Subsidizing Mass Adoption of Electric Vehicles: Quasi-Experimental Evidence from California

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Abstract

Little is known about demand for EVs in the mass market. In this paper, we exploit a natural experiment that provides variation in large EV subsidies targeted at low- and middle-income households in California. Using transaction-level data, we estimate two important policy parameters using triple differences: the subsidy elasticity of demand for EVs and the rate of subsidy pass-through. Estimates show that demand for EVs amongst low- and middle-income households is price-elastic and pass-through is complete. We use these estimates to calculate the expected subsidy bill required for California to reach its goal of 1.5 million EVs by 2025.

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1 Introduction

Electrification of the vehicle fleet is seen by 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. In the past year, countries announcing plans to ban ICEs sales include France and UK (by 2040), Norway (by 2025), India (by 2030), and China (timetable not set). Germany has announced plans to put 1 million electric vehicles on the road by 2020.[1] In the U.S., California is leading the charge. In 2013, Governor Brown issued an Executive order to put 1.5 million so-called "Zero Emissions Vehicles" (ZEVs) on the road by 2025 (and 5 million by 2030) as part of a goal to reduce transportation emissions by 50 percent by 2030. To spur adoption, policy makers pair these targets with generous subsidy programs. The cost of these programs is considerable. California has spent roughly $400 million on the state-wide vehicle incentives since 2010 and recent proposals seek to allocate another $3 billion in California. Federal incentives for electric vehicles total up to $1.5 billion per manufacturer.

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 also 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, the take-up of which, Borenstein and Davis (2016) notes, is strongly correlated with income. High income households were significantly more likely adopt EVs and claimed the vast majority of associated vehicle incentives. As such, elasticities derived from early adoption may be less relevant for assessing the impacts or costs of policies or targets that require wide-spread

[1] `http://money.cnn.com/2017/09/11/autos/countries-banning-diesel-gas-cars/index.html`, `https://www.theguardian.com/world/2017/sep/11/china-to-ban-production-of-petrol-and-diesel-cars-in-the-near-future`

[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, the chairwoman 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. `http://www.latimes.com/politics/essential/la-pol-ca-essential-politics-updates-california-on-pace-to-meet-goal-of-1-5-1517253069-htmlstory.html`

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 program 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. This allows us 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. We estimate a triple difference model that exploits geographic, temporal and subsidy-exposure variation. We retrieve estimates of two policy-relevant parameters: the rate of subsidy pass-through and the elasticity of demand for EVs among low- to middle-income buyers. The estimated rate of subsidy pass-through is 80 to 100 percent. In all specifications, the estimate is indistinguishable from full passthrough, which coincides with intentions of the program designers. Our preferred triple-difference estimated demand elasticity is -3.9, implying that a subsidy that decreases the buy-price of an EV by 10 percent will increase demand for that EV by 39 percent. While this may seem like a large effect at first glance, the small baseline quantity implies that even a large elasticity translates into a modest number of additional EVs.

Together, and under assumptions about generalizability, these objects can be combined to estimate the magnitude of subsidy funds that would be required to achieve a policy goal along the lines of "put 1.5 million ZEVs on the road". Assuming generalizability of our preferred estimates of the subsidy elasticity and conservative estimates of the baseline (no-subsidy) rate of EV growth in California going forward, we place the likely required subsidy bill at upwards of \$9-\$14 billion for a program that would subsidize new EVs. Two factors may lead California policymakers to consider alternative ways to achieve their ZEV adoption goals. The magnitude of the estimated subsidy bill is large, and significant uncertainty remains about certain key unobservable parameters that may inflate the bill substantially relative to our conservative estimates. Alternative policies such as a mandate or a "feebate" would shift the burden of the policy away from California taxpayers, as would a continuation of the existing federal EV tax credit that is also presently being debated.[4]

While we are encouraged to offer an estimate of the EV demand elasticity in California that is retrieved using quasi-experimental variation, there are several reasons to be cautious about these results. The suitability of these estimates for general use as demand elasticities is imperfect due to concerns about construct validity and unmeasured interactions with existing subsidy policies. On construct validity, one may be concerned that subsidy eligibility under EFMP is linked to having a car to scrap, and also the targeting of marketing efforts (particularly in one of the Air Quality Management Districts). The presence of large federal and state subsidies for new EVs affects the interpretation of our results since many of the new EVs purchased under EFMP also were likely to earn 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 these programs, the extent to which our elasticity estimates that reflect marginal subsidy changes would apply to ranges of prices on the inframargin is an open question.

Notwithstanding these caveats, this paper makes several 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 the key identifying assumption to be tested directly. Specifically, our matched triple-difference approach achieves parallel trends in differences in the pre-period. 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. Third, our estimates of subsidy pass-through contribute to the long literature on incidence. Fourth, we use our elasticity and incidence estimates to offer the first estimate in the literature of the range of subsidies required to meet California's 2025 EV adoption targets. This contributes to an important contemporary policy debate that is likely to be repeated in jurisdictions across the globe in coming years.

The paper proceeds by presenting Institutional Details and Data (Section 2), the Empirical Methodology (Section 3), Results (Section 4), a Policy Discussion (Section 5) and Conclusions (Section 6).

[4] Three proposals currently being considered by the U.S. Congress are discussed here: https://electrek.co/2018/10/16/tesla-federal-tax-credit-electric-car-new-billl-republican/

2 Institutional Details and Data

In this paper, we estimate the effect on electric vehicle sales by the EFMP, 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.[5] The EFMP was initially designed as a retire-and-replace program along the lines of cash-for-clunkers.[6] In April 2015, California Air Resources Board ("ARB") redesigned the program 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"). [7] 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. Over the first two years, the pilot program received $72 million in state funding.[8]

2.1 Subsidy Generosity and Eligibility

The pilot program is restricted to participants residing in the two AQMDs and retiring a qualifying vehicle.[9] Within the AQMD, EFMP targets: (a) households living in or near "disadvantaged" communities and (b) low- and middle-income households at or below 400% of the federal poverty line. The EFMP program rules offer a subsidy that varies in generosity. Table 1 lists the subsidies that we study in this paper, which are available for program participants who trade in their vehicle for an electric vehicle.[10]

A household's eligibility and the generosity of the subsidy depend on three factors: a household's income, location, and the possession of a qualifying trade-in vehicle.[11] A household's income, relative to the federal poverty line ("FPL"), determines the generosity of the incentive.

[5]EFMP also provides subsidies for the purchase of new and used hybrid vehicles and high fuel economy internal combustion vehicles. California also offers direct incentives to private consumers purchasing alternative fuel vehicles through the Clean Vehicle Rebate Program ("CVRP"). CVRP is available state-wide and, until recently, was available to all private buyers of qualified vehicles.

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

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

[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]The EFMP program also offers subsidies of approximately equal magnitude that are available according to slightly different rules and eligibility criteria. These are netted out in our empirical design and are not used to identify our parameters of interest.

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

Households below the 225% of the FPL are eligible for the most generous incentives: $5,000. As household income rises, subsidy generosity declines until a household is no longer eligible for the program, above 400% of the federal poverty line.

Whether a household qualifies for the incentive depends on whether the household resides in a disadvantaged community within a participating AQMD. 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) at the census-tract level.[12] Disadvantaged census tracts with the CES score of 2.0 fall within the *top quartile* of the state-wide CES distribution. Although the CES score (and disadvantaged designation) is defined at the tract level, a household qualifies for the subsidy if it resides in a *zip code that (wholly or partially) contains a disadvantaged census tract*.

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 piloted the EFMP program over 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 both grey and pink would be eligible for the subsidy. Outside of the grey and pink boundaries of the two participating AQMDs and disadvantage zip codes, households would be ineligible.

Figure 2 plots the histogram 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. Roughly 80 percent of the population of the San Joaquin Valley ACMD and South Coast AQMD live in zip codes classified as DACs.

Disadvantaged zip codes also tend to have lower incomes and contain a higher fraction of households with eligible incomes based on the program's means-testing. Figure 3 plots the CDFs of population below 400% of the FPL, as well as program take-up by zip CES score, for the two participating AQMDs. Roughly 85% of household with incomes below 400 percent of the federal poverty line (and possibly eligible for the EFMP program) live in disadvantaged zip codes.

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

2.2 Additional EFMP Implementation Details

The ARB sets general rules for the pilot program, but allows AQMDs latitude with respect to implementation. Each district developed their own outreach program for interested buyer and dealerships and set program rules, within the bounds set by the ARB rule-making. In both South Coast and San Joaquin Valley, the AQMD determines if a participant is eligible for a rebate and, if so, the level of incentives for which he or she is eligible. Dealerships must be "pre-approved" by the AQMD and agree to a set of consumer protections, including "no-haggle" posted prices, limitations on dealership financing, required information provision and inspection for used vehicles.

However, the two programs take different approaches to 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 determined 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 Data and Summary Statistics

We merge three datasets: (1) disadvantaged community designations available from CalEPA, (2) program rebate data and (3) transaction-level data on the universe of new and used EVs purchased by California buyers.

The DAC designations are publicly available at the census tract level.[13] Following the program rules, we map census tracts to zip codes and classify a zip code as disadvantaged if it contains part or all of a disadvantaged census tract. 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 name and location of the dealer that sold the vehicle.

