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ABSTRACT

This paper presents evidence that gasoline prices have a larger effect on demand for electric vehicles (EVs) than electricity prices in California. We match a spatially-disaggregated panel dataset of monthly EV registration records to detailed records of gasoline and electricity prices in California from 2014-2017, and use these to estimate the effect of energy prices on EV demand. Two distinct empirical approaches (panel fixed-effects and a utility-border discontinuity) yield remarkably similar results: a given change in gasoline prices has roughly four to six times the effect on EV demand as a similar percentage change in electricity prices. We explore the implications for optimal EV subsidies, which promote externality reduction benefits and correct for consumer misoptimization stemming from the undervaluation of future electricity costs.

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1 Introduction

There is an ongoing tension in environmental and transportation policy between advocates of price-based mechanisms, such as pollution and congestion pricing, and supporters of more direct interventions such as mileage standards and subsidies for alternative fuel vehicles. Supporters of direct regulations express skepticism over the ability of price-based incentives to effect sufficient change. This view is partly influenced by a belief that customers do not properly internalize the future savings enjoyed from more fuel-efficient vehicles, and therefore are less willing to pay for fuel efficiency in new cars. If true, this behavioral bias would partially offset the effects of carbon pricing and create a justification for further regulations (see e.g., Allcott et al. (2014)).

The goal of this paper is to test this assertion in the context of electric vehicles (EVs): Do EV buyers make purchase decisions that suggest they fully-internalize the future operational costs of electricity? Although a number of recent studies find evidence that conventional vehicle buyers (more-or-less) properly value fuel efficiency (Busse et al. (2013), Allcott and Wozny (2014), Sallee et al. (2016)), there are reasons both to expect or not expect buyers to value electric prices properly. On one hand, the literature on conventional vehicles suggests that fuel costs are an important consideration for prospective vehicle buyers. Differential fuel efficiency between vehicles is, in principle, highlighted on fuel economy stickers on all new passenger cars, EV savings calculators, and promotional materials from EV manufacturers. However, there are also reasons to expect that buyers are less sensitive to electricity prices than gasoline prices. Two recent papers support this view (Leard et al. (2021) and Gillingham et al. (2021)) in the context of gasoline cars, a setting where car buyers have extensive experience with the link between gasoline prices and vehicle use. The consumer experience with electricity stands in contrast, and the link between vehicle use, home charging and electricity bills might be less well understood. Ito (2014) finds evidence that consumers poorly understand the marginal electricity price they face, and, to the extent there are meaningful differences in electricity prices (as documented by Borenstein and Bushnell (2019)), Davis and Metcalf (2016) suggests that energy savings calculations performed at the national-level might abstract away from important elements of electricity costs.

This question takes on practical importance as EVs (paired with a green electricity grid) are viewed by policymakers as a central element to reducing carbon emissions from the transportation sector. During our study period, federal incentives for EV manufactures totaled up to \$1.5 Billion. California (and other states) offered generous incentives to encourage buyers to adopt EVs.[1] These incentives are often linked to ambitious policy goals - an executive order by former Governor Brown called for 5 million "zero-emissions vehicles" (ZEVs) by 2030 as part of an ambitious goal to reduce transportation emissions by 50% by 2030 (Muehlegger and Rapson (2018)). More recently, Governor Newsom issued a second executive order mandating that, by 2035, all new cars and passenger trucks sold in California be zero-emission vehicles – banning sales of new conventional vehicles.

In this paper, we study the census block-group level adoption of EVs in California over the period from 2014-2017. During this period, the EV passenger fleet in California tripled in size, growing by over 200,000 vehicles. For identification we leverage differences in electricity prices between municipally-owned electric utilities (such as Sacramento Municipal Utility District) and investor-owned utilities (such as Pacific Gas and Electric). We exploit the discontinuity in electricity prices along the borders of neighboring electric utility service territories and test how EV adoption varies amongst geographically proximate CBGs. These CBGs should share comparable unobservables factors, such as commuting patterns, local EV charging infrastructure density, and other factors that might influence EV adoption, but face dramatically different prices. In many cases, customers served by municipal utilities face marginal electricity prices that are a fraction of those faced by customers served by investor-owned utilities. By comparing the sensitivity of EV adoption decisions to differences in electricity and gasoline prices, we test whether EV buyers respond commensurately to changes in these two prices.

We find that fuel prices do indeed influence vehicle technology choice, although not in a symmetric fashion. While consumers appear to be influenced by both gasoline and electricity prices when making the decision to adopt EV technology, the influence of gasoline prices is roughly four to six times stronger, relative to operating costs, than is the influence of electricity prices. In light of this apparent undervaluation of electricity costs, we consider optimal subsidy policy which now must address two sources of inefficiency. First, if electricity prices or gasoline prices do not reflect social marginal cost, the optimal subsidy incorporates any unpriced environmental externalities imposed by the operation of an EV relative to a gasoline-powered vehicle. This is the traditional environmental rationale for subsidizing durable goods purchases. However, if consumers mis-estimate the costs associated with the future operation of a vehicle, the optimal subsidy also addresses the "internality" (to use the language of Allcott et al. (2014)) – the cost or benefit that a consumer's durable good decision imposes on their fu-

[1] Although not the focus of this paper, there has also been considerable attention devoted to the impact of EV subsidies and the deployment of charging networks (Springel (2017), Li (2017), Li et al. (2017)), and supply-side mandates such as the zero-emissions vehicle mandate in California.

ture self. Calibrating with data from California, we find the optimal policy (on net) subsidizes EV purchases. The overall subsidy combines two conflicting effects: on one hand, EVs can impose lower externalities than gasoline-powered vehicles in California (see e.g., Holland et al. (2016); on the other hand, since most customers in California face high marginal electricity prices, internalities imposed by mis-estimation of electricity prices motivate *taxing* EVs.

The role that *relative* fuel prices play on the choice of vehicle is particularly important given the fact that most plans for deep decarbonization in developed economies call for a large degree of electrification of transportation and other sectors (see Borenstein and Bushnell (2019) and Rapson and Muehlegger (2021)). While states such as California have devoted substantial resources toward subsidizing both EV purchases and supporting infrastructure, many of these programs, somewhat ironically, are funded directly or indirectly through electric rates. Furthermore, as carbon policy increasingly involves tradeoffs between energy sources the relative prices of these sources, and consumer responses to them, becomes a critical component of that policy.

In section 2 we describe our framework for modeling consumer utility from vehicles and the empirical specifications we adopt to estimate their response to the relative prices. Section 3 summarizes our data sources, and sections 4 and 5 present results from panel fixed effect and border discontinuity approaches, respectively. Policy and welfare implications are discussed in section 6, and we conclude in section 7.

2 Methodological Framework

The goal of this paper is to test whether the marginal electric vehicle buyer respond equivalently to electricity and gasoline prices when making the decision about what vehicle to purchase. To motivate our empirical specification and the interpretation of our coefficients, we consider a simple discrete choice framework of a consumer choosing between an electric vehicle ("BEV") and a conventional vehicle ("ICE").[2]

We model the utility of risk-neutral prospective vehicle buyer, indexed by i with demand

[2] In the appendix, we illustrate that this framework can be easily extended to a consumer choosing amongst multiple electric and conventional vehicles.

for travel VMT_i, as a function of three components.

$$U_i^{BEV} = \alpha^{BEV} + \gamma_e \sum_{t=0}^{\infty} \delta^t \left[E[P_t^e] \left(\frac{kwh}{mile} \right) \right] VMT_i S^{BEV}(t) + \epsilon_i^{BEV} \quad (1)$$

$$U_i^{ICE} = \alpha^{ICE} + \gamma_g \sum_{t=0}^{\infty} \delta^t E[P_t^g] \left(\frac{gal}{mile} \right) VMT_i S^{ICE}(t) + \epsilon_i^{ICE} \quad (2)$$

In addition, the buyer has the outside option of choosing to not purchase a new vehicle, for which we normalize the utility to be zero.

As the focus of this paper is how consumers value energy costs, the framework abstracts away from many of the common elements of utility of purchasing a particular vehicle. The first term captures the utility a buyer received from purchasing a particular vehicle - inclusive of observable and unobservable characteristics unrelated to the costs of operation. This term includes many of the standard vehicle attributes included in a discrete choice model (e.g., weight, power, price, etc), with the exception of fuel efficiency. The last term reflects the idiosyncratic utility buyer i derives from purchasing an electric vehicle (in equation (1)) or a conventional vehicle (in equation (2)).

The second term reflects expected future costs of operation. At the time of purchase, the buyer forms expectations of future electricity and gasoline prices. Depending on the number of miles a buyer anticipates traveling (VMT_i) and the powertrain for the vehicle the buyer selects, the buyer faces a future costs of operating the vehicle, which are discounted by a common discount factor δ. In addition, the future costs of operation are adjusted to account for the likelihood of scrappage, where $S(t)$ reflects the probability the vehicle survives through period t.

Although we assume that buyers discount their future operational costs of an electric vehicle at a similar discount factor as the future operational costs of a conventional vehicle, the buyer might have an imperfect understanding of future operational costs, reflected in the parameters γ_g and γ_e. If buyers fully-internalize the future operational costs of a vehicle (as suggested for gasoline by Busse et al. (2013) and others), we would expect γ_g and γ_e to be equal to one. However, if buyers treat electricity prices and gasoline prices differently when making purchase decisions, those differences would be reflected in the values of γ_g and γ_e. We assume a buyer applies a common discount factor to both future electricity and future gasoline costs. If consumers are not forward looking, employ high discount rates, or hyperbolically discount future energy costs, we assume that these distortions are present for both gasoline and electricity. If a buyer discounts future electricity prices or gasoline prices in a fundamentally different way, it would be nested in the parameters γ_g and γ_e.

We make several simplifying assumptions to link the model above to our empirical specification. First, we assume that consumers have "no-change" forecasts for gasoline and electricity prices.[3] Second, we assume that at the time of purchase, the consumer believes that the scrappage rates of the two vehicles are equal, implying the electric vehicle and the conventional vehicle are equally likely to survive through period t (i.e., $S^{BEV}(t) = S^{ICE}(t)$). And finally, we assume that the buyer intends on driving a certain amount of miles regardless of the vehicle chosen.[4] In the context of a single vehicle household, this assumes no rebound effect. But, in the context of a multi-vehicle household, this assumption implies that they household would substitute miles between vehicles on a one-for-one basis – that is, overall household mileage would not change with the purchase of an electric vehicle.

Under these assumptions and standard logit assumptions for the idiosyncratic utility, we can represent the change in probability of purchasing an electric vehicle with respect to the price of electricity and gasoline as:

$$\begin{aligned} \frac{dPr(BEV)}{dP_0^e} &= \gamma_e \left(\frac{kwh}{mile}\right) VMT_i \sum_{t=0}^{\infty} \delta^t * Pr(BEV) * (1 - Pr(BEV)) \\ \frac{dPr(BEV)}{dP_0^g} &= -\gamma_g \left(\frac{gal}{mile}\right) VMT_i \sum_{t=0}^{\infty} \delta^t * Pr(BEV) * Pr(ICE) \end{aligned} \tag{3}$$

where $Pr(BEV)$ and $Pr(ICE)$ denote the probabilities with which the buyer purchases the electric vehicle or the conventional vehicle, respectively.

Rather than focusing on estimating the values of γ_g and γ_e directly (which would entail also estimating the discount factor, δ), our coefficient of interest is the ratio of γ_e to γ_g, which we denote γ. If people value electricity and gasoline costs similarly when making their purchase decisions, we would expect γ to be close to one. But, if buyers value the future operational costs using electricity less (more) than the future operational costs of gasoline, we would expect γ to be below (above) one.

In our empirical specification, we will estimate the effect of electricity and gasoline prices on electric vehicle sales. Equations (3) and(4) correspond to the response of sales to electricity and gasoline prices respectively. Denoting the estimated coefficients as $\hat{\beta}^e$ and $\hat{\beta}^g$, we can derive an

[3]Anderson et al. (2013) finds evidence that use of a "no-change" forecast accurately captures consumer beliefs of future gasoline prices; we are unaware of similar research examining consumer beliefs of future electricity prices.

