Energy Prices and Electric Vehicle Adoption

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Abstract

This paper provides the first evidence on how electric vehicle (EV) sales respond to energy prices. Using EV registrations in California, we use a border-discontinuity strategy exploiting sharp changes in residential electricity prices between utilities. EV sales are four to six times more sensitive to gasoline prices than to electricity prices. However, EV retention decreases with local electricity prices, suggesting that owners learn about operating costs through experience. Results inform optimal subsidy and tax policy. If consumers underestimate EV cost of ownership at the time of purchase, optimal purchase incentives combine a subsidy to address external benefits with a *tax* to address consumer mis-optimization.

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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 vehicle standards or mandates for more efficient or alternative-fuel technologies. Supporters of direct regulations express skepticism over the ability of price-based incentives to affect 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 could partially offset the effects of carbon pricing and create a justification for further regulations. The customer bias creates a dual justification for mandates and standards: they help the environment and help (or force) customers to make the "right" choice at the time of a durable-goods purchase. Regulatory cost-benefit analyses frequently point to these consumer benefits to support the adoption of such regulations.[1]

The goal of this paper is to test this assertion in the context of electric vehicles (EVs)[2]: Do EV buyers make purchase decisions that suggest they fully-internalize the future operational costs of electricity?[3] To our knowledge, this is the first study using revealed preference to estimate the causal relationship between energy prices and EV adoption.[4] Although a number of studies find evidence that conventional vehicle (CV) buyers fully value (e.g., Busse et al. (2013), Sallee et al. (2016)) or close-to-fully value (e.g., Allcott and Wozny (2014), Grigolon et al. (2018)) fuel efficiency, disagreement remains (e.g., Leard et al. (2021) and Gillingham et al. (2021)). When considering EVs, there are reasons to expect that buyers might accurately value differences in future operating costs. EV savings calculators are readily available and promotional materials often highlight the operational cost savings enjoyed by EV drivers. But, there are also reasons to be skeptical of full valuation. Savings calculators and promotional materials often base estimates on average nationwide fuel prices. These will mislead consumers whose local electricity and gasoline price differentials differ from the national average (Borenstein and Bushnell (2022)) and Davis and Metcalf (2016)).

[1]For example, private energy-cost savings to car buyers constitute the majority of total social benefits in the Regulatory Impact Analysis of federal fuel economy standards (e.g. Environmental Protection Agency (2021)).

[2]Throughout the paper, unless otherwise noted, we use the term electric vehicle to refer to vehicles that operate entirely on electricity, distinct from plug-in hybrid electric vehicles that can use electricity for short trips but can also operate on gasoline.

[3]A rational consumer would be willing to pay $100 more for a car that saves them $100 in present value operating expenses, all else equal.

[4]Li et al. (2017b) and Sierzchula et al. (2014) run cross-country regressions that include average electricity price as an explanatory variable.

Buyers have extensive experience with the link between gasoline prices and conventional vehicle use, and gasoline prices are amongst the most salient in the economy. In contrast, electricity price tariffs are often complicated and the marginal price paid is poorly understood by the typical consumer.[5] Moreover, billing is infrequent and often occurs well-after consumption, making it more difficult for the typical household to understand how their decisions affect their monthly consumption.[6]

The question of how potential EV buyers perceive ongoing operational costs takes on practical importance as EVs (paired with a clean electricity grid) are viewed by policymakers as a central element to reducing carbon emissions from the transportation sector. During our study period, federal incentives amounted to up to $1.5 billion per EV manufacturer. California and other states also offered generous incentives to encourage buyers to adopt EVs.[7] These policies have continued through to the present. Most notably, the 2022 Inflation Reduction Act renewed the federal incentives, dropping the manufacturer limits in favor of restricting the subsidy to less expensive EVs finally-assembled in North America and means-testing household eligibility. These incentives are often linked to ambitious policy goals. For example, an executive order to ban gasoline cars in California was followed by a plan passed by regulators that would ban the sale of new gasoline cars entirely in California by 2035. The relative costs of driving on gasoline and electricity affect the financial incentives to choose an EV, and therefore may work to accelerate or retard progress towards these aspirations.

In this paper, we study the 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. To estimate the effect of electricity prices, we leverage large differences in the electricity prices paid by customers of municipally-owned electric utilities (such as Los Angeles Department of Water and Power) and investor-owned utilities (such as Southern California Edison). 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. We use two distinct samples and empirical approaches: a two-way fixed-effect model estimated on the entire sample of census block groups (CBGs), and a border discontinuity design that exploits discrete changes in electricity prices at boundary of neighboring electric utility service

[5] Ito (2014) and Shaffer (2020) find evidence that consumers poorly understand the marginal electricity price they face.

[6] Jessoe and Rapson (2014) demonstrate that residential electricity price elasticity is 2-3 times higher when consumers are provided information about the relationship between energy services and the quantity of electricity used.

[7] 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 (2021), Li (2017), Li et al. (2017a)), and supply-side mandates such as the zero-emissions vehicle mandate in California (McConnell and Leard (2021)).

territories. Both produce remarkably similar results.

The assumptions required for identification in the border discontinuity design are weak relative to methods deployed in the literature studying buyers of gasoline cars. Those typically estimate panel fixed-effects and structural demand models. In our setting, bordering CBGs share unobservables factors (e.g. commuting patterns and local EV charging station density) that are continuous at the border, but face dramatically different energy prices. 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. The discontinuity design offers opportunities to falsify the identifying assumptions and to assuage concerns about heterogeneity in miles traveled (Levinson and Sager (2023)), the importance of demographics in vehicle choice (Levinson and Sager (2023), Davis et al. (2023)) and non-monetary factors such as the availability of refueling and charging infrastructure, in car-buying decisions (Springel (2021), Li (2017), Li et al. (2017a)). We present an array of tests that support a causal interpretation of the findings.

We contribute two main empirical results and one theoretical result to the literature. First, fuel prices influence vehicle technology choice, but do so asymmetrically. While prospective EV buyers appear to be influenced by both gasoline and electricity prices when making purchase decisions, the influence of gasoline prices is roughly four to six times stronger than the influence of electricity prices, when both are measured on a "cost-per-mile" basis that reflects the relative fuel efficiency of gasoline and electric engines. We find that the asymmetric impacts of gasoline and electricity prices are robust across a wide set of alternative specifications, and falsification tests provide evidence that this result is unlikely to be an artifact of municipal boundaries. It is only present along boundaries that exhibit discontinuous electricity price differences.

Our second result provides validation of the first and hints at a potential mechanism. If EV buyers mis-estimate the costs of ownership at the time of purchase, they likely learn about the cost of vehicle operation through experience. We track the ownership patterns of EVs to demonstrate that vehicle retention decisions are correlated with the electricity prices in the way that theory predicts. EV buyers in areas with higher electricity prices are more likely to resell their vehicles within four years of initial purchase.

Finally, we formalize optimal EV subsidy policy in light of this apparent undervaluation of electricity costs at the time of purchase. Notably, the optimal subsidy policy must address two sources of inefficiency. First, if electricity or gasoline prices do not reflect social marginal cost, the optimal subsidy seeks to correct 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 clean durable goods. 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 purchase decision imposes on their future self. Typically, the internality is created by customers under-estimating the savings from increased energy efficiency. Thus both the externality and the internality increase the optimal subsidy level. That is not the case in our setting, where the two effects are conflicting. On one hand, EVs impose lower externalities than gasoline-powered vehicles in California; on the other hand, since most customers in California face high marginal electricity prices, internalities imposed by under-estimation of electricity costs motivate a countervailing *tax* on EVs. Calibrating with data from California, we find that the optimal policy (on net) subsidizes EV purchases, but at levels below the contemporaneous (or current as of 2024) policy.

The role that relative energy prices play on the choice of vehicle is particularly important given the fact that most plans for deep decarbonization in developed economies call for widescale electrification of transportation (see, e.g., Borenstein and Bushnell (2022), Rapson and Muehlegger (2023) and Rapson and Bushnell (2024)). 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. As carbon policy increasingly involves substitution between carbon-intensive and less-carbon intensive sources of energy, the relative prices of these sources and the consumer responses to those prices is of critical importance.

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. Vehicle retention is explored in section 6, policy and welfare implications are discussed in section 7, and we conclude in section 8.

2 Methodological Framework

The goal of this paper is to test whether the marginal EV buyer responds 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 EV and a conventional vehicle ("CV").[8]

We model the utility of a risk-neutral prospective vehicle buyer, indexed by i with demand for travel VMT_i, as a function of three components.

$$U_i^{EV} = \alpha^{EV} + \gamma_i^e \sum_{t=0}^{\infty} \delta^t \left[E[P_{it}^e] \left(\frac{kWh}{mile} \right) \right] E[VMT_i(P_{it}^e)] S^{EV}(t) + \epsilon_i^{EV} \quad (1)$$

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

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. 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.

The first terms in (1) and (2) captures the utility a buyer receives from purchasing either an EV or CV, inclusive of observable and unobservable characteristics unrelated to the costs of operation. The first term in each equation reflects many of the standard vehicle attributes included in a discrete choice model (e.g., weight, power, price, etc), with the exception of fuel efficiency.[9] The last term reflects the idiosyncratic utility buyer i derives from purchasing an EV (in equation (1)) or a CV (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. These prices are scaled by the fuel efficiency of the relevant powertrain to place both electricity prices and gasoline prices on a cost-per-mile driven basis. The cost-per-mile of the EV and CV are multiplied by the number of miles a buyer expects to travel, based on the price of energy of using that mode of transport ($VMT_i(P)$) and the likelihood of scrappage, where $S(t)$ reflects the probability the vehicle survives through period t. Finally, expected future fuel costs are discounted by a factor, δ, common across both types of vehicles.

We maintain two assumptions. First, we assume that buyers discount their future operational costs identically, as reflected by the parameter δ, regardless of the vehicle. But, we allow that the buyer i might have an imperfect understanding of future operational costs of gasoline

[8] In Appendix A.1, we illustrate that this framework can be easily extended to a consumer choosing amongst multiple EVs and CVs.