[13] See `https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-version-20`

We summarize transaction counts, prices and subsidies in table 2, breaking out zip codes into whether or not they are in South Coast or San Joaquin Valley (AQMD = 1) and whether they are classified as a disadvantaged zip code by the pilot program (DAC = 1). We also report socioeconomics characteristics of the zip codes.

Roughly half of the population of California resides in the participating AQMDs, of which the majority live in communities classified as disadvantaged for purposes of the AQMD pilot program. Disadvantaged communities tend to be lower income than non-disadvantaged communities - both in and out of the participating AQMDs. The fraction of households living at or below 225% of the poverty line is greater in disadvantaged zip codes than non-disadvantaged zip codes.

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. That said, EFMP transactions are a small fraction of overall EV sales. In disadvantaged communities during the pilot program, roughly two percent of the transactions received an EFMP subsidy.

3 Methodology

The features of EFMP program lend themselves to a triple-differenced specification comparing disadvantaged and non-disadvantaged zip codes, in and out of the two participating AQMDs, before and after the start of the pilot program.[14] Using this framework, we estimate two policy parameters of interest: (1) the incidence of the EFMP subsidies and (2) the elasticity of demand for alternative fuel vehicles, specifically amongst low- and middle-income customers targeted by the EFMP.

3.1 Conditioning on Vehicle Composition

Two empirical challenges influence our triple-difference specification. The first relates to a shortcoming of the publicly-available incentive data. 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

[14] While the discontinuous nature of disadvantaged community assignment might suggest a regression discontinuity design is appropriate, most of the relevant variation occurs well away from the discontinuity. This can be seen in Figure 5.

by electric vehicles purchased by households at the zip-quarter level. As a result, we aggregate our data to the zip-quarter level, the level at which we observe our subsidy data.

After aggregation, the average price of vehicles purchased at the zip-quarter level is driven both by incentives, but also by the composition of vehicles purchased by the households. As the EFMP program offers incentives for households to purchase both new *and used* electric vehicles, we might expect the composition of vehicles to shift in response to the program.[15]

Thus, before we aggregate to the zip-quarter level, we regress transaction-level vehicle prices on 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 vehicle, zip, model, model year and year of purchase as i, z, m, y and t respectively, we regress:

$$SalesPrice_{izmyt} = \alpha_{myt} + \beta_1 Odometer_i + \beta_2 Lease_i + \epsilon_i \tag{1}$$

and average the residuals, ϵ_i, of all purchases within a zip-year-quarter. Formally, denoting N_{zt} as the total number of vehicles sold in zip z and time t, we have

$$ResidualSalesPrice_{zt} = \sum_{i \in z,t} \epsilon_i / N_{zt} \tag{2}$$

In doing so, we condition on the composition of vehicles purchased in a zip-quarter, by comparing the pricing of those vehicles to vehicles of identical make and model year, purchased in the same quarter elsewhere in California. In this context, the interpretation of $ResidualSalesPrice_{zt}$ is whether, for example, dealerships in a particular zip code received more or less than the state-wide average for vehicles of identical make and model-year (e.g., 2015 Nissan Leaf) purchased in the same quarter and year (e.g., first quarter of 2017). Interpretation of the pass-through regressions is a bit more straightforward using the price *buyers paid net of subsidies* as the dependent variables. Thus, we net out the average subsidy in zip z and time t from the sales price to construct our dependent variable:

$$ResidualBuyPrice_{zt} = ResidualSalesPrice_{zt} - \overline{EFMP}_{zt} \tag{3}$$

where $\overline{EFMP}_{zt}$ is the average EFMP subsidy received by all electric vehicles in a zip-quarter.

For quantities, the aggregation is more straightforward. As our dependent variable, we use

[15] In fact, anecdotal evidence supports this—the EFMP 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 which they are purchased, suggestive that they are used, rather than new vehicles. In contrast, 87 percent of all electric vehicles in the transaction data would be classified as used by this definition.

the log of total EV sales at the zip-year-quarter level.

3.2 Matching on Pre-Trends

The second empirical consideration follows from the histograms of CES scores plotted in Figure 2. Although the distributions of CES scores overlap near the DAC threshold, 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. If pre-trends differ for disadvantaged zip codes with extremely high CES scores relative to disadvantaged zip codes outside of the participating AQMDs, our triple difference estimates will be biased.[16]

While we run (and report in the specification tables below) specifications using the full set of zip codes in our data, we also use nearest-neighbor matching to pair zip codes in participating AQMDs with "control" zip codes in non-participating AQMDs. We match based on the pre-period trends in average prices or quantities and force matched zip codes to share disadvantaged status, following the synthetic control literature (e.g. Abadie and Gardeazabal (2003), Abadie et al. (2010)).

Figure 4 plot the mean differences between disadvantaged and non-disadvantaged zip codes, by AQMD over time. In each graph, the red line corresponds to the mean difference for zip codes in the participating AQMDs; the blue line plots the analogous difference for non-participating AQMDs. The top graphs plot the mean differences for residual prices, the bottom graphs plot the mean differences for log quantities. Finally, the left panels of each set graph the unweighted averages of all zip codes. The right panels graph the differences in trends after matching on pre-trends.

Pre-period trends in both the residual prices (after conditioning as described above) and log quantities differ in the overall data. Matching ensures parallel trends in the pre-period. Regardless, for completeness, we report the results using both the matched and unmatched samples in all results tables below and find that, on net, our results are qualitatively similar using either the matched or unmatched samples.

[16]Differential pre-trends amongst non-disadvantaged zip codes would also invalidate the triple-difference specification.

3.3 Specifications

The design of the program lends itself to a triple-difference estimation strategy. A zip code is in treatment status if it resides 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"). The unit of observation in our data is the zip-quarter. That is both the finest level of temporal and spatial disaggregation for which we have subsidy data, and it is also the geographic level of treatment assignment.

We are interested in two sets of policy relevant parameters: (1) the amount of the subsidy that accrues to EFMP participants, and the pass-through of the subsidy, and (2) estimates of the response of demand to the EFMP subsidy.

To retrieve an estimate of the intent-to-treat effect of the former, one could estimate

$$ResidualBuyPrice_{zt} = \alpha_1 \mathbf{1}_D \mathbf{1}_A \mathbf{1}_P + \nu_{tD} + \gamma_z + \epsilon_{zt} \tag{4}$$

where $\mathbf{1}_D$, $\mathbf{1}_A$ and $\mathbf{1}_P$ are indicators for AQMD=1, DAC=1, and Post=1, respectively. Zip code and DAC-by-quarter-by-year effects are conditioned out via γ_z and ν_{tD}. The coefficient α_1 will reflect the intent-to-treat estimate—the average decrease in the residual buy price for all buyers residing in a treated zip code.

The magnitude of α_1 will depend mechanically on the proportion of EV transactions that receive the EFMP subsidy. As noted in table 2, only two percent of EV sales receive the EV subsidy in treated zip codes. Thus, we anticipate the intent-to-treat estimates to be very small as they reflect the average of a few treated transactions with many transactions for which the subsidy was not claimed. Thus, we construct a continuous treatment variable, λ_{zt}, to be the fraction of EV purchases that receive an EFMP subsidy in each zip-quarter.

$$\lambda_{zt} = \frac{\sum_i \mathbf{1}(Subsidy_{izt} > 0, zip = z, time = t)}{\sum_i \mathbf{1}(zip = z, time = t)} \tag{5}$$

Using λ_{zt} as a continuous treatment in place of the treatment dummy in (4), we estimate the treatment-on-treated, β_1. Intuitively, one may think of this as a continuous treatment that scales up the intent-to-treat estimate α_1 to reflect that λ_{zt} fraction the transactions in each zip-quarter are affected by the EFMP program.

$$ResidualBuyPrice_{zt} = \beta_1 \lambda_{zt} + \nu_{tD} + \gamma_z + \epsilon_{zt} \tag{6}$$

The estimate of the treatment-on-treated measures the change in the price paid for vehicles by recipients of the EFMP subsidy, relative to buyers of the same model and vintage who did not receive the EFMP subsidy.[17]

Cost effectiveness of the program is determined in part by the extent to which the subsidy affects the price paid by the consumer. Upstream manufacturers and dealers may be able to capture some of the incentive, thus resulting in incomplete pass-through. We can estimate pass-through directly via the following equation:

$$ResidualBuyPrice_{zt} = \gamma_1 \overline{EFMP}_{zt} + \nu_{tD} + \gamma_z + \epsilon_{zt} \tag{7}$$

where, as above, the average EFMP subsidy received by all electric vehicles in a zip-quarter is denoted $\overline{EFMP}_{zt}$.

Here, we can interpret the coefficient γ_1 as the fraction of the subsidy captured by recipients of the EFMP program (as opposed to the dealerships), i.e. the pass-through of the subsidy to consumer prices. These estimates also serve as a check on results from equation (6). We use similar specifications to estimate the response of demand to the program. We replace $ResidualBuyPrice_{zt}$ with the $logQ_{zt}$ as the dependent variable in equations (6) and (7) above.

3.4 Instrumental Variables and Endogeneity

In the purchase data, we do not observe in which transactions subsidies were applied. Hence, our primary variables of interest is the EFMP-share of total transactions and the average subsidy across all transactions. Both are constructed by normalizing by the total quantity of electric vehicles in a zip*quarter. This creates a structural endogeneity between the error term and the dependent variable, especially clear in regressions where the dependent variable is a log-quantity. As total transactions are the denominator of our variables of interest, we would expect the OLS coefficient to be biased downward in log-quantity regressions.

