP subsidies have a meaningful impact on the prices paid by the vast majority of buyers who do not.

The details of the program allow us to test for spillover effects directly by examining the effect of EFMP-induced demand on prices in zip codes outside the participating air quality districts. We implement this by restricting the sample to sales outside the pilot regions and collapsing the data to quarter-of-sample by make/model-year observations. We then regress the average residual sales price on the share of vehicles of that make-model-model-year purchased under the EFMP program in that quarter.

$$P_{jt}^{AQMD=0} = \alpha s_{jt} + \mu_j + \nu_t + \epsilon_{jt} \tag{17}$$

where s_{jt} is the fraction of vehicle j at time t purchased with an EFMP subsidy, μ_j are model fixed effects and ν_t are time fixed effects. The test compares the prices for make-model-modelyears popular amongst EFMP buyers to those unpopular amongst EFMP buyers. If the treatment influences the prices paid in non-participating regions, we would expect the average prices of popular models to increase in non-participating regions after the start of the EFMP program relative to the prices of unpopular models. The coefficient of interest is α, which will be positive if the statewide share of the price of cars purchased in non-participating regions is positively correlated with the fraction of those vehicles sold under the EFMP program.

We find that a small but statistically insignificant effect exists. The change in s_{jt} from zero to one represents a shift from zero percent to 100 percent of MMY vehicles being sold under the EFMP program. Our estimate shows that this would, on average, increase the transaction prices by \$4,486. Adjusting for the share of EVs sold under EFMP (1.2 percent overall), this implies an average increase of \$53 for each such vehicle sold in non-participating AQMDs. Adjusting instead by share of used EVs sold under EFMP (3.5 percent), it would imply an average increase of $157 per vehicle in non-participating AQMDs.

The existence of these effects implies that the "true" treatment effect on EV prices reported in Table 4 may be slightly overstated, and one may wish to adjust these coefficients towards zero by $50-$150 when interpreting these results. The qualitative and policy implications are unaffected, however, as these spillover effects are one-to-two orders of magnitude smaller than the average treatment effect on treated vehicles. Moreover, the presence of these market adjustments reflects the efficiency with which vehicle markets operate.

5 Discussion and Conclusion

In this paper, we exploit variation arising from rules governing the availability of EV subsidies in California. Using a unique dataset of both transaction prices and subsidy levels, we estimate the elasticity of demand amongst low- and middle-income households and the fraction of the subsidy captured by consumers. It is difficult to estimate these statistics in a credible way when examining many of the other EV rebate policies that have been available in the California and the United States in recent years. Both the federal EV tax credit and the California Clean Vehicle Rebate Project subsidies were (until recently) available to any EV buyer in their jurisdiction, making it difficult to construct a credible control group. Yet, in our setting, the rules governing the EFMP program in California are well suited to deploying a credible methodology for program evaluation. When we do, we estimate a subsidy elasticity of EV demand of -2.1 and an average subsidy pass-through rate in the vicinity of 80 percent.

The elasticity estimates speak to the responsiveness of low- and middle-income households to EV incentives. Although mass electrification of the transportation sector will require adoption by these households, until now, little was known about the demand elasticity for this important group. The means-testing and geographic targeting of the EFMP allow a rare opportunity to study the adoption decisions of low- and middle-income buyers. One challenge to generalizability is the EFMP requirement that recipients trade in an old car for scrap. This lowers the true subsidy-eligible population under EFMP and may lead readers to consider our main (ToT) elasticity estimates as lower than what would arise in the absence of such a requirement.

One instructive comparison is to benchmark our elasticity estimate of -2.1 against implied elasticities from the earlier literature on hybrid vehicle incentives that likely reflect the responsiveness of higher income, early adopters. Gallagher and Muehlegger (2011) and Chandra et al. (2010) exploit the timing and coverage of U.S. state and Canadian province hybrid vehicle incentives, and estimate that a $1000 tax incentive was associated with 31 to 38 percent increase in hybrid vehicle adoption. Even if the incentives are fully passed through to consumers, the estimates imply responsiveness greater than our estimate for low- and middle- income households. In contrast, recent papers estimating the demand elasticity for early EV adopters (e.g., Li et al. (2017), Li (2017), and Springel (2017)) tend to estimate less elastic demand for early EV adopters. Either way, historical evidence of the effect of subsidies obtained by early adopters may prove a poor guide for policies aspiring to mass market adoption.

In addition, the pass-through results are informative for policy. Distributional objectives are one of the primary motivations for the means-testing of the EFMP pilot (and other means-tested environmental subsidies). We find that buyers capture the majority of the EFMP subsidies, consistent with the funding being transferred to households below the income cutoffs. Yet the program induces a reasonably strong demand response amongst the eligible population, suggesting that some of the participating buyers would not have purchased an EV in the absence of the subsidy. A back-of-the-envelope calculation yields a cost of public funds of roughly 32 cents on the dollar associated with redistributing a dollar through the EFMP program. As the EFMP pilot was means-tested, the program provides a closer analogue to many recent subsidy programs, such as those offered as part of the Inflation Reduction Act of 2022, that also rely on means-testing as a way to target subsidy dollars towards less-advantaged households.