[9] There may also be real or perceived differences in the ongoing cost of ownership beyond fuel costs, such as less routine maintenance or the need for battery replacement in EVs. To the extent that these costs are more time based than usage based, they would be absorbed by α. Even if these differences were linked to VMT, it would only be an issue for our identification if those VMT differences were discontinuous across the utility boundaries we describe later.

and electricity, reflected in the parameters γ_i^g and γ_i^e, respectively. If buyers internalize the future operational costs of both gasoline and electric vehicle similarly, we would expect γ_i^g and γ_i^e to be equal. However, if buyers respond asymmetrically to electricity prices and gasoline prices, the values of γ_i^g and γ_i^e would differ. Such asymmetry might arise if consumers have a differential understanding of electricity and gasoline prices, if one price is more salient than the other, or if the consumer applies different discount rates to future electricity prices and gasoline prices. Second, we assume that consumers have "no-change" forecasts for gasoline and electricity prices.[10]

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

$$\frac{dPr(EV)}{dP_{i0}^e} = \gamma_i^e \left((1+\varepsilon_{VMT_i}) \frac{kWh}{mile} \right) VMT(P_{i0}^e) \sum_{t=0}^{\infty} \delta^t S^{EV}(t) * Pr(EV) * (1 - Pr(EV)) \quad (3)$$

$$\frac{dPr(EV)}{dP_{i0}^g} = -\gamma_i^g \left((1+\varepsilon_{VMT_i}) \frac{gal}{mile} \right) VMT(P_{i0}^g) \sum_{t=0}^{\infty} \delta^t S^{CV}(t) * Pr(EV) * Pr(CV) \quad (4)$$

where $Pr(EV)$ and $Pr(CV)$ denote the probabilities with which the buyer i purchases the EV or the CV, respectively.

To map the framework above into our empirical specification, we make two additional assumptions. First, we assume that the scrappage rates of the two vehicles are equal (i.e., $S^{EV}(t) = S^{CV}(t)$). To our knowledge, there is no direct evidence that quantifies the long-term durability or reliability of electric and conventional vehicles. Second, we assume that, at current energy prices, overall household mileage would not change depending on the type of vehicle purchased. This is a potentially strong assumption, particularly for single-vehicle households. Evidence from the period suggests EVs were driven less than their CV counterparts (Davis (2018) and Burlig et al. (2021)), and a long literature finds that the relationship between fuel economy and VMT is relatively inelastic. Gillingham et al. (2016) surveys this literature) and, more recently, Levinson and Sager (2023) find little correlation between VMT and fuel economy. During this period, the vast majority of EV-owning households owned multiple vehicles Davis (2018).[11]

[10] Anderson et al. (2013) finds evidence that use of a "no-change" forecast accurately captures consumer beliefs of future gasoline prices. Although are unaware of similar research examining consumer beliefs of future electricity prices, this is a common maintained assumption in studies of energy costs and durable goods (e.g., Houde and Myers (2021)).

[11] As a preview, we explore the robustness of our analysis to these assumptions and do not find that these assumptions qualitatively change our results, as we show in Figure 7.

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

In our empirical specification, we do not estimate buyer-specific values for γ_i. Rather, we estimate the average value across the population. To do so, we estimate the effect of electricity and gasoline prices on EV sales, averaged across buyers, denoting the estimated coefficients as $\hat{\beta}^e$ and $\hat{\beta}^g$. We manipulate the expressions for (3) and (4) to derive an estimate for γ:[12]

$$\bar{\gamma} = \frac{-\hat{\beta}^e * \left(\frac{miles}{kWh}\right)}{\hat{\beta}^g * \left(\frac{miles}{gal}\right)}. \tag{5}$$

Intuitively, the numerator of equation (5) reflects the impact of per-mile electricity costs of the EV and the denominator reflects the impact of per-mile gasoline costs of the CV. 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 EVs and gallons-per-mile for CVs). Although, ultimately, we will have to take a stand on the relative fuel efficiencies of the electric and CVs, the comparison of the *relative* response to electricity and gasoline prices allows us to side-step the question of how myopic consumers are overall.

3 Empirical Setting and Data

Our empirical approach exploits panel variation in gasoline and electricity prices across census block-groups (CBGs) in California.[13] Our preferred approach focuses on CBGs that are in close proximity to electric utility service territory 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

[12]Manipulating (3) and (4), we can express γ as: $\hat{\gamma} = \frac{-\hat{\beta}^e*\left(\frac{miles}{kWh}\right)}{\hat{\beta}^g*\left(\frac{miles}{gal}\right)} * \frac{Pr(CV)}{1-Pr(EV)}$. In our framework, consumers either purchase an EV or CV in which case $Pr(CV) = 1 - Pr(EV)$. But, if consumers can also select an outside option (i.e., not purchasing a vehicle at all), $\frac{Pr(CV)}{1-Pr(EV)} < 1$ implying that equation (5) provides an upper bound for γ.

[13]There are roughly 23,000 CBGs in California, each comprised of approximately 600 to 3,000 people, or 200 to 1,000 households.

making use of three main datasets, one each for EV purchases, retail electricity prices and retail gasoline prices during the period from 2014 to 2017.[14]

The vehicle purchase data covers the universe of EVs purchased in California from 2014 through 2017. Our data originates from the California Department of Motor Vehicles (DMV) and was purchased through a third-party data provider. The data include each vehicle's identification number (VIN), purchase date and CBG in which the vehicle is registered. We aggregate these purchases to the CBG-month-of-sample level and normalize by the population of the CBG.[15]

Electricity prices come from two sources and cover both major types of electric utility companies in California: (1) the three investor-owned utilities (IOUs): Pacific Gas & Electric (PGE), Southern California Edison (SCE), and San Diego Gas and Electric, and (2) and municipal utilities such as Los Angeles Department of Water and Power, Sacramento Municipal Utility District, 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. For municipal utilities, we augment the EIA data with rates obtained from utility websites or service representatives.

The electricity prices faced by customers in different service territories varies immensely. Figures A1 and A2 display the rates for households on the top rate tier[16] 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. Notably, customers on the top step of Pacific Gas and Electric's or Southern California Edison's rate schedule pay a residential price for electricity that can be significantly higher (and sometimes a multiple of) the price paid by

[14]Note that prices are reported in nominal terms throughout the paper.

[15]As described above, we focus our attention vehicles that operate entirely on electricity (e.g., Tesla Model 3), distinct from plug-in hybrid electric vehicles (e.g., Toyota Prius Prime). Our motivation for this focus is two-fold. First, plug-in hybrids operate on both gasoline and electricity and have the ability to substitute between the two fuels in ways that conventional vehicles and electric vehicles do not. Second, even if we knew precisely the share of electric and gasoline miles, theory does not provide a clear guide as to whether we would expect PHEV quantities to rise or fall with gasoline prices and electricity prices. If consumers view PHEVs as substitutes for both conventional vehicles and EVs, the effect of energy prices on plug-in hybrid adoption might be limited, much in the same way that Busse et al. (2013) finds little response of median fuel economy vehicles to higher gasoline prices.

[16]Investor-owned utility price schedules increase in a stepwise fashion with total monthly usage. With increasing block rates, households charging an electric vehicle at home will likely find themselves on or near the top tier of the residential rates schedule.

residential customers in neighboring municipal utilities.

A challenge to understanding the effect of electricity prices on EV demand is the myriad of potential prices that EV owners may pay. The spectrum of candidate prices is linked to both 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. 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.

We focus on the residential rates at the CBG in which the vehicles were registered. 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 (California Air Resources Board (2020)), the majority of EV owners charge at home, either completely or primarily, 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 price for unleaded regular gasoline for all stations within 3 miles of the zip code centroid, reflective of the set of stations that might serve a particular community.[17] 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.

We summarize the relevant data in Table 1. Our primary source of electricity price variation comes from differences between locations served by investor-owned utilities and municipal utilities, thus 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 CBGs in California. In columns (3) and (4), we limit the sample to the CBGs used to estimate the border discontinuity specification.

Several patterns become clear from the summary statistics. First and foremost, customers served by municipal utilities in California face prices that are a fraction of those faced by customers of investor-owned utilities in California. The top-tier marginal price for municipal util-

[17]In the absence of data on commuting patterns to inform the "true" gasoline price that consumers face (e.g. Houde (2012)), we consider several alternative measures. We use radii of 1 mile, 5 miles and 10 miles to calculate 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 Appendix Tables A2 and A3.

ities averages 21.6 cents per kilowatt-hour, roughly one-third lower than the average top-tier marginal price of 31.7 cents per kilowatt-hour for investor-owned utilities, during our sample period. Translated into dollar terms, this 10 cent per kilowatt hour difference equates to 2.5 cents per mile (for a Tesla Model 3) or and annual cost of $250 for an EV driven ten thousand miles per year. As a second comparison, these annual costs are roughly comparable to the annual costs associated with a 75 cent per gallon change in gasoline prices for a CV with a fuel economy of 30 miles per gallon. Notably, although municipal utility customers tend to pay much lower prices than investor-owned utility customers in California, Californians on the top tier tend to pay more for electricity than residential customers elsewhere in the U.S. The average residential electricity price in 2017 in the U.S. was 12.8 cents per kilowatt hour.[18]

Second, the summary statistics highlight that the utility service territory boundaries are not evenly distributed throughout the state. 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 the Los Angeles metro area is home to over a dozen municipal utilities. Hence, a higher fraction of CBGs near utility boundaries are located in SCE's service territory. The CBGs near the boundaries tend to be located in parts of the state with slightly higher levels of EV adoption and slightly higher incomes, but are roughly comparable along other demographics.

Finally, the summary statistics highlight similarities and differences between the CBGs in the investor-owned utilities and the municipal utilities. The average census block in the municipal utility service territories tends to have slightly higher population density, a higher share of households living in multi-unit dwellings (MUDs) and lower incomes than CBGs in investor-owned utility service territories. However, the share of luxury and hybrid vehicles, and the average fuel economy of vehicles owned by drivers in the two groups of census tracts are roughly comparable. We will explore both the differences and similarities in further detail in our empirical exercises.

