

Correcting Estimates of Electric Vehicle Emissions Abatement: Implications for Climate Policy

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Abstract

Transportation electrification is viewed by many as a cornerstone for climate change mitigation, with the ultimate vision to phase out conventional vehicles entirely. In a world with only electric vehicles (EVs), transportation pollution would be primarily determined by the composition of the electricity grid. For the foreseeable future, however, environmental benefits of EVs must be measured relative to the (likely gasoline) car that *would have been bought instead*. This so-called “counterfactual” vehicle cannot be observed, but its fuel economy can be estimated. A quasi-experiment in California allows us to show that subsidized buyers of EVs would have, on average, purchased relatively fuel-efficient cars had they not gone electric. The actual incremental pollution abatement arising from EVs today is thus substantially smaller than one would predict using the fleet average as the counterfactual vehicle. We discuss implications for climate policy and how to accurately reflect EV choice in integrated assessment models.

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1 Introduction

Policy-makers in the U.S. and worldwide view adoption of electric vehicles (EVs) as central to addressing urban air pollution, lowering carbon emissions and reducing petroleum consumption. The long-run vision is one of a fully electrified transportation sector powered by clean, renewable energy and achievable through a combination of generous subsidies and government mandates.¹ The setting for this paper, California, provides one such example. California is at the forefront of the EV transition in the world.² Still, this transition remains in the early stage. Less than 5 percent of the California light-duty vehicle fleet is electric and, according to the California Energy Commission, roughly 27 percent of California’s electricity is obtained from renewable sources. Both of these are increasing rapidly. California’s Governor Brown issued an Executive Order that calls for 1.5 million zero-emission vehicles statewide by 2025 as part of a goal to reduce petroleum use in cars and trucks by 50 percent by 2030. More recently, Governor Newsom issued a subsequent Executive Order calling for the state to phase-out sales of gasoline-powered cars entirely by 2035. In tandem, California’s Renewable Portfolio Standard calls for 50 percent of electricity to be generated from renewable sources by 2030, and Senate Bill 100 mandates a path to a 100 percent renewable grid by 2045.

EV adoption contributes to emissions reductions according to the difference between emissions produced from driving EVs and the emissions that would have been produced from the car that otherwise would have been bought (the so-called “counterfactual” vehicle). Holding driving patterns constant, EV emissions are primarily determined by the composition of electricity generation on the grid, which is relatively easy to observe. Knowing the fuel economy of the “counterfactual” vehicle is less straightforward, but is equally important for the calculation of EV net benefits. Intuitively, a household that switches to an EV will generate large environmental benefits if it displaces a gas guzzler, and small benefits if it displaces a gas sipper or another EV.³ Importantly, to determine emissions savings it is insufficient to simply observe what car is sold, exchanged or retired when a household buys an EV, since that likely does not reflect the true “counterfactual”.

¹Some countries have also announced intentions to ban conventional vehicle sales, including France and the United Kingdom (by 2040), Norway (by 2025), India (by 2030), and China.

²In 2020, roughly half of all EVs on the road in the US are in California, representing close to 10 percent of the global fleet.

³Although not the focus of this paper, there are also important considerations on the supply side. If EV penetration proceeds far in advance of electric grid transformation, the maximum potential environmental benefits will be capped as a result of powering transportation with fossil fuels. Furthermore, as Jenn et al. (2016) notes, interactions between policies may offset the environmental benefits of electric vehicles by allowing automakers to more flexibly sell less efficient vehicles.

Every estimate of the pollution abatement benefits of EVs either implicitly or explicitly assumes a counterfactual vehicle. In most cases, researchers use some a combination of stated preference data and/or assume a particular model pair for comparison (e.g. Holland, Mansur, Muller and Yates (2016), Archsmith, Kendall and Rapson (2015)), but these assumptions are rough approximations and not based on empirical evidence. In this paper, we present a causal estimate of the fuel economy of the cars that are displaced when California households buy EVs.

Our approach builds on Muehlegger and Rapson (2018) that documents a causal increase in EV purchases induced by a major California EV subsidy policy called the Enhanced Fleet Modernization Program (EFMP). The pilot program began in July 2015, and over the first two years allocated roughly \$72 million in state funding. The eligibility rules of this program expose households that retire an old vehicle to thousands of dollars of subsidies for a new EV purchases, while withholding those subsidies from others in a way that allows for a “treatment versus control” comparison. This allows us to compare the distribution of vehicles purchased in locations in which the EFMP induced people to adopt fuel-efficient EVs to the distribution in locations where consumers were ineligible for the program.

We find evidence that (1) the program increases the average fuel economy of the set of vehicles purchased in a zip code, but that (2) subsidy participants would have purchased relatively fuel-efficient vehicles in the absence of the program. Our results imply that, in the absence of the program, households would have purchased vehicles with an average fuel economy of approximately 35 miles per gallon (MPG). That is substantially higher than the average fuel economy of light-duty passenger vehicles purchased in California over our sample period (22 MPG). Notably, the studied subsidy was not available to all – the EFMP pilot targeted subsidies at low- and middle-income households, specifically. Although historical adoption of electric vehicles has been heavily tilted toward high-income households, electrifying the entire transportation sector requires adoption by low- and middle-income households. This paper provides some of the first evidence about the choice patterns, and the environmental benefits arising from EV adoption amongst this large and important segment of vehicle buyers. Our findings align qualitatively and quantitatively with a complementary paper, Xing et al. (2019), which estimates a structural vehicle choice model using survey data on second choices. Our paper relies on a different source of variation (arising from policy), a different empirical estimation strategy (differences-in-differences) and focuses on a different sub-population (middle- and lower-income households in California), yet the qualitatively similar results support the

importance of such considerations for policy.

Our results have implications for policy, and climate modeling that supports policy decisions. Climate change modeling efforts must make assumptions about the fleet mix far into the future. Most forecasts, including the models that underlie the Intergovernmental Panel on Climate Change fifth assessment, project only partial adoption of EVs through 2100.⁴ Yet assumptions about EV emissions benefits (as determined by assumptions about the counterfactual vehicle) in academic and policy circles, as well as in practice, are often overly optimistic. As one example, the U.S. Department of Energy's Alternative Fuel Data Center emissions calculator uses the fleet-average as a point of reference in their EV benefit tool for consumers.⁵

In cases where the true counterfactual vehicle is more fuel-efficient than what is assumed, the analyst dramatically overstates the true greenhouse gas savings. The extent of overstatement (holding reference vehicles constant) depends on the composition of the marginal source of electricity powering the EV. We show that if the EV is charged by an efficient natural gas generator, the implied CO₂ emissions savings would be overstated by roughly six times; if the EV is charged by a 50/50 mix of natural gas and renewables, CO₂ savings would be overstated by fifty percent. We hope it goes without saying that these are very large discrepancies that, if ignored and unaddressed, will contribute to persistent underperformance of climate change mitigation efforts relating to transportation electrification.

Our results also speak to more near-term policy considerations. First, our results suggest that early adopters substitute towards electric vehicles from relatively fuel efficient vehicles. As a result, policy makers aiming for near-term carbon impacts may wish to not only subsidize cleaner technologies, but also to push for policies that disincentivize combustion of polluting fuels to shift other buyers away from gas-guzzlers. This observation reinforces the importance of a carbon price or gasoline tax, and potentially scrappage incentives for gasoline cars, as policy instruments. For example, the substitution away from conventional vehicles has important fiscal implications due to the reliance on gasoline taxes for road infrastructure maintenance. Like many other states, gasoline consumption per capita in California has declined over the past decade. A widespread transition to electric vehicles would accelerate a transition away

⁴Quoting Sims et al. (2014), "Uncertainties as to which fuel becomes dominant, as well as on the role of energy efficiency improvements and fuel savings, are relevant to the stringent mitigation scenarios.(van der Zwaan et al. (2013)) Indeed, many scenarios show no dominant transport fuel source in 2100, with the median values for electricity and hydrogen sitting between a 22–25 percent share of final energy, even for scenarios consistent with limiting concentrations to 430–530 ppm CO₂eq in 2100." These forecasts are consistent with Leard (2018) that documents a preference for gasoline-powered vehicles even at price-parity.

⁵https://afdc.energy.gov/vehicles/electric_emissions_sources.html

from fuel taxes as a primary means of support for infrastructure investment.⁶ To the extent that EVs are more likely to displace relatively high fuel economy vehicles, which contribute less to fiscal coffers on a per-mile basis, this will influence the rate at which policymakers may wish to transition to alternative methods of financing infrastructure.