That said, two features of the program may temper the distributional benefits. First, the scope of the program was very small. We find that the program had very little effect on the price of vehicles for ineligible buyers. As noted by Busse et al. (2013), purchases of new vehicles might easily adjust to demand induced by a larger program. But, for lower- and middle-income households who are more likely to buy used vehicles, a larger program offering subsidies for used vehicles might impact prices, reducing the effective fraction of the subsidy captured by households. Second, within the group of low- and middle-income households, the benefits of means-tested EV subsidies accrue to a select group of low- and middle-income households. In particular, these subsidies are more likely to benefit households residing in single-family dwellings, with easy access to dedicated charging infrastructure. As noted by Hsu and Fingerman (2021), access to charging infrastructure is lower for households that live in multi-unit dwellings and households living in Black and Hispanic majority-neighborhoods. As a consequence, these households may be less likely to benefit from EV subsidies despite similar (or lower) household incomes.

California's EV trajectory has been an exception in the U.S. To date, California buyers accounted for roughly 40 percent of national EV registrations. This is due, at least in part, to the robust growth of the market share of EVs in California, both before and after our study period. At the end of 2017, roughly five percent of new vehicles registered in California were plug-in or battery EVs.[28] By 2022, EV market share in the state had risen to over fifteen percent. The experience of low- and middle-income buyers in California over our study period is likely still relevant to California buyers today, as higher market shares require purchases by lower-income customers. Our estimates also provide a guide to present-day adoption in other parts of the U.S. Excluding California, the national share of new EV registrations is just reaching levels seen in California towards the end of our study period. Although vehicle preferences and environmental attitudes may plausibly explain some the differences in adoption to date (see, e.g., Archsmith et al. (2021) and Filippini and Wekhof (2021)) and both demand and supply of EVs continues to evolve quickly, California's experience and our estimates provide a window into the adoption trajectory for the nation as a whole.

There are reasons to believe that widespread adoption will encounter challenges that are not present in the EV market to date. In addition to a low stated willingness to pay for BEV technology (Helveston et al. (2015)), consumers often fail to think about fuel prices in a systematic way (Turrentine and Kurani (2007), Bushnell et al. (2022)). EVs can take hours to charge, and charging infrastructure will need to expand dramatically to meet the demand of a larger EV fleet. Evidence from early adopters in California also raises questions about the extent to which EVs are being used as substitutes for gasoline cars (Burlig et al. (2021)). It is not yet known how well the electricity market will adapt to meeting a higher proportion of energy demand from the transportation sector, nor how the carbon intensity of electricity production will evolve to meet increasing vehicle charging demand.