[4]This is a potentially strong assumption in light of evidence that EVs are driven substantially less than their ICE counterparts (Davis (2018) and Burlig et al. (2021)).

upper bound[5]

$$\bar{\gamma} = \frac{-\hat{\beta}^e * \left(\frac{miles}{kwh}\right)}{\hat{\beta}^g * \left(\frac{miles}{gal}\right)} \tag{4}$$

Intuitively, the numerator of equation (4) reflects the impact of per-mile electricity costs of the electric vehicle and the denominator reflects the impact of per-mile gasoline costs of the conventional vehicle. In both cases the impact of electricity prices and gasoline prices, $\hat{\beta}^e$ and $\hat{\beta}^g$, are scaled by the relative fuel efficiencies of the two vehicles (in terms of kwh-per-mile for electric vehicles and gallons-per-mile for conventional vehicles). Although, ultimately, we will have to take a stand on the relatively fuel efficiencies of the electric and conventional vehicles, the comparison of the *relative* response to electricity and gasoline prices allows us to side-step the question of whether consumers are myopic with respect to the operational costs of the vehicle. Not only is this question still under debate in the context of conventional vehicles (e.g., Sallee et al. (2016), Allcott and Wozny (2014), Busse et al. (2013), Gillingham et al. (2021), Leard et al. (2021), to name a few), but it is easier to estimate in the context of conventional vehicles, for which fuel prices fluctuate at high frequency, in a setting where consumers have ample experience with fueling and operational costs, and where a robust secondary market exists.

3 Empirical Setting and Data

Our empirical approaches exploits temporal and cross-sectional variation in gasoline and electricity prices across census block-groups in California.[6] Our preferred approach focuses only on CBGs that are in close proximity to electric utility boundaries, allowing for a border discontinuity design that compares EV purchase behavior in CBGs on one side of a utility boundary to purchase behavior in CBGs on the other side. As an alternative, we also consider a panel model with fixed effects that uses data from all of California. Each of these approaches requires making use of three main datasets, one each for EV purchases, retail electricity prices and retail gasoline prices during the period 2014-2017.

The vehicle purchase data originates from the California Department of Motor Vehicles (DMV) and was purchased through a third party data provider. The data include a vehicle

[5]Manipulating (3) and (4), we can express gamma as: $\hat{\gamma} = \frac{-\hat{\beta}^e * \left(\frac{miles}{kwh}\right)}{\hat{\beta}^g * \left(\frac{miles}{gal}\right)} * \frac{Pr(ICE)}{1-Pr(BEV)}$. Noting that $\frac{Pr(ICE)}{1-Pr(BEV)}$ is strictly less than one, equation (4) provides an upper bound for γ.

[6]There are roughly 23,000 Census Block Groups (CBGs) in California, each comprised of approximately 600 to 3,000 people, or 200 to 1,000 households.

identification number (VIN), purchase date and census block-group in which the vehicle is registered for the universe of EVs purchased in California from 2014-2017. We aggregate these purchases up to the CBG-month-of-sample level and normalize by the population of the block group.

Our electricity prices come from two sources and cover both major types of electric utility companies in California: (1) investor-owned utilities (IOUs) Pacific Gas & Electric, Southern California Edison, and San Diego Gas and Electric, and (2) and municipal utilities such as Los Angeles Department of Water and Power, Sacramento Municipal Utility District (SMUD) and roughly two dozen smaller municipal utilities scattered throughout the state. Retail electricity price data are collected as part of the Form EIA-861 survey published by the US Energy Information Administration. The survey is administered to electric utilities, and the resulting dataset provides information on electricity sales, prices, customer counts by type, and a variety of other information about the utility companies and regulatory regimes. Here we focus on the residential electricity price. The EIA-861 data provide rate schedules for IOUs but not for municipal utilities. For municipal utilities, we augment the EIA data with rates retrieved directly from the utility websites or service representatives.

The electricity prices faced by customers in different service territories varies immensely, and often increases in a stepwise fashion with total monthly usage. In such cases of increasing block rates, households charging an electric vehicle at home will likely find themselves on the top tier of the residential rates schedule. Figures 1 and 2 display the rates for households on the top rate tier for utilities in the Bay Area and greater Los Angeles, highlighting the substantial variation in residential marginal electricity prices likely faced by electric vehicle owners.

A challenge to understanding the effect of electricity prices on EV demand is the myriad potential prices that EV owners may pay. The spectrum of candidate prices is linked both to the potential locations at which owners can charge their vehicles (e.g. home, at work, or at public charging stations) as well as the variety of prices that they may face at each of these charging locations. For example, some EV owners may charge at work for free, or they can pay a private charging station a monthly subscription, a price per hour at the plug, or on a pay-as-you-go basis per kWh. For people charging at home, their price will depend on the installed metering infrastructure and the pricing plans made available by their electric utility company. According to both survey evidence (see e.g., Hardman et al. (2018), Dunckley and Tal (2016)), evidence tracking home electricity usage (see e.g., Burlig et al. (2021)), and regulatory data relating to the Low Carbon Fuel Standard (Board (2020)), the majority of EV owners charge at home, either completely or in part, and do so via their home master electricity meter. For these EV owners during our sample period, nearly all (over 90 percent) are subject to the default residential tariff as opposed to an EV (time-of-use) rate.

Retail gasoline prices come from the Oil Price Information Service (OPIS) which tracks daily prices of fuels at the geolocated station-level. For each zip code, we construct the monthly average gasoline prices for all stations within 3 miles of the zip code centroid, reflective of the set of stations that might serve a particular community.[7] We merge gasoline prices to the vehicle data (at the CBG-by-month level) by matching each CBG to prices from the zip code with the greatest geographic overlap with the CBG. Perhaps surprisingly to some (as it was to us), there is a substantial amount of cross-sectional variation in gasoline prices between adjacent CBGs across utility boundaries.

We summarize the relevant data in Table 1. As our primary source of electricity price variation comes from differences between locations served by investor-owned utilities and municipal utilities, we report the summary statistics separately for areas served by the two types of electricity providers. In columns (1) and (2), we report summary statistics for all locations in California. In Columns (3) and (4), we limit the sample of locations to those used to estimate the border discontinuity regressions. Several patterns become clear from the summary statistics. First, the summary statistics highlight the location of the utility boundaries. State-wide, roughly equal numbers of census tracts are located in PGE's and SCE's service territories. Yet, SCE's service territory is more irregular and, hence, a higher fraction of census block groups *near boundaries* are located in SCE's service territory. In addition, the census block groups near the boundaries tend to be located in parts of the state with slightly higher levels of EV adoption. The summary statistics also highlight several differences between census block groups in the investor-owned utilities and the municipal utilities. Most relevant for our work is the difference in electricity prices - customers of municipal utilities face top-tier prices that are roughly one-third lower (on average) than those of customers of investor-owned utilities. Translated into dollar terms, a 10 cent per kilowatt hour difference is equal to roughly 2.5 cents per mile or and annual cost of $250 for a vehicle drive ten thousand miles per year. For a comparable gasoline vehicle (with fuel economy of 30 mpg), a similar change in annual costs would imply a roughly 75 cent per gallon increase in gasoline prices. The census block groups in the municipal utility service territories also tend to have higher density and lower incomes than census

[7] As an alternative, we also consider alternative radii of 1 mile, 5 miles and 10 miles, average gasoline prices that are inverse-distance weighted, and average gasoline prices for stations within the same zip code. We present the regression results using these alternative gasoline price measures in the Appendix.

block groups in investor-owned utility service territories.

4 Panel Regressions

We implement two different empirical strategies to estimate the coefficients $\hat{\beta}^e$ and $\hat{\beta}^g$ from which we can back out estimates of our parameter of interest, γ. As a starting point, consider a panel regression given by:

$$BEVSalesPerCapita_{ct} = \beta^e P^e_{ct} + \beta^g P^g_{ct} + \gamma_c + \lambda_t + \epsilon_{ct} \tag{5}$$

where c denotes census block-group and t denotes time.

Relative to the regression discontinuity approach, the panel design offers an approach that draws upon census block groups throughout California and directly conditions-out time-invariant unobservables through the block-group fixed effects. In the panel regression, identification follows from differential changes in electricity prices and gasoline prices across census block-groups over time. Most of the longer-term variation in the data arises from the regulatory price setting process - for instance, from the resetting of residential rates for California investor-owned utilities in response to changes in capital investments. If EV sales rise more quickly in block-groups that experience faster than average growth in electricity prices, all else equal, the panel specification would estimate a positive relationship between electricity prices and EV adoption.

In addition, a subset of utilities (both investor-owned and municipal) have rates that vary seasonally. We estimate versions of (5) at both the month level and at the annual level, the latter of which averages out seasonal rates over the course of the year and primarily estimates the effect of longer-term variation in residential electricity prices.

4.1 Results

Table 2 presents results corresponding to Equation 5, which regresses a count of BEV sales per capita in a given CBG on the price of electricity, price of gasoline, and control variables. Columns 1 and 2 are aggregated by month, allowing for higher-frequency fluctuations in energy prices to be reflected in changes in EV demand; columns 3 and 4 are aggregated annually. The coefficient estimates in columns 1 and 3 have the opposite signs to what one would expect – the electricity price coefficient is positive and the gas price coefficient negative. This reflects underlying correlations between unobservable patterns in the demand for EVs and energy prices across CBGs – demand for EVs tends to be high in areas with high electricity prices

In columns 2 and 4, we include block-group fixed effects and time fixed effects, capturing time-invariant and space-invariant unobserved drivers of EV demand. Here, variation comes from differential changes in gasoline and electricity prices – in this case, the latter are driven largely by panel variation in the regulated prices that the utilities are allowed to set. After conditioning on time-invariant unobservables at the block-group level, we estimate a negative coefficient on electricity prices and a positive coefficient on gasoline prices, consistent with theory.

The coefficient on cents/kwh in column 2 can be interpreted as follows: for every one cent increase in the price of electricity per kilowatt-hour, monthly EV sales fall by roughly 0.4% in the CBG, comparing the magnitude of the coefficient to mean annual EV sales from columns 1 and 2 of Table 1. Similarly, an increase of one cent per gallon of gasoline will increase sales by roughly 0.5%. At the moment, these coefficients present an apples-to-oranges comparison of the relative importance of electricity and gasoline prices on EV demand. To interpreting them in a more meaningful way, we must re-introduce the concept of engine efficiency.

Recall from equation 4 that $\hat{\gamma}$ reflects the weight that the consumer places on electricity costs relative to gasoline costs. Consider a consumer whose preferences reflect the panel results in column table 2. In a state of the world where this consumer is deciding between a Toyota Camry, an ICE that gets 30 miles-per-gallon, and a Tesla Model 3, which gets 4 miles-per-kWh, $\hat{\gamma} = \frac{0.0035*4}{0.0041*30} \approx 0.113$. In this case, the 1 cent per kilowatt-hour increase in electricity price translates into a 0.25 cent per mile increase in the cost of driving an electric vehicle. We estimate that a change of this magnitude generates a more modest impact than a 1 cent per gallon increase in gasoline costs, which would increase the cost of driving a Toyota Camry by *only* 0.03 cents per mile. The interpretation is that the customer places roughly one eighth the weight on electricity prices as she does on the price of gasoline.[8]

Panel identification relies on the assumption that there are no unobservables correlated with both the electric vehicle adoption and electricity or gasoline prices, after conditioning on block-group and time fixed effects. If unobservables affecting EV demand are correlated with changes in electricity prices, our coefficients will subsume the effect of the unobservable. For instance, if electricity prices rise in areas for which the charging station network is expanding quickly, we might mis-attribute the effect of the charging station network to electricity prices

[8]Note that this interpretation does depend on the choice of the reference vehicle. As the comparison EV gets more efficient, or the comparison ICE less efficient, $\hat{\gamma}$ increases and the behavioral interpretation would shift towards the consumer appearing to care more about the price of electricity. Although in this case, the coefficients

and underestimate the amount to which demand for EVs would respond to prices.

5 Regression Discontinuity across Utility Boundaries

As an alternative to the panel regression, we exploit the sharp changes in residential electricity prices that arise at utility service territory boundaries. As noted above, customers served by investor-owned utilities in California face residential electricity prices that are significantly higher than the electricity prices faced by consumers in neighboring, municipal utility service territories. Narrowing the focus to census block-groups locations along utility service territory boundaries, we can compare census block groups live in close proximity, where households likely face similar commutes and have similar access to public charging infrastructure, but potentially face *very* different electricity prices.

With a single boundary between an investor-owned utility and a municipal utility, we could consider estimating sales as a function of demographics, electricity prices, gasoline prices and distance to the utility service territory boundary. In the standard RD specification, we would allow the slope of the running variables (in this case, distance to the boundary) to differ on either side the border to capture omitted trends in BEV adoption further from the service territory boundary. Formally,

$$\begin{aligned} BEVSalesPerCap_{ct} &= \Theta X_c + \nu_1 Dist + \nu_2 Dist * 1[IOU_c] + \\ &\quad \beta^e \Delta P_t^e 1[IOU_c] + \beta^g P_{ct}^g + \epsilon_{ct} \end{aligned} \tag{6}$$

where ΔP_t^e is the difference in electricity price faced by consumers in the investor-owned utility relative to the neighboring utility, and $1[IOU_c]$ is an indicator variable for whether the consumer lives in the investor-owned utility service territory. Here, β^e would reflect the magnitude of the discontinuity in the dependent variable at the utility service territory boundary, measured in terms of the difference in price per kilowatt-hour.