2 Data

We obtained data, covering 2015 to 2017, from a third-party data source that aggregates information about all vehicles purchased and registered within California. We observe total monthly vehicle purchases made by consumers (i.e., excluding fleet or government purchases) in each of California's roughly 8,000 census tracts at the make-model-model-year-engine level (e.g., 2013 Toyota Camry Hybrid). We match vehicles by make, model, model-year and engine technology to fuel economy data from www.fueleconomy.gov⁷ and construct the distribution of fuel economy ratings for purchased vehicles for each census-tract-month during our study period.

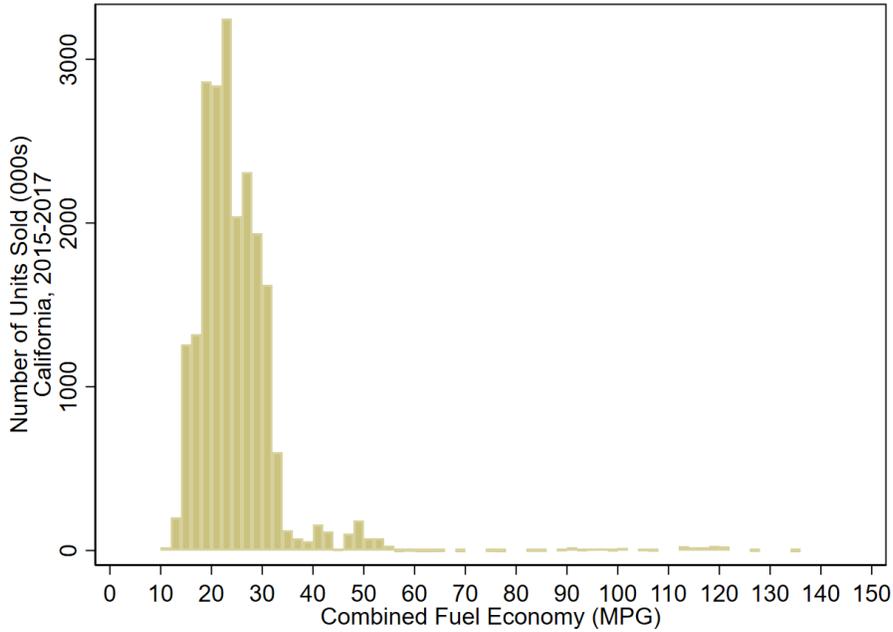
As expected, the distribution of fuel economy, plotted in Figure 1 is heavily skewed - the vast majority of vehicles purchased during our study period are those with combined fuel economy ratings between 20 and 30 miles per gallon. This is partially driven by the fact that our vehicle purchase data includes both new and used vehicles, and used vehicles tend to have lower fuel economy.

Figure 2 plots the quarterly trend in both CA vehicle sales (in millions of units on the primary axis) and mean fuel economy (in miles per gallon on the secondary axis). Although sales did not meaningfully change over the study period, the market shifted towards a higher fuel economy equilibrium.

⁶Davis and Sallee (forthcoming) document that electric vehicles have led to a \$250 million decrease in gasoline tax revenues, and go on to explore the optimal electric vehicle mileage tax.

⁷We string-match our transaction data to the EPA fuel economy rating database in three steps. First, we match make-model names across the two datasets, conditional on fuel and engine type. For vehicles that do not match, we then remove drive-train information from both datasets (e.g., AWD), again conditioning on fuel and engine type. We hand-code the remaining matches. The level of aggregation of our sales data forces us to make two assumptions about fuel economy. First, where multiple trim lines of a make-model-model-year share the same engine technology (e.g., the 2013 Toyota Camry ICE has two trim lines with fuel economies of 25 and 28 combined MPG), we assign the average fuel economy within make-model-model-year-engine grouping. Second, the sales data groups vehicles into four engine types: ICEs, diesels, hybrids (including both PHEVs and traditional hybrids) and BEVs. In a few instances, a manufacturer offers a model with both traditional hybrid and plug-in hybrid engines as powertrain options. One such example is the 2012 - 2015 Toyota Prius, before Toyota renamed the PHEV version as the "Prius Prime" beginning with the 2016 model year. Sales of "hybrid" vehicles with both traditional hybrid and plug-in hybrid engines account for less than 1 percent of the sales in CA during our sample period. In our main specification, we use the average fuel economy within make-model-model-year-engine grouping. We examine the robustness of our results to assumptions about the fuel economy of these models in appendix tables A.4 and A.5 and find that using either the maximum or

Figure 1: MPG distribution, Light-duty vehicles purchased in CA, 2015-2017



Note: The figure plots the number of units sold in California between 2015 and 2017, binned by fuel economy (measured in miles per gallon).

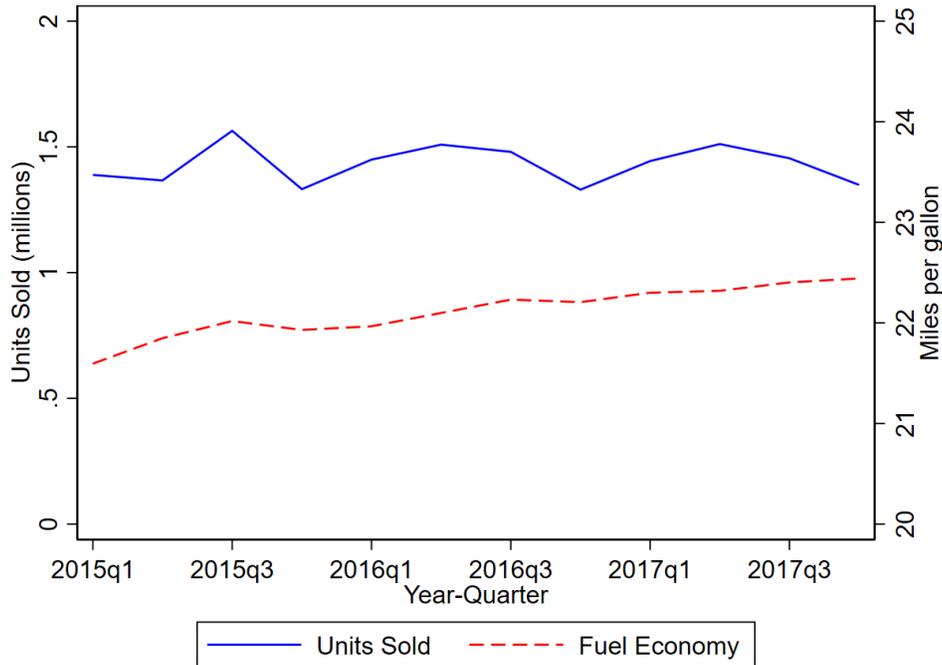
3 Program Details

To examine fuel economy of the displaced vehicles, we leverage variation from the EFMP pilot. We have previously examined the impact of the pilot program on the adoption of electric vehicles in Muehlegger and Rapson (2018). We briefly summarize the important details of the program here. The EFMP program offers incentives to low- and middle-income households to replace a current vehicle with a cleaner and more fuel efficient EV. During our study period, EFMP-eligibility was limited to two pilot regions: San Joaquin Valley and the South-Coast Air Quality Management District (i.e., roughly the Los Angeles metropolitan area). Within these locations, eligibility was limited to households with incomes under 400 percent of the federal poverty line with lower-income households receiving more generous incentives. In addition, households within “disadvantaged communities” (DACs) as defined by the CalEPA EnviroScore, were eligible for more generous incentives.

Figure 3 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 over our study period. The zip codes in pink are those that contain a disadvantaged

minimum fuel economy ratings do not meaningfully impact our results.

Figure 2: Sales and mean fuel economy of purchased vehicles



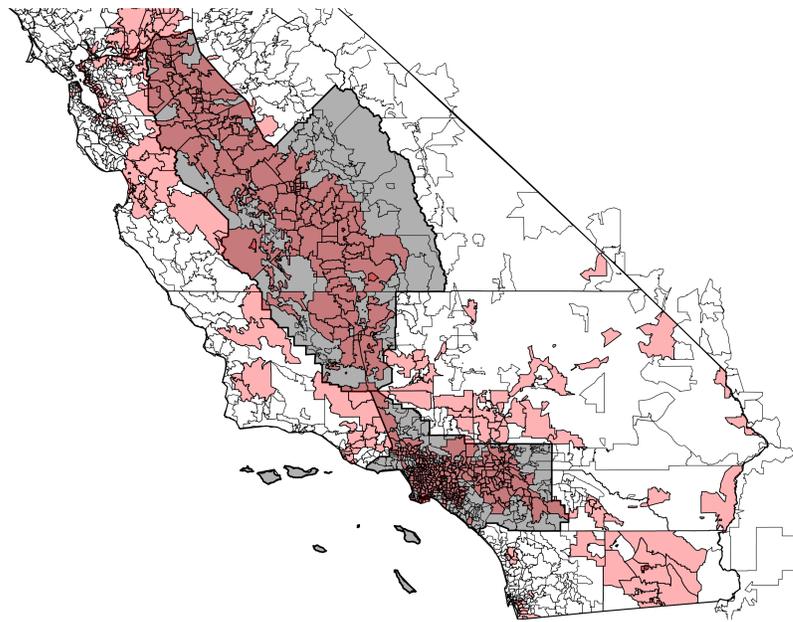
Note: The figures plots quarterly sales in California (on the primary axis, in millions of units) and the mean fuel economy of those vehicles (on the secondary axis, in miles per gallon).