We address this by constructing an instrument for the EFMP-share (and an analogous instrument for average subsidies). We instrument for EFMP-share using the count of EFMP transactions in zip z at time t, normalized by average total number of transactions in that zip in all quarters except the current one, scaled by the ratio of sales in all other zips in AQMD*DAC in the current time period relative to others. Formally, denoting the number of post-period quar-

[17]By construction, the average residual buy price in a zip-quarter is given by, $ResidualBuyPrice_{zt} = \lambda_{zt}(P_0 - S) + (1 - \lambda_{zt})P_0 = P_0 - \lambda_{zt}S$, where P_0 and S denote the price paid by non-recipients and the dollar value of the subsidy received by the EFMP recipient. Estimating 6, β_1 provides an estimate of S.

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

$$IV_{zt} = \frac{\sum_i \mathbf{1}(Subsidy_{izt} > 0, zip = z,\, time = t)}{\frac{\sum_{r \neq t, r \geq t*} Q_{zr}}{T-1} \frac{\sum_{x \neq z} Q_{xt}}{\sum_{r \geq t*} \sum_{x \neq z} Q_{xr}/T-1}} \tag{8}$$

The numerator of the instrument is identical to that of EFMP-share. However, the denominator is constructed as a proxy for the total number of transactions in zip z at time t. The first term in the denominator is the average number of total transactions in zip z in the post period, leaving out the current time period. Absent autocorrelation in sales, this breaks the structural endogeneity arising from the total number of transactions entering both the dependent variable and the the denominator of EFMP share. As the average in all other periods is an imperfect proxy for contemporaneous transactions, we scale first term by the relative sales in all other zip codes in that period that share DAC and AQMD with zip code z.[18]

4 Results

Table 3 displays results from equation 6. The first two columns present the OLS results for the unmatched and matched samples. Columns 3 and 4 present IV results for the unmatched and matched samples using the preferred instruments. Columns 5, 6 and 7 present results for the matched sample using alternative instruments, described further in the appendix.[19]

Our OLS results suggest that buyers with the subsidy pay \$3,439 to \$4,042 less for a vehicle, net of the subsidy, relative to non-participants purchasing the same make, model and model-year elsewhere in California. After instrumenting, the effect on prices rises modestly. We estimate EFMP subsidies reduce the price to the buyer, net of subsidies, by an average of \$4,379 to \$4,992. While there is roughly a fifteen percent difference between the unmatched estimates and the estimates using the matched samples. These differences are not statistically significant. We thus conclude that the EFMP program is successful in reducing the price paid by buyers of EVs.

[18] We also explore three alternative instruments described in further detail in the appendix: (1) EFMP transactions normalized by the average total transactions in the zip code, leaving out the current period, (2) the average number of transactions in all other zips that share DAC and AQMD status in that quarter, and (3) a shift-share instrument that interacts cross-sectional variation in the fraction of the population below 225% of the poverty line with time-series variation in total state-wide EFMP transactions.

[19] Column 5 presents the IV results normalizing EFMP transactions by the average of the states own sales, in different periods. Column 6 presents the instrument that uses transactions in all other zips sharing DAC and AQMD with zip z. Finally. column 7 presents the results of shift-share IV using cross-sectional variation in the fraction of the households below 225% of the poverty line (the means-testing cutoff for the most generous EFMP incentives) interacted with time-series variation in total EFMP transactions state-wide.

The rate of subsidy pass-through is high, between 70 to 80 percent in the OLS specifications, although both estimates are indistinguishable from full pass-through. As above, the coefficients are slightly higher in the IV regressions, again suggesting that consumers capture the lion's share of the subsidy. This reflects stated efforts on the part of program designers who sought to channel most of the subsidy dollars to buyers rather than sellers or upstream market participants. Our pass-through estimates are consistent with previous work examining the pass-through of earlier hybrid vehicles subsidies. Gulati et al. (2017) finds that new vehicle buyers with access to subsidies capture 80 to 90 percent of the value of an incentive. However, 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. Thus, our estimates likely reflect something close to true pass-through, even though we cannot directly observe options packages.

Table 4 shows the effect of the EFMP subsidies on the quantity of EVs transacted. We condition our sample on zips for which there is ever a non-zero number of EVs transacted, and create a balanced panel of transaction counts that includes zeros. As with the price regressions, we present OLS estimates in columns 1 and 2, and IV results in columns 3 through 7.

Coefficients should be interpreted as zip-level percentage changes in quantity resulting from EFMP program exposure moving from zero to 100 percent eligibility. Zip codes in treatment status with full eligibility experience, on average, a 35 to 43 percent ($= 100x(exp(0.30) - 1)$) increase in the quantity of new EVs purchased relative to zip codes with zero program eligibility.

As we note in the discussion of the instrument above, the structural endogeneity created by total quantity appearing on both the right and left-hand sides would bias downwards the OLS estimate of EFMP on sales. The IV results in columns 3 and 4 confirm this. The preferred IV point estimates are more than double the OLS estimates, at .72 to .76 log-points for the unmatched and matched samples, respectively. The point estimates are higher for the shift-share IV, although in this case, the coefficients are less precisely estimated due to the weaker first-stage of the instrument.

4.1 Elasticities

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:

$$log(Q_{zt}) = log(N\eta Q_E(P_0 - \beta S) + N(1-\eta)Q_I(P_0)) \tag{9}$$

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:

$$\lambda\phi = \frac{-\eta\beta N\frac{dQ_E}{dP}}{N\eta Q_E + (1-\eta)Q_I}. \tag{10}$$

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 (10) as the response of the log sales of the EFMP-eligible consumers to a unit change in subsidy S:

$$\frac{dlog(N\eta Q_E)}{dS} = \frac{N\eta\frac{dQ_E}{dP}\beta}{N\eta Q_E(P_0 - \beta S)} = \phi. \tag{11}$$

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

$$\varepsilon^P_{Q_E} = \frac{\phi}{\beta}P_E. \tag{12}$$

Inserting estimates of pass-through (79%) and the impact of a $1,000 subsidy (0.073) from column 6 of Tables 3 and 4, and the average price of eligible vehicles in EFMP locations, we have an estimate of the elasticity of demand for EFMP-eligible buyers, $\varepsilon^P_{Q_E} \approx -\frac{0.073}{0.79} * 26 = -2.4$. Using the preferred IV coefficients, the elasticity of demand for EFMP-eligible buyers rises to -3.9.

4.2 Supplementary Results

4.2.1 Effects by Air District

We do not separately estimate the effects by AQMD in our main results. Yet, program rules allow each air district flexibility in the operation of the pilot program. Although ARB rules specify the incentive generosity schedule and set general guidelines related to dealership participation, the districts choose to how to market the program, handle applications and coordinate with participating dealerships.

The program in South Coast operates largely through online presence, with relative modest targeted marketing. Interested consumers apply on-line at which time the air district verifies that they have a eligible trade-in. After being pre-approved, they contact a participating dealership and select a vehicle. The air district then confirms that the vehicle is eligible for the incentive (i.e., not subject to recalls), that the financing meets program requirements, and that the household has not participated in the program previously. If approved, the air district contacts the dealership and the transaction is completed, with the buyer paying the price of the vehicle less the EFMP incentive.

In contrast, the program in San Joaquin engages in direct marketing to low-income and minority households. During the study period, entry into the program occurred exclusively through in-person attendance at local "Tune-in, Tune-up" smog testing events.[20] "Tune-in, Tune-up" events occur every couple of weeks, and rotate between regional population centers in the San Joaquin Valley. 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 follow up with potentialy applicants to help them complete their application. Once pre-approved, households are directed to dealership websites, all of which are required to post "no-haggle" prices (e.g., Carmax). Pending approval of a final selection by the air district, the transaction is completed and, as in South Coast, the buyer pays the price of the vehicle less the EFMP incentive.

Table 5 present the results allowing the coefficients of interest to vary by air district. The four left-most columns report the OLS and IV results for prices, and the four right-most columns report the OLS and IV results for log quantities. All specifications are based on the matched samples.[21]

[20] Since the end of the study period, program officials in the San Joaquin Valley have begun to take online applications.
[21] Appendix table A1 report the IV results for the unmatched and matched specifications.

When disaggregating by AQMD, the average treatment effect on price is larger in San Joaquin Valley than in South Coast. These differences may reflect the greater guidance towards "no-haggle" dealerships with posted online prices given to program participants in the San Joaquin Valley. However, the differences are not large enough in magnitude to be statistically distinguishable. Likewise, point estimates for pass-through rates are higher in both the OLS and IV specifications for San Joaquin Valley, although again, the point estimates are not statistically distinguishable across the two regions, nor are individual pass-through estimates statistically distinguishable from complete pass-through of the subsidies to buyers.

Columns 5 through 8 present the results for EV sales. Here, the point estimates for the effect on sales is slightly higher for South Coast compared to San Joaquin Valley. We estimate each $1,000 in subsidy treatments increases EV adoption by 19 and 14 percent in South Coast and San Joaquin Valley respectively, although as with prices, the differences are not large enough to be statistically distinguishable. The relative magntitude of the point estimates is consistent with the more restrictive nature of the program in San Joaquin Valley, where participation in the program required in-person attendance at local events, in addition to all other program requirements.