In our setting, though, we have many utility area boundaries. We scale the approach above to estimate the coefficients using variation in prices across all borders between investor-owned utilities and other utilities in the data. Formally, for each block-group proximate to the utility area boundary, we pair the block group, c, with the closest block group, c', in the neighboring service territory. We then estimate the model using the difference in adoption and our covariates within each pair of block-groups, $i = (c, c')$. Given the volatility of electric vehicles sales (at the census-block-group level) and the desire to limit the variation in electricity prices arising from predictable seasonal rates, we aggregate the sales annually and estimate data at the "pair"-year level.

$$\begin{aligned} \Delta BEVSalesPerCapita_{it} &= \beta^e \Delta P^e_{it} + \beta^g \Delta P^g_{it} + \Theta \Delta X_{it} + \\ &\quad \nu_{1b} D_c + \nu_{2b} D_{c'} + \epsilon_{it} \end{aligned} \tag{7}$$

where ΔP^e and ΔP^g denote difference in the marginal price of electricity (cents/kwh) and gasoline (cents/gallon) between the two census block groups and D_c and $D_{c'}$ are the distances to the service territory boundary.

The border discontinuity refines the comparison group to a narrow band around utility district boundaries. This allows us to appeal to the intuition that underpins standard regression discontinuity approaches. In our application of the RD, CBGs on one side of the border may differ on average from CBGs on the other on any number of variables that enter the demand equation. The treatment effect of discontinuous differences in energy prices on EV purchases will be identified so long as unobserved non-energy price determinants of demand vary continuously across the border. Although not directly testable, we can test for discontinuities in observable factors correlated with EV adoption, such as incomes or population density. The absence of discontinuities in observable covariates might provide indirect evidence supporting the identification assumptions underlying the border discontinuity design.

5.1 RD Results

Our preferred specification allows EV sales to vary linearly on either side of *each* service territory boundary and identifies the coefficient on electricity price from the discrete change in EV sales crossing from one service territory to another. In contrast, the coefficient on gasoline prices is identified from panel variation within the zip codes in which each CBG are located. To illustrate the variation, we plot the distributions of the difference in electricity prices and gasoline prices between pairs of block-groups in our data in figures 5 and 6, respectively. The large differences in electricity prices between neighboring block groups is unsurprising as we pick block groups that fall on either side of utility service territory boundaries. Yet, we also see variation (albeit more modest) in gasoline prices in the neighborhoods around each of the paired block groups.

Results from the border discontinuity are presented in Table 3. Column 1 presents the results of a specification that only includes the difference in electricity price and gasoline price between the pairs of census block-groups located on either side of the utility boundary, along with linear functions of distance that capture how far the centroid of each block group is from the utility service territory boundary. In columns 2 and 3, we progressively add the difference in demographic variables between the paired census block groups to account for observable differences in demographics plausible correlated with electric vehicle adoption. Finally, in column 4, we further include utility fixed effects to capture time invariant adoption within the three investor owned utilities - arising, potentially from unobservable policies related to EV adoption at the utility-level. The fixed effects subsume much of the variation in electricity prices used to identify the coefficients of interest in columns 2 and 3 – the standard error, particular of the estimate of the coefficient on electricity price, rises substantially with the inclusion of the fixed effects.

Across the four specifications, we estimate negative relationships between electricity price and EV sales, although in columns 1 and 4, the estimates are statistically indistinguishable from zero. Since many of the non-investor owned utilities in the data are municipal electricity companies, the service territory boundaries commonly run along municipal boundaries. As one example, one of the boundaries we use in the data is the boundary between Pacific Gas and Electric and the city of Palo Alto, which provides electricity through a municipal utility. Demographics across some of the boundaries plausible vary in a discontinuous way as households sort between communities. Once we control for observable demographic characteristics of the census block group, we estimate a negative and significant relationship between electricity prices and EV sales.

We find results of the opposite sign for gasoline prices - across all four specifications, higher gasoline prices in a location are associated with greater electric vehicle adoption. The coefficients on the difference in demographics are, generally, consistent with earlier evidence on the characteristics of early EV-adopting households from Borenstein and Davis (2016). Higher incomes or greater preferences for high fuel economy vehicles or luxury vehicles prior to the introduction of EVs are associated with higher EV sales, whereas high population density and a high fraction of households in multiunit dwellings (where charging an EV might be more difficult) are associated with lower EV sales.

Following a similar approach to that in the panel regressions, we can back out an estimate of $\hat{\gamma}$, the weight that the consumer places on electricity costs relative to gasoline costs, from the coefficients on electricity and gasoline prices. Again using a Toyota Camry and Tesla Model 3 as the reference vehicles, our estimates in column 3 imply a $\hat{\gamma} = \frac{0.20*4}{0.17*30} = 0.157$, remarkably similar to the estimate from the panel specification, again suggesting that consumers substantially underweight future electricity prices relative to the weight they place on future gasoline costs. Figures 8 and 9 provide a graphical illustration of the results in column 3 of Table 3. In each panel, we residualize fuel price and electric vehicle adoption, bin the observations by residualized fuel price and plot the relationship between residualized gasoline price and adoption in panel (a) and residualized electricity price and adoption in panel (b). Figure 8 recreates the coefficients estimated from the regression, where gasoline prices and electricity prices are measured on a cents per gallon and cents per kilowatt-hour basis. The bottom two panels (in Figure 9, plots the exact same points after transforming the x-axis into a measure of cents per mile for both gasoline and electricity. The ratio between the slopes in Figure 8, panels (a) and (b) is the estimate of gamma – large changes in electricity costs (on a per mile basis) are necessary to generate similar changes in EV adoption as much smaller changes in gasoline costs (on a per mile basis).

5.2 Falsification Tests

The RD approach lends itself to natural falsification tests. Most utility borders in our sample are also municipal borders; but most municipal borders are not utility borders. We can therefore falsify the hypothesis that our estimated RD treatment effect is driven by non-energy price determinants of demand along municipal borders. We do so by estimating a placebo treatment effect along municipal boundaries across which there is no price change. A non-zero coefficient supports rejecting the hypothesis that non-price discontinuities are related to propensity to purchase an EV.

Recall that the main identifying assumption of the border discontinuity design is that unobserved non-energy price determinants of demand are 'smooth' across the utility border, allowing the causal effect of a discontinuous price change to be isolated. As in our main RD specifications, the ordering of CBGs within border CBG pairs is important for the falsification tests. Whereas in the main RD ordering occurred based on relative electricity price, in the falsification tests we order according to three demographic variables – income, population, and population density – thereby allowing a test for determinants of EV demand that are correlated with these variable.[9] We implement two versions of ordering rules, with one based on the entire shared portion of the border between two municipalities (i.e. which side of the boundary

[9] Recall from Table 1 that there were statistically insignificant but potentially economically-relevant differences in income and population density between IOU and municipal CBGs in the RD subsample. These falsification tests allow for the possibility that any discontinuities in these variables are correlated with determinants of EV demand.

has, say, higher average income) and the other allowing for CBG-level ordering (i.e. where, say, some CBGs on the municipality A and municipality B boundary are higher income in municipality A, and others in municipality B, and are ordered at the CBG-pair level).

Three demographic variables and two ordering rules lead to six separate tests, the results of which are presented in Table 6. Evidence against the main identifying assumption would be found in a non-zero coefficient estimate. In all six tests, we find little evidence of discontinuous changes in adoption across the boundaries between municipalities.

6 Welfare and EV Subsidies

Finally, we take our estimates of the degree to which consumers under-account for operating costs of electric vehicles and consider the implications for optimal EV subsidy policy. Sharing the spirit of Allcott et al. (2014), we consider the case of conventional and electric vehicles, where the buyer of a potential vehicle undervalues the savings associated with purchasing an electric vehicle. Our exercise share similarities to Holland et al. (2016) that models the environmental impacts conditional on current energy prices, but abstracts away from capturing the role of policy to address the "internality" of consumer inattention and Houde and Myers (2019) that examines heterogeneity in consumer inattention in the appliance market.

In our setting, optimal policy addresses two market failures. First, the marginal operational costs of using electricity or gasoline may not reflect social marginal cost, inclusive of externalities created by the use of electricity or gasoline. This externality-motive for subsidies (or taxes) is the focus of Holland et al. (2016). In addition though, if buyers do not fully incorporate electric prices into their decisions, the buyers impose an internality on their future selves. In our case, the internality shares the spirit of that in Allcott et al. (2014), in which goods varied with respect their energy efficient and a buyer mis-valued future energy savings. Here, though, the internality arises from the mis-estimation of one energy source (electricity) relative to another (gasoline).

To formalize our model, we build upon the stylized discrete choice model in Section 2. We assume that a population of consumers, with types denoted by i, varies with respect to the amount they plan to drive, with fraction η_i driving VMT_i miles per year. We focus on the decision on the extensive margin, assume $V\bar{M}T_i$ is equal regardless of the type of vehicle purchased.

Consumers incur cost and generate externalities when using either technology. We denote per-mile marginal external costs of gasoline and electricity as ϕ_g and ϕ_e respectively, the per-mile marginal private costs of each fuel, c_g and c_e, and the per-mile tax rates on gasoline and electricity as τ_g and τ_e. If the marginal private costs of gasoline or electricity do not align with marginal social costs, a rationale for subsidies (or taxes) might exist.

Yet, importantly, the perceived costs of using an electric vehicle may not reflect the true experiential costs of using that vehicle. This distinction, between the "decision" utility one uses to decide which durable good to purchase, and the "experience" utility received by actually using that good, is the source of the "internality." As discussed above, such a distinction between "decision" and "experience" utility might result from a range of possible sources, including an imperfect understanding of one's marginal electric price (e.g., Ito (2014)), biased beliefs about energy prices, rational inattention (e.g., Allcott et al. (2014)), or imperfect energy-efficiency labelling (see e.g., Davis and Metcalf (2016)). To provide a more concrete starting point, we assume that: (1) consumers accurately value gasoline prices (along the lines of Busse et al. (2013), Allcott and Wozny (2014) and others) and (2) we can parameterize consumers beliefs about electricity prices as a weighted average between an accurate estimate of future electricity prices and an alternative prior, θ (for example, the fuel cost savings suggested by the EPA fuel savings calculator). Here our parameter of interest γ is the relative weighting of the accurate estimate relative to the (possibly) biased prior.

Within each type i, consumers vary with respect to their idiosyncratic preference for electric vehicles relative to conventional vehicles, ϵ. We assume ϵ is mean-zero and identically distributed, with distribution $G(e)$, max value $\bar{\epsilon}$. For each type, we define $\hat{\epsilon}_i$ as the value that equates the utility of the conventional vehicle and electric vehicle for that type at the *at the time the consumer decision*. This means that if a consumer undervalues the savings associated with driving an electric vehicle at the time of purchase, $\hat{\epsilon}_i$ would be a function of the undervaluation.

We define $\hat{\epsilon}_i$ as:

$$\hat{\epsilon}_i = \alpha_{ICE} - \alpha_{BEV} - (p_{ICE} - p_{BEV} - S) - V\bar{M}T_i(c_g + \tau_g - \gamma(c_e + \tau_e) - (1 - \gamma)\theta) \qquad (8)$$

Letting $\lambda_i(V\bar{M}T_i, \tau_g, \tau_e, S)$ denote the fraction of consumers of type i that would purchase an electric vehicle, based on the distribution of ϵ. The policy maker collects or redistributes tax revenues or subsidy costs through lump sum transfers and maximizes welfare given by:

$$\begin{aligned} W \quad = \quad & \sum_i \eta_i [\qquad \left(\alpha_{ICE} + Y - p_{ICE} - V\bar{M}T_i(c_g + \tau_g)\right) + \\ & \int_{\hat{\epsilon}_i}^{\bar{\epsilon}} \left(\alpha_{BEV} - \alpha_{ICE} - (p_{BEV} + S - p_{ICE}) - V\bar{M}T_i(c_e + \tau_e - (c_g + \tau_g)) + \epsilon\right) dG(\epsilon) \\ & \left(\tau_g(1-\lambda_i)V\bar{M}T_i + \tau_e V\bar{M}T_i\lambda_i - S\lambda_i\right) + \\ & \left(-\phi_g V\bar{M}T_i(1-\lambda_i) - \phi_e V\bar{M}T_i\lambda_i\right) \qquad] \end{aligned} \tag{9}$$

Here, the first line reflects the mean utility enjoyed by a consumer of type i if they drove a conventional vehicle. The second line reflects the additional *experience* utility enjoyed for those consumers who, based on their *decision* utility, purchase an electric vehicle. This inconsistency between the utility a buyer anticipates at the time of vehicle purchase and the actual experience utility enjoyed creates an internality that the buyer imposes on his or her future self. The third line captures the lump sum transfer of resources either as a result of energy taxes or required to fund electric vehicle subsidies. Finally, the fourth line are the external costs of gasoline and electricity consumption.