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.

Although the EFMP offered large incentives (up to \$9,500 for low income households living in disadvantaged zip codes to purchase battery electric and plug-in hybrid vehicles), smaller incentives were also offered if qualifying households purchased a “conventional” hybrid vehicle. From publicly available data on program participation, we observe 2,474 participants in the program over the sample period. Although the pilot program offered generous subsidies, the scope of the pilot program limited was small relative to overall vehicle purchases – roughly 1.8 million vehicles were purchased by Californians during the sample period. Focusing on sales in the zip codes eligible for the most generous EFMP subsidies, subsidized vehicles accounted for roughly 2 percent of the battery electric vehicle sales, and 0.25 percent of overall vehicle sales.

Table 1 reports the number and average fuel economy (in gallons per mile or GPM-equivalent) of the battery-electric vehicles (BEV), a plug-in hybrid vehicles (PHEV) and hybrid vehicles (HEV) purchased through the program. Hybrid vehicles were the most popular category pur-

Figure 3: Map of EFMP pilot regions and Disadvantaged Zip Codes



Note: Figure maps zip code boundaries in California. Regions in grey are the two EFMP pilot regions (i.e., San Joaquin Valley and South Coast Air Quality Management District). Zip codes in pink are zip codes that partially or wholly contain a census tract classified as disadvantaged by the CalEPA EnviroScore 2.0.

chased by program participants - roughly 45 percent of participants choose a hybrid vehicle. Roughly 38 percent chose a plug-in hybrid; the remainder chose battery electric vehicles. The average fuel economy (in gallons per mile) of the different vehicles lines up as expected. Hybrid vehicles are the “least” fuel efficient of the three (at 0.0269 GPM or roughly 37 miles per gallon), although they are still substantially more fuel efficient than the average conventional vehicle. Plug-in hybrids are slightly more fuel efficient at close to 40 miles per gallon equivalent⁸ while battery electric vehicles are the most fuel efficient at over 100 miles per gallon equivalent. For reference, we also report the average fuel economy of all 18.6 million vehicles purchased by consumers in California between 2015 and 2017. All of the vehicles purchased under the program are substantially more fuel efficient than the average vehicle, with a fuel economy of roughly 22 miles per gallon.

Table 1: **Vehicle fuel economy (2015-2017)**

	Number of Vehicles	Gallons Per Mile			
		Mean	SD	Min	Max
<u>EFMP Subsidy Vehicles</u>					
BEV	431	.0093	.0008	.0074	.0132
HEV	1106	.0269	.0027	.0208	.0459
PHEV	937	.0249	.0031	.0185	.0398
All Vehicles	2474	.0231	.0069	.0074	.0459
All CA Vehicle Transactions	18.6 M	.0452	.0120	.0074	.1250

Notes: calculated from EFMP participant records, fleet data and the fueleconomy.gov website.

Average fuel economy by engine type mask substantial variation within group. For ease of interpretation, we group vehicles by their combined miles-per-gallon rating (or MPGe rating for battery electric vehicles). While plug-in hybrid vehicles are more fuel efficient on average than conventional hybrid vehicles, the fuel economy distributions of the two groups of vehicles overlap substantially. In contrast, battery electric vehicles are substantially more fuel efficient than all plug-in and conventional hybrid vehicles.

Since EFMP program eligibility is set at the zip-code level, we aggregate our census tract-level sales up to the zip-quarter level, and follow the rules of the EFMP program to determine whether households in a particular zip code are eligible for the most generous incentives. Specifically, if a zip code: (a) contains partially or wholly a census tract classified as disadvan-

⁸The fuel economy of a plug-in hybrid vehicle depends on the fraction of miles that are driven via electricity relative to gasoline. Here, we follow the assumptions used by the EPA when calculating real-world fuel economy for PHEVs, namely that the fraction of miles a PHEV driver uses electricity is an increasing function of the electric-only range of the PHEV. The EPA’s assumptions about the fraction of “electric miles” vary substantially by model, from a low of roughly 25 percent (for 2012-2015 Prius Plug-in Hybrids with an electric-only range of 11 miles) to a high of approximately 90 percent (for the 2019 BMW i3, with an electric-only range of 126 miles).

tagged by the CalEPA EnviroScore 2.0, and (b) is located in either the San Joaquin Valley Aid District or the South Coast Air Quality Management District, we classified the zip code as eligible for the EFMP Plus-Up program. According to program rules, zip codes that do not contain a disadvantaged census tract or are outside of the pilot region are classified as not eligible for the program.

The gradual shift in fuel economy noted statewide in Figure 2 is present in both the EFMP-eligible and ineligible zip codes. Figure 4 plots the annual distributions of vehicle fuel economy (measured in gallons per mile or the equivalent thereof) for the “treated” locations (i.e., disadvantaged zip codes in the pilot regions) and “control” zip codes. The left panel of Figure 4 shows how the distribution of GPMs of the transacted vehicles has shifted downward from 2014 to 2017 in the treated zip codes (DAC = 1, AQMD = 1). The right panel of Figure 4 shows the same thing but for untreated zip codes (DAC = 0 or AQMD = 0). This highlights one advantage of our empirical approach. As average fuel economy is changing throughout California over this period if we were to simply compare mean fuel economy in EFMP-eligible zip codes before and after the introduction of the program, we might misattribute the general trend towards more fuel efficient vehicles to the EFMP program. Rather, by comparing similar locations inside and outside of the pilot regions, we can control for state-wide trends in purchases and better isolate effect of the program as distinct from shifting preferences for Californians.

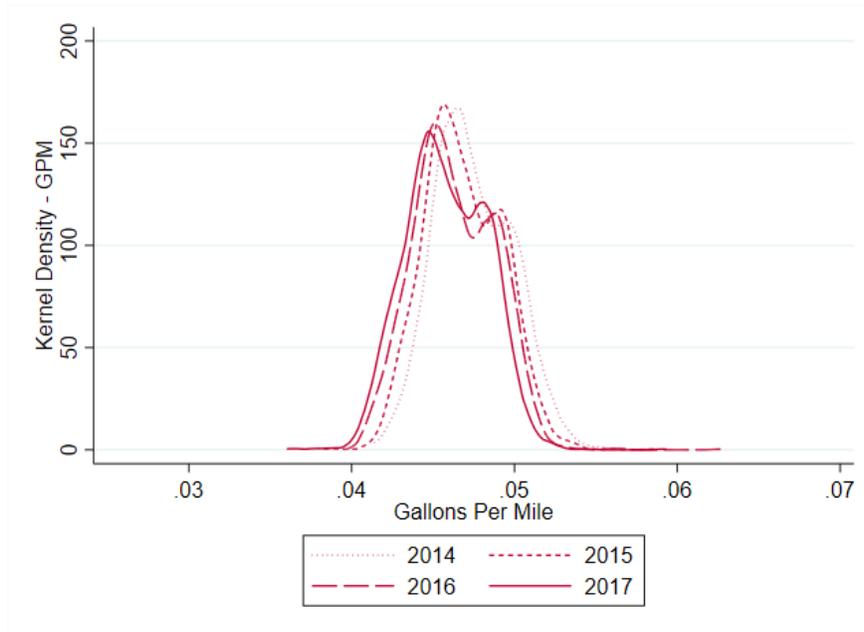
4 Empirical Approach

Our empirical strategy is based on the implementation rules for the EFMP pilot program. To be eligible for the most generous subsidies, applicants must live within DACs within the pilot program regions. The eligibility rules allow us to compare locations that are similar with respect to demographic characteristics, pre-program adoption patterns and their level of “disadvantage” as measured by the Cal EPA EnviroScore, but which differ in eligibility by whether or not they are located within the two pilot air districts.