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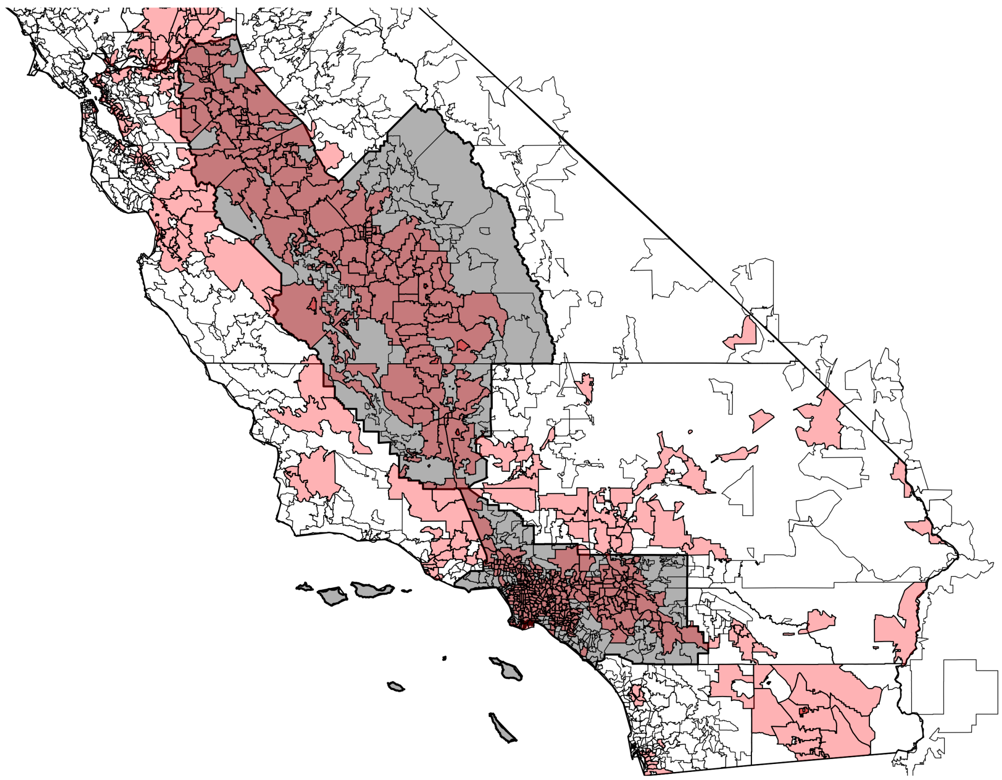
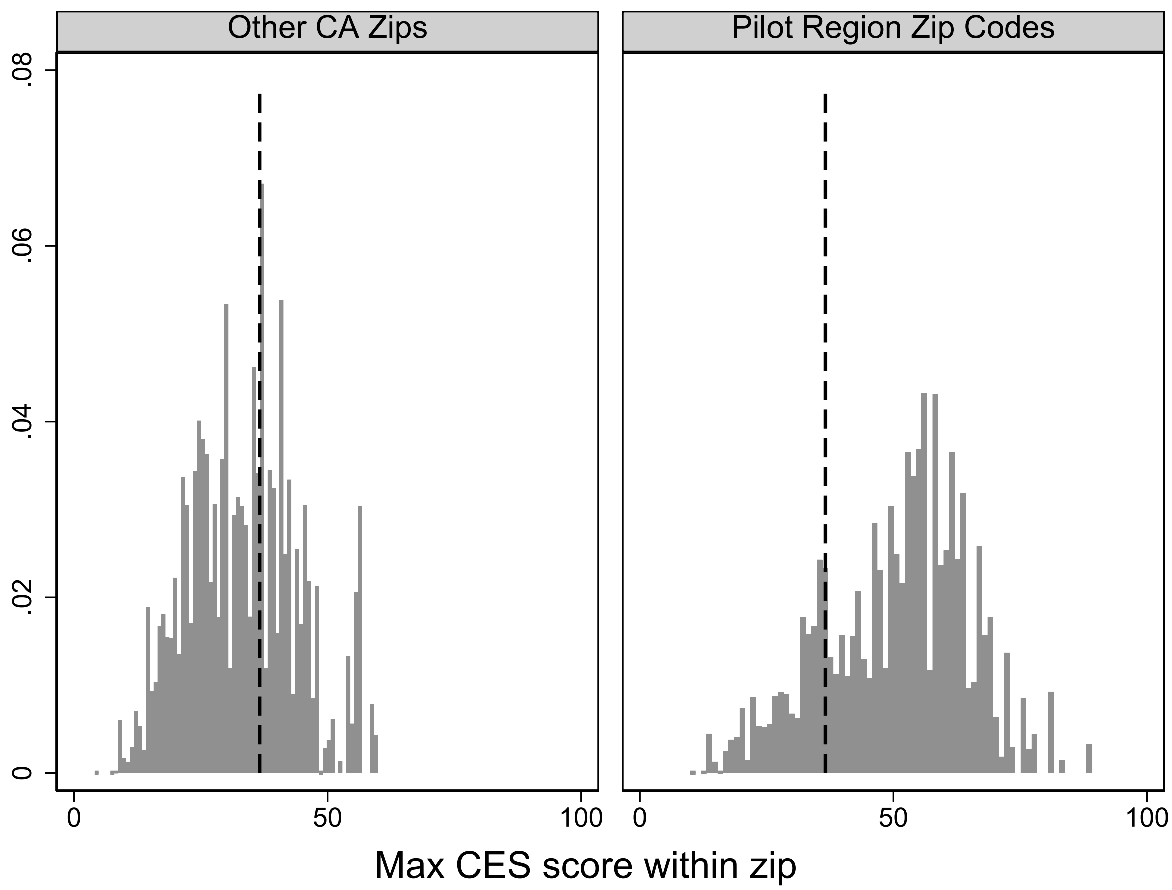
Figure 1: DAC Zip Codes, South Coast and San Joaquin Valley AQMDs



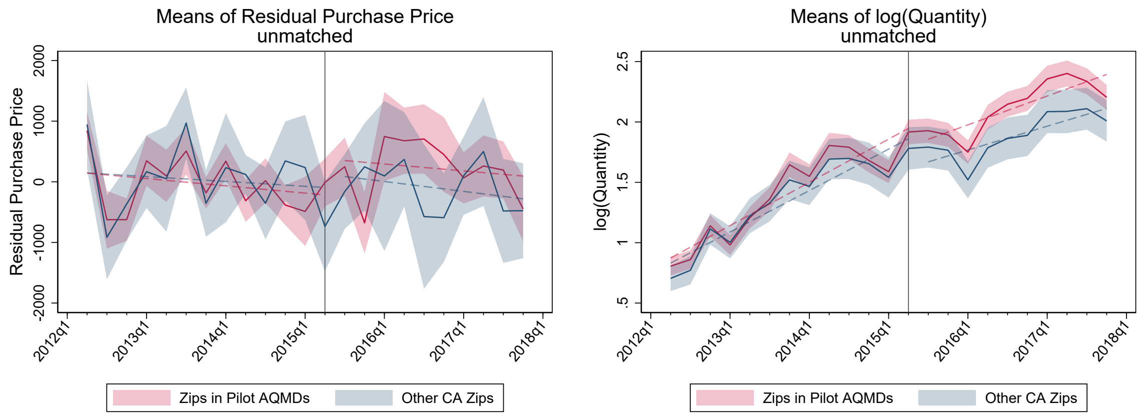
Note: The figure maps zip codes in California and the boundaries of the two air quality management districts that were part of pilot program. Disadvantaged zip codes are shaded red. The area of two participating AQMDs are shaded gray.