The social planner has three policy instruments at their disposal: (1) a subsidy for electric vehicles S, (2) a tax on electricity τ_e, and (3) a tax on gasoline τ_g. This shares some similarity to both Allcott et al. (2014) and Holland et al. (2016), although we note the main differences. Allcott et al. (2014) considers both internalities and externalities, but focus on the decision between conventional vehicles that vary with respect to fuel efficiency. Undervaluation in this context leads to an internality whereby, in the absence of subsidies, a buyer underinvests in fuel efficiency on the margin. In contrast, mis-estimation of the costs of driving an electric vehicle generates an internality that can be positive or negative. Holland et al. (2016) considers optimal subsidies for electric vehicles, but focuses entirely on the external costs of pollution.

6.1 First-best subsidies

We begin by considering the case in which the social planner takes τ_e and τ_g as exogenous. We first consider the case in which the social planner can observe a buyer's type and designs take-it-or-leave it electric vehicle subsidies for each type i. Additive separability of W, implies that the first-best subsidies satisfy:[10]

$$S_i^*(V\bar{M}T_i) = V\bar{M}T_i[(\phi_g - \tau_g) - (\phi_e - \tau_e)] - [1-\gamma]V\bar{M}T_i[(c_e + \tau_e) - \theta] \tag{10}$$

[10]Details of all derivations are provided in the appendix.

The first term in the expression captures the relative degree to which the external costs of gasoline and electricity are not reflected in the the per-unit taxes, scaled by the vehicle miles travelled. The latter term is the internality that a buyer imposes on their future self, if they mis-estimates the future costs of operation for an electric vehicle.

Two special cases help to illuminate the drivers of the first-best subsidy. The first special case is the one in which consumers accurately assess the future operational costs of an electric vehicle (i.e., $\gamma = 1$). Here, buyers accurately incorporate future electricity and gasoline costs into their purchase decision. In this case, the subsidy captures the cumulative unpriced externality associated with driving an electric vehicle relative to conventional vehicle that arises if the social planner fails to set the Pigouvian tax rates for electricity and gasoline. Taken to the extreme case, in which electricity and gasoline are both priced at private marginal costs (i.e., $\tau_g = \tau_e = 0$), the optimal subsidy is equal to cumulative lifetime externality imposed by a conventional vehicle relative to an electric vehicle, $S^*(V\bar{M}T_i) = V\bar{M}T_i(\phi_g - \phi_e)$, and aligns with the optimal subsidies from Holland et al. (2016).

The second special case focuses on the "internality" in which the regulator sets Pigouvian taxes obviating an externality rationale for subsidies. Here, the optimal subsidy reflects the internality that the buyer's decision imposes on his or her future self. The sign of the subsidy captures whether the buyer over- or under-estimates the operational costs of driving an electric vehicle. If the buyer overestimates the cost (i.e., $\theta > (c_e + \tau_e)$), the first-best subsidy is equal to the net present value of the difference between the actual and estimated operational costs of driving the vehicle. Optimally set, the subsidy equates the decision and experience utility of the buyer, so as to induce the buyer to make the decision that is optimal from the perspective of their future self. If, on the other hand, the buyer underestimates the cost of operation at the time of purchase, (i.e., $theta < (c_e + \tau_e)$, the optimal policy *taxes* electric vehicles.

The comparative statics with respect to τ_g and τ_e illustrate the relationship between other policy levers an optimal EV subsidies.

$$\frac{\partial S_i^*(V\bar{M}T_i)}{\partial \tau_g} = -V\bar{M}T_i \tag{11}$$

$$\frac{\partial S_i^*(V\bar{M}T_i)}{\partial \tau_e} = \gamma V\bar{M}T_i \tag{12}$$

Abstracting away from the response of VMT to tax-inclusive prices, the first-best subsidy offsets a change in the gasoline tax on a one-for-one basis (when scaled by VMT) – as the gasoline tax increases, the unpriced externality from gasoline consumption declines and the social planner provides a lower subsidy for electric vehicles. If the buyer fully internalizes the cost of operation of an electric vehicle, electricity taxes (or regulated per-unit markups above marginal cost) have very similar effects on the optimal subsidy. If electricity taxes rise, so does the optimal subsidy so as to match any un-priced (or over-priced) externality. Yet, if buyers mis-estimate the costs of operation ($\gamma < 1$), the effect of the electricity tax on the internality and externality push in opposite directions. Although higher electricity taxes may necessitate an offsetting electric vehicle subsidy, higher electricity taxes also impose a greater cost on the experiential utility of a buyer who is mis-estimating the future operational costs of the vehicle.

In figure 10, we illustrate these relationships between τ_g, τ_e, and γ and the first-best subsidy in the context of California. In each of the panels, we decompose the first-best subsidy into an externality-driven component (green line) and a internality-driven component (red-line). The shaded region reflects the optimal annualized subsidy, the sum of the two components, measured on an annualized basis.[11]

In the panel (a), we decompose the first-best subsidy for a range of residential electricity prices spanning those charged by both municipal and investor-owned utilities in California. As noted by the comparative statics in equation (12), for low values of gamma, the total subsidy does not vary substantially with electricity prices – optimal annual subsidies are roughly \$200 - \$300 across the range of electricity prices observed in California utilities. Scaled up to account for the length of time a typical vehicle is owned, these optimal subsidies are similar in magnitude to the base subsidy offered through the Clean Vehicle Rebate Program, California's main state-wide subsidy for EV buyers. Yet, the relatively constant total subsidy masks two competing effects. As electricity prices increase, the mis-priced externalities imply greater and greater optimal subsidies. Interestingly, in the case of California, actual gasoline taxes (roughly 2.26 cpg for a 30 mpg conventional vehicle) are relatively close to the marginal external costs per mile (2.55 cpm) estimated in Holland et al. (2016). Rather, the externality-driven subsidy here addresses the mis-pricing of *electricity*. In California, marginal electricity prices across both municipal and investor-owned utilities exceed social marginal cost – the optimally set subsidy corrects for the sub-optimally set marginal electricity prices.

Yet, as the mis-pricing of electricity increases (e.g., by comparing the marginal prices of municipal and investor-owned utilities), the subsidy does not increase commensurately. Rather,

[11] We calibrate the first-best subsidies based on data from California. The mean self-reported mileage from the 2017 NHTS for California (10,793 miles per year). State gasoline taxes are estimated at 68.3 cents per gallon. Per-mile externalities for gasoline-powered and electric vehicles are taken from Holland et al. (2016). Marginal private cost of electricity in California is taken from Borenstein and Bushnell (2019). Except where notes, all panels assume a value of γ equal to 0.157.

the optimal subsidy also accounts for the internality a buyer who mis-estimates the cost of operation imposes on their future self, a cost which is greater for a buyer living in a high marginal price utility than a low-marginal price utility. For the vast majority of Californians, for whom the marginal electricity price they face is greater than electricity price used by the EPA and Tesla fuel savings calculators, this implies that the externality-driven subsidy for electric vehicles is offset by an internality-driven *tax* on electric vehicles. The lack of relationship between electricity prices and the optimal subsidy runs counter to the standard intution, that subsidies and low-electricity prices are policy substitutes as both reduce the "all-in" price of owning an electric vehicle. But, if consumers mis-estimate the future costs of operation, the optimal subsidy does not decline on a commensurate basis with electricity prices.

In panel (b), we perform a similar decomposition of the first-best subsidy based on gasoline taxes. Unlike electricity prices gasoline taxes only affect the first-best subsidy through the mis-pricing of the externality. As gasoline taxes increase, the optimal subsidy declines commensurately.

Finally, in panel (c), we examine variation in values of γ. Here, the gamma only impacts the internality-driven component of the subsidy. Namely as the degree to which a buyer's mis-estimation of the cost of operation declines, the incentive to tax electric vehicles so as to align the decision utility and experience utility of the buyer declines.

6.2 Second-best subsidies

We also, briefly, explore the second best subsidy and examine implications for California vehicle policy. If the regulator cannot observe buyer type, and it still limited to using S as the single policy variable, the second-best subsidy maximizes W conditional on the distribution of buyer types. The derivation is analogous to that above, retaining the weighting η_i for each of the buyer types.

$$S^* = \sum_i \eta_i V\bar{M}T_i \left[[(\phi_g - \tau_g) - (\phi_e - \tau_e)] - (1-\gamma)[(c_e + \tau_e) - \theta] \right] \tag{13}$$

Here, the second-best subsidy reflects the externality generated and the internality borne by a buyer who drives an amount equal to the weighted average number of vehicle miles in the population. The degree to which the undifferentiated subsidy is suboptimally set is a function of the vehicle miles travelled by type i.

$$S^* - S_i^*(V\bar{M}T_i) = [(\sum_i \eta_i V\bar{M}T_i) - V\bar{M}T_i] \left[[(\phi_g - \tau_g) - (\phi_e - \tau_e)] - (1-\gamma)[(c_e + \tau_e) - \theta] \right] \tag{14}$$

For buyer types that drive less (more) than $\sum_i \eta_i V\bar{M}T_i$, the optimal policy is set too high (low) relative to the first-best policy.

In Figure 11, we again adapt the framework to examine California vehicle policy. The histogram in Figure 11 plots the distribution of self-reported VMT by California drivers. We calculate a second-best (state-wide) subsidy as the weighted average of the first-best (VMT-specific) subsidy, where the weights are given by the fraction of CA drivers reporting different levels of vehicle miles travelled. The difference between the second-best (state-wide) subsidy and the first-best (VMT-specific) subsidy is plotted as the green line. Values above zero reflect drivers for whom the second-best subsidy exceeds the first-best subsidy they would receive based on their vehicle miles travelled. In other words, these drivers are "oversubsidized" relative to the first-best, while the drivers to the right, for whom the difference is negative, are "undersubsidized" relative to the first-best.

7 Conclusion

The prominence of gasoline prices in peoples' car purchase decisions aligns with existing evidence in the literatures on vehicle choice and consumer behavior in electricity markets. Buyers of conventional vehicles exhibit awareness of differences in the ongoing operational costs of gasoline-powered cars based on their fuel efficiency. This makes sense for several reasons. Gasoline prices are prominently displayed in view drivers passing by; gasoline expenditures tend to comprise a significant share of the household budget, and so it is reasonable that consumers would be attentive to any changes in incentives on this margin; and introduction of alternative modes of transportation interact in the way economists would predict. For example, when a new public transit option opens nearby, house values adjust to a degree that compensates homeowners for the change in potential fuel expense from commuting to city centers (Blake (2016)).

Consumers know far less about electricity prices. Again, there are several potential reasons for this. Electricity prices are very different from place-to-place. The consumption expenditure share of electricity is smaller than that of gasoline, and this diminishes the incentive for consumers to inform themselves about how to optimize on this margin. Of course, this expenditure share will increase dramatically for most EV drivers, and so one might also suspect that their awareness of electricity prices would increase around an EV purchase event.

While the results presented in this paper are consistent with what we know about how consumers relate to gasoline and electricity prices, there are also reasons to believe that a shift towards EVs would also change the way consumers relate to these input prices. If and when that occurs, the present electricity price schedules in California would create dramatically different incentives for vehicle choice in some utility districts than in others. This mis-pricing has clear efficiency considerations since the marginal benefit of EV adoption and use is likely continuous across utility boundaries, whereas prices are not. Moreover, policymakers concerned with stimulating demand for EVs (e.g. to reach EV adoption goals in California and other jurisdictions) will be constraining their ability to do so if input prices create incentives that differ dramatically based on location and in important cases disincentivize the behavior they are aiming to promote.