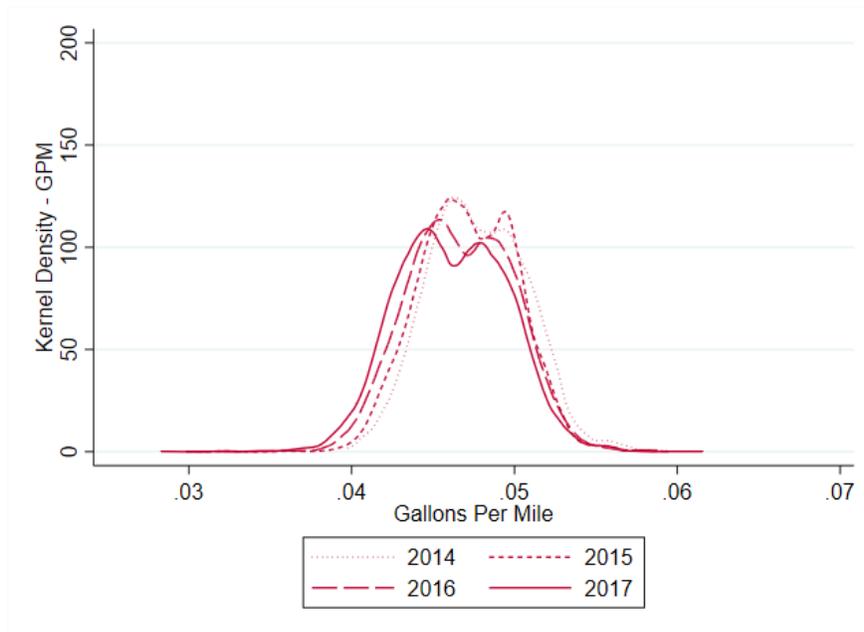
We compare the average fuel economy of vehicles purchased in disadvantaged zip codes inside and outside of the two participating AQMDs, before and after the start of the EFMP pilot program. We regress the average fleet fuel economy in a zip-month on λ_{zt} , the fraction of purchases that receive an EFMP subsidy relative to all vehicle transactions in the zip-quarter. We include zip-code fixed effects to control for time-invariant zip code preferences related to fuel economy and region-time fixed effects to control for unobservable changes in the preferences

Figure 4: Distribution of GPM for “Treated” and “Untreated” zip codes

(a) Treated Zip Codes



(b) Untreated Zip Codes



Note: The figures plot the annual distributions of fuel economy ratings, measured in gallons per mile (or gpm equivalent), for census tracts eligible for the EFMP Plus Up Incentive (left) and the census tracts ineligible for the EFMP Plus Up incentive (right).

for fuel economy inside and outside the pilot regions.

Formally, we estimate

$$Y_{zt} = \beta_1 \lambda_{zt} + v_{tA} + \gamma_z + \epsilon_{zt} \quad (1)$$

where our dependent variable Y_{zt} is the average fuel economy of vehicles purchased by households in zip z in month t . In the tables below, we scale up λ_{zt} from fractions to percentage points, and interpret the coefficient β_1 as changes in GPM by a one-percentage-point increase in the share of transactions that received the EFMP plus-up subsidy.⁹

Our primary parameter of interest is the fuel economy of the marginal vehicle *replaced* as a result of the incentive. From our estimate of the impact of the incentive on average fuel economy, $\hat{\beta}_1$, we can back out an estimate of the fuel economy of the vehicle which would have been purchased, absent the incentive as:

$$\widehat{GPM}_c = GPM_{EFMP} - \hat{\beta}_1 * 100, \quad (2)$$

where GPM_{EFMP} is the average fuel economy of cars purchased under the EFMP program. Where we report the counterfactual MPG, it is simply the reciprocal of \widehat{GPM}_c .¹⁰

To illustrate the intuition, suppose we observe two zip codes that are identical but for their EFMP eligibility status. If the average fuel economy in the EFMP-eligible zip code increases significantly when an electric vehicle is purchased through the program relative to the fuel economy in a zip code in which households are not eligible, it suggests that the electric vehicle is substantially different than the vehicle that would have been purchased absent the subsidy. In contrast, if the average fuel economy does not differ between the two locations when electric vehicles are purchased through the EFMP program, it suggests that the subsidized vehicle was similar in fuel economy to the vehicle that would have otherwise been purchased absent the subsidy. To estimate the fuel economy of the marginal replacement vehicle, we subtract our estimated coefficient from the average fuel economy of the vehicles chosen under the program. For each regression specification, we report the fuel economy rating (in MPG) of the marginal replacement vehicle in at the bottom of each result column.

The interpretation of our results is affected by assumptions about (unobserved) changes in the composition of household car portfolios and the distribution of driving within a household across their cars as their portfolio changes. To the extent program subsidies induce the pur-

⁹In Section A.2 we describe an alternative specification that uses instrumental variables along the lines of Muehlegger and Rapson (2018), and present results using that strategy.

¹⁰An expanded derivation of equation 2 is shown in Appendix A.1.

chase of an *additional* car and/or an expansion of household miles traveled relative to untreated households, the environmental benefit that we estimate and attribute to EVs is an upper bound on the true environmental benefit. There is evidence that EV purchases in California over this period are, in general (not just under the EFMP program), adding to the size of the household portfolio and driven substantially less than gasoline cars (Burlig et al. (2021)). However, means testing in the present setting selects low-income households into the program. These tend to have substantially fewer cars per household (see Figure A.2), thereby increasing the likelihood that the new EV is a replacement car. Moreover, program eligibility requires an old vehicle to be retired in order to receive a subsidy as part of the program (although this vehicle does little to inform the counterfactual).

4.1 Alternative specifications

Whether the empirical strategy above provides an accurate estimate of the impact of the EFMP program on the average fuel economy in a location depends on an assumption that that fuel economy in locations that avail themselves of the program would have followed a similar path absent the program to locations that either did not participate or were not eligible.¹¹ Evidence in favor of this assumption can be found in parallel trends in fuel economy across treated and control zip codes before the introduction of the program. If treated and control locations differed along some dimensions that affect trends in fuel economy, we might misattribute ex post differences in fuel economy to the program. Thus, we consider three additional specifications: (1) a “matched” specification, (2) a triple-differences specification, and (3) a within-zip code specification.

In the “matched” specification, we use nearest-neighbor matching (Abadie and Imbens (2006)) to pair disadvantaged zip codes in participating AQMDs with “control” disadvantaged zip codes in non-participating AQMDs, where we match zip codes by pre-period trends in GPM. Although all disadvantaged zip codes have somewhat different socio-demographics than non-disadvantaged zip codes, the eligible set of DACs might differ along dimensions that are correlated with trends in fuel economy preferences. The “matched” specification places additional weight on zip-code that have more similar trends in fuel economy in the pre-program period.

¹¹Along similar lines, the coefficients of interest would be biased if treatment induces general equilibrium effects on vehicle prices in control zip codes. Muehlegger and Rapson (2018) estimates these effects to be between \$53 and \$157 per vehicle, and statistically indistinguishable from zero. The negligible general equilibrium effects likely stem from the relative size of the program, which comprises under 0.02 percent of new and used car purchases in California over the sample period. We thus proceed under the assumption of no general equilibrium effects.

The “triple-differenced” specification includes as an additional set of controls the non-DACs in the pilot and non-pilot regions. To the extent that fuel economy in pilot and non-pilot regions were trending differentially over time, the additional set of non-DACs in and out of the pilot regions allow us to control for those differences. Formally, the specification 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 DACs and time-invariant zip-level differences.

$$Y_{zt} = \beta_1 \lambda_{zt} + \nu_{tA} + \phi_{tD} + \gamma_z + \epsilon_{zt} \quad (3)$$

Finally, we consider a “within-zip” specification that focuses only on the treated zip codes and identifies the coefficients from quarter-by-quarter variation the number of people who receive subsidies within each “treated” zip code. As above, we include zip code fixed effects, the coefficient estimate identified from a comparison of a given zip code in a quarter in which many people purchase a vehicle through the EFMP program to that same zip code in a quarter in which few people receive a subsidy.

5 Results

We present our results in Table 2. Column (1) corresponds to our primary “difference-in-differences” specification from equation (1). Columns (2) through (4) correspond to our alternative “matched”, “triple-differenced” and “within-zip code specifications. In panel A, the explanatory variable of interest is the fraction of transactions (in percentage points) in a zip*quarter purchased via an EFMP subsidy. Across all the different specifications, we estimate negative coefficients that within a relatively narrow range. These coefficients are consistent with the subsidized vehicles being more fuel-efficient than the average vehicle purchased in a zip-quarter. Interpreting the coefficient in column (1), if 10 percent of vehicles in a zip-quarter receive an EFMP subsidy, the mean fuel economy (measured in gallons per mile) decreases by -0.00055 gallons per mile. Although the point estimate is statistically significant, the 95 percent confidence interval just excludes zero, and the point estimate is modest in magnitude relative to the mean fuel economy of vehicles purchased in the zip codes eligible for the most generous subsidies (0.046 gallons per mile). Translated into miles per gallon, if 10 percent of the vehicles in a zip-quarter receive an EFMP subsidy, average fuel economy rises by roughly three-tenths

of a mile per gallon.¹²

The relatively modest increase is reflective of two features of the EFMP program. The first is that roughly 80 percent of the vehicles purchased under the EFMP program during this period were plug-in or conventional hybrid vehicles. Although both are more fuel efficient than the fleet average, they are significantly less fuel efficient than battery electric vehicles, which were purchased much less frequently under the program.