Figure 2: Average Income and Max-CES Score



Note: Left histogram presents the distribution of zip-level maximum CES scores for non-pilot regions. Right histogram presents the distribution of zip-level maximum CES scores for the pilot regions. The dashed vertical line corresponds to the disadvantaged community CES score cutoff of 36.6.

Figure 3: Trends in Prices and Quantities, Disadvantaged Communities in and out of Pilot Regions



Note: Red and blue lines correspond to the unweighted average prices and log quantities in disadvantaged communities in and out of the pilot regions, respectively. Vertical line corresponds to the start quarter for the EFMP program. Price graphs plot the mean residual prices for disadvantaged communities in an out of the pilot regions after conditioning on make-model-modelyear fixed effects.

Table 1: EFMP Incentive Schedule for BEVs and PHEVs

Income	Base Subsidy	Plus-Up Subsidy
$<$ 225% FPL	$4,500	$5,000
225-300% FPL	$3,500	$4,000
300-400% FPL	$2,500	$3,000

Table 2: Summary Statistics

	Non-participating AQMDs		Participating AQMDs (South Coast/San Joaquin)	
	non-DAC	DAC	non-DAC	DAC
EV Sales, Pre	60,789	26,993	31,524	39,424
EV Sales, Post	85,677	29,840	45,316	63,692
EV Sales Per Capita (per 000 pop), Pre	5.73	3.97	7.92	2.35
EV Sales Per Capita (per 000 pop), Post	8.08	4.39	11.38	3.79
Mean Sales Price ($), Pre	37,391.4	33,964.5	38,516.7	34,470.5
Mean Sales Price ($), Post	39,110.1	35,997.8	41,596.1	36,544.0
Count of EFMP EV trans., Pre	0	0	0	0
Count of EFMP EV trans., Post	0	0	29	1,330
EFMP Frac. of Sales, Pre	0	0	0	0
EFMP Frac. of Sales, Post	0	0	0.001	0.021
Mean Subsidy ($), Pre	0	0	0	0
Mean Subsidy ($), Post	0	0	2.01	191.20
Frac. zips in SCAQMD	0	0	0.860	0.684
Population (MMs)	10.61	6.798	3.983	16.81

The table reports statistics the transaction data (top panel) and subsidy data (middle panel) for the three groups of untreated zip codes in the first three columns and for disadvantaged zip codes in the participating AQMDs in the fourth column.

Table 3: Demographic Summary Statistics

		Population Weighted		Sales Weighted	
	All CA	Non-pilot DACs	Pilot DACs	EV Sales (2014-2018)	EFMP Sales
Mean Income ($000)	93.1	85.9	76.2	128.0	75.9
	(38.6)	(29.3)	(24.5)	(52.1)	(22.0)
Frac. HH < FPL (%)	35.0	38.0	42.8	23.9	42.0
	(16.2)	(13.6)	(15.6)	(13.3)	(14.4)
Frac. HH < 225% FPL (%)	39.1	41.9	47.5	26.8	46.8
	(17.0)	(14.6)	(15.6)	(14.2)	(14.6)
Frac. HH < 300% FPL (%)	50.8	54.2	60.5	35.8	60.2
	(19.2)	(16.4)	(16.5)	(16.9)	(15.5)
Frac. HH < 400% FPL (%)	62.5	66.0	72.2	46.3	72.1
	(19.2)	(16.1)	(15.6)	(18.4)	(14.3)
Adult HS Grad (%)	79.8	78.0	71.9	88.7	72.9
	(14.3)	(11.5)	(14.5)	(9.7)	(13.2)
Fraction Hispanic (%)	37.7	38.6	51.9	23.1	48.6
	(23.7)	(20.6)	(22.1)	(17.5)	(21.2)
Fraction African American (%)	5.8	8.5	7.0	4.2	6.2
	(8.0)	(8.5)	(9.6)	(6.0)	(8.2)
Fraction Asian American (%)	13.2	14.8	12.0	18.1	16.8
	(13.5)	(13.8)	(12.6)	(15.8)	(16.4)
Unemployment Rate (%)	11.2	12.4	12.5	8.9	12.7
	(3.8)	(3.8)	(3.6)	(2.9)	(4.1)
Max CES score in Zip	42.8	44.1	55.9	35.5	56.1
	(15.4)	(6.3)	(10.0)	(13.6)	(9.5)

The table reports the mean and standard deviation for zip code demographics, income and the Cal Enviro Score. The averages for all of California are reported in column 1. Column 2 and 3 report summary statistics separately for untreated and treated zip codes, respectively. Columns 4 and 5 report state-wide means weighted by electric vehicles sales and EFMP subsidies rather than population, respectively.