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Figure 1: Residential Retail Electric Prices
Bay Area (Top Tier, 2014-2017)

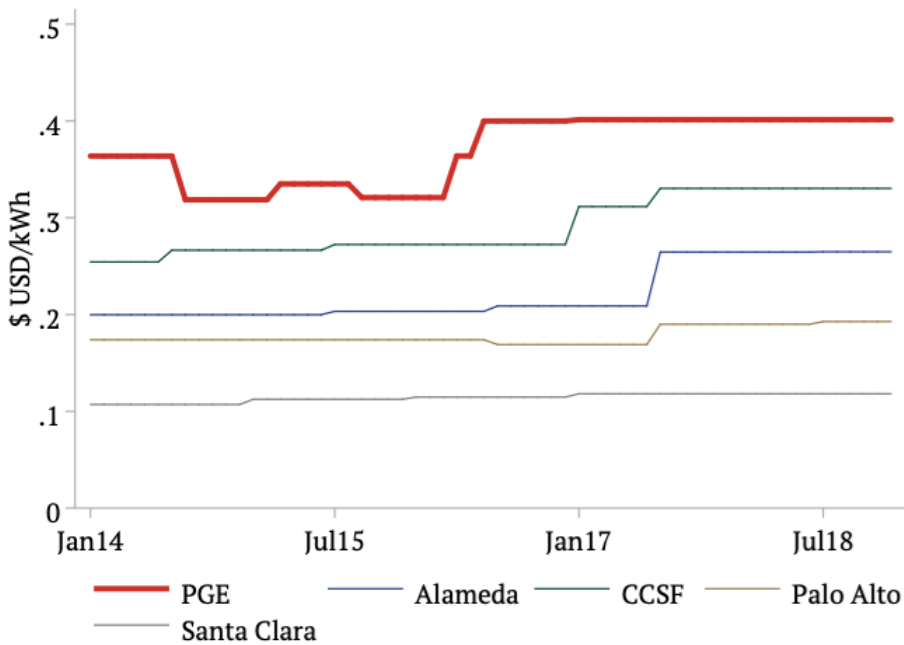


Figure 2: Residential Retail Electric Prices
Los Angeles (Top Tier, 2014-2017)

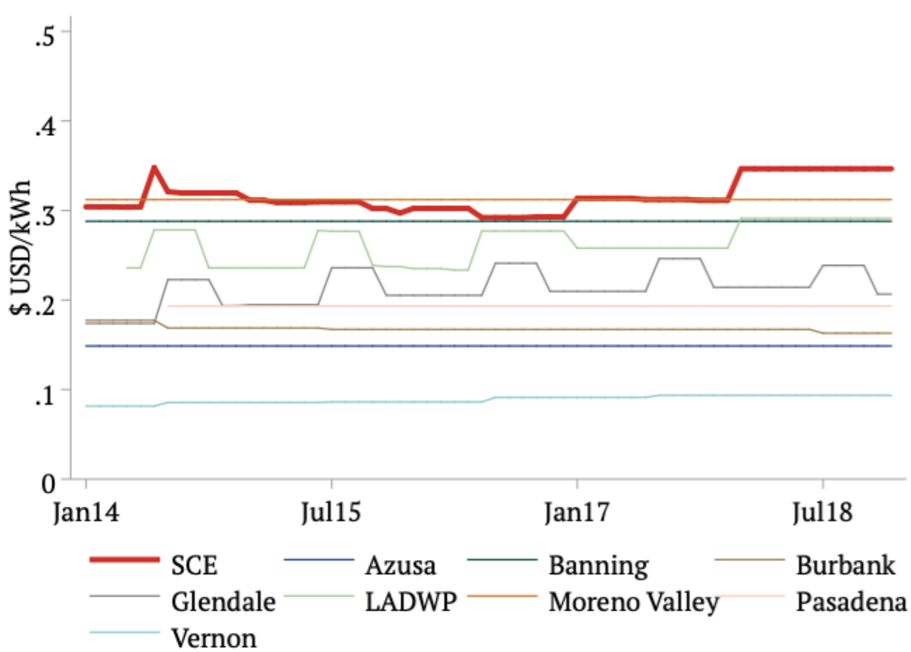


Figure 3: Gasoline prices in California

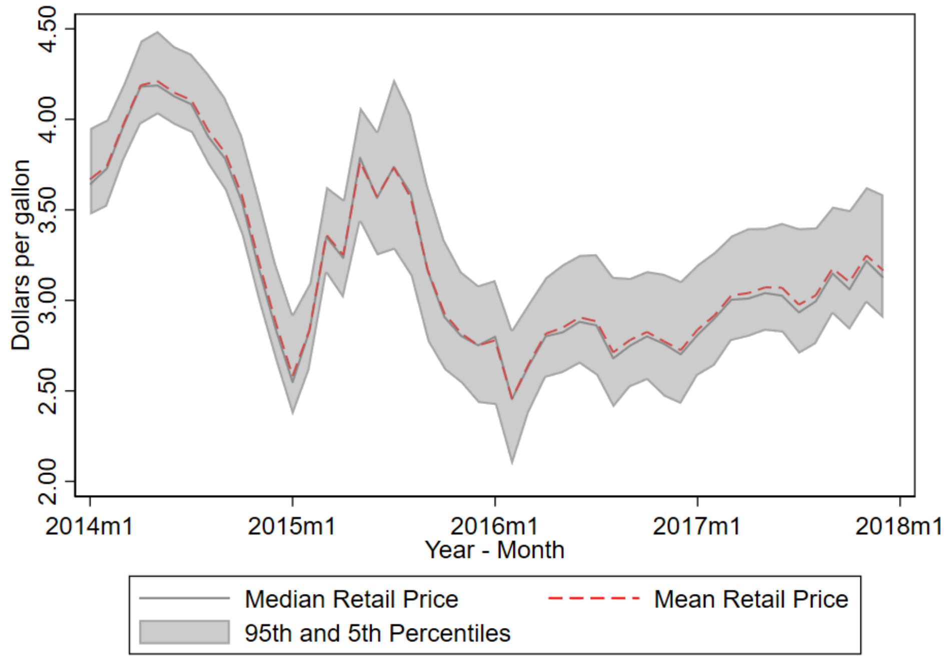


Figure 4: Example: Utility Boundaries and CBG "Adjacency" & Distance

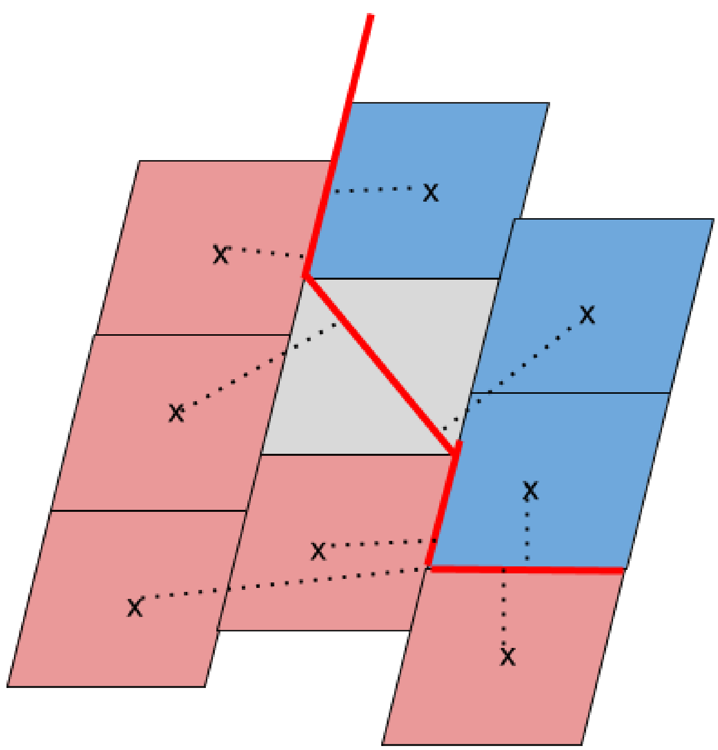


Figure 5: Electricity Price Differences between Block-Group Pairs

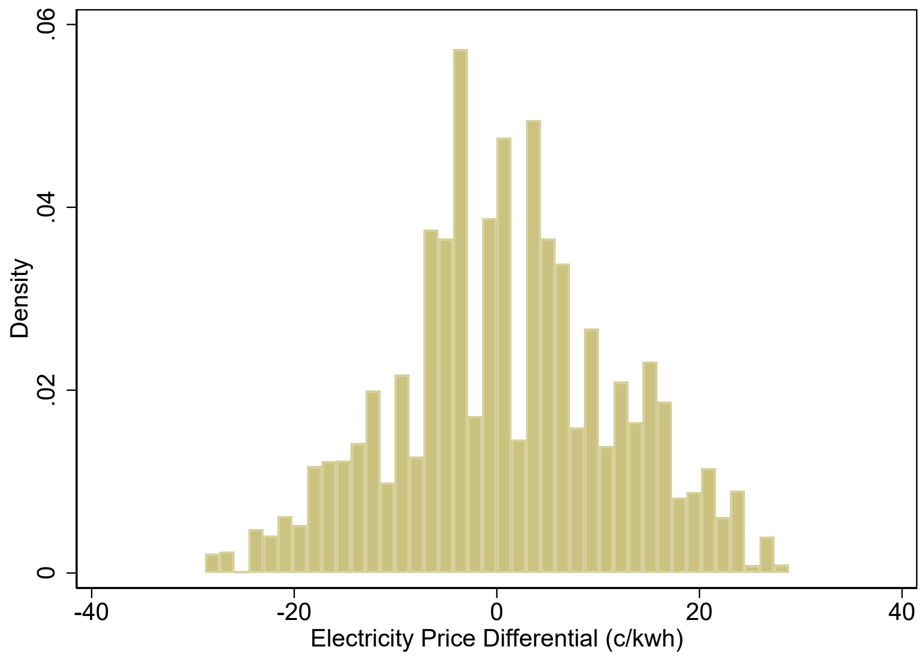


Figure 6: Gasoline Price Differences between Block-Group Pairs

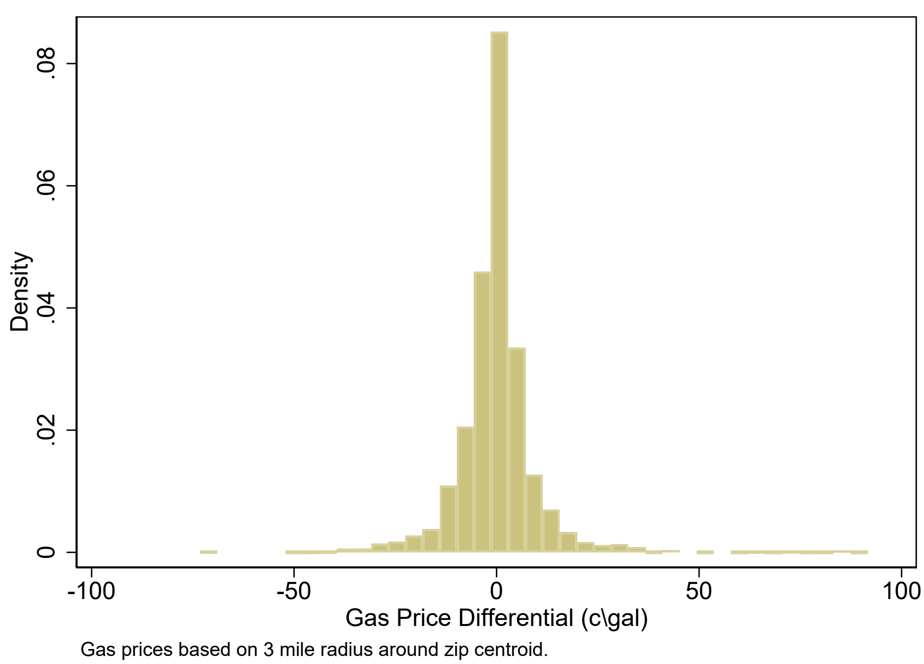
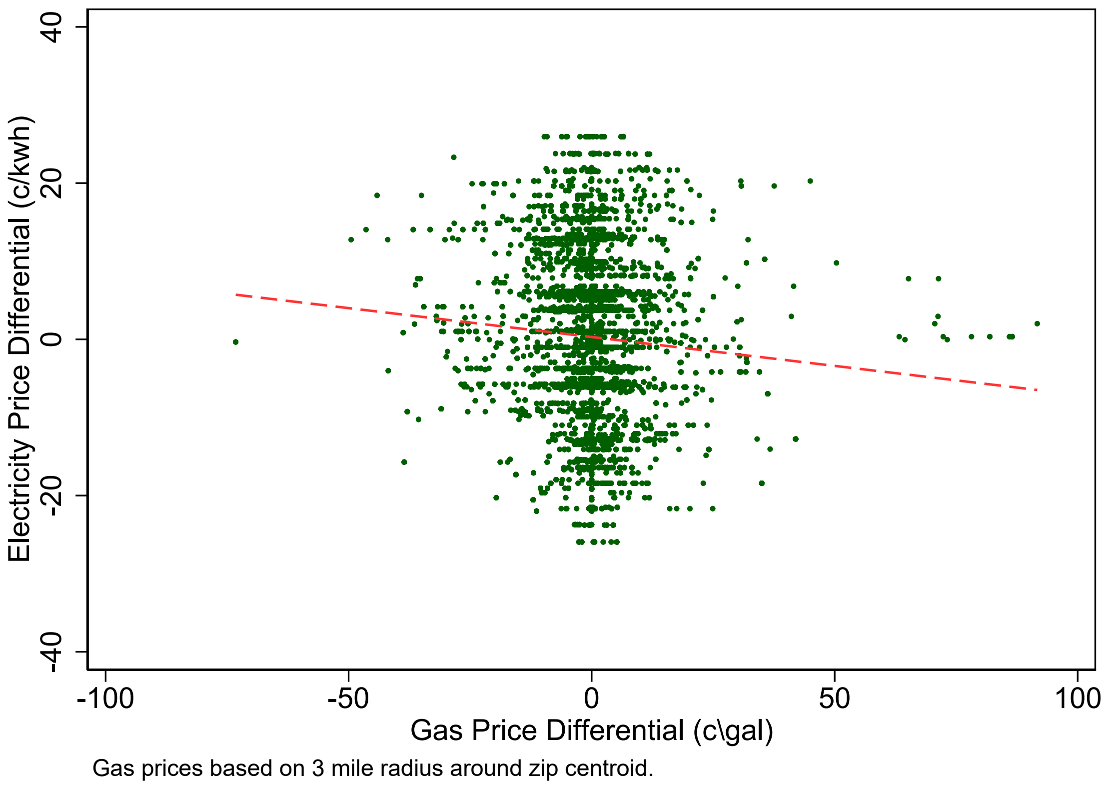