4.2.2 Price Effect on Non-Participants

An implicit assumption in the analysis above is that the EFMP does not affect the price paid by individuals living in the program areas who were not eligible through, for example the program acting as a shock to aggregate demand. Put formally and ignoring fixed effects for simplicity, the mean residual buy price, by construct, is an average of the price for recipients (fraction λ_{zt}) and non-recipients (fraction 1 - λ_{zt}). Denoting the price for non-recipients, P_0 and the dollar value of the subsidy captured by a recipient, we can denote the average price as:

$$ResidualBuyPrice_{zt} = \lambda_{zt}(P_0(\lambda_{zt}) - S) + (1 - \lambda_{zt})P_0(\lambda_{zt}) = P_0(\lambda_{zt}) - \lambda_{zt}S. \tag{13}$$

If we regress $ResidualBuyPrice_{zt}$ on a constant and λ_{zt}, as in:

$$ResidualBuyPrice_{zt} = \alpha + \hat{\beta}_1\lambda_{zt} + \nu_{zt}, \tag{14}$$

we introduce omitted variable bias if $\frac{dP_0(\lambda_{zt})}{d\lambda_{zt}} \neq 0$. If the policy increases the price of EVs purchased by non-participants, our specification would provide an overestimate of the true rate of pass-through.

In our empirical context, though, two points suggest that the relationship between P_0 and λ is unlikely to significantly bias our estimates of pass-through and the amount of the subsidy captured by the consumer. First, the fraction of buyers who receive the EFMP is small—in "treated" zips, two percent of vehicles on average receive an EFMP subsidy. Second, our level of analysis is at the zip-quarter level. So, the correlation that we would have to be concerned about would have to be one between the fraction of buyers in the zip who receive EFMP and the price paid by buyers from that zip who didn not receive the subsidy. However, the zip codes themselves are not isolated markets. Rather, these markets are part of large metro areas across which people purchase vehicles. More broadly, vehicles commonly flow between metro areas in response to local supply and demand conditions. 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.

Yet, the triple-differenced nature of our empirical strategy allows us to test for such spillover effects by examining the effect of EFMP-induced demand increases in treated zip codes on prices in zip codes outside the participating air quality districts. We implement this by restricting the sample to sales outside the participating regions and collapsing the data to quarter-of-sample by make/model-year observations, then regressing the average residual sales price on the share of vehicles purchased under the EFMP. Conceptually, our strategy compares average prices for make/model-years 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.

$$P^{MMY}_{t,AQMD=0} = \alpha s^{MMY}_t + X^{MMY}_t + \epsilon^{MMY}_t \tag{15}$$

In equation 15, MMY differentiates vehicles based on make and model-year, and the quarter-of-sample is denoted by t. The coefficient of interest is α, which will be positive if the statewide share of MMY cars sold under the EFMP program increases the price of those cars in non-participating regions.

We find that a small but statistically significant effect exists. The change in s^{MMY}_t 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 3 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 Policy Discussion

Estimates of the demand elasticity and rate of subsidy pass-through are important policy parameters. For example, the state of California is currently early in the legislative process that will determine the next allocation of state EV rebate funds intended to push the state across the target goal of 1.5 million EVs on the road by 2025. The demand elasticity and rate of pass-through are central to the question of how much funding would be required to achieve this goal. To be clear, there are several policies that reduce the retail price of EVs, including federal tax incentives, state consumer subsidies and supply-side policies like California's ZEV mandate, only some of which impose a direct fiscal cost on the state budget of California. As it is difficult to predict the exact form of state and federal subsidies in the future, we present some rough, back-of-the-envelope calculations meant to capture the total cost across all subsidies.

By the end of 2017 there were roughly 330,000 EVs on the road in California. The subsidy-inclusive growth rate in the California EV fleet can be retrieved directly from the data and was over 80 percent in 2014 and has steadily declined to 33 percent in 2017. In order to reach 1.5 million EVs in California by 2025, a 20.8 percent annual growth rate from 2018-2025 is required, after taking scrappage into account.[22] In order to estimate the subsidy bill required to reach 1.5 million EVs by 2025, it is necessary first to establish a no-subsidy baseline growth rate that would be expected to occur from 2018 - 2025 in the absence of subsidies. Using our elasticity estimates, we then calculate how much the purchase price of EVs would have to decline to shift from the no-subsidy baseline growth rate to the necessary 20.8 percent average growth rate.

The baseline rate of EV demand growth is a function of factors such as consumer preferences, relative prices and attributes of vehicles (e.g. battery range), the price of fuel inputs

[22] The rate of used EVs exported to other states/countries, totaled in accidents, or scrapped due to old age or lack of use are each important determinants of the number of EVs that will, at any point, be on the road.

(gasoline versus electricity), macroeconomic and credit conditions, and potentially myriad other considerations. These growth rates have been influenced by the presence of major subsidy programs, both federally and at the state level. In order to net out these subsidies and retrieve a no-subsidy baseline growth rate, we proceed under several conservative assumptions.[23] We assume a retrospective average new EV price of $35,000, and $10,000 in cumulative state and federal subsidies captured by consumers. Based on the preferred demand elasticity of -3.9 from out empirical estimates, we estimate that no-subsidy growth rates in 2015, 2016 and 2017 of 28.9, 21.7 and 18.6 percent, respectively, reflecting the growth rate if state and federal incentives had not been offered. Based on the historical pattern of new technology adoption, one would expect that the growth rate will continue to decrease over time as the market becomes more saturated. Therefore, we conjecture that a baseline growth rate between 2018 and 2025 of roughly 12 to 14 percent is conservative (again in the sense that it is likely even lower, which would lead to even higher estimates of the subsidy requirement)

Projecting forward, we need to make further assumptions about the vehicles purchased under a subsidy program and the rate at which on-road EVs exit the California fleet, either through accidents, exports out of California or scrappage. The subsidy program that we project is broadly consistent with the major existing subsidy programs – the California CVRP and the U.S. federal EV tax credit. Both of these programs offer subsidies for new EV purchases. To align this thought exercise most closely to our empirical results, we assume the going-forward (2018-2025) price of new EVs declines to approximately $26,000, which is the weighted average price received by sellers for the mix of vehicles purchased under the EFMP program. An average sale price of $26,000 is consistent with industry projections for entry-level EV models. We assume that 10 percent of the EV stock will be retired each year starting in 2020, capturing vehicle retirements, accidents and exports to other states and countries. If instead we were to consider an program that only applies to new vehicle purchases, similar to CVRP, the base prices of vehicles would be higher, implying that greater subsidies would be required. In addition, used vehicles (lacking any incentive) would be more likely to be exported out of state, implying a higher retirement rate. Both of these would tend to increase the total subsidy budget required to reach the 1.5 million EV goal.

Based on the number of EV sales predicted to occur under such conditions, there is an implied shortfall of EVs that the subsidies are intended to address. Table 6 presents the implied

[23]Throughout this section, "conservative" is intended to describe an assumption that will lead to an under-estimate of the implied subsidy bill to achieve 1.5 million EVs by 2025. For example, a "conservative" assumption would lead to a higher baseline growth rate, thus reducing the subsidy bill requirement.

total value of EV subsidies that would be required for California to have 1.5 million EVs on the road by 2025.[24] The table presents the subsidy bill estimates for various assumed levels of baseline growth in the EV stock. We present baseline growth rates in the range of 8 to 14 percent between 2018-2025. The implied required change in buy-price is retrieved by assuming a list price of $26,000 per EV and applying estimates of the subsidy elasticity of demand to the implied required percent change in quantity.

The results in Table 6 reflect total subsidy bills implied by combinations of baseline growth assumptions and subsidy elasticities of demand. Moving left-to-right, the columns assume higher baseline growth rates. Given the rate of historical decline in growth (which is natural in rapidly-growing markets), an expected annual growth rate of 12-14 percent from 2018-2025 seems to us to be plausible and even optimistic. Moving from top-to-bottom in the table, the demand elasticities are increasing. The top row elasticity of -2.4 reflects the OLS estimate. Our preferred elasticity is -3.9, which comes from estimates using our preferred instruments. The bottom row uses the elasticity implied by the shift-share IV point estimates. Recall that these were very imprecisely estimated and cannot be statistically distinguished from our preferred estimate. Nonetheless, we present it for completeness.

Moving from lower baseline growth rates to higher baseline growth rates, the necessary change in the price of new EVs and the cumulative subsidy bill decline. With higher baseline growth rates, less of a policy intervention is required to achieve target EV adoption goals. The implied change in prices and subsidy bill also decline if we assume that demand is more elastic over 2018 - 2025. If demand is more elastic, a subsidy of a given value has a greater impact on the rate of EV adoption, all else equal.

Together, these estimates reflect a high degree of uncertainty around the eventual subsidy requirement, but the most realistic range in our view – using our preferred elasticity estimate and corresponding to 12-14 percent growth – is $9 to $14 billion dollars. It is important to note that the presence of federal subsidies (including implicit subsidies such as the ZEV mandate) would reduce the amount for which California would be directly responsible. These estimates scale up significantly with more pessimistic realizations of demand elasticity and growth rates. For example, at an elasticity of -2.4 and a baseline growth rate of 12 percent, the subsidy requirement exceeds $22 billion.[25] On the other hand, if the demand elasticity is much higher, as in the bottom row of Table 6, the required subsidy bill will scale down significantly. Similarly, if

[24] A detailed description of the methodology used for these estimates can be found in Appendix section A.4.