Table 4: Pass-Through and EFMP Incentives - Full Subsidy

	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) DinD	(5) Matched DinD	(6) Triple Diff
% EFMP Transactions	-8005.0***	-6993.3***	-7900.6***			
	(1348.3)	(1582.1)	(1343.3)			
(mean) avgsubsidy_total				-0.85***	-0.73***	-0.84***
				(0.15)	(0.17)	(0.15)
Observations	12495	16415	25139	12495	16415	25139
R-Squared	0.12	0.096	0.14	0.12	0.096	0.14

The dependent variable is average residual subsidy-inclusive price in a zip*quarter, after conditioning on Make*Model*Model-year*Year of Sale fixed effects. Columns (1), (2), (4) and (5) include time and zip fixed effects. Columns (3) and (6) include time*AQMD, time*DAC and zip fixed effects. Standard errors are clustered by zip code.

Table 5: EV Sales and EFMP Incentives - Full Subsidy

	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) DinD	(5) Matched DinD	(6) Triple Diff
Lower Bound	0.028***	0.016**	0.011			
	(0.0057)	(0.0070)	(0.0067)			
Upper Bound				0.12***	0.13***	0.11***
				(0.011)	(0.013)	(0.010)
Observations	15801	19458	34477	15621	19278	34297
R-Squared	0.87	0.87	0.90	.	.	.
First-stage F-stat				170.2	120.7	168.9
Hansen Test p-value				0.64	0.33	0.89

The dependent variable is the inverse hyperbolic sine of sales in a zip*quarter. Control variables in all specifications are zip and quarter-of-sample fixed effects. Standard errors are clustered by zip code. Columns 1, 2 and 3 are OLS regressions for the unmatched Differences-in-Differences, the matched Difference-in-Differences and the Triple-differenced specifications, respectively. Columns 4, 5 and 6 present IV estimates of columns 1 through 3 using our preferred instrument described in Section 4.1.

Table 6: Demand Elasticity of Electric Vehicles - Full Subsidy

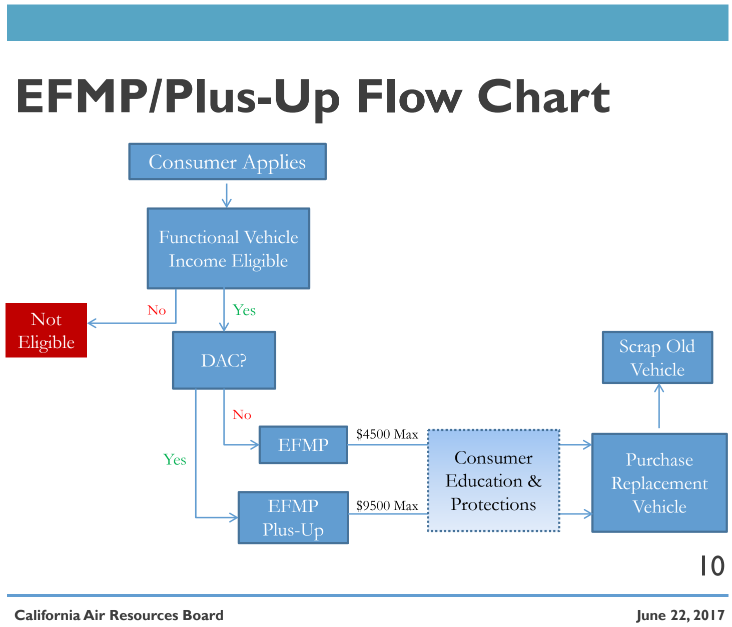
	(1) DinD	(2) Matched DinD	(3) DDD
Upper Bound	-3.10	-3.83	-2.83
	(0.51)	(0.94)	(0.47)
Direct Estimate (IV)	-2.10	-2.16	-2.14
	(0.46)	(0.57)	(0.47)
Lower Bound	-0.86	-0.57	-0.33
	(0.22)	(0.30)	(0.22)

Table 6 presents elasticity estimates obtained from Equation 15 using the "upper-" and "lower-"bound estimates from Table 5 in the top and bottom rows, respectively. Standard errors for these two rows are calculated via bootstrap (N=200 samples drawn with replacement at the zip-code level). The middle row of Table 6 ("Direct Estimate (IV)") presents our preferred estimates of the demand elasticity, which arise from estimating Equation 16.