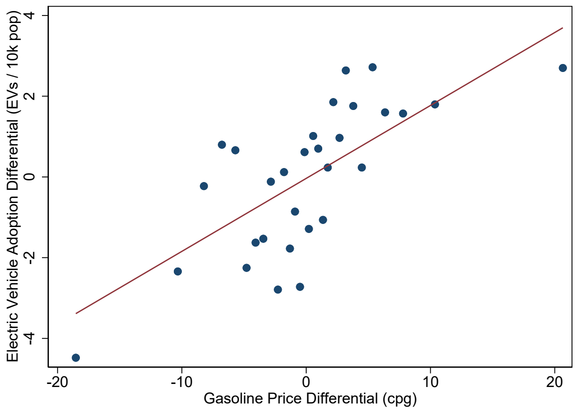
Figure 7: Electricity Price and Gasoline Price Differences between Block-Group Pairs



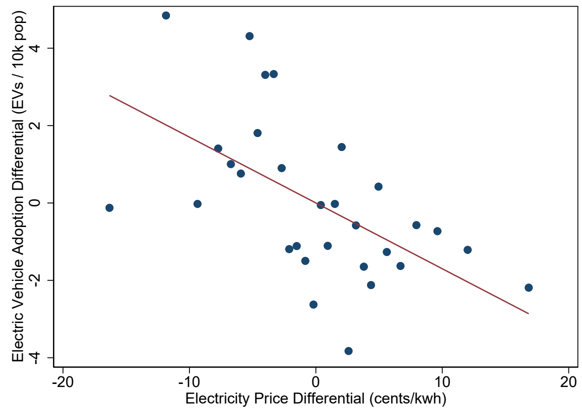
Notes: Figure plots the gasoline and electricity price differential for pairs of census block groups straddling utility area boundaries. Observations are annaul at the census-block-group pair level.

Figure 8: Electric Vehicle Adoption, Gasoline Prices and Electricity Prices

(a) Gasoline Prices



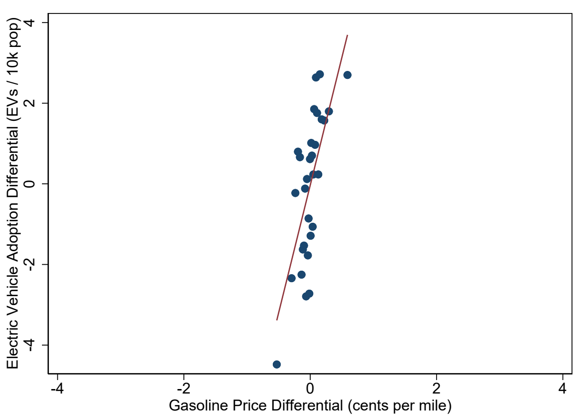
(b) Electricity Prices



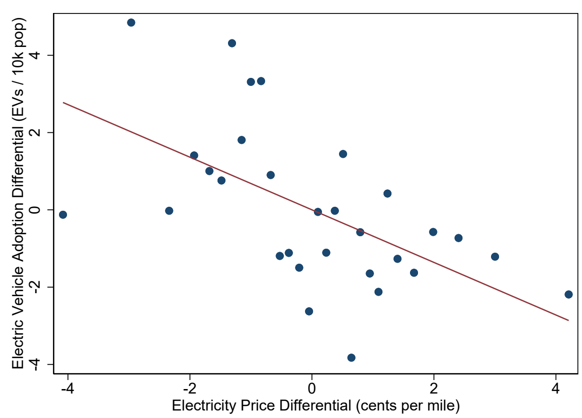
Notes: Figure plots the binned scatter plot of EV adoption against gasoline prices (Panel A) and electricity prices (Panel B) based on the paired RD design in equation 7. All variables are residualized by covariates included in column (3) of table 3, and binned into twenty quantiles of either gasoline price differential or electricity price differential.

Figure 9: Electric Vehicle Adoption, Gasoline Prices and Electricity Prices Per Mile

(a) Gasoline Prices



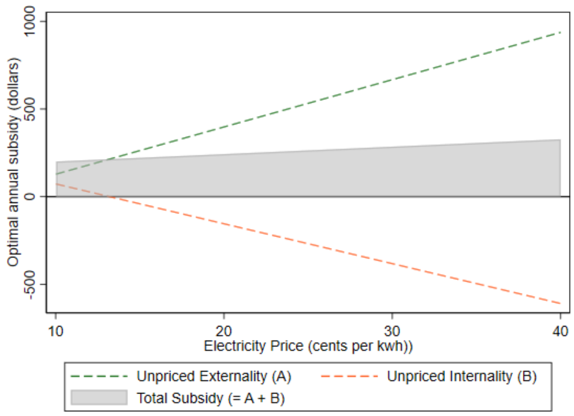
(b) Electricity Prices



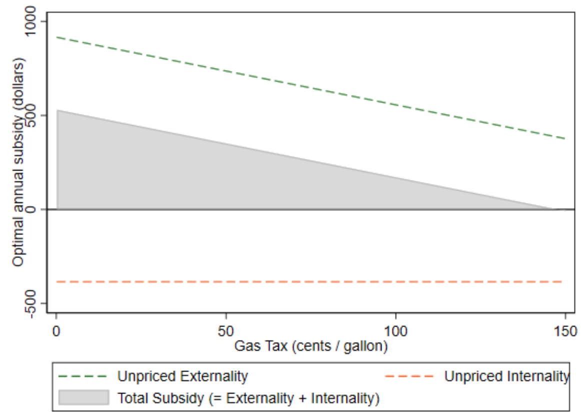
Notes: Figure plots the binned scatter plot of EV adoption against gasoline prices (Panel A) and electricity prices (Panel B) based on the paired RD design in equation 7. All variables are residualized by covariates included in column (3) of table 3, and binned into twenty quantiles of either gasoline price differential or electricity price differential.

Figure 10: Decomposition of optimal subsidy

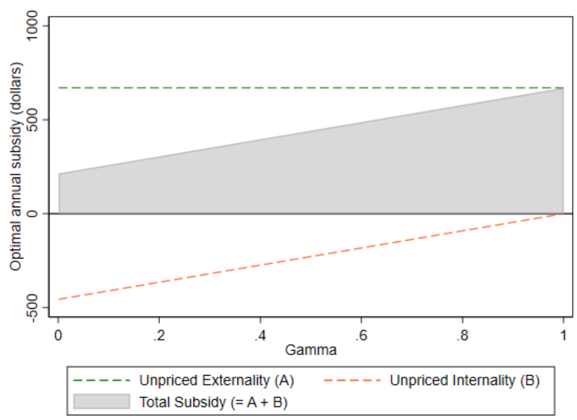
(a) Electricity Prices



(b) Gasoline Taxes Prices



(c) Gamma



Assumptions: Annual VMT equal to mean, self-reported VMT from 2017 NHTS for California (10793). BEV fuel efficiency = 4 mpKwH. ICE fuel efficiency = 30 mpg. Damages per mile for EVs and ICEs taken from Holland et al. (2016). Marginal private cost of electricity from Borenstein and Bushnell (2019). Electricity price implied by EPA fuel economy calculator = 13.2 cpm.

Figure 11: Difference between first and second-best subsidy, by VMT

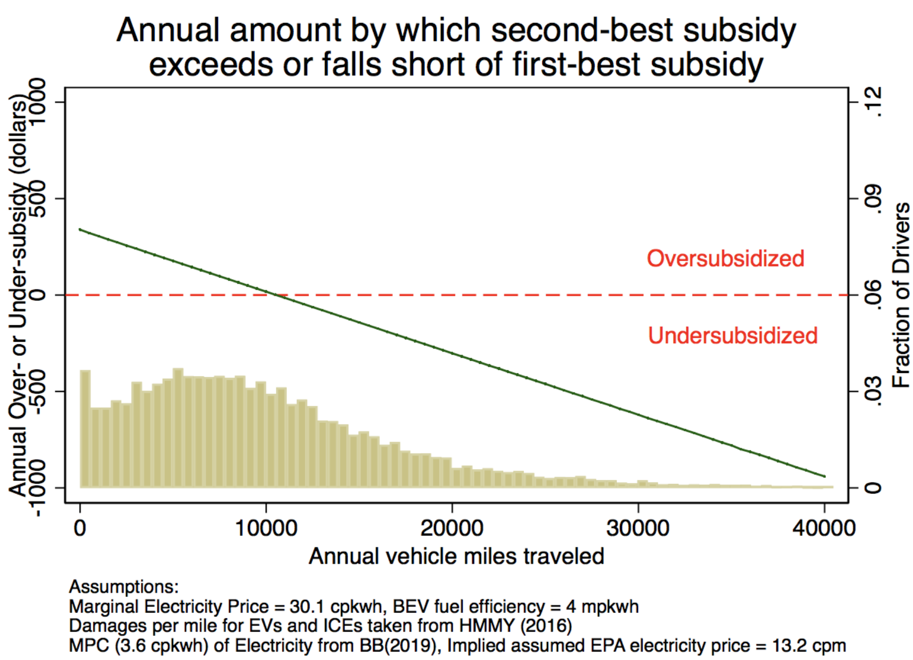


Table 1: Summary Statistics

	Full Sample		RD Subsample	
	IOU	Muni	IOU	Muni
Annual EV Sales per 10000 pop	10.93	8.798	14.26	12.44
	(19.21)	(16.67)	(22.50)	(20.37)
Marg. Elec. Price (cpkwh)	31.74	21.65	30.01	22.03
	(4.690)	(5.415)	(3.577)	(5.384)
Gasoline Price (cpg)	317.6	317.5	319.9	321.2
	(38.66)	(39.82)	(38.68)	(39.37)
Population (000s)	1.720	1.631	1.766	1.667
	(1.087)	(0.872)	(1.107)	(0.773)
Population Density	8.878	12.86	8.604	10.71
	(9.088)	(12.70)	(7.847)	(9.418)
Household Income (000s)	79.10	64.67	86.98	77.71
	(40.97)	(36.01)	(45.16)	(44.17)
Hybrid Fleet Share (2013)	0.0609	0.0559	0.0648	0.0657
	(0.0420)	(0.0419)	(0.0452)	(0.0489)
Luxury Fleet Share (2013)	0.0421	0.0408	0.0596	0.0549
	(0.0486)	(0.0470)	(0.0670)	(0.0647)
MUD HH share (2013)	0.326	0.430	0.316	0.403
	(0.310)	(0.334)	(0.308)	(0.322)
Fleet Fuel Economy (mpg, 2013)	23.09	23.07	23.03	23.11
	(1.233)	(1.160)	(1.249)	(1.257)
Fraction in PGE	0.458	0	0.256	0
	(0.498)	(0)	(0.437)	(0)
Fraction in SCE	0.424	0	0.742	0
	(0.494)	(0)	(0.437)	(0)
Fraction in SDGE	0.117	0	0.00123	0
	(0.321)	(0)	(0.0350)	(0)
Dist. to Util. Boundary (km)			0.610	0.776
			(1.391)	(1.680)
Observations	82449		6671	

Notes: Columns 1 and 2 summarize variables for all census block groups in California, separated by whether they are located in an Investor Owned Utility (IOU). Columns 3 and 4 summarize variables for census block groups located on either side of the IOU / Municipal utility boundaries.