[25] Note that our calculations hold the demand elasticity constant throughout the forecast period, which is another conservative assumption. As the size of the EV fleet grows, the demand elasticity is likely to decline as percentage changes in quantity imply an ever-growing increase in the number of subsidy-induced EV sales.

the baseline growth rate is higher than what we have assumed, the required subsidy bill would be lower for any given assumptions about the demand elasticity.

6 Conclusion

In this paper we exploit a natural experiment that arises from rules governing the availability of EV subsidies in California to estimate the elasticity of demand for EVs among low- to middle-income households. Using a unique dataset of both transaction prices and subsidy levels, we are also able to estimate the rate of subsidy pass-through. 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 Program subsidies were (until recently) available to any EV buyer in their jurisdiction, making it difficult to construct a credible control group.

The rules governing the EFMP Plus Up program in California are well suited to deploying a triple-difference methodology in program evaluation. When we do, we estimate a subsidy elasticity of EV demand of -3.9, and a subsidy pass-through rate of 80-100 percent. Assuming that these statistics are generalizable, we use them, under strong assumptions, to estimate the cumulative amount of additional subsidy dollars that will be required for California to meet its goal of having 1.5 million EVs on the road by 2025. Depending on the assumed baseline (no-subsidy) growth rate, our estimates lead us to believe that roughly \$9 - \$14 billion in total subsidies will be required.

One contribution of this paper is the relevance of our estimates to low- and middle-income households. While most EVs to date are owned by wealthy households, mass electrification of the transportation sector will require adoption in the mass market. The means-testing and geographic targeting of the EFMP allow a rare opportunity to study the adoption decisions of low- and middle-income buyers, whose demand and price sensitivity may be lower than those of high income households. One instructive comparison is to benchmark our elasticity estimate of -3.9 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. As a result, historical evidence of the effect of subsidies obtained by early adopters may prove a poor guide for policies requiring mass market adoption.

There are other 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)), there is widespread lack of awareness of EV technology or capabilities (see, e.g., Egbue and Long (2012), Krause et al. (2013)) and consumers often fail to think about fuel prices in a systematic way (Turrentine and Kurani (2007)). EVs take hours to charge, and charging infrastructure will need to expand dramatically to meet the demand of a larger EV fleet. 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 vehicle charging demand.

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

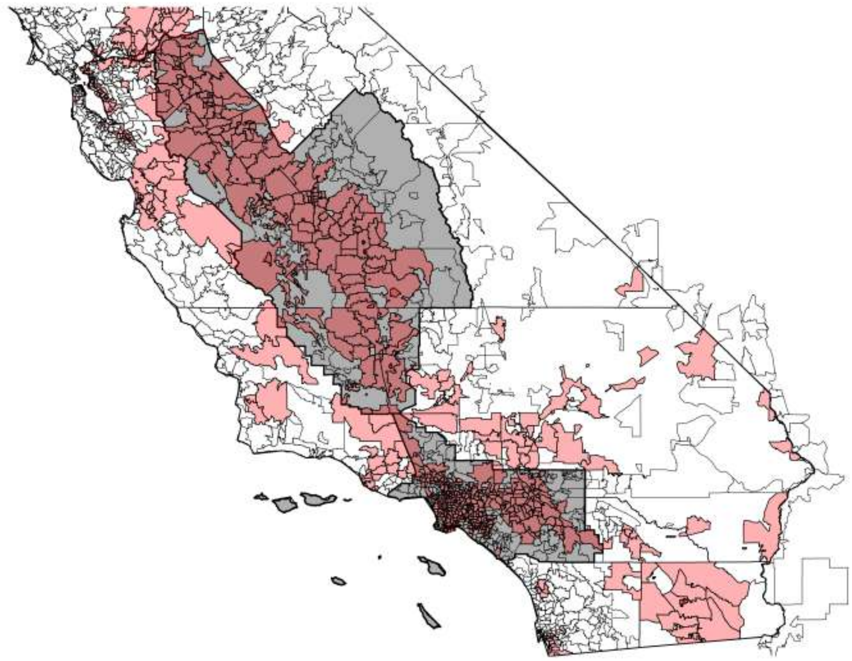


Figure 2: Average Income and Max-CES Score

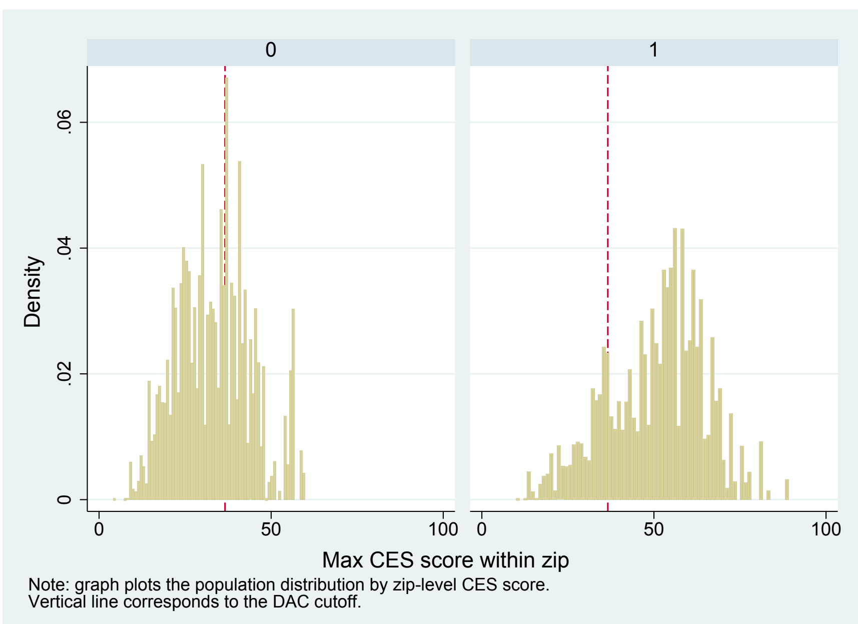
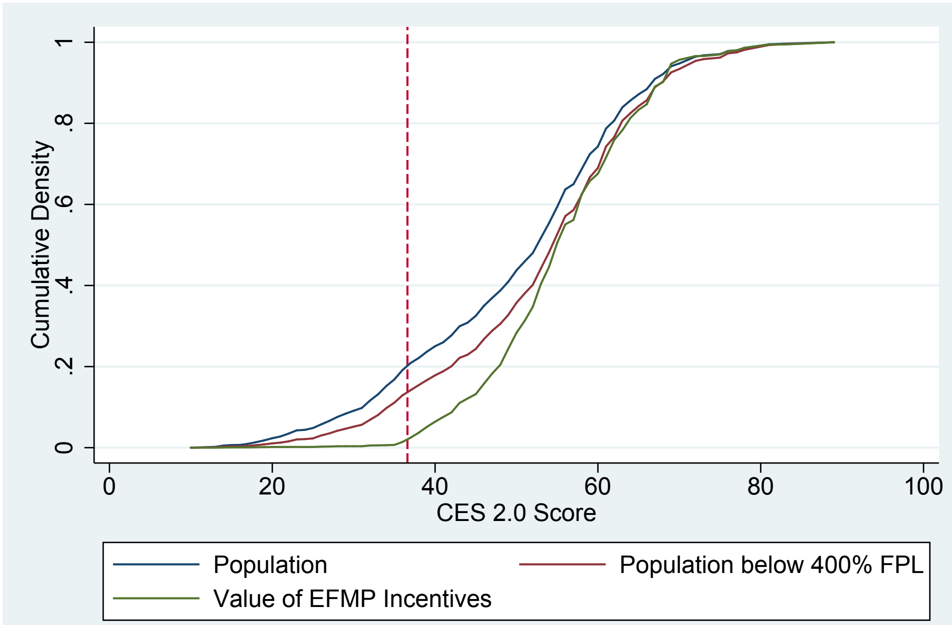
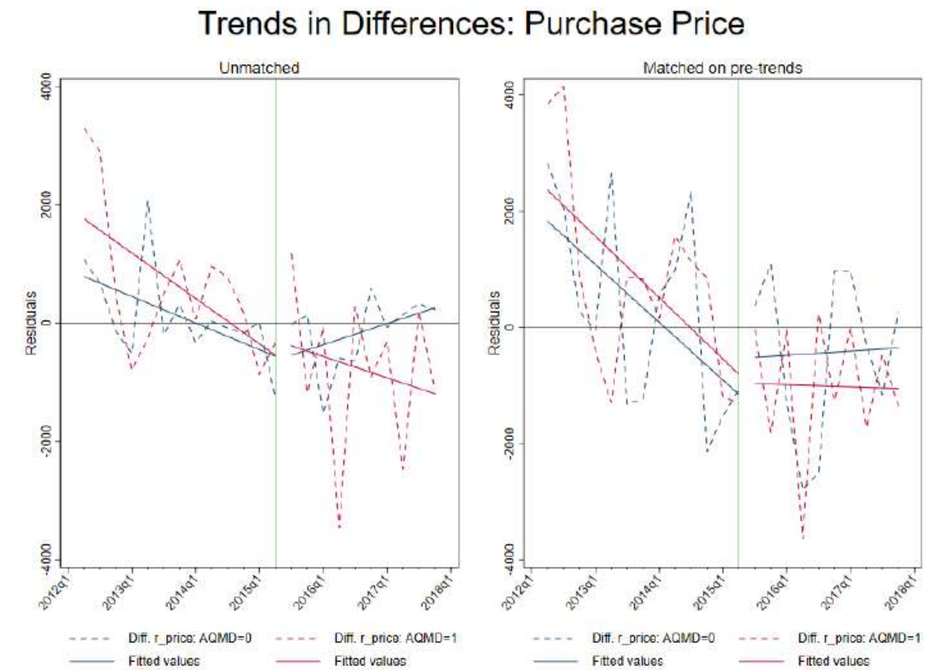