A Appendix

A.1 Supplementary Figures and Tables

Figure A1: EFMP Eligibility Flowchart



Source: https://www.arb.ca.gov/board/books/2017/062217/17-6-1pres.pdf

Figure A2: CalEnviroScreen Components

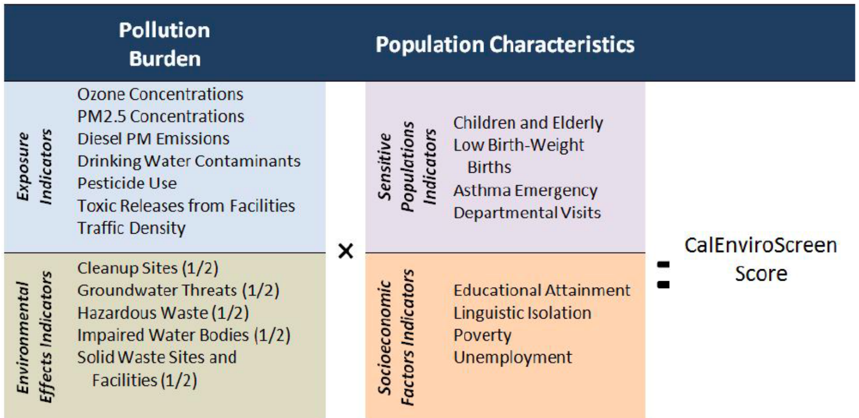
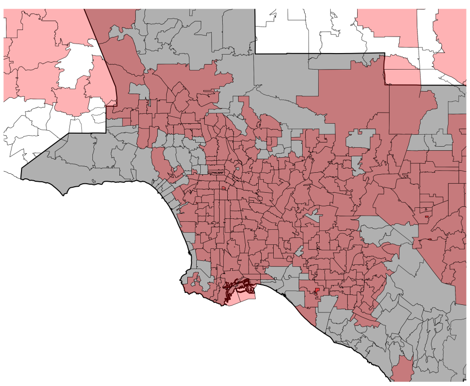
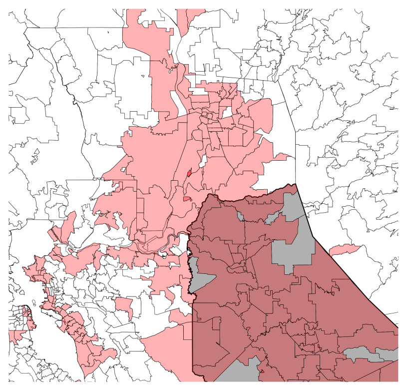


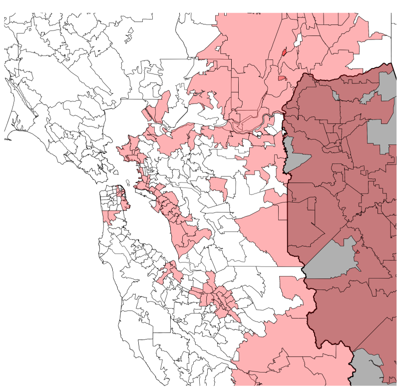
Figure A3: DACs and AQMD borders, Major Metro Areas



