Estimating Demand for Electric Vehicles in Low- and Middle-income Households

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Abstract

Governments in much of the developed world are attempting to stimulate adoption of electric vehicles (EVs). In this paper we exploit quasi-random variation in the availability of large EV subsidies in California to examine the effects of the policy. Using a unique dataset that includes both vehicle transaction prices and subsidy receipts, we deploy triple-difference and regression discontinuity methodologies to retrieve two main statistics of policy interest: the subsidy elasticity of demand for EVs and the rate at which those subsidies are passed through from upstream players to consumers. Our estimates show that while demand for EVs is price-elastic, pass-through may be incomplete. We use our estimates to predict that at least $6.3 to $10.3 billion in additional subsidies will be required for California to reach its goal of 1.5 million EVs on the road by 2025.

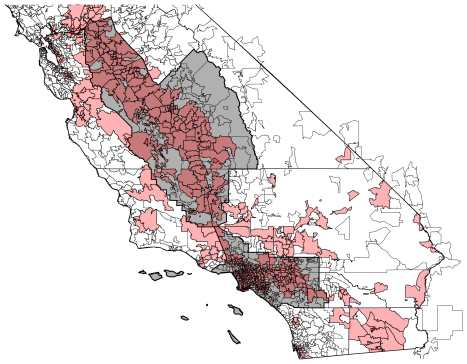
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1 Question & Setting

In this paper, we examine the effects of California's Enhanced Fleet Modernization Program - Plus Up ("EFMP-PU") pilot program. Features of the EFMP program allow us to causally identify: (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. To our knowledge, our paper is the first to estimate the response by mass-market consumers, and thus, is particularly relevant for assessing the impacts or costs of proposed policies that require wide-spread adoption of alternative fuel vehicles.[1]

The eligibility rules of the EFMP enable two different approaches to causal identification. The first is a triple-difference estimator that exploits geographical eligibility rules. This approach allows us to retrieve an average treatment effect estimated across the full range of treated geographic areas and eligible households. 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 contain disadvantaged census tracts. Post July 2015, low- and middle-income participants living in the grey areas were additionally eligible for the EFMP base subsidy, ranging between $2,500 and $4,500 for households purchasing a PHEV or BEV. Low- and middle-income households in the shaded-pink areas were eligible for both the EFMP base and plus-up subsidy, between $5,500 and $9,500 in total. In contrast, households outside the grey regions were not eligible for either the EFMP base, nor plus-up incentives, regardless of whether they lived in a zip code with a disadvantaged census tract or not.

Figure 1: DAC zip codes, South Coast and San Joaquin Valley AQMDs



An alternative identification strategy exploits the discontinuous assignment of zip codes to the Plus-up incentive. Eligibility for the program is defined at the zip code level. If a zip code contains a disadvantaged census tract, all eligible households within the zip code receive both the EFMP base and plus-up subsidy. Treating the maximum census-tract level CES score within each zip as the running variable, we examine outcomes at zip codes with maximum CES scores falling just above and below the 75th percentile of the CES score distribution, the criteria for the disadvantaged designation. Given the brevity of this proposal, we do not present any of the RD work here, but it is included in a working paper version of this project.

Using both identification strategies, we retrieve estimates of two policy-relevant parameters: the elasticity of demand for EVs among low- to middle-income buyers, and the rate of

[1] In contrast, much of the existing literature on vehicle incentives focus on policies offering equal benefits to all buyers (e.g., Chandra et al. (2010), Gallagher and Muehlegger (2011), Beresteanu and Li (2011)). As Borenstein and Davis (2016) notes alternative vehicle adoption has been strongly correlated with income historically - hence, earlier estimates may prove less valuable guides for policies requiring wide-spread adoption.

subsidy pass-through. The triple-difference estimated demand elasticity is -2.5, implying that a subsidy that decreases the buy-price of an EV by 10 percent will increase demand for that EV by 25 percent. The estimated rate of subsidy pass-through is 61 percent. Thus, to increase demand for a $30,000 EV by 25 percent, the buy price would have to decrease by $3,000, implying a required statutory subsidy of $4,918. 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".