Figure 3: Population and Subsidies by Max-CES Score

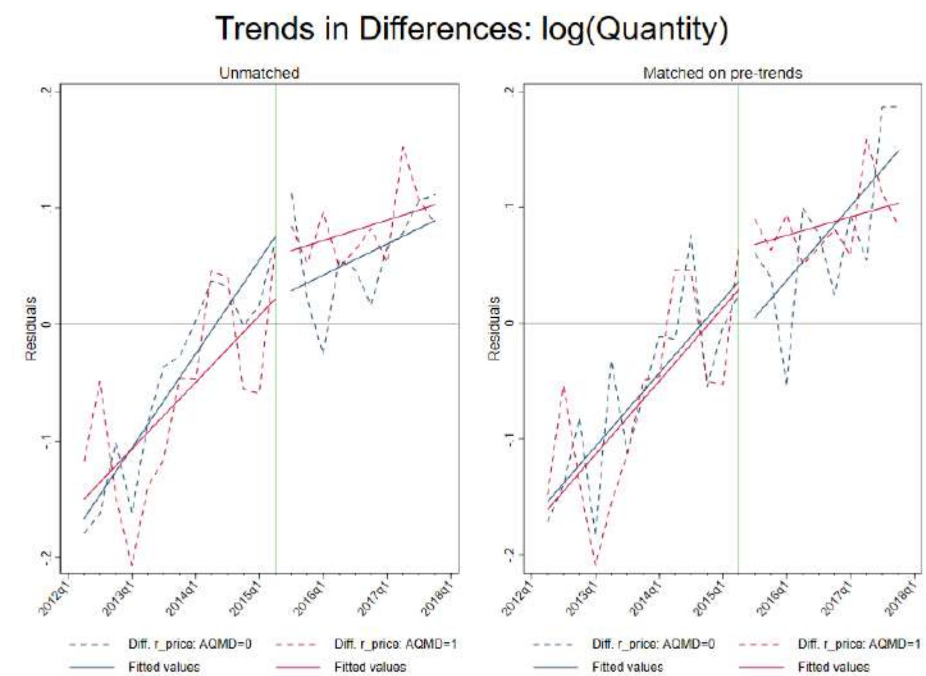


Note: The graph plots the cumulative distributions of population, population below 400% of FPL, Value of EFMP incentives within AQMD==1.

Figure 4: Matched and Unmatched Pre-Trends, Residual Prices



Note: Red lines correspond to zip codes in SCAQMD and SJV. Blue lines correspond to other CA zip codes.



Note: Red lines correspond to zip codes in SCAQMD and SJV. Blue lines correspond to other CA zip codes.

Figure 5: Sales and Average Subsidies, by CES Score

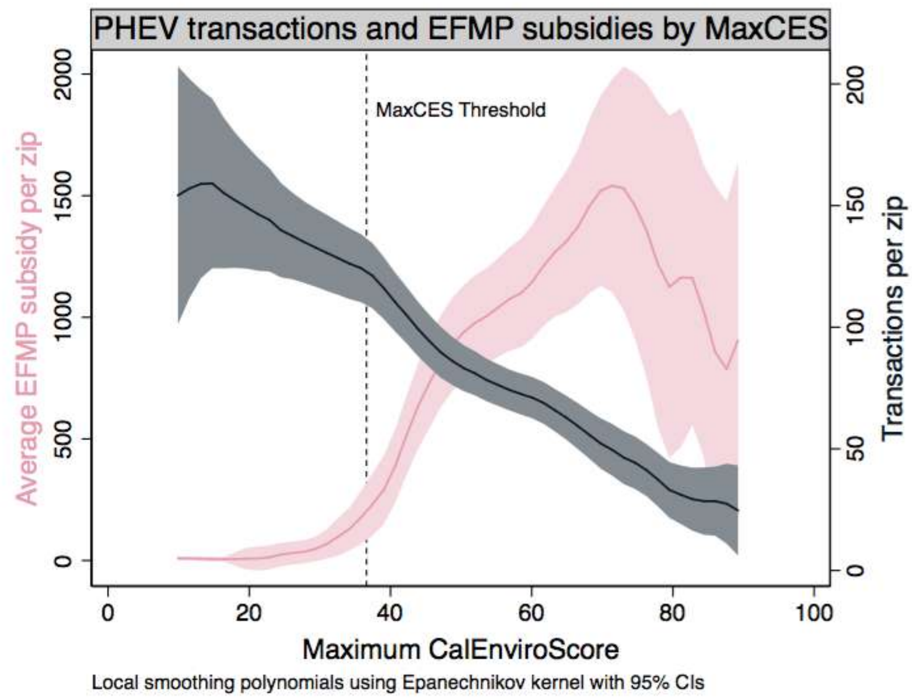


Table 1: EFMP Incentive Schedule for BEVs and PHEVs

Income	Subsidy
$<$ 225% FPL	$5,000
225-300% FPL	$4,000
300-400% FPL	$3,000

Table 2: Summary Statistics

	Non-participating AQMDs		Participating AQMDs (South Coast/San Joaquin)	
	non-DAC	DAC	non-DAC	DAC
Panel A: Subsidy and Transaction Data				
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	5.729	3.971	7.916	2.345
EV Sales Per Capita (per 000 pop), Post	8.075	4.390	11.38	3.789
Count of EFMP EV trans., Pre	0	0	0	0
Count of EFMP EV trans., Post	0	0	29	1330
EFMP Frac. of Sales, Pre	0	0	0	0
EFMP Frac. of Sales, Post	0	0	0.000640	0.0209
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
Mean Subsidy ($), Pre	0	0	0	0
Mean Subsidy ($), Post	0	0	2.008	191.2
Panel B: Zip-level Covariates				
Frac. HHs $<$ 225% of FPL	0.332	0.423	0.271	0.466
Frac. HHs 225-300% of FPL	0.109	0.123	0.0932	0.125
Frac. HHs 300-400% of FPL	0.116	0.115	0.111	0.114
Frac. zips in SCAQMD	0	0	0.860	0.684
Population (MMs)	10.61	6.798	3.983	16.81

Table 3: Pass-Through and EFMP Incentives

	OLS		Preferred IV		Alternative IVs		
	(1) Unmatched	(2) Matched	(3) Unmatched	(4) Matched	(5) IV2	(6) IV3	(7) IV4
% EFMP Transactions	-3439.2**	-4042.2**	-4378.9***	-4992.2***	-4873.9***	-5198.3***	-2995.9
	(1342.4)	(1601.3)	(1081.6)	(1267.9)	(1342.0)	(940.0)	(4619.3)
Observations	25139	22600	25139	22600	22600	22600	22600
R-Squared	0.13	0.11	0.0012	0.0020	0.0020	0.0019	0.0019

	OLS		Preferred IV		Alternative IVs		
	(1) Unmatched	(2) Matched	(3) Unmatched	(4) Matched	(5) IV2	(6) IV3	(7) IV4
Avg. PU Subsidy	-0.70**	-0.79**	-0.89***	-0.99***	-0.97***	-1.05***	-0.58
	(0.28)	(0.32)	(0.22)	(0.25)	(0.27)	(0.19)	(0.95)
Observations	25139	22600	25139	22600	22600	22600	22600
R-Squared	0.13	0.11	0.0012	0.0018	0.0018	0.0017	0.0018

Dependent variable is average residual price in a zip*quarter, after conditioning on Make*Model*Model-year*Year of Sale fixed effects. Standard errors are clustered by zip code. Columns 1 and 2 are OLS unmatched and matched regressions, respectively. Columns 3 and 4 replace columns 1 and 2 using our preferred instrument. Column 5 presents the IV results normalizing EFMP transactions by the average of the states own sales, in different periods. Column 6 presents the instrument that uses transactions in all other zip codes sharing DAC and AQMD with zip code z. Finally. column 7 presents the results of shift-share IV using cross-sectional variation in the fraction of the households below 225% of the poverty line (the means-testing cutoff for the most generous EFMP incentives) interacted with time- series variation in total EFMP transactions state-wide.