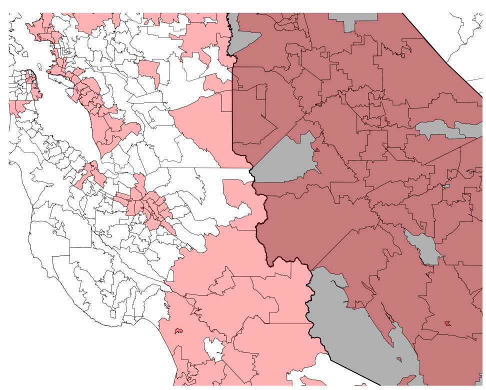
(a) Los Angeles



(b) Sacramento

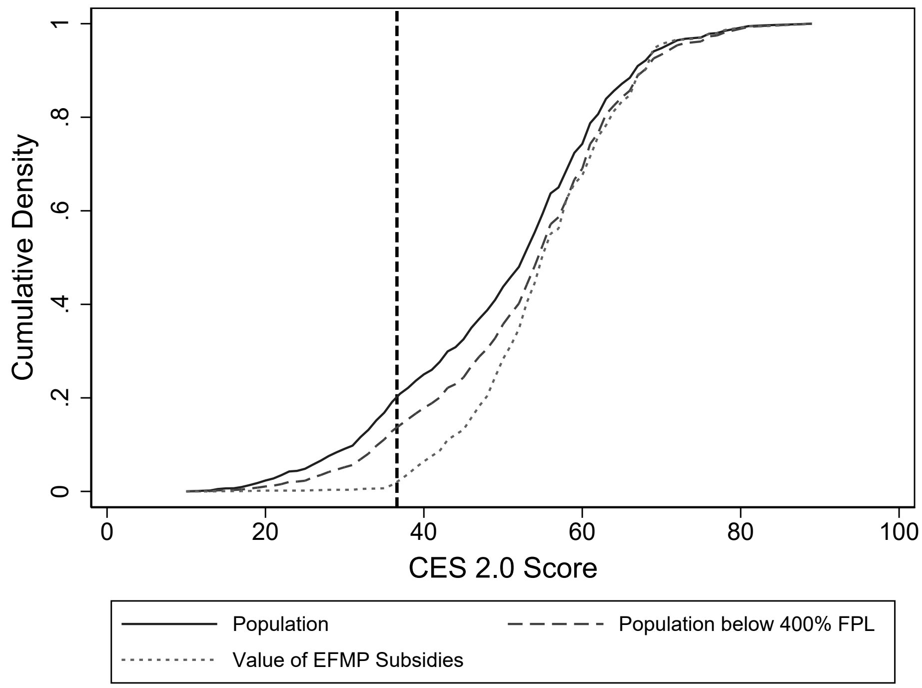


(c) San Francisco



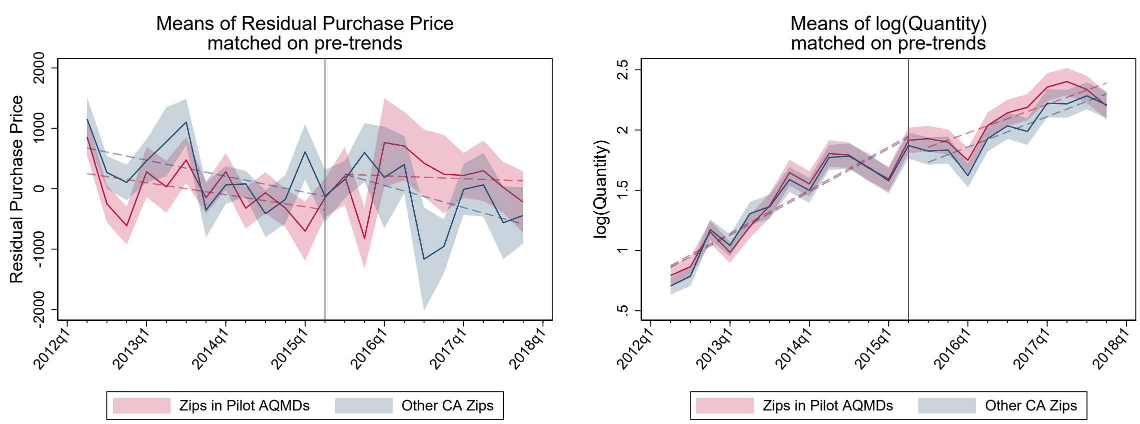
(d) San Jose

Figure A4: Population and Subsidies by Max-CES Score



Note: The graph plots the cumulative distributions of population, population below 400% of FPL, and value of EFMP subsidies within the Pilot Region AQMDs. The dashed vertical line corresponds to the disadvantaged community CES score cutoff of 36.6.

Figure A5: Trends in Prices and Quantities, Disadvantaged Communities in and out of Pilot Regions for samples matched on pre-trends



Note: Red and blue lines correspond to the unweighted average prices and log quantities in disadvantaged communities in and out of the pilot regions, respectively. Vertical line corresponds to the start quarter for the EFMP program. Price graphs plot the mean residual prices for disadvantaged communities in an out of the pilot regions after conditioning on make-model-modelyear fixed effects.

Table A1: Pass-Through and EFMP Incentives

	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) DinD	(5) Matched DinD	(6) Triple Diff
% EFMP Transactions	-9602.6***	-8510.8***	-9701.7***			
	(1162.3)	(1208.5)	(1165.7)			
(mean) avgsubsidy_total				-1.04***	-0.89***	-1.05***
				(0.14)	(0.16)	(0.14)
Observations	12468	16415	25112	12468	16415	25112
R-Squared	.	.	.	.	.	.
First-stage F-stat	95.9	69.7	95.5	182.5	244.6	181.1
Hansen Test p-value	0.78	0.15	0.76	0.64	0.23	0.62

Dependent variable is average residual subsidy-inclusive price in a zip*quarter, after conditioning on Make*Model*Model-year*Year of Sale fixed effects. Columns (1), (2), (4) and (5) include time and zip fixed effects. Columns (3) and (6) include time*AQMD, time*DAC and zip fixed effects. All specifications are IV specifications, using the instruments described in section 4.1. Standard errors are clustered by zip code.

A.2 Instrumental Variables

Our primary variables, EFMP-share of total transactions and the average subsidy across all transactions, are normalized by the total quantity of electric vehicles in a zip*quarter. This creates a structural endogeneity between the error term and the dependent variable, most clear in regressions where the dependent variable is log of total transactions. When constructing an instrument, the relevant exclusion restriction is that the error term is uncorrelated with the instrument. A necessary condition for the exclusion restriction to hold is that contemporaneous quantities in a zip code does not enter the construction of the instrument, either directly or indirectly.