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 two-way fixed effects, panel regression given by:

$$EVSalesPerCapita_{ct} = \beta^e P^e_{ct} + \beta^g P^g_{ct} + \Theta X_{ct} + \delta_c + \lambda_t + \epsilon_{ct} \tag{6}$$

[18]U.S. Energy Information Administration, Electric Power Monthly, Short-term Energy Outlook.

where c denotes CBG and t denotes time, δ_c and λ_t denote census block group and time fixed effects, and X_{ct} denotes sociodemographic covariates.

The panel design uses data on all CBGs in California and directly conditions out time-invariant unobservables through the CBG fixed effects. As a subset of utilities (including both investor-owned and municipal) have rates that vary seasonally, we estimate versions of (6) 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.

Identification follows from differential changes in electricity prices and gasoline prices across CBGs over time. For electricity prices, 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 CBGs 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 this setting identification relies on the assumption that there are no unobservables correlated with both the EV adoption and electricity or gasoline prices after conditioning on CBG 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 more quickly in areas in which the charging station network is expanding more rapidly, we might mis-attribute the effect of the charging station network to electricity prices and underestimate the amount to which demand for EVs would respond to prices.

4.1 Results

Table 2 presents results corresponding to Equation 6, which regresses EV sales per capita in a given CBG on the price of electricity, price of gasoline, and control variables. Columns 1 through 3 are aggregated by month, allowing for higher-frequency fluctuations in energy prices to be reflected in changes in EV demand; columns 4 through 6 are aggregated annually. Columns 1 and 4 omit two-way fixed effects for location and time. In these specifications, the signs of the coefficients on gasoline and electricity prices are the opposite of what theory would predict. EV sales are positively correlated with electricity prices and negatively correlated with gasoline prices. The signs of the coefficients in columns 1 and 4 reflect the spatial correlation between the demand for EVs and energy prices across CBGs. Demand for EVs tends to be high in areas with high electricity prices.

Columns 2 and 5 include CBG fixed effects and time fixed effects, capturing time-invariant and space-invariant unobserved drivers of EV demand. Columns 3 and 6 further add demographic controls for income, race, education and age taken from the American Community Survey. With the inclusion of fixed effects, variation comes from differential changes in gasoline and electricity prices. The inclusion of the fixed effects reverses the signs of the coefficients of interest. The coefficient on electricity price is negative and the coefficient on gasoline price is positive, as theory would predict. The coefficient on electricity price 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%. Having not yet accounted for differences in vehicle fuel efficiency, these coefficients present an imperfect comparison of the relative importance of electricity and gasoline prices on EV demand.

To interpret the relative magnitude of the coefficients, we scale each coefficient by the engine efficiency of the technology. Recall from equation (5) that $\bar{\gamma}$ reflects the weight that the consumer places on electricity costs relative to gasoline costs when both costs are placed on a comparable cent-per-mile basis. Consider a consumer whose preferences reflect the panel results in column 2 of Table 2. In a state of the world where this consumer is deciding between a Toyota Camry, the most popular conventional vehicle in California during our study period, that gets 30 miles-per-gallon, and a Tesla Model 3, which gets 4 miles-per-kWh, $\bar{\gamma} = \frac{0.0035*4}{0.0041*30} \approx 0.114$.[19] In this case, the 1 cent per kilowatt-hour increase in electricity price translates into a 0.25 cents per mile increase in the cost of driving an EV. 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 a mere 0.03 cents per mile. The relative response to gas and electricity prices implies that such a customer places roughly one-eighth the weight on electricity prices as they do on the price of gasoline.[20] The implied underweighting of electricity prices, relative to gasoline, does not change with the further inclusion of demographic covariates (in column (3)). Estimates of $\bar{\gamma}$ based on annual data similarly imply that the response to annual variation in electricity prices is substantially less than commensurate

[19]We calculate standard errors for $\bar{\gamma}$ via the delta method.

[20]This interpretation depends on the choice of the reference vehicle. As the comparison EV gets more efficient, or the comparison CV less efficient, $\bar{\gamma}$ increases and the behavioral interpretation would shift towards the consumer appearing to care more about the price of electricity. However, empirical evidence from Xing et al. (2021) and Muehlegger and Rapson (2023) suggests that, if anything, the CVs that would have been purchased in the absence of EVs tend to be more fuel-efficient, not less.

changes in gasoline prices averaged over longer time frames.

5 Border Discontinuity across Utility Boundaries

We exploit the discrete boundaries of the utility service territories to estimate γ under weaker assumptions using a border discontinuity design. 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 CBGs along utility service territory boundaries, we can compare CBGs in close proximity, where households likely face similar commutes and have similar access to public charging infrastructure, but potentially face very different electricity prices. As an illustration, Figure 1 plots a binned scatter plot of electricity prices at CBGs within five kilometers on either side of the border between an investor owned utility (on the left) and a municipal utility (on the right). The points in Figure 1 aggregate all of the CBGs close to the twenty boundaries between municipal utilities and investor-owned utilities in California. On the municipal side of the boundary, electricity prices average between 20 and 25 cents per kilowatt-hour.[21] On the investor-owned utility side of the boundary, the electricity price faced by customers is roughly fifty percent higher, on average.

With a single boundary between an investor-owned utility and a municipal utility, we could estimate sales as a function of demographics, electricity prices, gasoline prices and distance to the utility service territory boundary. Following Lee and Lemieux (2010), the standard RD specification would allow the slope of the running variables (in this case, distance to the boundary) to vary on either side of the border to capture omitted trends in EV adoption further from the service territory boundary. Formally,

$$\begin{aligned} EVSalesPerCap_{ct} \quad = \quad & \nu_1 D_c + \nu_2 D_c * 1[IOU_c] + \beta^e \Delta P^e_t 1[IOU_c] + \\ & \beta^g P^g_{ct} + \Theta X_c + \epsilon_{ct} \end{aligned} \tag{7}$$

where ΔP^e_t is the difference in electricity price faced by consumers in the investor-owned utility relative to the neighboring utility, $1[IOU_c]$ is an indicator variable for whether the consumer lives in the investor-owned utility service territory, and D_c is the distance from the CBG to the utility area boundary.[22] Here, we replace the typical dummy variable capturing the change

[21] Variation on either side of the boundary arises from the fact that points aggregate across multiple IOUs and municipal utilities.

[22] We further interact distance with a dummy variable equal to one for census tracts on the investor-owned side of

in the outcome variable at the discontinuity ($1[IOU_c]$) with a term that includes the difference in electricity prices on either side of the service territory boundary ($\Delta P_t^e 1[IOU_c]$). This allows the magnitude of the discontinuity to vary over time as electricity prices change. Under the identifying assumptions of the RD model, the coefficient β^e is the effect of a one cent per kilowatt-hour change in electricity prices at the utility service territory boundary.[23]

In our setting, we have many service territory boundaries between the three investor-owned utilities and the municipal utilities. We scale the approach above to utilize variation in prices across all borders between investor-owned utilities and other utilities in the data. To do so, we create pairs of CGBs that straddle the service territory boundary, following an approach similar in spirit to Bayer et al. (2007) that matches census blocks across high- and low-achieving school area boundaries in the Bay Area. Formally, we match each CBG (c) on one side of the service territory boundary with the closest CBG (c') on the opposite side of the boundary, in the neighboring utility. We then estimate the model using the difference in adoption and covariates within each pair of CBGs, $i = (c, c')$. Given the volatility of EVs sales at the CBG 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.

$$\begin{aligned} \Delta EVSalesPerCapita_{it} &= \beta^e \Delta P_{it}^e + \beta^g \Delta P_{it}^g + \Theta \Delta X_{it} + \\ &\quad \nu_{1b} D_c + \nu_{2b} D_{c'} + \epsilon_{it}, \end{aligned} \tag{8}$$

where ΔP^e and ΔP^g denote difference in the marginal price of electricity (cents/kWh) and gasoline (cents/gallon) between the two CBGs. As in the single boundary case in equation (7), D_c and $D_{c'}$ are the distances to the service territory boundary. The coefficients on D_c and $D_{c'}$ are allowed to vary on each side of each boundary in our estimation sample.

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. The coefficient on gasoline prices is identified from panel variation in local gasoline prices. To illustrate the variation, we plot the difference in electricity prices and gasoline prices between pairs of CBGs in our data in Figure 2. The large differences in electricity prices between neighboring CBGs is unsurprising, as we pick CBGs that fall on either side of utility service territory boundaries. Yet we also

the boundary to allow for the slope of unobservables to vary on either side of the utility boundary.

[23] Also following Lee and Lemieux (2010), we include demographics for CBG c. The inclusion of covariates provides a falsification test of one of the identifying assumptions of the RD model. Under the assumption that assignment is random, the inclusion of covariates should leave the coefficient on electricity price unchanged.

see variation (albeit more modest) in gasoline prices in the neighborhoods around each of the paired CBGs.

Relative to the panel fixed-effects approach, the border discontinuity refines the comparison group to a narrow band around utility district boundaries and offers several advantages. 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 the side of the border in unobservable ways. 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 – e.g. distribution of preferences for driving (Levinson and Sager (2023)), political affiliation (Davis et al. (2023)), availability of charging infrastructure (Springel (2021), Li (2017), Li et al. (2017a)), etc. – vary continuously across the border. We can indirectly test for discontinuities in observable factors correlated with EV adoption, such as incomes or past vehicle preferences. The absence of discontinuities in observable covariates provides evidence supporting the identification assumptions underlying the border discontinuity design.

Following Lee and Lemieux (2010), we present binned scatter plots and fourth degree polynomials for the seven covariates in Figure 3. We further test for discontinuities by regressing our covariates upon fourth-degree polynomials that are allowed to vary on either side of the discontinuity and a municipality fixed effect. Across the demographic variables, five of the seven covariates (income, fuel economy, shares of hybrid and luxury vehicles, and population) do not exhibit statistically significant discontinuities at the boundary. Population density and the fraction of households that live in multi-unit dwellings are borderline significant at the 5 percent level.