Table 4: EV Sales and EFMP Incentives

	OLS		Preferred IV		Alternative IVs		
	(1) Unmatched	(2) Matched	(3) Unmatched	(4) Matched	(5) IV2	(6) IV3	(7) IV4
% EFMP Transactions	0.30***	0.36***	0.72***	0.76***	0.77***	1.31***	1.44*
	(0.059)	(0.067)	(0.097)	(0.12)	(0.12)	(0.12)	(0.80)
Observations	34477	27554	34477	27554	27554	27554	27554
R-Squared	0.90	0.89	-0.0010	-0.00032	-0.00041	-0.0088	-0.012

	OLS		Preferred IV		Alternative IVs		
	(1) Unmatched	(2) Matched	(3) Unmatched	(4) Matched	(5) IV2	(6) IV3	(7) IV4
Avg. PU Subsidy	0.063***	0.073***	0.15***	0.15***	0.15***	0.26***	0.30*
	(0.012)	(0.014)	(0.020)	(0.024)	(0.025)	(0.024)	(0.16)
Observations	34477	27554	34477	27554	27554	27554	27554
R-Squared	0.90	0.89	-0.00088	-0.00026	-0.00033	-0.0086	-0.013

Dependent variable is the log of the count of EV sales in a zip*quarter, after conditioning on Make*Model*Model-year*Year of Sale fixed effects. Standard errors are clustered by zip code. Columns 1 and 2 are OLS unmatched and matched regressions, respectively. Columns 3 and 4 replace columns 1 and 2 using our preferred instrument. Column 5 presents the IV results normalizing EFMP transactions by the average of the states own sales, in different periods. Column 6 presents the instrument that uses transactions in all other zip codes sharing DAC and AQMD with zip code z. Finally. column 7 presents the results of shift-share IV using cross-sectional variation in the fraction of the households below 225% of the poverty line (the means-testing cutoff for the most generous EFMP incentives) interacted with time-series variation in total EFMP transactions state-wide.

Table 5: Results by Air District

	DepVar = Price				Dep Var = Log Q			
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
% EFMP * South Coast	-3265.7	-3909.5**			0.46***	0.93**		
	(2472.9)	(1871.5)			(0.17)	(0.44)		
% EFMP * San Joaquin	-4342.0**	-5391.2***			0.33***	0.71***		
	(1984.9)	(1578.1)			(0.068)	(0.089)		
Avg. PU Subs. * South Coast			-0.63	-0.79**			0.095***	0.19**
			(0.51)	(0.38)			(0.035)	(0.094)
Avg. PU Subs. * San Joaquin			-0.85**	-1.06***			0.068***	0.14***
			(0.40)	(0.31)			(0.014)	(0.018)
Observations	22600	22600	22600	22600	27554	27554	27554	27554
R-Squared	0.11	0.0020	0.11	0.0018	0.89	-0.00032	0.89	-0.00026

The dependent variables in columns 1 through 4 and columns 5 through 8 are average residual prices and log quantities respectively. Odd-numbered columns report the OLS results. Even-numbered columns report IV results using the preferred instruments. All specifications are based on the matched sample. Standard errors are clustered at the zip code.

Table 6: Estimated CA Subsidy Required to Meet 1.5Million ZEV by 2025 Goal

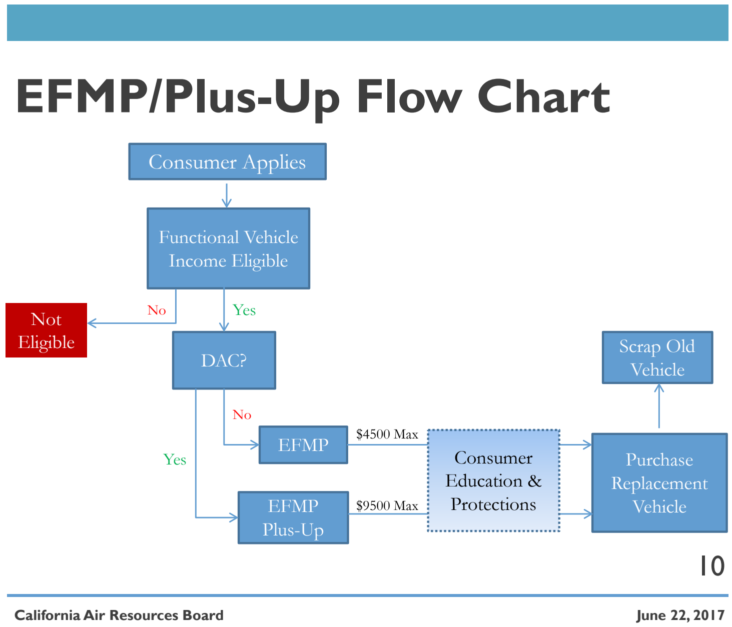
	Baseline Growth Rate in EVs (2018-2025)			
	10%	12%	14%	16%
Elasticity = 2.4				
Implied required change in Buy Price	N/A	$ (17,475)	$ (11,737)	$ (7,532)
Cumulative Subsidy Bill ($ Billions)	N/A	$ 22.5	$ 15.1	$ 9.7
Elasticity = 3.9 (preferred)				
Implied required change in Buy Price	$ (15,659)	$ (10,658)	$ (7,158)	$ (4,593)
Cumulative Subsidy Bill ($ Billions)	$ 20.1	$ 13.7	$ 9.2	$ 5.9
Elasticity = 7.8				
Implied required change in Buy Price	$ (7,909)	$ (5,383)	$ (3,615)	$ (2,320)
Cumulative Subsidy Bill ($ Billions)	$ 10.2	$ 6.9	$ 4.7	$ 3.0

Notes: Estimates assume that 10% of the EV fleet is retired or exported each year starting in 2020 and a weighted-average (over new and used) EV price of approxiately $26,000. There are 333,000 EVs assumed to be in the fleet at the beginning of 2018. By our estimates, the zero-subsidy growth rate of California EVs in 2015, 2016 and 2017 were 28.9, 21.6 percent and 18.5 percent respectively. "N/A" reflects subsidies that exceed 100 percent of the assumed value of the car.

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

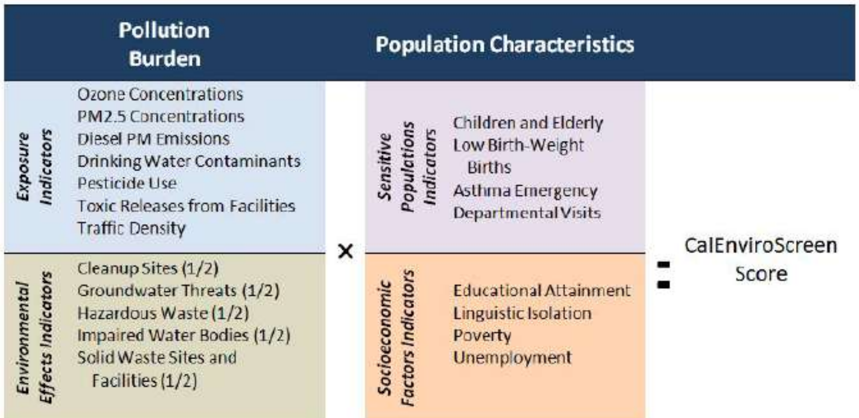
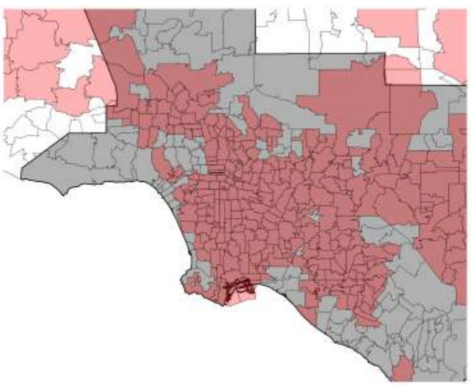
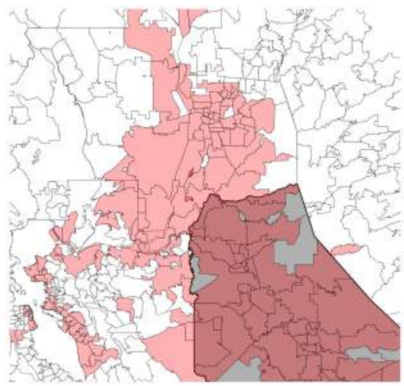


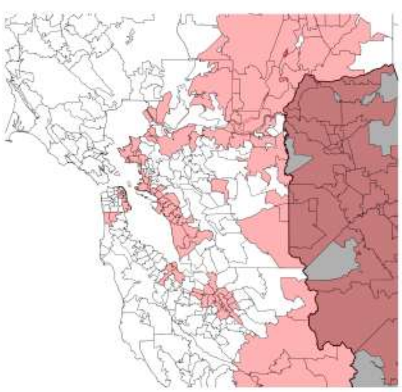
Figure A3: DACs and AQMD borders, Major Metro Areas



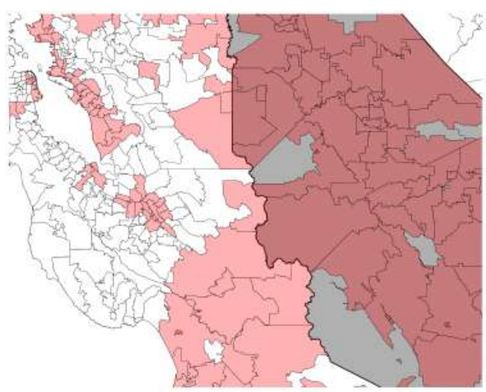
(a) Los Angeles



(b) Sacramento



(c) San Francisco



(d) San Jose

Table A1: Effects by Air District

	DepVar = Price				Dep Var = Log Q			
	(1) Unmatch	(2) Matched	(3) Unmatch	(4) Matched	(5) Unmatch	(6) Matched	(7) Unmatch	(8) Matched
% EFMP * South Coast	-2986.4	-3909.5**			0.84**	0.93**		
	(1824.6)	(1871.5)			(0.36)	(0.44)		
% EFMP * San Joaquin	-4778.0***	-5391.2***			0.70***	0.71***		
	(1278.8)	(1578.1)			(0.081)	(0.089)		
Avg. PU Subs. * South Coast			-0.62*	-0.79**			0.17**	0.19**
			(0.37)	(0.38)			(0.077)	(0.094)
Avg. PU Subs. * San Joaquin			-0.97***	-1.06***			0.14***	0.14***
			(0.26)	(0.31)			(0.016)	(0.018)
Observations	25139	22600	25139	22600	34477	27554	34477	27554
R-Squared	0.0012	0.0020	0.0012	0.0018	-0.0011	-0.00032	-0.00095	-0.00026