2 Preliminary Results from the Triple-Difference

A zip code treated 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-car type. 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.[2] We estimate

$$P^{buy}_{izkt} = \alpha_1 \lambda^{PU}_{zkt} \mathbf{1}_A \mathbf{1}_D \mathbf{1}_P + \alpha_2 \lambda^{B}_{zkt} \mathbf{1}_A \mathbf{1}_P + \beta \mathbf{1}_D \mathbf{1}_P + \gamma_z + \mu_k + \nu_t + \epsilon_{izkt} \quad (1)$$

where $\mathbf{1}_D$, $\mathbf{1}_A$ and $\mathbf{1}_P$ are indicators for AQMD=1, DAC=1, and Post=1, respectively. Zip code, car type and quarter-by-year fixed effects are conditioned out via γ_z, μ_k and ν_t. λ_{zkt} serves as a scaling factor the adjusts estimates according to the fraction of EV purchases by buyers eligible for an EFMP-PU subsidy.[3] The coefficient α_1 will reflect the average decrease in the buy price (P^{buy}_{izkt}) resulting from residing in an EFMP-PU eligible zip code.

Cost effectiveness of the EFMP-PU 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, which will also serve as a sanity check on results from equation 1:

$$P_{ijkt} = \alpha_1 \lambda^{PU}_{zkt} \overline{EFMPPU}_{ikt} + \alpha_2 \lambda^{B}_{zkt} \overline{EFMP}_{ikt} + \beta \mathbf{1}_D \mathbf{1}_P + \gamma_z + \mu_k + \nu_t + \epsilon_{izkt} \quad (2)$$

Table 1 displays results from equation 1. Note that the coefficients associated with EFMP-PU are identified from the triple difference, while the EFMP base subsidy coefficients are from difference-in-differences between AQMD=0/1 and Post=0/1. The results are estimated and presented separately for new and used EV purchases. EFMP-PU subsidies reduce the buy price of new EVs by just over $2,200. This average treatment effect on treated EFMP-PU recipients is quite precisely estimated, and is identified from over 330,000 zip-quarter observations. The average estimated pass-through rate is just over 60 percent, but this is imprecise and distinguishable from zero with only 90 percent confidence. Still, taken at face value, for every EFMP-PU subsidy dollar, 40 percent is captured by upstream market participants and the rest is enjoyed by the buyer. The estimated effects on used car prices are far less precise due to the relative newness of the used car market for EVs. There are fewer than 15 percent of the number of zip-quarter observations in the used market compared to new. We view this as the main reason behind a suspiciously large coefficient on the EFMP-PU coefficient in column 3. While the rate of pass-through is roughly similar for used cars as it is for new, neither zero or 100 percent pass-through can be rejected.

Table 2 shows the effect of the EFMP subsidies on the quantity of EVs transacted. The estimating sample differs in two ways from that used in Table 1. First, the effect on prices were

[2] We distinguish between two types of electric vehicles: battery only ("BEVs") and plug-in hybrids ("PHEVs").

[3] We are currently in the process of estimating eligibility proportions at the zip code level based on data from the US Census. In the meantime, however, we present results using (admittedly endogenous) weights equal to the number of EVs purchased in a zip that receive a subsidy, relative to the total number of EVs purchased.

Table 1: Pass-through and EFMP Incentives

	New		Used	
	(1) BuyPrice	(2) BuyPrice	(3) BuyPrice	(4) BuyPrice
% EFMP PU	-2207.3***		-6799.2***	
	(468.9)		(1879.0)	
% EFMP	-3464.0***		-434.5	
	(604.6)		(1853.9)	
Avg. EFMP PU Subsidy		-0.61*		-0.68
		(0.32)		(0.48)
Avg. EFMP Subsidy		-1.23***		-1.12**
		(0.21)		(0.44)
Observations	336695	336695	43360	43360
R-Squared	0.77	0.77	0.17	0.17

conditional on transactions having occurred, the quantity regressions can exploit information from zip-county observations in which zero transactions occurred. We thus 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. Second, in the price regressions, we left battery electric vehicles ("BEVs") and plug-in hybrid electric vehicles ("PHEVs") separate. In the quantity regressions, we aggregate sales of BEVs and PHEVs to use sales quantities for all EVs as our outcome variable. Coefficients reported in the first row are percentage changes in