5.1 Results

Results from the border discontinuity are presented in Table 3. Column 1 presents the results of the most parsimonious specification that includes only the difference in electricity price and gasoline price between the pairs of CBGs 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 CBGs to condition on observable differences in demographics between pairs of CBGs. We do not find that the inclusion of the covariates has a statistically significant effect on the coefficient on electric prices. 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, particularly of the estimate of the coefficient on electricity price, rises substantially with the inclusion of the fixed effects.

In columns 5 through 8, we re-run the specifications in columns 1 through 4, limiting the sample to CBG pairs that are within 8 kilometers of each other. Although the summary statistics reported in Table 1 suggest that the centroids of most of the CBGs bordering the boundary are within a kilometer, CBGs vary in size. Urban CBGs, like those in Los Angeles, are significantly smaller than rural CBGs that might spread over a larger region and encompass a more diffuse community.

Across the eight 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 plausibly vary in a discontinuous way as households sort between communities. Once we control for observable demographic characteristics of the CBG, 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 eight specifications, higher gasoline prices are positively correlated with greater EV 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 population density and the fraction of households living in multi-unit dwellings (where charging an EV might be more difficult) are associated negatively with EV sales.[24]

The panel and border discontinuity results reflect different methodologies deployed on

[24]The addition of covariates (e.g., comparing the coefficients in columns 1 and 3) lead to changes in the coefficients on gasoline and electricity prices as well as an increase in fraction of variation explained by the regression. In the spirit of Altonji et al. (2005) and Oster (2019), we consider the stability of the coefficients by constructing the bounds proposed and validated using randomized studies in Oster (2019). Using this approach, we estimate bounds for the coefficient on gasoline price of $[0.094, 0.170]$ and bounds for the coefficient on electricity price of $[-0.238, -0.201]$.

overlapping but distinct samples, yet they are similar. Take, for example, the panel results in Table 2 column 6 and the discontinuity results in Table 3 column 3. Note that an apples-to-apples comparison draws from the annual, not monthly, specifications in Table 2. After scaling appropriately for differences in EV sales shares across the two samples in Table 1, equality of the electricity and gasoline price coefficients across panel and discontinuity specifications cannot be rejected.

Following a similar approach to that in the panel regressions, we can back out an estimate of 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 $\bar{\gamma} = \frac{0.20*4}{0.17*30} = 0.157$, remarkably similar to the estimate from the panel specification.[25] Once again, equivalent valuation of gasoline and electricity costs would imply a value of $\bar{\gamma}$ equal to one. In all eight columns, our estimates of $\bar{\gamma}$ are statistically less than one, suggesting that consumers substantially underweight future electricity costs relative to the weight they place on future gasoline costs.

Figure 4 provides a graphical illustration of the results in column 3 of Table 3. In each panel, we residualize fuel prices and EV adoption, bin the observations by residualized fuel prices and plot the relationship between residualized gasoline price and adoption in panel (a) and residualized electricity price and adoption in panel (b). We scale the x-axis in both cases to the common unit of cents-per-mile (rather than cents per kilowatt-hour and cents per gallon) using the fuel efficiencies of the reference CV and EV. The ratio between the slopes in Figure 4, panels (a) and (b) is the estimate of γ. Large changes in electricity costs (on a cost per mile basis) are necessary to generate similar changes in EV adoption to much smaller changes in gasoline costs (also on a cost per mile basis).

5.2 Robustness Tests

We consider three sets of robustness tests. Our first set of robustness checks relates to the specification of the border discontinuity design. Following Lee and Lemieux (2010), we first re-estimate the regression discontinuity framework using alternative "bandwidths" as reflected by the maximum distance between CBG pairs for inclusion. Figure 5 plots the estimates and the shaded confidence intervals of γ for bandwidths from one to twenty kilometers. Although the precision of the estimate of γ increases with larger bandwidths, we see that the point estimates for γ using bandwidths between 3km and 20km are virtually identical. Second, we

[25] Conducting the bounding exercise proposed by Oster (2019) for gasoline and electricity prices, and constructing the associated values of γ yields the set $[0.157, 0.340]$

re-estimate the model allowing for alternative polynomials of distance on either side of each service territory boundary. From left to right, Figure 6 plots the estimates and confidence intervals of γ omitting distance, allowing for a linear relationship (our baseline specification) and allowing for 2nd, 3rd and 4th order polynomials. We see that parametrization of distance has little impact on the point estimates of gamma.[26] For all alternative bandwidths and different parameterizations for distance, estimates of γ are statistically different from one, the value that corresponds to equivalent valuation of electricity and gasoline costs.

Our second set of robustness checks relate to the set of service territory boundaries used to estimate the border discontinuity specification. First, we exclude all boundaries between municipal utilities and Pacific Gas and Electric's service territory. Of the three investor-owned utilities, only Pacific Gas and Electric offered a time-of-use electricity rate schedule for households with EVs with meaningful take-up during the study period. By 2017, roughly fifty thousand Californian households were on time-of-use rates, of which roughly 75% were in PGE service territory. Although state-wide this amounts to less than 15% of of the 366,000 EV sales, we exclude the observations from pairs of CBGs at the boundary of PGE's service territory as a check. Second, as we note above in Figure 3, we find that the population density and share of multi-unit housing are both borderline-significantly higher on the municipal side of the boundaries, on average across all of the borders. As a second check, we calculate the average difference in population density and the share of multi-unit housing along each of the twenty borders in our border discontinuity regression. We then re-estimate the model excluding block-pairs along municipal-IOU borders for which the municipal-IOU difference in either population density or the share of multi-unit housing is the top quartile.[27] After imposing the restriction, we no longer find a statistically significant discontinuity in population density or the share of multi-unit housing (or any of the other demographic variables) at the border between the municipal utilities and investor-owned utilities.

Both sets of estimates are presented in Table 4. For reference, column (1) presents our main estimates from column (3) of Table 3. The results excluding the borders shared by PGE (in column (2)) and excluding the borders for which the municipal-IOU difference in either population density or the share of multi-unit housing is the top quartile (in column (3)). We find that both robustness checks have little impact on our conclusions. Relative to an estimated value

[26]For transparency, we also plot the point estimates and standard errors for the coefficients on electricity price and gasoline price in Appendix Figures A3 and A4. As is the case with the estimates of gamma, the choice of bandwidth or polynomial for distance has little qualitative impact on the coefficient estimates.

[27]In Appendix Figure A5, we plot the average difference municipal and investor-owned CBG population density (on the y-axis) and share of multi-unit housing (on the x-axis).

of γ of 0.157, the estimates of γ when excluding PGE and excluding the borders for which the demographic changes are most abrupt are 0.190 and 0.146, respectively. In both cases, the estimates are statistically distinguishable from one, the benchmark for equivalent treatment of gasoline and electricity prices.

Finally, we consider a set of robustness checks that demonstrate that our estimates of γ remain substantially below one for a wide range of alternative assumptions (or combinations of alternative assumptions) supported by the literature. In our baseline specification, we make deterministic assumptions to calculate gamma, including assumptions about the fuel efficiency of the alternative conventional vehicle, the marginal price of electricity facing a household owning an EV, the usage of the electric vehicle relative to an alternative conventional vehicle and the rate at which electric vehicles might depreciate or be scrapped relative to conventional vehicles.[28] If we were able to observe or estimate the joint probability distribution of these parameters, such as the covariance between fuel economy of the alternative conventional vehicle and the amount by which a driver would reduce mileage if they drove an electric vehicle, we could simulate a distribution of values for gamma. In the absence of distributional evidence, we recalculate γ under alternative assumptions. Although our estimate of γ does reflect, partially, the assumptions made, we find the undervaluation of electricity prices relative to gasoline prices to be persistent.

We present γ calculated under alternative sets of assumptions in Figure 7. For reference, we plot the implied value of γ under our base assumptions in row [1], corresponding to the specification in column (3) of table 3. The right-most dotted vertical line (at a value of 1) corresponds to the value that would imply equivalent valuation of electricity and gasoline. The remaining rows plot the point estimate and confidence interval for our estimate of γ under a range of assumptions related to: the fuel economy of the alternative conventional vehicle [2], the vehicle miles traveled for an electric vehicle relative to the alternative conventional vehicle [3], assumptions related to the charging behavior or electricity price faced by households [4 - 7], assumptions related to the relevant gasoline price for fueling of a conventional vehicle [8], and assumptions related to the rate of scrappage of electric vehicle relative to conventional vehicles [9 - 10].[29] To facilitate comparison with the base case, the left-most dotted vertical line is plotted at the value for the base case. Although point estimates and confidence intervals for γ vary from near zero to 0.254, in all cases we find implied values of γ that are significantly dif-

[28]Our base assumptions simplify the expression for the implied value of γ to the expression in equation (5). In the Appendix, we write the expression for the implied value of γ without these simplifying assumptions.

[29]For references, details of the alternative assumptions used in each row are described in the table notes.

ferent than one, suggesting that our finding of undervaluation is not a product of assumptions. Finally, in row [11], we combine the assumptions of rows [2], [3], and [4], the set of alternative assumptions supported by previous academic evidence. Under this combination of assumptions, we find an implied γ of 0.257, consistent with four-fold undervaluation of electricity relative to gasoline.

5.3 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 alternative hypothesis that the observed 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 zero coefficient supports our identifying assumption that no non-price discontinuities are related to the 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 variables.[30] 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 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 estimates of the placebo treatment effect, the results of which are presented in Table 5. Evidence against the main identifying assumption would be found in a significant, non-zero coefficient estimate. In all six tests, we find no evidence of discontinuous changes in adoption across the non-utility boundaries between municipalities.

[30]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.

6 Energy Prices and Vehicle Retention

In the previous two sections, we have shown that potential EV buyers are more sensitive to gasoline prices than they are to electricity prices. In this section, we show that this is consistent with poor ex ante understanding of electricity prices and future EV operating costs. We demonstrate this by examining households' decisions about whether to retain or resell their EVs in the years following their purchase.