Formally, denoting the number of post-period quarters as T, the quarter in which the EFMP program becomes active as $t*$ and the average number of transactions in zip z in quarter t as $Q_{zt} = \sum_i \mathbf{1}(zip = z, time = t)$, we construct our preferred instrument for EFMP-share as:

$$PreferredIV_{zt} = \frac{\sum_i \mathbf{1}(Subsidy_{izt} > 0, zip = z, time = t)}{\frac{\sum_{r \neq t, r \geq t*} Q_{zr}}{T-1} \frac{\sum_{x \neq z} Q_{xt}}{\sum_{r \geq t*} \sum_{x \neq z} Q_{xr}/T-1}} \tag{18}$$

The numerator of the instrument is identical to the numerator of EFMP-share. On the other hand, the first term in the denominator is the average number of total transactions in zip z in the post period, leaving out the current period. This captures largely cross-sectional variation across zip codes reflecting how many EVs are typically purchased in a location. The second term is the ratio of contemporaneous sales in all other zip codes in the district, to the average sales in all quarters except this one. This largely captures time-series variation with regards to EV sales in the air district. Note that this instrument excludes contemporaneous quantities in a zip code at time t. Absent autocorrelation or spatial correlation of preferences, which would lead contemporaneous quantities in a zip code to be either correlated with the former or latter, respectively.

We also construct three alternative instruments. The first two relax the assumptions of spatial correlation and autocorrelation of preferences, respectively. Formally,

$$AlternativeIV1_{zt} = \frac{\sum_i \mathbf{1}(Subsidy_{izt} > 0, zip = z, time = t)}{\frac{\sum_{r \neq t, r \geq t*} Q_{zr}}{T-1}} \tag{19}$$

$$AlternativeIV2_{zt} = \frac{\sum_i \mathbf{1}(Subsidy_{izt} > 0, zip = z, time = t)}{\frac{\sum_{x \neq z} Q_{xt}}{\sum_{r \geq t*} \sum_{x \neq z} Q_{xr}/T-1}} \tag{20}$$

Alternative IV 1 is identical to our preferred instrument, but excludes the time-series variation provided by average EV sales of other zip in district. If we worry that spatial correlation of sales invalidates our preferred instrument, alternative IV 1 does not rely on contemporaneous sales at all. In a similar fashion, alternative IV 2 excludes the cross-sectional variation provided by the average sales in the zip leaving out contemporaneous sales, allowing for autocorrelation in sales.

Finally, the third alternative instrument is a traditional shift-share instrument, interacting cross-sectional variation in the fraction of households in the zip code below 225% of the federal poverty line with time-series variation in either state-wide EFMP share or state-wide mean EFMP subsidy.

A.3 Backing out an elasticity estimate

The coefficients estimated from the quantity regressions reflect the response of the log of all sales in a zip-quarter to the EFMP program. However, from a policy perspective, we may be interested in two expressions of interest, the percentage change in EV sales from offering a $1000 subsidy and the elasticity of demand, both specifically in relation to the population of EFMP-eligible individuals.

Letting η denote the fraction of EFMP-eligible buyers in a zip-quarter, N the number of buyers, P_0 the "buy price" for non-participants and $P_0 - \beta S$ as the "buy price" for participants, where S is the total value of the subsidy and β is the fraction of the subsidy captured by buyers, we can express the log of quantity as a function of the quantity for a representative eligible consumer, Q_E and an ineligible consumer, Q_I as follows:

$$log(Q_{zt}) = log(N\eta Q_E(P_0 - \beta S) + N(1-\eta)Q_I(P_0)) \tag{21}$$

Our specification regresses the log of quantity against the average subsidy in a quarter-zip (λS). Consequently, the estimated coefficient, ϕ, is an estimate of $\frac{dlogQ}{d\lambda S}$. Noting that $\frac{dS}{d\lambda S} = 1/\lambda$, taking the derivative of $log(Q_{zt})$ with respect to S gives:

$$\lambda\phi = \frac{-\eta\beta N\frac{dQ_E}{dP}}{N\eta Q_E + (1-\eta)Q_I}. \tag{22}$$

Noting that λ is the fraction of transactions that were part of the EFMP program, $\frac{\eta Q_E}{\eta Q_E + (1-\eta)Q_I}$, we can rewrite (22) as the response of the log sales of the EFMP-eligible consumers to a unit change in subsidy S:

$$\frac{dlog(N\eta Q_E)}{dS} = \frac{N\eta\frac{dQ_E}{dP}\beta}{N\eta Q_E(P_0 - \beta S)} = \phi. \tag{23}$$

Rearranging the latter quality, we can characterize the elasticity of demand of EFMP-eligible buyers as:

$$\varepsilon^P_{Q_E} = \frac{\phi}{\beta}P_E. \tag{24}$$