Table 2: Sales and EFMP Incentives

	New		Used	
	(1) logQ	(2) logQ	(3) logQ	(4) logQ
% EFMP PU	0.16***		0.39***	
	(0.062)		(0.035)	
% EFMP	0.24**		0.099**	
	(0.099)		(0.047)	
Avg. EFMP PU Subsidy (000s)		0.096		0.12***
		(0.074)		(0.018)
Avg. EFMP Subsidy (000s)		0.025		0.0038
		(0.052)		(0.017)
Observations	222592	222592	222592	222592
R-Squared	0.50	0.50	0.27	0.27

quantity resulting from exposure to the EFMP-PU program. Zip in treatment status on average experience a 16 percent increase in the quantity of new EVs purchased. Column two presents a measure of elasticity: for every $1,000 of EFMP-PU subsidy there is a 9.6 percent increase in the quantity of new EVs purchased. The results in column two are slightly less precise than in column one, and are statistically indistinguishable from zero.

Demand in the used market appears to be more elastic. Exposure to the EFMP-PU subsidies increases used car transactions by nearly 40 percent, and a $1,000 increase in the subsidy increases the equilibrium number of purchases by 12 percent. Both of these results are estimated with more precision in than in the new car market.

2.1 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 that will be 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 public funding would be required to achieve this goal. In this section we present some rough, back-of-the-envelope calculations.

Table 3: Estimated CA Subsidy Required to Meet 1.5Million ZEV by 2025 Goal

Assumed baseline growth in EV stock (2018-2025)	13%	15%	17%
# EVs Sold (2018-2025)	552,451	685,889	836,600
Add'l required to reach 1.5million	676,829	554,103	415,603
Implied required % change in Q	123%	81%	50%
Implied required change in Buy Price	$ (17,152)	$ (11,310)	$ (6,955)
Total subsidy, $Millions (100% pass-through)	$ 11,609	$ 6,267	$ 2,890
Total subsidy, $Millions (61% pass-through)	$ 19,031	$ 10,274	$ 4,738

Notes: Estimates assume that 10% of the EV fleet is retired each year starting in 2020, an EV list price of $35,000, and a subsidy elasticity of demand of -2.5. There are 333,000 EVs assumed to be in the fleet at the beginning of 2018.

Table 3 presents the implied total value of EV subsidies that would be required for California to meet its 1.5 million EV goal by 2025. The calculations begin with an assumed baseline (subsidy-free) rate of growth in the EV stock between 2018-2025, and include an assumption that 10 percent of the EV stock will be retired each year starting in 2020. Based on the number of EV sales predicted under such conditions, there is an implied shortfall of EVs that the subsidies are intended to address.[4] The implied required change in buy-price is retrieved by assuming a list price of $35,000 per EV and applying our estimate of the subsidy elasticity of demand to the implied required percent change in quantity. The total required subsidy budget is then calculated as a function of the rate of subsidy pass-through. We view 15 percent as an optimistic baseline growth rate, and use this as the midpoint in or calculations in Table 3. From a base rate of 15 percent and with 100 percent pass-through, $6.3 billion in cumulative subsidies (2018-2025) would be required to reach the 1.5 million EV goal by 2025. This scales up if the pass-through rate is less than one - at 61 percent pass-through, the subsidy requirement exceeds $10 billion.

3 Personnel & Conflict of Interest Statement

Erich Muehlegger and David Rapson, both Associate Professors of Economics at UC Davis, will carry out the study. Dr. Rapson owns more than $10,000 in stock that could be affected by regulation of the automotive market. Dr. Muehlegger has no financial conflicts.

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[4]Note that both due to the fact that in 2018 there will already be over 330,000 EVs in the state, and due to retirements, rows 2 and 3 do not sum to 1.5 million.