If buyers mis-estimate the cost of operation at the time of purchase, but learn of the true costs of operation upon use, subsequent retention decisions will, at least in part, reflect the updated information about the costs of operation. If the true costs of ownership are higher than a buyer anticipates when purchasing a vehicle, the buyer will (*ceteris paribus*) be more likely to resell or trade the vehicle than will a buyer facing lower ownership costs.

We test whether energy prices are correlated with subsequent vehicle retention decisions by exploiting the fact that we observe the vehicle identification number of each registered vehicle. Notably, we can observe whether the same vehicle is re-registered by another owner in California. If a vehicle is re-registered, we can calculate an upper bound on the duration of first ownership as the difference between the two registration dates. This requires two caveats relative to the "true" length of ownership, measured as the actual number of days for which a vehicle was owned. First, since we only observe registration dates and not sale dates, our measure includes any time required to resell the used vehicle. Second, we only observe registration data for California. If a resold vehicle was exported to another state, we do not observe the re-registration event and will fail to classify the vehicle as resold. Although there is evidence that some used EVs were exported from California, the overall number of exported vehicles is small relative to the size of the California market.[31] Moreover, for either of these explanations to bias the subsequent analysis, measurement error would have to be systematically correlated with whether a vehicle was purchased by an owner living in a location with high electricity prices.

To track resale, we apply several restrictions to the transaction data. First, we limit the sample to vehicles purchased between January 2014 and October 2015. We make this restriction in order to ensure that there is a sufficient post-purchase time period to test for differences in ownership duration.[32] Of the roughly 164,000 EVs purchased between 2014 and 2017, 50,000 were purchased between January 2014 and October 2015. We further limit the sample to households

[31] We thank Mannheim Automotive for sharing their used car auctions data from this period, which reveals origin and destination of cars transacted on their exchanges.

[32] We use a secondary DMV dataset that we were allowed to access for the purpose of calculating ownership durations, that allows us to track vehicle ownership through October 2019. We retain the vehicles for which we can observe at least four years of ownership history, post-purchase.

that did not move (i.e., re-register the vehicle in a new CBG) while they owned the vehicle. Applying both restrictions, our sample for the analysis consists of roughly thirty-four thousand vehicles, state-wide. For power, we include all of the CBGs used in the state-wide panel, since only three thousand EVs meet the sample restrictions described above and were also purchased by residents of the CBGs that border the utility area boundaries.

Figure 8 plots the histogram of ownership length for the vehicles that were purchased in January 2014 and re-registered by a new owner at some point before the end of October 2019. By construction, the maximum length of ownership we can observe for this group of vehicles is five years and ten months. Of the 1,300 vehicles purchased in January 2014, roughly 35 percent were registered by a new owner by October 2019. Conditional on resale, ownership length peaks shortly after three years. Roughly half of the EVs that were registered by a new owner were re-registered between three and four years after initial purchase. This pattern is reflective of two features of the EV market in California. First, three-year leases were relatively common amongst this class of vehicles, and leased vehicles that are not subsequently purchased are typically resold on the used vehicle market. Second, the eligibility rules for the main state-wide EV subsidy offered during this time (i.e., the Clean Vehicle Rebate Program) required owners to lease or own the vehicles for at least thirty months.

Since we only observe ownership history through October 2019, the length of ownership variable is right-censored. Rather than use length of ownership as our outcome variable of interest, the maximum value of which would be a function of when the vehicle was initially purchased, we construct a dummy variable equal to one if the vehicle was re-registered by a new owner within four years of its initial purchase. We present the results of a linear regression model, predicting whether a vehicle was resold within four years of initial purchase against electricity and gasoline prices faced by buyers at the time of purchase.[33] We include make/model/model-year fixed effects to control for unobservables correlated with both vehicle purchase and likelihood of resale. Month-year of purchase fixed effects control for variation in resale probabilities common to a cohort of buyers purchasing at a given point in time. Geographic controls, either in the form of block-group-level demographic covariates previously included in the border discontinuity analysis (e.g., income, population density, multi-unit dwelling share, historical fuel economy and historical shares of luxury and hybrid cars) or geographic fixed effects, control for unobservable geographic variation in EV adoption (and retention). The specification relies on variation within CBGs – conditional on purchasing the

[33] An alternative specification, in the spirit of Gillingham (2014), that regresses the re-registration dummy on average energy prices over four-year windows, yields qualitatively similar results and is presented in Appendix Figure A4.

same make/model/model-year, are buyers in locations where electricity prices are rising more quickly also more likely to sell their EV within four-years of purchase. Formally,

$$Pr(Resale_i) = \beta_e p_{ct}^e + \beta_g p_{ct}^g + \Theta X_c + \eta_m + \lambda_t + \epsilon_i \tag{9}$$

where i, m, c, t denote vehicle, make-model, CBG and time of purchase. p_{ct}^e and p_{ct}^g represent electricity and gasoline prices faced by buyers in CBG c at time t.

Table 6 presents the estimated coefficients on electricity and gasoline prices for four specifications that use increasingly fine geographic fixed effects. Across all four specifications, buyers who live in locations with higher marginal electricity prices are more likely to resell their vehicles within four years. The effects sizes are meaningful. We find that a one standard deviation increase in electricity prices (roughly equivalent to 5 cents per kwh) is associated with a 1.4 to 2.1 percentage point increase in the likelihood that a vehicle is re-registered within four years. This corresponds to a five to ten percent increase in the probability of resale. As points of reference, 28.8 percent of vehicles purchased in January 2014 were re-registered by a new owner by January 2018. 23.5 percent of vehicles purchased between January 2014 and October 2015 were re-registered by a new owner within four years of initial purchase.

These findings contribute to a sparse economic literature examining the choice to relinquish a vehicle. As in Jacobsen and Van Benthem (2015), we find evidence supporting a rational model of consumer behavior. In Jacobsen and Van Benthem (2015), consumers assign higher value to used vehicles that have fewer close substitutes entering the fleet via the new car market. In our case, car owners appear to be learning about the true operating costs of their vehicles, and exhibit a higher propensity to sell those that are (unexpectedly) more costly to operate. In principle, there might also be other channels of learning (e.g., through social networks) that could be relevant, but our setting is not well-suited to reliably differentiate between them.

7 Welfare and EV Subsidies

Finally, we consider the impact that consumer under-accounting for operating costs of EVs has on the design of optimal EV subsidy policy. Sharing the spirit of Allcott et al. (2014), we consider the case of CVs and EVs, where a potential vehicle buyer undervalues the savings associated with purchasing an EV.

In our setting, optimal subsidy 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 is the classic externality motive for a purchase subsidy or tax and is the focus of Holland et al. (2016). Second, if buyers do not fully incorporate electricity prices into their decisions (Houde and Myers, 2019), 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 to their energy efficiency and a buyer mis-values future energy savings. Here,the internality arises from the mis-estimation of the cost of using 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, each with income Y, choose between two vehicle technologies: gasoline (g) and electric (e). The two technologies have upfront cost to buyer of p_g and $p_e - S$ respectively, where p_g and p_e reflect the price of the two vehicles and S reflects the consumer subsidy offered to buyers of the electric vehicle.[34] The consumers are indexed by i, which captures how much they drive, with fraction η_i driving VMT_i miles per year. As before, we focus on the decision on the extensive margin, and, as before, assume $V\bar{M}T_i$ is equal regardless of the type of vehicle purchased.[35] Consumers incur operational costs and generate externalities when using either technology. The operational costs consist of 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. We denote per-mile marginal external costs of gasoline and electricity as ϕ_g and ϕ_e respectively.

In our setting, the perceived costs of using an EV 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 electricity price (e.g., Ito (2014), Jessoe and Rapson (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

[34] We focus on the setting in which the government only subsidies vehicles. An alternative would be to allow the government to use both subsidies and "feebate" taxes on vehicle purchases.

[35] For simplicity, we abstract away two considerations. First, we assume away a response on the intensive margin and any associated rebound effects. Second, we do to attempt to model the dynamic impacts of subsidies operating through either learning-by-doing or network externalities. In this sense, our optimal subsidy reflects an optimal "static" subsidy. Further work quantifying these dynamic margins and embedding them in an optimal subsidy framework might be important directions for future research.

of Busse et al. (2013) and Sallee et al. (2016)) 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 the 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 EVs relative to CVs, 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 CV and EV for that type *at the time of the consumer decision*. This means that if a consumer undervalues the savings associated with driving an EV at the time of purchase, $\hat{\epsilon}_i$ would be a function of the undervaluation.

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

$$\hat{\epsilon}_i = \alpha_{CV} - \alpha_{EV} - (p_{CV} - p_{EV} - S) - V\bar{M}T_i(c_g + \tau_g - \gamma(c_e + \tau_e) - (1-\gamma)\theta) \tag{10}$$

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 EV, based on the distribution of ϵ, and η_i denote the fraction of drivers who drive $V\bar{M}T_i$ miles, the policy maker maximizes welfare given by:

$$\begin{aligned} W = \sum_i \eta_i [\quad & \big(\alpha_{CV} + Y - p_{CV} - V\bar{M}T_i(c_g + \tau_g)\big) + \\ & \int_{\hat{\epsilon}_i}^{\bar{\epsilon}} \big(\alpha_{EV} - \alpha_{CV} - (p_{EV} + S - p_{CV}) - V\bar{M}T_i(c_e + \tau_e - (c_g + \tau_g)) + \epsilon\big)\, dG(\epsilon) + \\ & \big(\tau_g(1-\lambda_i)V\bar{M}T_i + \tau_e\lambda_i V\bar{M}T_i - \lambda_i S\big) + \\ & \big(-\phi_g(1-\lambda_i)V\bar{M}T_i - \phi_e\lambda_i V\bar{M}T_i\big) \quad] \end{aligned} \tag{11}$$

Here, the first line reflects the mean utility enjoyed by a consumer of type i if they drive a conventional vehicle. The second line reflects the additional *experience* utility enjoyed for those consumers who, based on their *decision* utility, purchase an EV. This inconsistency between the buyer's anticipated utility at purchase and their actual experience utility 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 EV subsidies. Finally, the fourth line reflects the external costs of gasoline and electricity consumption.