The second relates to what vehicle would have been purchased absent the incentive. By combining our estimates in Panel A with information about the average fuel economy of vehicles purchased under the EFMP program, we can obtain an estimate the fuel economy of the counterfactual vehicles that would have been purchased absent the incentive. To be clear, we don't observe this hypothetical purchase in our data; rather, we observe the purchases and average fuel economy in locations that are similar to the EFMP-eligible zip codes (i.e., also classified as "disadvantaged" by CalEPA), but were not eligible for the EFMP incentive by virtue of being located outside the pilot regions. Under the assumption that the similar, but ineligible location is reflective of what might have happened absent the EFMP program, we can back-out an estimate of the fuel economy of the vehicle that would have been purchased absent the subsidy. We report the fuel economy of the "marginal replacement" vehicle at the bottom of panel A.

Absent the subsidy, our results suggest that individuals who purchased vehicles during the study period would have tended to purchase relatively fuel efficient vehicles, with fuel economy averaging roughly 35 miles per gallon as alternatives. This moderates the impact of the EFMP program on environmental outcomes and fuel consumption, as it suggests program participants would have purchased "gas-sippers" rather than "gas-guzzlers" in the absence of the program. Below our point estimates, we present 95 percent bias-corrected bootstrapped confidence intervals. Across all vehicles purchased under the EFMP pilot, the bottom of the bootstrapped confidence intervals are roughly 30 - 32 miles per gallon, depending on the specification. Notably, these confidence intervals are all substantially higher than the average fuel economy of vehicles in either the treatment zip codes or all of California.¹³

¹²Panel B provides an alternative estimate based on the average subsidy received by vehicles in the zip code, in thousands of dollars. As noted above, only a small fraction of sales in a zip code receive an EFMP subsidy in any given period. But, the estimates imply that if the mean subsidy across all vehicles (both subsidized and non-subsidized) in a zip code was one thousand dollars vehicles, average fuel economy would increase by roughly 1.8 miles per gallon.

¹³Other methods to calculate bootstrapped standard errors (e.g., percentile and bias-corrected accelerated methods) yield similar confidence intervals.

Table 2: **Effect of EFMP Incentives on fleet GPM, main results**

Panel A: Impact of fraction of vehicles subsidized on average GPM

	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) Within Treatment Zip
% point EFMP Transactions	-0.000055** (0.000024)	-0.000045* (0.000025)	-0.000050** (0.000025)	-0.000055** (0.000024)
Observations	9230	12246	21294	6643
R-Squared	0.88	0.92	0.89	0.89
Marg. repl. MPG	35.0	36.3	35.7	35.0
MR Bootstrap C.I.	(30.2,45.3)	(32.1,47.9)	(31.2,50.4)	(30.8,46.3)

Panel B: Impact of average subsidy on average GPM

	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) Within Treatment Zip
Avg. PU Subsidy	-0.0016*** (0.00055)	-0.0013** (0.00057)	-0.0015** (0.00058)	-0.0016*** (0.00055)
Observations	9230	12246	21294	6643
R-Squared	0.88	0.92	0.89	0.89

Dependent variable is average GPM in a zip*quarter. Standard errors are clustered by zip code. Columns 1, 2, 3 and 4 reported regression results for the unmatched Differences-in-Differences, the matched Difference-in-Differences, the Triple-difference and the within-zip code specifications, respectively. In panel A, the explanatory variable of interest is the fraction of transactions (in percentage points) in a zip*quarter purchased with an EFMP subsidy. In Panel B, the explanatory variable of interest is the average plus-up subsidy (in thousands of dollars) received by buyers across all vehicles purchased in a zip*quarter.

5.1 Estimates by vehicle type

In this section we explore the possibility that the alternative vehicle that would have been chosen absent the incentive might vary by type of EV purchase. That is, the (unobserved) counterfactual vehicle may be different for households that purchase a BEV, households purchasing a PHEV, and households purchasing a conventional HEV. We directly test this by estimating separate coefficients for each engine type. Specifically, we estimate the average fuel economy in a zip-month as a function of the share of transactions receiving EFMP plus up, by each engine type (BEV, PHEV and HEV). As we did above, we then subtract the coefficients from the average fuel economy of the each engine type to estimate the fuel economy of the replaced vehicle.

We present the estimates of the specification in Table 3. Unsurprisingly, we find that battery electric vehicles purchased under the EFMP program have the largest impact on fleet fuel economy. This is consistent with summary statistic in Table 1, which shows that BEVs are substantially more fuel-efficient than either plug-in or conventional hybrid vehicles. Despite these considerations, we do not find strong differences when we estimate the marginal vehicles that would have been purchased in the absence of the program. As in Table 2, we also present bias-corrected bootstrapped confidence intervals for the fuel economy of the marginal replacement

vehicles, by engine-technology purchased under the EFMP program. Although estimating the marginal replacement vehicle separately for BEVs, PHEVs and HEVs reduces the precision of our estimates and increases the range of the bootstrapped confidence intervals, the majority of the bootstrapped confidence intervals exclude the average fuel economy of new vehicles purchased in California.

Table 3: **Effect of EFMP Incentives on fleet GPM , by vehicle type**

	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) Within Treatment Zip
% point EFMP BEV Transactions	-0.00018** (0.000085)	-0.00011 (0.000072)	-0.00018** (0.000085)	-0.00018** (0.000085)
% point EFMP PHEV Transactions	-0.000044 (0.000048)	-0.000035 (0.000037)	-0.000029 (0.000049)	-0.000044 (0.000048)
% point EFMP HEV Transactions	-0.000011 (0.000042)	-0.000023 (0.000042)	-0.000011 (0.000042)	-0.000011 (0.000042)
Observations	9230	12246	21294	6643
R-Squared	0.88	0.92	0.89	0.89
MR MPG BEV	37.1	48.9	37.1	37.1
Bootstrap C.I.	(21.7,78.2)	(27.5,132.7)	(23.7,98.9)	(21.3,98.7)
MR MPG PHEV	34.2	35.2	36.0	34.2
Bootstrap C.I.	(26.2,55.4)	(28.4,50.4)	(27.1,69.5)	(26.0,56.6)
MR MPG HEV	35.7	34.2	35.7	35.7
Bootstrap C.I.	(28.7,57.2)	(27.9,55.3)	(28.8,57.9)	(29.1,63.4)

Dependent variable is average GPM in a zip*quarter. Standard errors are clustered by zip code. Columns 1, 2, 3 and 4 reported regression results for the unmatched Differences-in-Differences, the matched Difference-in-Differences, the Triple-difference and the within-zip code specifications, respectively. In panel A, the explanatory variable of interest is the fraction of transactions, by engine type, (in percentage points) in a zip*quarter purchased with an EFMP subsidy. In Panel B, the explanatory variable of interest is the average plus-up subsidy, by engine type, (in thousands of dollars) received by buyers across all vehicles purchased in a zip*quarter.

5.2 Implications for Emissions Abatement

The true emissions abatement contribution of an EV purchase is a function of three main factors: 1) the difference between the fuel economy of the EV and the car that otherwise would have been purchased, 2) the amount the car will be driven (vehicle-miles traveled, or VMT), and 3) the upstream emissions profile of the electricity generators that power a plug-in EV. In this section, we use our estimates of counterfactual vehicle fuel economy to calculate the implied CO₂ abatement under two different electricity grid generation profiles.

Roughly speaking, the marginal source of electricity generation in much of the US is an efficient combined-cycle natural gas generator. It may be dirtier in some places (e.g. the Midwest) and cleaner in others (California and regions with a substantial endowment of hydroelectricity). While several recent papers have estimated the marginal emissions profile of EVs (e.g.