Table 2: Panel Results

	Monthly Sales Per Cap		Annual Sales Per Cap	
	(1)	(2)	(3)	(4)
Marg. Price (cents/kwh)	0.0036***	-0.0035**	0.030**	-0.062***
	(0.00096)	(0.0015)	(0.012)	(0.023)
Gas Price (cpg)	-0.0011***	0.0041***	-0.022***	0.16***
	(0.000078)	(0.00060)	(0.0013)	(0.013)
Time FE		X		X
CBG FE		X		X
Implied γ		.113		.052
		(.052)		(.02)
Observations	872314	870564	73351	73160
R-Squared	0.00030	0.15	0.0020	0.61

Dependent variable is EV sales per 10,000 population. Standard errors (in parentheses) are two-way clustered by IOU census block group and municipal census block group. Implied value of γ assumes fuel efficiencies of 4 miles / kwh for EVs and 30 miles / gallon for the alternative conventional vehicle.

Table 3: Border Discontinuity Results

	(1)	(2)	(3)	(4)
Δ Marg. Price (cents/kwh)	-0.11	-0.17***	-0.20***	-0.070
	(0.079)	(0.058)	(0.064)	(0.15)
Δ Gas Price (cpg)	0.35***	0.32***	0.17***	0.16***
	(0.10)	(0.096)	(0.054)	(0.054)
Δ Population (000s)		-1.23***	-1.08***	-1.05***
		(0.35)	(0.34)	(0.34)
Δ Pop Density (000s ppl/sqm)		-0.31***	-0.15***	-0.16***
		(0.047)	(0.041)	(0.043)
Δ Income ($000)		0.17***	0.084***	0.083***
		(0.023)	(0.020)	(0.020)
Δ Mean Fuel Econ (mpg, 2013)			2.53***	2.55***
			(0.94)	(0.94)
Δ Hybrid Fleet Share (2013)			-12.4	-11.2
			(30.1)	(29.9)
Δ Luxury Fleet Share (2013)			127.8***	128.5***
			(20.4)	(20.3)
Δ MUD HH share (2013)			-3.45**	-3.49***
			(1.34)	(1.34)
IOU FE				X
Implied γ	.042	.071	.157	.058
	(.033)	(.034)	(.074)	(.124)
Observations	7179	6779	6759	6759
R-Squared	0.097	0.27	0.33	0.33

Dependent variable is EV sales per 10,000 population. Standard errors (in parentheses) are two-way clustered by IOU census block group and municipal census block group. Implied value of γ assumes fuel efficiencies of 4 miles / kwh for EVs and 30 miles / gallon for the alternative conventional vehicle.All specifications allow coefficients on distance to the utility boundary to vary on either side of every utility boundary.

Table 4: Border Discontinuity Results

	(1)	(2)	(3)	(4)
Δ Marg. Price (cents/mile)	-0.44	-0.69***	-0.79***	-0.28
	(0.32)	(0.23)	(0.26)	(0.60)
Δ Gas Price (cents/mile)	10.4***	9.66***	5.02***	4.85***
	(3.12)	(2.88)	(1.62)	(1.62)
Δ Population (000s)		-1.23***	-1.08***	-1.05***
		(0.35)	(0.34)	(0.34)
Δ Pop Density (000s ppl/sqm)		-0.31***	-0.15***	-0.16***
		(0.047)	(0.041)	(0.043)
Δ Income ($000)		0.17***	0.084***	0.083***
		(0.023)	(0.020)	(0.020)
Δ Mean Fuel Econ (mpg, 2013)			2.53***	2.55***
			(0.94)	(0.94)
Δ Hybrid Fleet Share (2013)			-12.4	-11.2
			(30.1)	(29.9)
Δ Luxury Fleet Share (2013)			127.8***	128.5***
			(20.4)	(20.3)
Δ MUD HH share (2013)			-3.45**	-3.49***
			(1.34)	(1.34)
IOU FE				X
p-value, $H0 : \beta^g = \beta^e$	.001	0	0	.003
Implied γ	.042	.071	.157	.058
	(.033)	(.034)	(.074)	(.124)
Observations	7179	6779	6759	6759
R-Squared	0.097	0.27	0.33	0.33

Dependent variable is EV sales per 10,000 population. Standard errors (in parentheses) are two-way clustered by IOU census block group and municipal census block group. Cost of gasoline and cost of electricity are transformed into cents per mile using fuel efficiencies of 30 miles per gallon and 4 miles per kwh, respectively. All specifications allow coefficients on distance to the utility boundary to vary on either side of every utility boundary.

Table 5: RD regressions - Robustness Checks

	(1) Full Sample	(2) CBG dist < 5km	(3) Excl. PGE CBGs	(4) Pairwise Best Matches	(5) No Duplicate Pairs
Δ Marg. Price (cents/kwh)	-0.20***	-0.17*	-0.33***	-0.011	-0.21***
	(0.064)	(0.094)	(0.088)	(0.17)	(0.067)
Δ Gas Price (cpg)	0.17***	0.14	0.23***	0.065	0.17***
	(0.054)	(0.10)	(0.072)	(0.23)	(0.054)
Δ Population (000s)	-1.08***	-2.01***	-1.03**	0.23	-1.09***
	(0.34)	(0.49)	(0.41)	(0.92)	(0.34)
Δ Pop Density (000s ppl/sqm)	-0.15***	-0.11***	-0.18***	-0.21**	-0.15***
	(0.041)	(0.041)	(0.040)	(0.10)	(0.044)
Δ Income ($000)	0.084***	0.11***	0.062**	0.19***	0.080***
	(0.020)	(0.022)	(0.025)	(0.056)	(0.021)
Δ Mean Fuel Econ (mpg, 2013)	2.53***	2.42***	1.82**	1.23	2.65***
	(0.94)	(0.91)	(0.85)	(1.26)	(1.00)
Δ Hybrid Fleet Share (2013)	-12.4	-18.1	-29.1	1.16	-14.5
	(30.1)	(32.6)	(36.2)	(54.8)	(29.2)
Δ Luxury Fleet Share (2013)	127.8***	148.3***	114.4***	154.7***	127.6***
	(20.4)	(22.0)	(19.5)	(53.6)	(20.7)
Δ MUD HH share (2013)	-3.45**	-1.13	-3.45**	8.01*	-3.95***
	(1.34)	(1.45)	(1.45)	(4.07)	(1.37)
Implied γ	.157	.157	.19	.023	.168
	(.074)	(.15)	(.08)	(.362)	(.077)
Observations	6759	5012	4956	521	6234
R-Squared	0.33	0.35	0.28	0.45	0.33

Dependent variable is EV sales per 10,000 population. Standard errors (in parentheses) are two-way clustered by IOU census block group and municipal census block group. Implied value of γ assumes fuel efficiencies of 4 miles / kwh for EVs and 30 miles / gallon for the alternative conventional vehicle.All specifications allow coefficients on distance to the utility boundary to vary on either side of every utility boundary and covariates.

Table 6: Falsification Tests

	(1) Income	(2) Population	(3) Pop. Density
CBG	0.627	0.991	0.879
	(0.772)	(0.898)	(0.915)
Municipality	0.398	-2.006	1.103
	(0.977)	(1.846)	(1.052)
Observations	5,030	5,202	5,202

Dependent variable is EV sales per 10,000 population. Each observation is a CBG pair along municipal borders within IOUs that are not also IOU borders. Observations are ordered within a pair with respect to the column header variable, by CBG and Municipality respectively. Standard errors (in parentheses) are two-way clustered by IOU census block group and municipal census block group. Cost of gasoline and cost of electricity are transformed into cents per mile using fuel efficiencies of 30 miles per gallon and 4 miles per kwh, respectively. All specifications allow coefficients on distance to the utility boundary to vary on either side of every utility boundary.

A Appendix

A.1 Allowing for multiple vehicles

The framework in equations (1) and (2) can be easily extended to a world in which a buyer considers a BEV and multiple conventional vehicles that differ with respect to fuel efficiency. Consider a set of electric vehicles denoted by k and a set of conventional vehicles denoted by j, with fuel economies $(\frac{kwh}{mile})_k$ and $(\frac{gal}{mile})_j$, respectively.

Under the set of assumptions described in section 2, we can represent

$$\frac{dPr(BEV)}{dP_0^e} = \gamma_e \left(\sum_k \frac{Pr(BEV_k)}{Pr(BEV)} (\frac{kwh}{mile})_k VMT \sum_{t=0}^{\infty} (\delta^t S^{BEV}(t)) \right) * Pr(BEV) * (1 - Pr(BEV)) \tag{15}$$

$$\frac{dPr(BEV)}{dP_0^g} = -\gamma_g \left(\sum_j \frac{Pr(ICE_j)}{Pr(ICE)} (\frac{gal}{mile})_j VMT \sum_{t=0}^{\infty} (\delta^t S^{ICE}(t)) \right) * Pr(BEV) * Pr(ICE)$$

where $Pr(BEV)$ denotes the probability of purchasing any one of the electric vehicles denoted by k and $Pr(BEV_k)$ denotes the probability of purchasing electric vehicle k. Notably, these expressions are identical to those of (1) and (2), with the exception that the fuel economies for the single electric and conventional vehicles have been replaced by weighted average fuel economies of the fleet of electric vehicles and the fleet of conventional vehicles.

A.2 Social Planner Problem

The social planner maximizes

$$\begin{aligned} W = \sum_i \eta_i [\quad & \left(\alpha_{ICE} + Y - p_{ICE} - V\bar{M}T_i(c_g + \tau_g)\right) + \\ & \int_{\hat{\epsilon}_i}^{\bar{\epsilon}} \left(\alpha_{BEV} - \alpha_{ICE} - (p_{BEV} + S - pICE) - V\bar{M}T_i(c_e + \tau_e - (c_g + \tau_g)) + \epsilon\right) dG(\epsilon) \\ & \left(\tau_g(1-\lambda_i)V\bar{M}T_i + \tau_e V\bar{M}T_i\lambda_i - S\lambda_i\right) + \\ & \left(-\phi_g V\bar{M}T_i(1-\lambda_i) - \phi_e V\bar{M}T_i\lambda_i\right) \quad] \end{aligned} \tag{16}$$

where

$$\hat{\epsilon}_i = \alpha_{ICE} - \alpha_{BEV} - (p_{ICE} - p_{BEV} - S) - V\bar{M}T_i(c_g + \tau_g - \gamma(c_e + \tau_e) - (1-\gamma)\theta) \tag{17}$$

, $G(\epsilon)$ denotes the distribution of idiosyncratic utility, η_i denotes the fraction of buyers of type i with vehicle miles travelled VMT_i, $\lambda_i(S, \tau_g, \tau_e, \gamma)$ denotes the fraction of consumers of type i who purchase an electric vehicle, S denotes the electric vehicle subsidy, and c_g, τ_g, ϕ_g and c_e, τ_e, ϕ_e denote the tax-exclusive price, tax and external cost, all on a per-mile basis, of gasoline and electricity, respectively.