We consider the case in which the social planner sets a subsidy for EVs S_i based on each buyer's travel, VMT_i, a given tax on electricity τ_e, and a tax on gasoline τ_g. Notably, this is distinct from a true first-best policy that would allow the policy maker to change the subsidy as well as the taxes on gasoline and electricity. Here, we take the price of electricity and gasoline as fixed and consider the welfare-maximizing subsidy, conditional on exogenous values of τ_e and τ_g.[36]

Additive separability of W, implies that the optimal subsidies satisfy:

$$S_i^*(V\bar{M}T_i) = V\bar{M}T_i[(\phi_g - \tau_g) - (\phi_e - \tau_e)] - [1-\gamma]V\bar{M}T_i[(c_e + \tau_e) - \theta] \tag{12}$$

The first term in the expression captures the relative degree to which the external costs of gasoline and electricity are not reflected in 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-estimate the future costs of operation for an EV.

Two special cases illuminate the role of the optimal subsidy in addressing both the internality and externality. The first special case is the one in which consumers place full weight on the actual operational costs that they face if they buy an EV (i.e., $\gamma = 1$). Here, buyers accurately incorporate future electricity and gasoline costs into their purchase decision. In this case, the subsidy exclusively captures the cumulative unpriced externality associated with driving an EV relative to conventional vehicle that arises if the social planner fails to set the Pigouvian tax rates for electricity and gasoline. This is the traditional externality-based motivation for a subsidy or tax at the time of purchase. If the tax rates on energy sources are not set at marginal external costs, a forward-looking consumer will not face the correct incentives on the extensive margin. Here, the purchase subsidy or tax is meant to correct the incentive on the extensive margin. 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 EV, $S^*(V\bar{M}T_i) = V\bar{M}T_i(\phi_g - \phi_e)$, and aligns with the optimal subsidies from Holland et al. (2016).

The second special case focuses on the "internality" in which Pigouvian taxes remove the 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 EV. If the buyer over-estimates the cost (i.e., $\theta > (c_e + \tau_e)$), the optimal 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

[36] Details of all derivations are provided in the Appendix A.3.

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* EVs.

When considering externality- and internality-correcting policy together, the optimal subsidy has implications for policy design and differentiates our setting from the related setting of Allcott et al. (2014) and energy efficient durables. In Allcott et al. (2014), remedies for the internality and externality both operate in the same direction. That is, if consumers are myopic and the polluting energy input is underpriced, the optimal subsidy is unambiguously positive. In our setting, future EV fuel costs are sub-optimally high (P>SMC), so failure to account for them implies the optimal internality correction is a *negative* subsidy.

At first consideration, information provision seems like a natural remedy for an internality. Even in the case where θ is less than one, if each buyer can be educated so that θ reflects the actual electricity price they face, the buyer's decision utility is equal to their experience utility. However, information provision corrects the internality only if information can be tailored to each buyer, reflecting buyer-specific electricity prices as in Davis and Metcalf (2016).[37] While customized information is increasingly feasibly from a technical perspective, labelling programs to date typically only provide average or aggregated information.

In the absence of an information intervention that aligns a buyer's decision and experience utility, a corrective tax or subsidy at the time of purchase can serve a similar role. As an illustrative benchmark, we calculate the optimal subsidies for the mean California driver in 2017. We use the mean self-reported mileage from the 2017 NHTS for California (10,793 miles per year) and assume that the driver faces gasoline taxes of 68.3 cents per gallon. We take per-mile externalities for gasoline-powered and EVs from Holland et al. (2016) and the marginal private cost of electricity in California from Borenstein and Bushnell (2022). Using our preferred specification, that yields an estimate for γ of 0.157, we calculate an externality- correcting subsidy of \$670 per year and an offsetting internality-correcting tax of \$384 per year, implying an optimal subsidy of roughly \$286 per year.[38] Notably, this estimate is based on the driving patterns reported by the average California driver. There is a roughly three-fold difference between VMT in California at the 25th and 75th percentiles in 2017, (4,721 and 13,845, respectively). Since the optimal subsidy is calculated on a per-mile basis, the optimal subsidy for drivers at the 75th

[37]Moreover, there is evidence that information interventions in the setting of durable energy investments can be ineffective (e.g. Allcott and Greenstone (2017), Allcott and Knittel (2019)).

[38]In Figure 7, we calculate values of γ under alternative assumptions, ranging from roughly 0 to 0.256. The corresponding optimal subsidies vary from \$215 to \$330 per year. This range is comparable to the optimal subsidies that would be implied by the upper and lower bounds of the 95% confidence interval of γ from our preferred specification, \$220 to \$352 per year.

and 25th percentiles of the driving distribution would be roughly \$366 per year and \$125 per year, respectively.[39] This heterogeneity in driving patterns illustrates both the shortcomings of subsidies tailored to the patterns of the "mean" driver, which "oversubsidize" low-mileage drivers and "undersubsidize" high-mileage drivers, and another potential wrinkle to tailoring an information intervention to correct the internality on a driver-by-driver basis.

The comparative statics with respect to τ_g and τ_e illustrate how the other potential policy instruments, i.e., taxes on gasoline and electricity, relate to the optimal purchase subsidy for EVs.

$$\frac{\partial S_i^*(V\bar{M}T_i)}{\partial \tau_g} = -V\bar{M}T_i \tag{13}$$

$$\frac{\partial S_i^*(V\bar{M}T_i)}{\partial \tau_e} = \gamma V\bar{M}T_i \tag{14}$$

Abstracting away from the response of VMT to tax-inclusive prices, the optimal subsidy offsets a change in the gasoline tax on a one-for-one basis (when scaled by VMT). In a world in which gasoline taxes are set below the Pigouvian level, if the gasoline tax increases, the unpriced externality from gasoline consumption declines as does the optimal EV subsidy. Similarly, if the buyer fully internalizes the cost of operation of an EV, electricity taxes (or regulated per-unit markups above marginal cost) have equivalent effects on the optimal subsidy. If electricity taxes rise, so does the optimal subsidy so as to correct any un-priced (or over-priced) externality.

However, if buyers mis-estimate the costs of operation for an EV ($\gamma < 1$), an increase in the electricity tax has two opposing effects on the optimal subsidy. On one hand, an increase in the electricity tax increases the externality-based rationale to subsidize EVs. On the other hand, higher taxes impose a greater costs on the experiential utility of an EV buyer who mis-estimates the future operational costs at the time of purchase. This effect pushes in the opposite direction to the first. Although higher electricity taxes increase the need to subsidize EVs on the extensive margin, the same increase in the electricity tax would imply a countervailing need to *tax* the purchase of EVs if buyers mis-estimate the costs of operation. This secondary effect attenuates the relationship between the tax on electricity and the optimal EV purchase subsidy. At the extreme, when γ is equal to zero, the tax on electricity has no impact on the extensive margin and a change in the tax has no impact on the optimal purchase subsidy for EVs.

[39] Differences in reported vehicle miles traveled increase in the tails of the distribution. There is roughly a ten-fold difference in reported VMT (and corresponding optimal subsidy) at the 10th and 90th percentiles (1,996 and 20,136, with corresponding optimal subsidies of \$52 and \$533, respectively).

In Figure 9, we illustrate these relationships between τ_g, τ_e, and γ and the optimal annualized subsidy using California as an example. In each of the panels, we decompose the optimal annualized subsidy into an externality-driven component (green dashed line) and a internality-driven component (red dashed line). The shaded region reflects the optimal annualized subsidy, the sum of the two components, measured on an annualized basis. The solid vertical lines in each panel correspond to the average marginal electricity price for investor owned utilities in panel (a), the combined state and federal gasoline taxes in 2017 in California in panel (b) and our estimate of γ from Table 3, column (3) in panel (c).

In the panel (a), we decompose the optimal 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 (14), 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. The relatively constant total subsidy aggregates 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 cpm 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). 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 optimal subsidy corrects for marginal electricity prices that are, themselves, set sub-optimally.

As the extent of 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, 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 EVs is offset partially by an internality-driven *tax* on EVs. The more nuanced relationship between electricity prices and the optimal subsidy runs counter to the standard intuition that subsidies and low-electricity prices are policy substitutes, as both reduce the "all-in" price of owning an EV. 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 optimal subsidy based on gasoline taxes. Unlike electricity prices gasoline taxes only affect the optimal 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, γ only impacts the internality-driven component of the subsidy. As the degree to which a buyer's mis-estimation of the cost of operation declines, the incentive to tax EVs so as to align the decision utility and experience utility of the buyer declines. If γ rises over time, as suggested by our result on vehicle retention, households learn about the cost of operation through usage, thereby reducing the future need for a subsidy to address the internality. With symmetric valuation of gasoline and electricity ($\gamma = 1$), the buyer's experience and decision utilities are equivalent. In such a case, there is not longer a need for internality-addressing policy and the optimal subsidy is set to solely reflect the unpriced externality.

8 Conclusion

The light duty vehicle market (and transportation sector more broadly) is in the midst of a shift towards new technologies. At this relatively early stage of the transition, government policies are first-order determinants of the incentives that encourage consumers to adopt EVs or shun CVs. In this paper, we provide the first causal evidence of the impact of energy prices on EV purchase decisions.

Our findings are three-fold. First and foremost, we use two different identification strategies to find consistent evidence that potential EV buyers are substantially less sensitive to electricity prices than to gasoline prices. In some ways, this isn't surprising. Consumers have vast experience using gasoline. Gasoline prices are prominently displayed and are amongst the most salient of prices in the economy. Payment occurs at the time of fueling and gasoline expenditures comprise a significant share of the typical household budget. It is reasonable that consumers would be attentive to any changes in incentives on this margin.[40] In contrast, consumers appear to know far less about electricity prices. Electricity prices vary geographically, tariff schedules are non-linear and often exhibit increasing-block prices, payment typically occurs weeks after usage, and the consumption expenditure share of electricity is smaller than

[40]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. The 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)).

that of gasoline.