All specifications use the preferred set of instruments. Standard errors 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:

$$PreferredIV_{zt} = \frac{\sum_i \mathbf{1}(Subsidy_{izt} > 0, zip = z, time = t)}{\frac{\sum_{r \neq t, r \geq t*} Q_{zr}}{T-1} \frac{\sum_{x \neq z} Q_{xt}}{\sum_{r \geq t*} \sum_{x \neq z} Q_{xr} / T-1}} \tag{16}$$

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,

$$AlternativeIV1_{zt} = \frac{\sum_i \mathbf{1}(Subsidy_{izt} > 0, zip = z, time = t)}{\frac{\sum_{r \neq t, r \geq t*} Q_{zr}}{T-1}} \tag{17}$$

$$AlternativeIV2_{zt} = \frac{\sum_i \mathbf{1}(Subsidy_{izt} > 0, zip = z, time = t)}{\frac{\sum_{x \neq z} Q_{xt}}{\sum_{r \geq t*} \sum_{x \neq z} Q_{xr} / T-1}} \tag{18}$$

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 Income Distribution Estimation

Section 2 describes the EFMP the structure of discontinuities in income related to the EFMP's means-testing incentive structure, which for our regression discontinuity design, requires estimating the proportion of the population around the means-tested discontinuity. Below is the generalized equation for estimating the treatment effect at the discontinuity,

$$\tau_c = \underbrace{E\left[P_{c_j,1} - P_{c_j,0} \middle| Inc_i \sim c_j\right]}_{\text{treatment effect}} \underbrace{Pr\left[Inc_i \sim c_j\right]}_{\text{population weight}},$$

where c_j is the discontinuity in income leading to different subsidy levels, and Inc_i is the income of individual i around the discontinuity.

As researchers we cannot observe micro-level data of the proportion of individuals around the discontinuity at the same geographic resolution[26] as the program, and thus we have developed a method of using Census data to approximate tract-level income distributions. Following Salem and Mount's (1974)[27] use of the lognormal and generalized gamma distributions, we construct income distributions for each census tract using median income and its standard deviation from data provided by the Census Bureau. Then from the income distributions we then are able to calculate the population weight for the RDD.

A.3.1 Data

The data comes from the American Census Bureau's 5-year American Community Survey (ACS). The primary data set is census tract-level median income and the standard deviation for households separated by the number of occupants.[28] The data is primarily drawn from the 2010 ACS, which coincides with the decennial Census survey, providing coverage of 98.9% of

[26]We observe the subsidy and sales at the ZIP- and Census tract-level.

[27]Salem, Ali BZ, and T. D. Mount. "A convenient descriptive model of income distribution: the gamma density." *Econometrica: journal of the Econometric Society* (1974): 1115-1127.

[28]The set of household occupant sizes are separated into the set $\{1, 2, 3, 4, 5, 6, 7+\}$.

census tracts in California. Data will be compared to the 2015 ACS data, however 51.5% of data is missing for the 2015 vintage.

Furthermore, additional data will be included as constraints or tests, including the number of households in different regions of the federal poverty level (FPL), e.g. 100-125%, and the number of households in different income ranges, e.g. $40,000-$44,999.

Lastly, the Census Bureau releases the Integrated Public Use Microdata Series (IPUMS) at the county-level, in which we observe the true mass of individuals that are from 0%-500% of FPL. This data is used to compare the estimation procedures for the lognormal and generalized gamma distributions, which is necessary since we do not observe micro-level data at a higher resolution than the county-level.

A.3.2 Estimation

The estimation procedure occurs in three separate work flows to produce tract-level income distributions. First, the Census ACS data is collected and transformed from $2011 US Dollars to a corresponding percent of the FPL, and the IPUMS data is collected and binned by household size. Starting with a general check, we take each county within our study region and run a maximum likelihood routine to estimate the the lognormal and generalized gamma distributions on the IPUMS data. These distributions are used to determine the precision of fit, and to be used later to check the tract-level estimates.

Second, estimating tract level distributions for the the lognormal, we use the delta method, however the estimation procedure described below will be used to estimate the lognormal if necessary.

The last stage of the estimation procedure follows in four steps. (1) Using Salem and Mount (1974) we take the tract-level estimates and use a basic heuristic to transform the median and standard deviation parameters into a guess of the two (shape and scale) parameters for the generalized gamma distribution. (2) With the initial guess, we then take 10,000 random draws from the generalized gamma distribution and use a generalized method of moments (GMM) estimator with the moment conditions,

$$E\begin{bmatrix} med\left[ACS_i\right] - \hat{med}\left[\gamma_n(\alpha_n, \lambda_n)\right] \\ Var\left[ACS_i\right] - \hat{Var}\left[\gamma_n(\alpha_n, \lambda_n)\right] \end{bmatrix} = \mathbf{0}.$$

With $med\left[ACS_i\right]$ and $Var(ACS_i)$ as the median and variance estimates from the Census Bureau, and $\gamma_n(\cdot)$ as the iterate value $n \in \{0, 1, \ldots, N\}$ of the generalized gamma distribution. Then, (3) the previous step is repeated until the estimates of the shape and scale converge to a desired tolerance. The GMM procedure estimates the distribution function for all census tracts jointly to increase the stability of estimation. Lastly, (4) the distribution function is used to estimate the number of individuals at the tract-level whom possess income levels in the tiers of the EFMP.

Once all census tracts have been estimated, then we will use the additional data to estimate accuracy. One concern is that we cannot directly observe the income distribution at each census tract, and moreover do not have overlapping data in which to use as direct constraints on the estimation procedure. For example, at each tract we know the number of people in different regions of the FPL and the number of households in different income brackets, however we do not know the number of occupants of the households. Therefore, the data will be tested against the companion data sets, but techniques have not yet been developed to directly incorporate the constraints.

Once distributions have been estimated and checked against related data, we will then possess weights to precisely estimate the treatment effects across all the discontinuities in the Enhanced Fleet Modernization Program.

A.4 Subsidy Bill Calculation Details

In this section we describe how the subsidy bill estimates are calculated. First we calculate a net-of-subsidy growth rate of EVs in California and use this trend as a guide for what may happen in the absence of future subsidies. To the extent the projected cumulative EV registration count in 2025 using the net-of-subsidy growth rate falls short of 1.5 million, demand for these cars must be stimulated via subsidies. We use the mass-market demand elasticity estimates that are the central contribution of this paper to retrieve the subsidy bill that would allow California to reach the 1.5 million EVs by 2025 goal.

Table A2: EV Growth Rates: Subsidy and Net-of-Subsidy Estimates

Year	Cumulative EVs	Raw Growth Rate	Net-of-Subsidy Sales Estimate	Net-of-Subsidy ("Base") Growth Rate
2013	42,545		20,062	
2014	102,030	82.3%	28,050	65.9%
2015	164,247	46.7%	29,338	28.8%
2016	239,412	37.2%	35,444	21.6%
2017	333,114	32.7%	44,185	18.5%

Note: Net-of-subsidy sales calculated assuming a subsidy elasticity of -3.9, \$10,000 in subsidies.

To calculate the baseline EV growth rate we begin with data on EV registration growth in California from 2013-2017, which is shown in Table A2 (the "Cumulative EVs" column). This growth combines a baseline growth rate (that would have occurred in the absence of subsidies) and the incremental demand that was induced by subsidies. The column "Net-of-Subsidy Sales Estimate" reflects our estimate of no-subsidy sales. For the purposes of this calculation we consider California and federal EV credits and rebates, which sum to $10,000 for most EVs during this period, and assume complete pass-through to consumers.[29] We then assume a subsidy elasticity of demand of -3.9 (our preferred estimate from this paper) and apply all of this to a $35,000 new EV price, reflecting the fact that the vast majority of EVs sold through 2017 were new. This allows us to net out subsidy-induced growth from baseline growth. Finally, we assume that 10 percent of the EV fleet is removed from the California fleet (e.g. via retirements and exports) each year beginning in 2020.

For the purposes of projecting the baseline growth rate into the future, it is natural to expect that it will continue to decline. This is consistent with an increase in the absolute number of EVs sold that is compared to an increasing cumulative fleet size. Since the rate of decline in the growth rate is not knowable, we present subsidy bill estimates for baseline growth rates ranging from 10 to 16 percent. Table 6 reflects the importance of this key parameter in determining the subsidy bill: moving from a 14 to 10 percent baseline growth rate more than doubles the required subsidy bill.

[29]There were other monetary and non-monetary subsidies during this period as well, including the potentially-large ZEV mandate credits. Quantifying these is difficult, and omitting them from our baseline growth rate calculation will have the effect of biasing the estimate of this rate upwards.