Holland, Mansur, Muller and Yates (2016) and Archsmith, Kendall and Rapson (2015)), here we acknowledge that the grid composition is changing and readers with interests across varying jurisdictions may wish to apply different grid emissions profiles. We thus use two reference points: one in which EVs are charged by a natural gas plant (0.418 kg of CO₂ per kWh¹⁴), and a second that uses 50 percent natural gas and 50 percent carbon-free electricity (0.209 kg of CO₂ per kWh). These assumptions conform to actual policy and other contributions to the literature.¹⁵

Table 4: **Implied CO₂ savings (kg per EV per year)**

Electric Generation Source	Reference Vehicle		
	Counterfactual	Avg. new car purchased	Avg. new or used car purchased
<i>Panel A: EV VMT = NHTS ICE</i>			
Natural Gas	134	815	1,148
50% Natural Gas, 50% Renewable	1,311	1,992	2,325
<i>Panel B: EV VMT = NHTS EV VMT</i>			
Natural Gas	434	1,115	1,448
50% Natural Gas, 50% Renewable	1,461	2,142	2,475
<i>Panel C: EV VMT = NHTS; Remainder NHTS ICE</i>			
Natural Gas	-54	627	960
50% Natural Gas, 50% Renewable	1,217	1,898	2,231
Reference Vehicle MPG	35.0	27.48	24.87
Reference Vehicle GPM	.0286	.0364	.0402

Notes: Each panel reflects a different assumption about how VMT is displaced, drawing on the 2017 NHTS for VMT by car type. Panel A assumes that the new EV travels as far as the typical gasoline-powered car in California, 9,800 miles. Panel B assumes that new BEVs and PHEVs travel 6,300 and 7,800 miles per year, respectively, and that overall VMT is reduced to this level. Panel C allocates VMT of 6,300 and 7,800 respectively to the newly purchased BEV or PHEV, and assumes that overall VMT does not change. Implicitly, the assumption here is that the difference between average annual ICE VMT and EV VMT is shifted to some other travel mode with the average fleet fuel economy (e.g. another car in the household portfolio, taxis, ride shares, etc.). Rows assume electricity generation mix; columns assume reference vehicle.

Table 4 reports estimates of annual CO₂ savings per EV. Within each panel, the two rows reflect assumptions about electricity generation, and the columns reflect different reference vehicles. The columns contrast our preferred estimates of CO₂ savings (the estimated “counterfactual” vehicle) with the estimated savings were one to make a more naive assumption about the reference vehicle. The center column assumes the reference vehicle has fuel economy equal to that of the average new car, and the rightmost column reflects the average new or used car

¹⁴U.S. Energy Information Administration

¹⁵The California cap-and-trade program assumes a generic electricity source emits 0.428 kg of CO₂ per kWh (Borenstein, Bushnell, Wolak and Zaragoza-Watkins (2019)).

fuel economy.

Comparing results across columns, one can see the inverse relationship between EV CO_2 savings and fuel economy of the comparison vehicle. Abatement relative to the (fuel-efficient) counterfactual vehicle that we estimate in this paper is substantially lower than when the reference vehicle is less efficient, as would be the case with a reference vehicle reflective of new (or new and used) vehicle purchases over the same period. Moreover, abatement would be substantially lower, and can be negative, depending on how VMT is either eliminated or replaced by higher-polluting transportation options. If, as displayed in Panel C, EV buyers shift only part of their VMT to their new, cleaner EV, and use lower fuel-economy alternatives (e.g. taxis, ride shares, or a dirtier ICE in their home portfolio) to meet the rest of their transportation needs, their emissions would actually increase. Archsmith et al. (2020) present evidence that such intra-household substitution patterns cannot be ruled out.

To the extent EV subsidies are intended to promote CO_2 abatement, the policy implications of these results are profound. Our results imply relatively modest CO_2 abatement from recent subsidies and suggest that if future EV buyers are similar to those encouraged to buy by the subsidy, future estimates of the carbon abatement will overstate the true estimates of abatement. If a policy-maker were to assume the reference vehicle is an average new car purchased over our sample period, the true CO_2 savings would be less than one-sixth what may be expected if the grid is powered by natural gas. For cleaner grids, the error would be smaller but still substantial – roughly 33 percent less emissions reductions than anticipated when the grid emissions profile is halfway between natural gas and zero-carbon.

6 Conclusion

In a world where the electric grid is 100 percent renewable and the vehicle fleet is 100 percent electric, calculating emissions abatement from vehicle choices is straightforward. There is no need to understand what vehicle is replaced because no cars are polluting. However, for the foreseeable future, fossil fuels will continue to generate a significant fraction of electricity and the internal combustion engine will likely remain the primary engine technology for light duty vehicles. Any effort to estimate or forecast emissions abatement from EV adoption requires taking a stand on what vehicle was displaced by the EV purchase.

In this project we estimate the fuel economy of this counterfactual vehicle. We implement multiple variants on a simple empirical design that allows us to estimate the distribution of fuel economy of cars that would have been purchased if an EV had not. The eligibility rules of

this program expose some households to thousands of dollars of subsidies for EV purchases, while withholding those subsidies from others. We exploit the quasi-experimental nature of the EFMP program rollout, which allows us to compare the distribution of fuel economy of cars purchased by households living in EFMP-eligible zip codes to that of cars purchased in EFMP-ineligible zip codes. Our results are robust to changes in specifications, with estimates of the replaced vehicle fuel economy falling within a very narrow range.

We find evidence that EVs increases the average fuel economy of vehicles purchased, but that subsidy participants were most likely to have purchased relatively fuel efficient vehicles in the absence of the program. This second point has important implications for climate policy due to the fact that it moderates the potential air emissions or fuel savings benefits of EVs. If the “reference” vehicle were assumed to have a fuel economy equal to the average new car purchased, which is common in transportation emissions models, a policy-maker would dramatically overstate the true greenhouse gas savings from EVs. The extent of overstatement depends on the composition of electricity generation sources powering the EV. If the EV is charged by an efficient natural gas generator, the implied CO_2 emissions savings would be overstated by roughly six times; if the EV is charged by a 50/50 mix of natural gas and renewables, CO_2 savings would be overstated by fifty percent. These results suggest that this overstatement of benefits is likely to be particularly pronounced in the near term for two reasons. First, as suggested by Holland et al. (2020), the electricity used to charge electric vehicles is becoming more clean over time. In addition, as electric vehicles become a larger share of the vehicle fleet, we would expect that the fuel economy of the marginal replacement vehicle to move closer to the fleet average.

For those wishing to maximize environmental benefits of EV adoption, these insights highlight the importance of increasing prices on polluting activities. A carbon price, which can be achieved through taxes or tradable permits under a binding CO_2 cap, would make it more expensive to operate cars with high levels of pollution. Scrappage programs may also be desirable to accelerate the retirement of fuel-inefficient ICEs. In turn, a growing body of evidence indicates that consumers account for most, if not all, of the ongoing flow of these increased costs when they choose what car to buy.¹⁶ The results presented in this paper lend further evidence why carbon prices should be prioritized in the suite of climate change mitigation policies.

¹⁶See, for example, Busse et al. (2013), Allcott and Wozny (2014), Sallee et al. (2016), and Grigolon et al. (2018).

References

- Abadie, Alberto and Guido Imbens**, “Large Sample Properties of Matching Estimators for Average Treatment Effects,” *Econometrica*, 2006, 74, 235–267.
- Allcott, Hunt and Nathan Wozny**, “Gasoline prices, fuel economy, and the energy paradox,” *Review of Economics and Statistics*, 2014, 96 (5), 779–795.
- Archsmith, James, Alissa Kendall, and David Rapson**, “From Cradle to Junkyard: Assessing the Life Cycle Greenhouse Gas Benefits of Electric Vehicles,” *Research in Transportation Economics*, 2015, 63 (3), 397–421.
- , **Kenneth T Gillingham, Christopher R Knittel, and David S Rapson**, “Attribute substitution in household vehicle portfolios,” *The RAND Journal of Economics*, 2020, 51 (4), 1162–1196.
- Borenstein, Severin, James Bushnell, Frank Wolak, and Matthew Zaragoza-Watkins**, “Expecting the Unexpected: Policy Choice and Emissions Market Design,” *American Economic Review*, 2019, 109 (1), 3953–3977.
- Burlig, Fiona, James Bushnell, David Rapson, and Catherine Wolfram**, “Low energy: Estimating electric vehicle electricity use,” 2021, 111, 430–35.
- Busse, Meghan R, Christopher R Knittel, and Florian Zettelmeyer**, “Are consumers myopic? Evidence from new and used car purchases,” *American Economic Review*, 2013, 103 (1), 220–56.
- Davis, Lucas W and James M Sallee**, “Should Electric Vehicle Drivers Pay a Mileage Tax?,” *NBER Environmental and Energy Policy and the Economy*, forthcoming.
- Grigolon, Laura, Mathias Reynaert, and Frank Verboven**, “Consumer Valuation of Fuel Costs and Tax Policy: Evidence from the European Car Market,” *American Economic Journal: Economic Policy*, 2018, 10 (3), 193–225.
- Holland, Stephen, Erin Mansur, Nicholas Muller, and Andrew Yates**, “Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors,” *American Economic Review*, 2016, 106 (12), 3700–3729.
- Holland, Stephen P, Erin T Mansur, Nicholas Z Muller, and Andrew J Yates**, “Decompositions and policy consequences of an extraordinary decline in air pollution from electricity generation,” *American Economic Journal: Economic Policy*, 2020, 12 (4), 244–74.