While the main result may be surprising to some, it arises from a regression discontinuity design that relies on weaker assumptions for identification than many of our intellectual antecedents. These typically deploy more conventional panel fixed-effects or structural estimation methods. Moreover, the RD offers opportunities to falsify the identifying assumptions. We show that most observable covariates are smooth across the discontinuities, and that municipal boundaries do not exhibit treatment effects unless they are accompanied by discontinuous electricity price differentials.

This result has clear policy implications for environmental policy, as taxes on gasoline and the pricing of residential electricity are two of the main levers available to policymakers concerned with stimulating demand for EVs. To the extent buyers are systematically less sensitive to electricity prices, as results suggest in our setting, policies aiming to increase EV ownership by lowering the marginal price of electricity may prove ineffective even when lowering the (counterfactual) total cost of ownership. Moreover, geographic variation in regulated electricity rates may prove much less of an incentive (or deterrent) to EV adoption than one might expect from a simple evaluation of the private savings. To the extent poor information about the relative cost of EVs persists, our results suggest that a gasoline (or carbon) tax would be far more effective.

Second, our findings have implications for corrective purchase subsidies and taxes in this setting. When consumers undervalue electricity prices, a welfare-maximizing planner would either subsidize or tax the extensive margin, even if optimal Pigouvian taxes are set for the energy inputs.[41] If the actual operating costs a buyer faces are above or below what they expect to pay, a buyer's decision utility (at the time of purchase) will not accurately reflect their experience utility (at the time of usage). Optimal purchase subsidies would align the prospective buyer's decision and experience utility, and could be positive or negative (a tax).

Finally, our third finding offers evidence of one potential mechanism driving the main result and points to the need for a dynamic view of optimal policy. As with most new technologies, a substantial learning curve may exist for new users. In the case of EV ownership, a buyer who mis-estimates the cost of operation may learn over time about the operational costs of charging an EV at home. As they update their understanding of the operational costs of an electric vehicle, they would also update their utility of owning the EV.[42] We find that buyers

[41]Note that our analysis abstracts away from other potential reasons to subsidize EV purchases, such as network externalities or non-appropriable learning-by-doing.

[42]Although we focus exclusively on the extensive margin in this paper, learning of the operational costs may also have important implications for the intensive margin of use, reflecting a sort of "behavioral rebound". Such effects might

who live in areas with relatively high electricity prices are more likely to resell their vehicles within four years than buyers who live in areas with low electricity prices. Admittedly, this is indirect evidence. However, it is consistent with a model in which poorly-informed EV buyers learn about the costs of operation through use. Under these conditions, we would expect that second-time owners would become more elastic with respect to electricity prices, and the "true" value of γ in the population would change over time as improved awareness of the true cost of operating EVs is socialized. In such a world, the optimal subsidy regime is also dynamic. In the early stages of adoption, the optimal subsidy will be higher to account for the benefits of learning about relative costs. The need for corrective taxation to address the internality would gradually diminish, however, as consumers converge towards a more accurate understanding of relative electricity and gasoline costs.

References

Allcott, Hunt and Christopher Knittel, "Are consumers poorly informed about fuel economy? Evidence from two experiments," *American Economic Journal: Economic Policy*, 2019, *11* (1), 1–37.

_ **and Michael Greenstone**, "Measuring the welfare effects of residential energy efficiency programs," Working Paper, National Bureau of Economic Research 2017.

_ **and Nathan Wozny**, "Gasoline prices, fuel economy, and the energy paradox," *Review of Economics and Statistics*, 2014, *96* (5), 779–795.

_ **, Sendhil Mullainathan, and Dmitry Taubinsky**, "Energy policy with externalities and internalities," *Journal of Public Economics*, 2014, *112*, 72–88.

Altonji, Joseph G, Todd E Elder, and Christopher R Taber, "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools," *Journal of political economy*, 2005, *113* (1), 151–184.

Anderson, Soren T, Ryan Kellogg, and James M Sallee, "What do consumers believe about future gasoline prices?," *Journal of Environmental Economics and Management*, 2013, *66* (3), 383–403.

be particularly pronounced in locations such as California, where the operational costs of an electric vehicle might be significantly higher than "typical" operational costs advertised by dealers, savings calculators or EPA estimates.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan, "A unified framework for measuring preferences for schools and neighborhoods," *Journal of political economy*, 2007, *115* (4), 588–638.

Blake, Thomas C., "Commuting Costs and Geographic Sorting in the Housing Market," *Real Estate Economics*, 2016, *00*, 1–29.

Borenstein, Severin and James B Bushnell, "Do two electricity pricing wrongs make a right? Cost recovery, externalities, and efficiency," *American Economic Journal: Economic Policy*, 2022, *14* (4), 80–110.

_ **and Lucas W Davis**, "The distributional effects of US clean energy tax credits," *Tax Policy and the Economy*, 2016, *30* (1), 191–234.

Burlig, Fiona, James Bushnell, David Rapson, and Catherine Wolfram, "Low energy: Estimating electric vehicle electricity use," *AEA Papers and Proceedings*, 2021, *111*, 430–35.

Busse, Meghan R, Christopher R Knittel, and Florian Zettelmeyer, "Are consumers myopic? Evidence from new and used car purchases," *American Economic Review*, 2013, *103* (1), 220–56.

California Air Resources Board, "Low Carbon Fuel Standard Quarterly Summary of Data," Technical Report 2020.

Davis, Lucas, Jing Li, and Katalin Springel, "Political Ideology and U.S. Electric Vehicle Adoption," Working Paper 2023.

Davis, Lucas W, "Evidence of a homeowner-renter gap for electric vehicles," *Applied Economics Letters*, 2018, pp. 1–6.

_ , "How much are electric vehicles driven?," *Applied economics letters*, 2019, *26* (18), 1497–1502.

_ **and Gilbert E Metcalf**, "Does better information lead to better choices? Evidence from energy-efficiency labels," *Journal of the Association of Environmental and Resource Economists*, 2016, *3* (3), 589–625.

Dunckley, J and G Tal, "Plug-In Electric Vehicle Multi-State Market and Charging Survey," *EVS29*, 2016, pp. 1–12.

Environmental Protection Agency, "Revised 2023 and Later Model Year Light-Duty Vehicle GHG Emissions Standards: Regulatory Impact Analysis. Report EPA-420-R-21-028.," 2021.

Gillingham, Kenneth, "Identifying the elasticity of driving: evidence from a gasoline price shock in California," *Regional Science and Urban Economics*, 2014, *47*, 13–24.

__ , David Rapson, and Gernot Wagner, "The rebound effect and energy efficiency policy," *Review of Environmental Economics and Policy*, 2016.

Gillingham, Kenneth T, Sebastien Houde, and Arthur A van Benthem, "Consumer myopia in vehicle purchases: evidence from a natural experiment," *American Economic Journal: Economic Policy*, 2021, *13* (3), 207–38.

Grigolon, Laura, Mathias Reynaert, and Frank Verboven, "Consumer valuation of fuel costs and tax policy: Evidence from the European car market," *American Economic Journal: Economic Policy*, 2018, *10* (3), 193–225.

Hardman, Scott, Alan Jenn, Gil Tal, Jonn Axsen, George Beard, Nicolo Daina, Erik Figenbaum, Niklas Jakobsson, Patrick Jochem, Neale Kinnear et al., "A review of consumer preferences of and interactions with electric vehicle charging infrastructure," *Transportation Research Part D: Transport and Environment*, 2018, *62*, 508–523.

Holland, Stephen P, Erin T Mansur, Nicholas Z Muller, and Andrew J Yates, "Are there environmental benefits from driving electric vehicles? The importance of local factors," *American Economic Review*, 2016, *106* (12), 3700–3729.

Houde, Jean-François, "Spatial differentiation and vertical mergers in retail markets for gasoline," *American Economic Review*, 2012, *102* (5), 2147–2182.

Houde, Sébastien and Erica Myers, "Heterogeneous (mis-) perceptions of energy costs: Implications for measurement and policy design," Working Paper, National Bureau of Economic Research 2019.

__ and __ , "Are consumers attentive to local energy costs? Evidence from the appliance market," *Journal of Public Economics*, 2021, *201*, 104480.

Ito, Koichiro, "Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing," *American Economic Review*, 2014, *104* (2), 537–63.

Jacobsen, Mark R and Arthur A Van Benthem, "Vehicle scrappage and gasoline policy," *American Economic Review*, 2015, *105* (3), 1312–1338.

Jessoe, Katrina and David Rapson, "Knowledge is (less) power: Experimental evidence from residential energy use," *American Economic Review*, 2014, *104* (4), 1417–1438.

Leard, Benjamin, Joshua Linn, and Yichen Christy Zhou, "How much do consumers value fuel economy and performance? Evidence from technology adoption," *The Review of Economics and Statistics*, 2021, pp. 1–45.

Lee, David S and Thomas Lemieux, "Regression discontinuity designs in economics," *Journal of Economic Literature*, 2010, *48* (2), 281–355.

Levinson, Arik and Lutz Sager, "Who Values Future Energy Savings? Evidence from American Drivers," *Journal of the Association of Environmental and Resource Economists*, 2023, *10* (3), 717–751.

Li, Jing, "Compatibility and Investment in the U.S. Electric Vehicle Market," Working Paper 2017.

Li, Shanjun, Lang Tong, Jianwei Xing, and Yiyi Zhou, "The market for electric vehicles: indirect network effects and policy design," *Journal of the Association of Environmental and Resource Economists*, 2017, *4* (1), 89–133.

Li, Xiaomin, Pu Chen, and Xingwu Wang, "Impacts of renewables and socioeconomic factors on electric vehicle demands–Panel data studies across 14 countries," *Energy Policy*, 2017, *109*, 473–478.

McConnell, Virginia and Benjamin Leard, "Pushing New Technology into the Market: California's Zero Emissions Vehicle Mandate," *Review of Environmental Economics and Policy*, 2021, *15* (1), 169–179.

Muehlegger, Erich J and David S Rapson, "Correcting estimates of electric vehicle emissions abatement: Implications for climate policy," *Journal of the Association of Environmental and Resource Economists*, 2023, *10* (1), 263–282.

Oster, Emily, "Unobservable selection and coefficient stability: Theory and evidence," *Journal of Business & Economic Statistics*, 2019, *37* (2), 187–204.