A.2.1 First-best subsidy

The first-best subsidy for buyer i, holding τ_e and τ_g fixed, maximizes W_i, the welfare generated by buyer i. Taking the derivative of W_i with respect to S, we have:

$$\begin{aligned}\frac{dW_i}{dS} &= \int_{\hat{\epsilon}_i}^{\bar{\epsilon}} G(\epsilon)d\epsilon - \frac{d\hat{\epsilon}_i}{dS}G(\hat{\epsilon}_i)[V\bar{M}T_i((1-\gamma)(c_e+\tau_e)+(1-\gamma)\theta)] \\ &\quad -\frac{d\lambda_i}{dS}V\bar{M}T_i(\tau_g-\tau_e) - S\frac{d\lambda_i}{dS} - \lambda_i \\ &\quad +\frac{d\lambda_i}{dS}V\bar{M}T_i(\phi_g-\phi_e)\end{aligned} \tag{18}$$

Noting that $\int_{\hat{\epsilon}_i}^{\bar{\epsilon}} G(\epsilon) = \lambda_i$ and $\frac{d\hat{\epsilon}_i}{dS}G(\hat{\epsilon}_i) = \frac{d\lambda_i}{dS}$, the above expression simplifies to:

$$S^*(V\bar{M}T_i) = V\bar{M}T_i[(\phi_g-\tau_g)-(\phi_e-\tau_e)] - [1-\gamma]V\bar{M}T_i[(c_e+\tau_e)-\theta)] \tag{19}$$

A.2.2 Undifferentiated subsidy

If the regulator cannot observe buyer type, and it still limited to using S as the only policy variable, the optimal subsidy maximizes W. The derivation is analogous to that above, retaining the weighting η_i for each of the buyer types.

$$S^* = \sum_i \eta_i V\bar{M}T_i\left[[(\phi_g-\tau_g)-(\phi_e-\tau_e)] - (1-\gamma)[(c_e+\tau_e)-\theta)]\right] \tag{20}$$

A.2.3 Second-best subsidy

If the regulator cannot observe buyer type, and it still limited to using S as the only policy variable, the optimal subsidy maximizes W. The derivation is analogous to that above, retaining the weighting η_i for each of the buyer types.

$$\begin{aligned}\frac{dW}{dS} &= \sum_i \eta_i\Big[\int_{\hat{\epsilon}_i}^{\bar{\epsilon}} G(\epsilon)d\epsilon - \frac{d\hat{\epsilon}_i}{dS}G(\hat{\epsilon}_i)[V\bar{M}T_i((1-\gamma)(c_e+\tau_e)+(1-\gamma)\theta)] \\ &\quad -\frac{d\lambda_i}{dS}V\bar{M}T_i(\tau_g-\tau_e) - S\frac{d\lambda_i}{dS} - \lambda_i \\ &\quad +\frac{d\lambda_i}{dS}V\bar{M}T_i(\phi_g-\phi_e)\Big]\end{aligned} \tag{21}$$

$$S^* = \sum_i \eta_i V\bar{M}T_i\left[[(\phi_g-\tau_g)-(\phi_e-\tau_e)] - (1-\gamma)[(c_e+\tau_e)-\theta)]\right] \tag{22}$$

A.3 Supplementary Figures and Tables

Table A1: Panel regressions - Different FE

		Monthly Sales Per Cap				Annual Sales Per Cap		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Marg. Price (cents/kwh)	0.0036***	-0.0091***	-0.00042	-0.0035**	0.030**	-0.13***	-0.012	-0.062***
	(0.00096)	(0.00072)	(0.00076)	(0.0015)	(0.012)	(0.0092)	(0.0094)	(0.023)
Gas Price (cpg)	-0.0011***	-0.0023***	-0.00093*	0.0041***	-0.022***	-0.046***	-0.0070	0.16***
	(0.000078)	(0.000082)	(0.00056)	(0.00060)	(0.0013)	(0.0015)	(0.0082)	(0.013)
Controls		X	X	X		X	X	X
Time FE			X	X			X	X
CBG FE				X				X
Observations	872314	870564	870564	870564	73351	73175	73175	73160
R-Squared	0.00030	0.078	0.085	0.15	0.0020	0.33	0.34	0.61

Standard errors clustered by census block-group.

Table A2: Panel regressions - Prices Individually

	Monthly Sales Per Cap			Annual Sales Per Cap		
	(1)	(2)	(3)	(4)	(5)	(6)
Marg. Price (cents/kwh)	-0.0040***		-0.0035**	-0.095***		-0.062***
	(0.0014)		(0.0015)	(0.022)		(0.023)
Gas Price (cpg)		0.0042***	0.0041***		0.16***	0.16***
		(0.00060)	(0.00060)		(0.013)	(0.013)
Observations	978348	876711	870564	82140	73204	73160
R-Squared	0.14	0.15	0.15	0.60	0.61	0.61

Standard errors clustered by census block-group. All specifications include census block-group fixed effects and time fixed effects. Columns (3) and (6) are identical to columns (2) and (4) from the text.

Table A3: RD regressions - Prices Individually

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Marg. Price (cents/kwh)	-0.034		-0.11	-0.17***		-0.20***	-0.098		-0.070
	(0.061)		(0.079)	(0.056)		(0.064)	(0.11)		(0.15)
Δ Gas Price (cpg)		0.35***	0.35***		0.18***	0.17***		0.16***	0.16***
		(0.10)	(0.10)		(0.055)	(0.054)		(0.054)	(0.054)
Δ Population (000s)				-0.56**	-1.10***	-1.08***	-0.55**	-1.05***	-1.05***
				(0.27)	(0.34)	(0.34)	(0.27)	(0.34)	(0.34)
Δ Pop Density (000s ppl/sqm)				-0.18***	-0.14***	-0.15***	-0.18***	-0.16***	-0.16***
				(0.040)	(0.042)	(0.041)	(0.041)	(0.043)	(0.043)
Δ Income ($000)				0.084***	0.083***	0.084***	0.084***	0.083***	0.083***
				(0.016)	(0.020)	(0.020)	(0.016)	(0.020)	(0.020)
Δ Mean Fuel Econ (mpg, 2013)				2.52***	2.54***	2.53***	2.52***	2.54***	2.55***
				(0.86)	(0.95)	(0.94)	(0.86)	(0.95)	(0.94)
Δ Hybrid Fleet Share (2013)				-6.66	-9.74	-12.4	-6.10	-11.8	-11.2
				(26.3)	(30.3)	(30.1)	(26.0)	(29.9)	(29.9)
Δ Luxury Fleet Share (2013)				125.8***	126.9***	127.8***	126.1***	128.2***	128.5***
				(19.5)	(20.8)	(20.4)	(19.5)	(20.6)	(20.3)
Δ MUD HH share (2013)				-2.10*	-3.22**	-3.45**	-2.10*	-3.47***	-3.49***
				(1.20)	(1.36)	(1.34)	(1.22)	(1.33)	(1.34)
IOU FE							X	X	X
Observations	9188	7224	7179	8688	6792	6759	8688	6792	6759
R-Squared	0.084	0.096	0.097	0.31	0.33	0.33	0.31	0.33	0.33

Standard errors two-way clustered by census block-group. All specifications allow coefficients on distance to the utility boundary to vary on either side of every utility boundary. Columns (1) - (3) do not include covariates. Columns (4) - (6) include demographic covariates. Columns (7) - (9) additionally include IOU fixed effects.

Table A4: Panel Regression - Alternative Gasoline Prices

		Observation Weighted Average Prices				Inverse Distance Weighted Average Prices			
	(1) Avg Zip Price	(2) 1mi Radius	(3) 3mi Radius	(4) 5mi Radius	(5) 10mi Radius	(6) 1mi Radius	(7) 3mi Radius	(8) 5mi Radius	(9) 10mi Radius
Marg. Price (cents/kwh)	-0.0035**	-0.0017	-0.0035**	-0.0038***	-0.0034**	-0.0018	-0.0035**	-0.0037**	-0.0034**
	(0.0014)	(0.0018)	(0.0015)	(0.0015)	(0.0014)	(0.0018)	(0.0015)	(0.0015)	(0.0014)
(mean) P_gas	0.0027***	0.0046***	0.0041***	0.0033***	0.0033***	0.0046***	0.0039***	0.0034***	0.0032***
	(0.00062)	(0.00059)	(0.00060)	(0.00059)	(0.00080)	(0.00058)	(0.00059)	(0.00058)	(0.00076)
Time FE	X	X	X	X	X	X	X	X	X
CBG FE	X	X	X	X	X	X	X	X	X
Implied γ	.172	.05	.113	.151	.137	.052	.12	.146	.139
	(.078)	(.052)	(.052)	(.064)	(.066)	(.052)	(.055)	(.062)	(.067)
Observations	960587	670509	870564	926922	969459	670509	870564	926922	969459
R-Squared	0.14	0.14	0.15	0.15	0.14	0.14	0.15	0.15	0.14

		Observation Weighted Average Prices				Inverse Distance Weighted Average Prices			
	(1) Avg Zip Price	(2) 1mi Radius	(3) 3mi Radius	(4) 5mi Radius	(5) 10mi Radius	(6) 1mi Radius	(7) 3mi Radius	(8) 5mi Radius	(9) 10mi Radius
Marg. Price (cents/kwh)	-0.063***	-0.037	-0.062***	-0.061***	-0.051**	-0.039	-0.062***	-0.060***	-0.051**
	(0.021)	(0.028)	(0.023)	(0.022)	(0.021)	(0.028)	(0.023)	(0.022)	(0.021)
(mean) P_gas	0.11***	0.15***	0.16***	0.15***	0.14***	0.15***	0.15***	0.15***	0.14***
	(0.011)	(0.013)	(0.013)	(0.013)	(0.014)	(0.012)	(0.013)	(0.013)	(0.014)
Time FE	X	X	X	X	X	X	X	X	X
CBG FE	X	X	X	X	X	X	X	X	X
Implied γ	.074	.032	.052	.054	.048	.034	.054	.052	.048
	(.026)	(.025)	(.02)	(.02)	(.02)	(.025)	(.021)	(.02)	(.021)
Observations	80766	56429	73160	77948	81459	56429	73160	77948	81459
R-Squared	0.59	0.60	0.61	0.60	0.60	0.60	0.61	0.60	0.60

To be added.

Table A5: Border Discontinuity - Alternative Gasoline Prices

		Observation Weighted Average Prices				Inverse Distance Weighted Average Prices			
	(1) Avg Zip Price	(2) 1mi Radius	(3) 3mi Radius	(4) 5mi Radius	(5) 10mi Radius	(6) 1mi Radius	(7) 3mi Radius	(8) 5mi Radius	(9) 10mi Radius
Δ Marg. Price (cents/kwh)	-0.15***	-0.20**	-0.20***	-0.17***	-0.15***	-0.20**	-0.20***	-0.17***	-0.15***
	(0.051)	(0.080)	(0.064)	(0.060)	(0.055)	(0.080)	(0.064)	(0.060)	(0.055)
Δ Gas Price (cpg)	0.071*	0.082*	0.17***	0.080	0.053*	0.071*	0.12**	0.063	0.016
	(0.040)	(0.048)	(0.054)	(0.066)	(0.031)	(0.043)	(0.059)	(0.068)	(0.041)
Δ Population (000s)	-0.76***	-1.73***	-1.08***	-0.72**	-0.60**	-1.72***	-1.04***	-0.71**	-0.58**
	(0.25)	(0.38)	(0.34)	(0.31)	(0.28)	(0.38)	(0.33)	(0.31)	(0.28)
Δ Pop Density (000s ppl/sqm)	-0.17***	-0.067*	-0.15***	-0.16***	-0.17***	-0.072*	-0.15***	-0.16***	-0.17***
	(0.040)	(0.039)	(0.041)	(0.041)	(0.040)	(0.040)	(0.042)	(0.041)	(0.040)
Δ Income ($000)	0.074***	0.080***	0.084***	0.086***	0.085***	0.079***	0.083***	0.085***	0.085***
	(0.017)	(0.017)	(0.020)	(0.018)	(0.017)	(0.017)	(0.020)	(0.018)	(0.017)
Δ Mean Fuel Econ (mpg, 2013)	1.99***	1.02*	2.53***	2.90***	2.65***	1.05*	2.65***	2.89***	2.66***
	(0.72)	(0.55)	(0.94)	(0.93)	(0.90)	(0.55)	(0.98)	(0.93)	(0.91)
Δ Hybrid Fleet Share (2013)	-11.5	26.8	-12.4	-15.7	-7.87	25.8	-15.9	-15.9	-8.15
	(27.3)	(20.1)	(30.1)	(28.9)	(27.4)	(20.3)	(30.7)	(28.9)	(27.4)
Δ Luxury Fleet Share (2013)	123.2***	103.8***	127.8***	131.2***	128.9***	104.3***	130.5***	131.5***	129.0***
	(18.1)	(15.2)	(20.4)	(20.5)	(19.9)	(15.6)	(21.2)	(20.6)	(20.0)
Δ MUD HH share (2013)	-2.28*	-3.92***	-3.45**	-2.70**	-1.94	-4.04***	-3.50**	-2.77**	-1.95
	(1.19)	(1.32)	(1.34)	(1.23)	(1.19)	(1.35)	(1.38)	(1.24)	(1.19)
Implied γ	.284	.325	.157	.278	.388	.379	.218	.349	1.245
	(.185)	(.212)	(.074)	(.253)	(.251)	(.259)	(.128)	(.394)	(3.145)
Observations	8135	4428	6759	7588	8524	4428	6759	7588	8524
R-Squared	0.30	0.34	0.33	0.33	0.32	0.34	0.33	0.33	0.32

To be added.