- Jenn, Alan, Inês ML Azevedo, and Jeremy J Michalek**, “Alternative fuel vehicle adoption increases fleet gasoline consumption and greenhouse gas emissions under United States corporate average fuel economy policy and greenhouse gas emissions standards,” *Environmental science & technology*, 2016, 50 (5), 2165–2174.
- Leard, Benjamin**, “Fuelling behaviour change,” *Nature Energy*, 2018, 3 (7), 541–542.
- Muehlegger, Erich and David Rapson**, “Subsidizing Mass Adoption of Electric Vehicles: Quasi-Experimental Evidence from California,” Technical Report, National Bureau of Economic Research 2018.
- Sallee, James M, Sarah E West, and Wei Fan**, “Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations,” *Journal of Public Economics*, 2016, 135, 61–73.
- Sims, Ralph, Roberto Schaeffer, Felix Creutzig, Xochitl Cruz-Núñez, Márcio D’Agosto, Delia Dimitriu, M.J. Meza, Lewis Fulton, S. Kobayashi, Oliver Lah, Alan Mckinnon, P. Newman, Minggao Ouyang, J.J. Schauer, Daniel Sperling, and Geetam Tiwari**, “Transport In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change,” Technical Report 2014.
- van der Zwaan, Bob CC, Hilke Rösler, Tom Kober, Tino Aboumahboub, Katherine V Calvin, DEHJ Gernaat, Giacomo Marangoni, and David McCollum**, “A cross-model comparison of global long-term technology diffusion under a 2 C climate change control target,” *Climate Change Economics*, 2013, 4 (04).
- Xing, Jianwei, Benjamin Leard, and Shanjun Li**, “What Does an Electric Vehicle Replace?,” Technical Report, National Bureau of Economic Research 2019.

A Appendix

A.1 Estimating the marginal replacement vehicles

The coefficients in Tables 2 and 3 offer an intuitive step towards estimating the fuel economy of the counterfactual vehicle. For each percentage point increase in EFMP transactions, the coefficient reflects a difference in zip-level average GPM that is caused by EFMP program. A coefficient of zero would imply no EFMP-induced change in average GPM, and a large negative coefficient would imply that cars purchased under EFMP are substantially more fuel efficient than the counterfactual vehicle.

To demonstrate this intuition formally, we appeal to the standard potential outcome framework with never-takers (NT), compliers (C), and always-takers (AT). We consider this framework in the context of the intent-to-treat in with the difference-in-difference specification. Defining z_i as the intent to treat indicator, and D_i to be the treatment “take-up”, i.e. the adoption of EVs. Given that the observation i is at the zip-year level, we interpret that within each observation, a fraction of it has $D_i = 1$, and 0 for the rest. The fractions of populations within zip-quarter that fall into each of the treatment- and assignment blocks are shown as follows:

Table A.1: Potential treatment framework: Share of population within each treatment-assignment (ITT) status

	$z_i = 0$	$z_i = 1$
$D_i = 0$	$\pi^{NT} + \pi^C$	π^{NT}
$D_i = 1$	π^{AT}	$\pi^{AT} + \pi^C$

Our outcome of interest is the fuel economy measure (average-gallons per mile), which will be expressed as a function of D_i .

$$E[Y_i|z_i = 1] = \pi^{NT}E[Y(0)|NT] + \pi^CE[Y(1)|C] + \pi^{AT}E[Y(1)|AT] \quad (4)$$

$$E[Y_i|z_i = 0] = \pi^{NT}E[Y(0)|NT] + \pi^CE[Y(0)|C] + \pi^{AT}E[Y(1)|AT] \quad (5)$$

In our setting, average gallons per mile is a function of the fuel efficiencies of the vehicles purchased by three groups: the never-takers (NT), the always-takers (AT), and the compliers (C). Intuitively, the first and second groups are unaffected by the policy, always purchasing vehicles with average fuel economy of $E[Y(0)|NT]$ and $E[Y(1)|AT]$, respectively. In contrast, the compliers (C) adjust their decision when they are treated (i.e., have access to the subsidy).

Subtracting equation (5) from (4), the intent-to-treat estimate is:

$$E[Y_i|z_i = 1] - E[Y_i|z_i = 0] = \pi^C(E[Y(1)|C] - E[Y(0)|C]) \quad (6)$$

In our specifications, we scale the treatment by the zip-year level realizations of π_i^C . Given that the share of compliers is small and has minimal effect on the shares of always-takers and never-takers, and assuming that there are no heterogeneous treatment effects by the realized complier shares, z_i is 0 in the non-assigned zip-years and π_i^C in assigned zip-years

$$E_i[Y_i|z_i = \pi_i^C] - E_i[Y_i|z_i = 0] = \pi_i^C(E[Y(1)|C] - E[Y(0)|C]) \quad (7)$$

So the coefficient on the share variable estimates $(E[Y(1)|C] - E[Y(0)|C])$, the amount by which the fuel efficiency of the compliers changes when offered the subsidy. To estimate the replacement vehicle fuel economy for the compliers, i.e. $E[Y(0)|C]$, we subtract the coefficient of π_i^C from the average fuel economy of vehicles chosen by the subsidy recipients.

A.2 Endogeneity and Instrumental Variables

Given that the denominator of the main regressor λ_{zt} includes all vehicles (including ICEs) transacted in the zip-quarter, rather than EVs only, we believe that the endogeneity issue is less of a concern. We still address this issue by constructing an instrument for the EFMP-share (and an analogous instrument for average subsidies). We instrument for EFMP-share (over all types of vehicles transacted) using the count of EFMP transactions in zip z at time t , normalized by average total (including ICE) 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 quarters 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 follows, where Q is now total transactions including ICEs:

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

Table A.2: Effect of EFMP Incentives on fleet GPM, main results

	OLS			IV		
	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) DinD	(5) Matched DinD	(6) Triple Diff
% point EFMP Transactions	-0.000055** (0.000024)	-0.000045* (0.000025)	-0.000050** (0.000025)	-0.000065*** (0.000024)	-0.000046* (0.000025)	0.00029 (0.00046)
Observations	9230	12246	21294	9230	12246	21294
R-Squared	0.88	0.92	0.89			
Marg. repl. MPG	35.0	36.3	35.7	166824.7	160295.8	128.7
MR Bootstrap C.I.	(30.2,45.3)	(32.1,47.9)	(31.2,50.4)	(28.8,41.1)	(32.1,48.0)	(-625.0,-122.6)

	OLS			IV		
	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) DinD	(5) Matched DinD	(6) Triple Diff
Avg. PU Subsidy	-0.0016*** (0.00055)	-0.0013** (0.00057)	-0.0015** (0.00058)	-0.0019*** (0.00058)	-0.0013** (0.00059)	0.0070 (0.011)
Observations	9230	12246	21294	9230	12246	21294
R-Squared	0.88	0.92	0.89			
F				13635.1	13344.5	253.1

Dependent variable is average GPM in a zip*quarter. 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 the instrument.

A.3 Robustness checks

Due to the level of aggregation of our data, we need to make several assumptions when mapping make-model-model-years to fuel economy ratings.

In our data, we cannot definitively identify from our data whether BMW I3s, that are technically classified in our data as battery-electric vehicles, have "range-extender options" that allow for a gasoline engine to recharge the battery. The range extender option provides functionality very similar to a plug-in hybrid vehicle (with commensurately lower fuel economy).

In addition, our data contains information on fuel type, (gasoline, diesel, hybrid, and electric), but does not offer distinctions between PHEVs and HEVs. This is an issue for the following models (model years in parentheses):

- Ford C-Max (2013-17)
- Ford Fusion (2013-18)
- Honda Accord (2014)
- Hyundai Sonata (2016-17)
- Toyota Prius (2012-15)

We test the robustness of our analysis to each of these groups of vehicles for which we cannot definitively assign fuel economy ratings. For the former (the BMW I3), we run specifications excluding the I3 from the fleet and find little impact on our results, consistent with the modest market share of the vehicle. For the latter group of vehicles, for which we do not know whether a given vehicle is a plug-in or conventional hybrid, we perform a bounding analysis, first under the assumption that all of the vehicles have the most "optimistic" fuel economy rating (as if all the vehicles sold were PHEVs) and then under the most "pessimistic" assumptions (that all the vehicles sold were conventional HEVs). We present our main specification under all three assumptions below.

Table A.3: Effect of EFMP Incentives on fleet GPM, dropping BMW I3

Panel A: Impact of fraction of vehicles subsidized on average GPM				
	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) Within Treatment Zip
% point EFMP Transactions	-0.000057** (0.000023)	-0.000046* (0.000024)	-0.000052** (0.000024)	-0.000057** (0.000023)
Observations	9230	12246	21294	6643
R-Squared	0.88	0.92	0.89	0.89
Marg. repl. MPG	34.7	36.2	35.4	34.7
MR Bootstrap C.I.	(29.7,44.8)	(31.9,46.8)	(31.0,48.8)	(30.3,45.5)

Panel B: Impact of average subsidy on average GPM				
	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) Within Treatment Zip
Avg. PU Subsidy	-0.0017*** (0.00056)	-0.0013** (0.00055)	-0.0015*** (0.00058)	-0.0017*** (0.00056)
Observations	9230	12246	21294	6643
R-Squared	0.88	0.92	0.89	0.89

Dependent variable is average GPM in a zip*quarter. 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. Column 4 presents the results restricting the sample to eligible zip codes (i.e., DACs within the relevant pilot regions). We dropped BMW I3 from the sample, because we could not be confident as to which of the transactions in our data had range extenders (which would make it a PHEV, and has significantly worse implied fuel economy than the pure BEV version).

Table A.4: Effect of EFMP Incentives on fleet GPM, with “optimistic” fuel type assumption

Panel A: Impact of fraction of vehicles subsidized on average GPM				
	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) Within Treatment Zip
% point EFMP Transactions	-0.000055** (0.000024)	-0.000044* (0.000025)	-0.000050** (0.000025)	-0.000055** (0.000024)
Observations	9230	12246	21294	6643
R-Squared	0.88	0.92	0.89	0.89
Marg. repl. MPG	35.1	36.3	35.7	35.1
MR Bootstrap C.I.	(30.2,45.6)	(32.1,47.9)	(31.3,50.0)	(30.9,46.2)

Panel B: Impact of average subsidy on average GPM				
	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) Within Treatment Zip
Avg. PU Subsidy	-0.0016*** (0.00055)	-0.0013** (0.00057)	-0.0015** (0.00058)	-0.0016*** (0.00055)
Observations	9230	12246	21294	6643
R-Squared	0.88	0.92	0.89	0.89

Dependent variable is average GPM in a zip*quarter. 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. Column 4 presents the results restricting the sample to eligible zip codes (i.e., DACs within the relevant pilot regions). The dependent variable for the treated group is constructed such that for make-model years for which we are uncertain about the engine type (PHEV or HEV, BEV or PHEV) we take the more fuel efficient type.

Table A.5: Effect of EFMP Incentives on fleet GPM with “pessimistic” fuel type assumption

Panel A: Impact of fraction of vehicles subsidized on average GPM				
	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) Within Treatment Zip
% point EFMP Transactions	-0.000055** (0.000024)	-0.000045* (0.000025)	-0.000049** (0.000025)	-0.000055** (0.000024)
Observations	9230	12246	21294	6643
R-Squared	0.88	0.92	0.89	0.89
Marg. repl. MPG	35.0	36.3	35.7	35.0
MR Bootstrap C.I.	(30.2,45.2)	(32.1,47.9)	(31.2,50.5)	(30.8,46.4)

Panel B: Impact of average subsidy on average GPM				
	(1) DinD	(2) Matched DinD	(3) Triple Diff	(4) Within Treatment Zip
Avg. PU Subsidy	-0.0016*** (0.00055)	-0.0013** (0.00057)	-0.0015** (0.00058)	-0.0016*** (0.00055)
Observations	9230	12246	21294	6643
R-Squared	0.88	0.92	0.89	0.89

Dependent variable is average GPM in a zip*quarter. 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. Column 4 presents the results restricting the sample to eligible zip codes (i.e., DACs within the relevant pilot regions). The dependent variable for the treated group is constructed such that for make-model years for which we are uncertain about the engine type (PHEV or HEV, BEV or PHEV) we take the less fuel efficient type.

A.4 Geographical units

One challenge in constructing the dataset is that policy assignment into the EFMP is done at the zip-code level, while the transaction data is at the Census tract level. In order to reconcile the discrepancies in the geographical units, we construct a merged dataset in which the unit of observation is zip-quarter. This is done by weighting the tract level observations by the share of geographical overlap with a given zipcode. We show the cross tabulation of treatment status at the tract level and that at the zipcode level. We see that there is one tract-zip overlap in which the tract was treated but the zip was not. This is fixed in the analysis data.

Table A.6: Cross-tabulation of tracts to zipcodes

DAC tract	0		DAC zip 1		Total	
	No.	%	No.	%	No.	%
0	7,727.0	55.6	6,178.0	44.4	13,905.0	100.0
1	1.0	0.0	3,834.0	100.0	3,835.0	100.0
Total	7,728.0	43.6	10,012.0	56.4	17,740.0	100.0

Figure A.1 shows the number of zipcodes that a given Census tract overlaps.

Figure A.1: Number of zip codes within census tracts

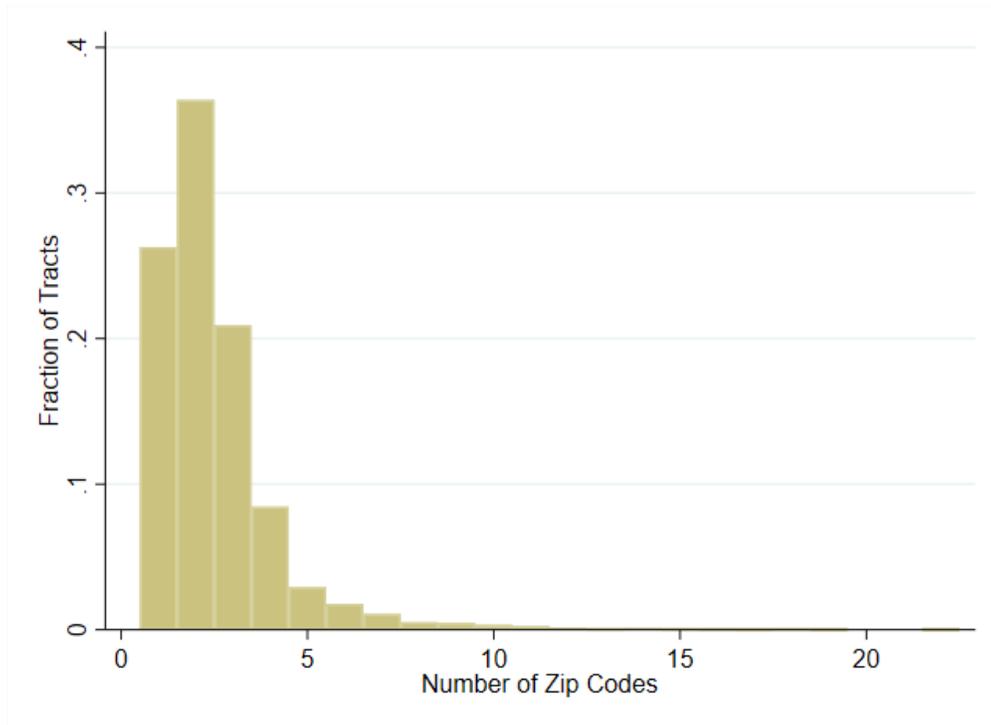
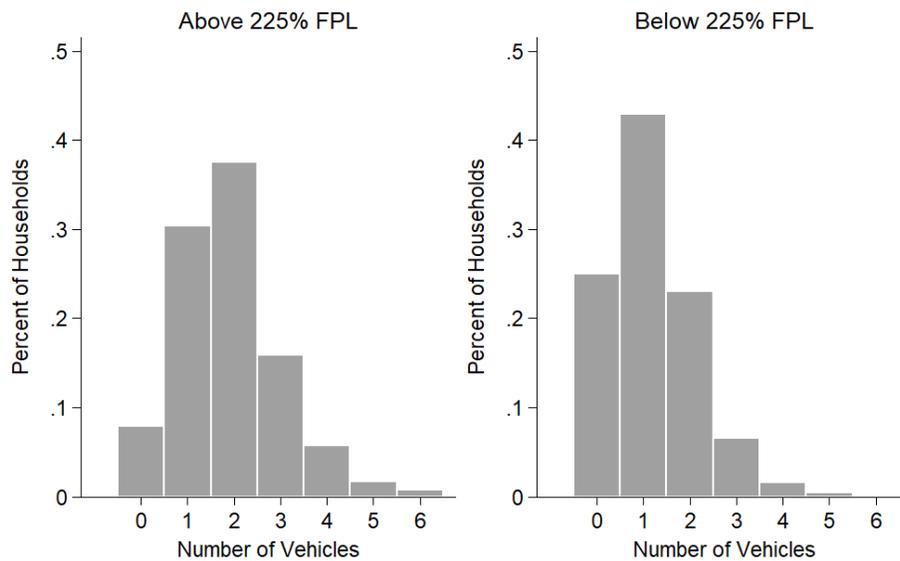


Figure A.2: Number of Vehicles per Household: by Income

Number of Vehicles in the Household By Poverty Status



Graphs by 225% of Poverty Line