Rapson, David and James Bushnell, "The Limits and Costs of Full Electrification," *Review of Environmental Economics and Policy*, 2024, *18* (1), 26–44.

Rapson, David S and Erich Muehlegger, "The economics of electric vehicles," *Review of Environmental Economics and Policy*, 2023, *17* (2), 274–294.

Sallee, James M, Sarah E West, and Wei Fan, "Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations," *Journal of Public Economics*, 2016, *135*, 61–73.

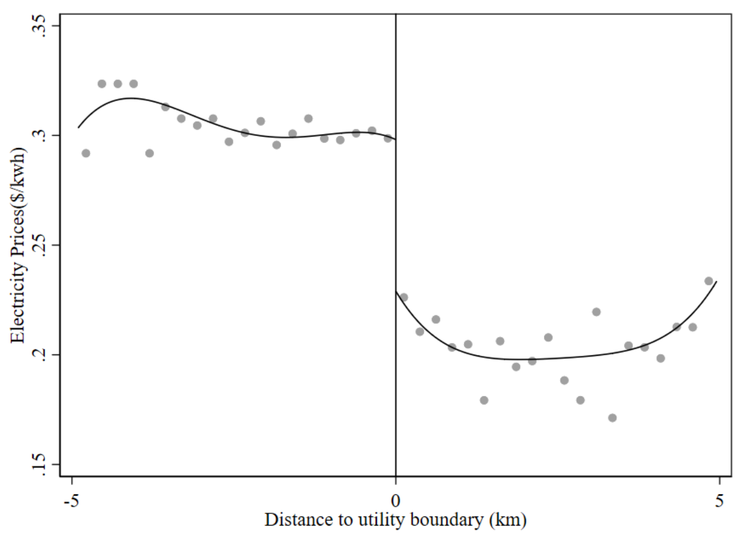
Shaffer, Blake, "Misunderstanding nonlinear prices: Evidence from a natural experiment on residential electricity demand," *American Economic Journal: Economic Policy*, 2020, *12* (3), 433–61.

Sierzchula, William, Sjoerd Bakker, Kees Maat, and Bert Van Wee, "The influence of financial incentives and other socio-economic factors on electric vehicle adoption," *Energy policy*, 2014, *68*, 183–194.

Springel, Katalin, "Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives," *American Economic Journal: Economic Policy*, 2021, *13* (4), 393–432.

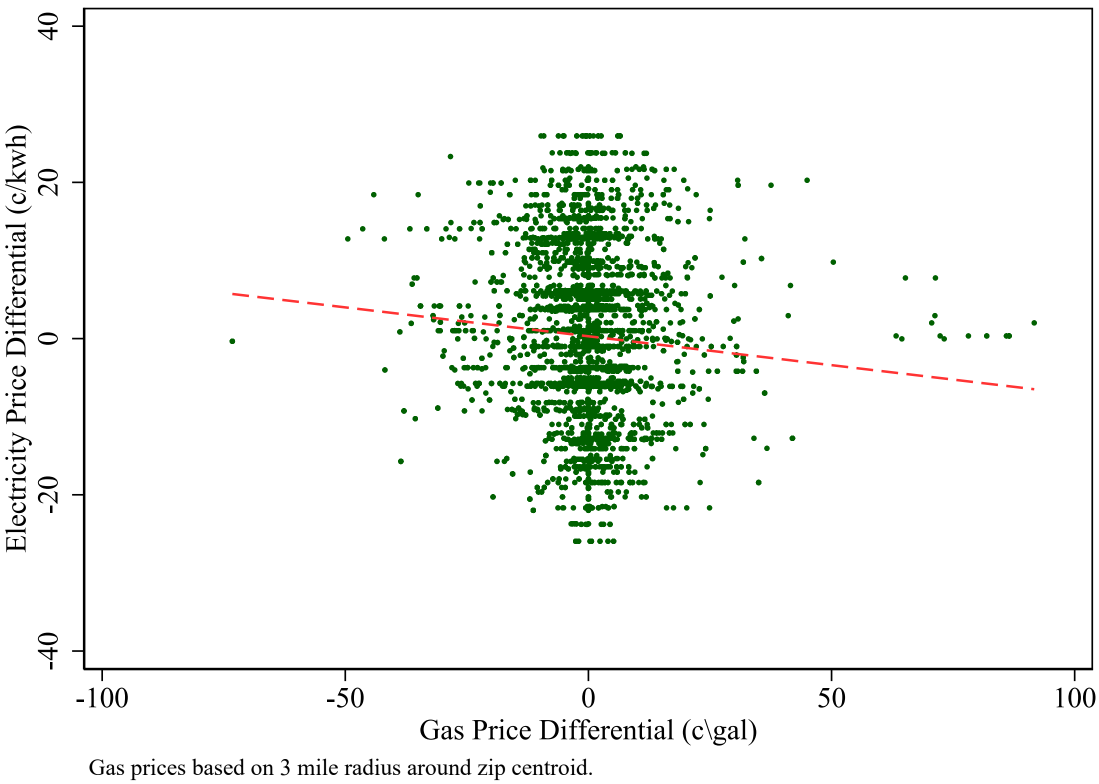
Xing, Jianwei, Benjamin Leard, and Shanjun Li, "What does an electric vehicle replace?," *Journal of Environmental Economics and Management*, 2021, *107*, 102432.

Figure 1: Electricity Prices across Utility Area Boundaries



Notes: The figure presents a binned scatter plot of electricity prices at quarter kilometer intervals along around the boundaries between investor-owned utilities (on the left) and municipal utilities (on the right). The line is a fourth-degree polynomial line of best fit. The x-axis distances correspond to the distance to the utility boundary.

Figure 2: Electricity Price and Gasoline Price Differences between Block-Group Pairs



Notes: The figure plots the gasoline and electricity price differential for pairs of census block groups straddling utility area boundaries. The gasoline price difference is plotted on the x-axis and the electricity price difference is plotted on the y-axis. The dashed red line corresponds to the line of best fit. Observations are annual at the census-block-group pair level.

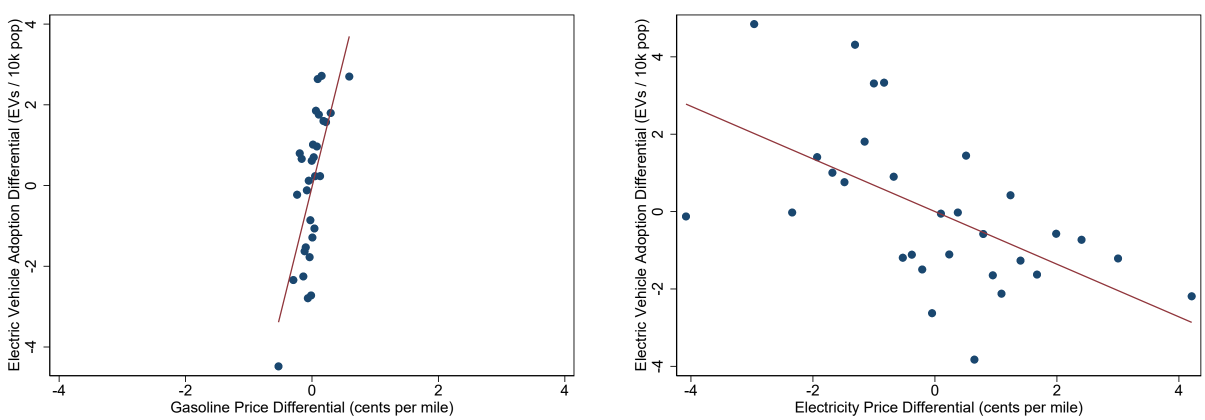
Figure 3: Covariates across Utility Area Boundaries

Notes: The figures present the average covariates at census block groups at various distances from utility area service territory boundaries. The line of best fit is a fourth-order polynomial that varies on either side of the boundary. Positive (Negative) distances (on the x-axis) correspond to the Municipal (IOU) side of the border.

Figure 4: Electric Vehicle Adoption, Gasoline Prices and Electricity Prices Per Mile

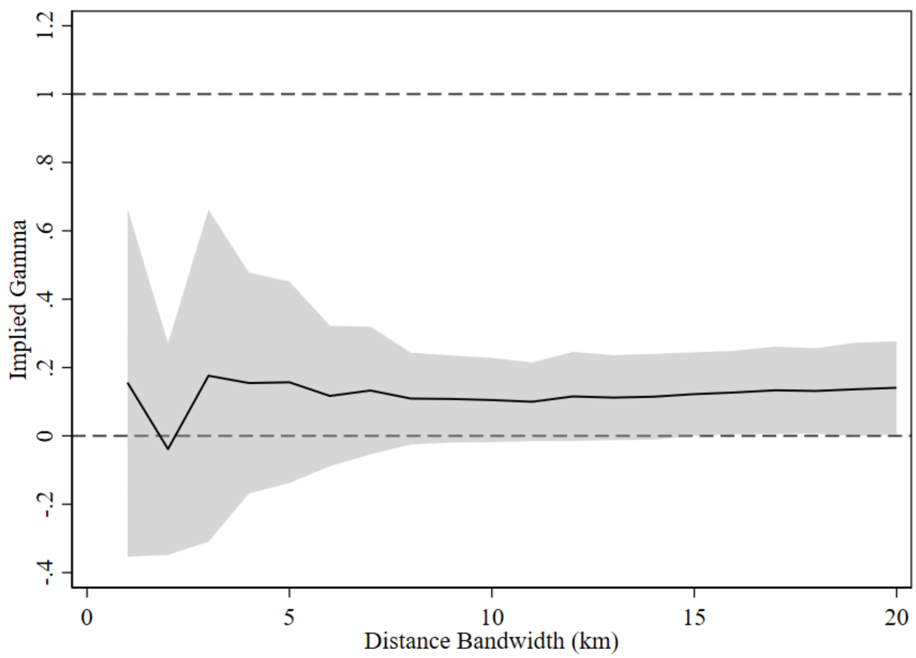
(a) Gasoline Prices

(b) Electricity Prices



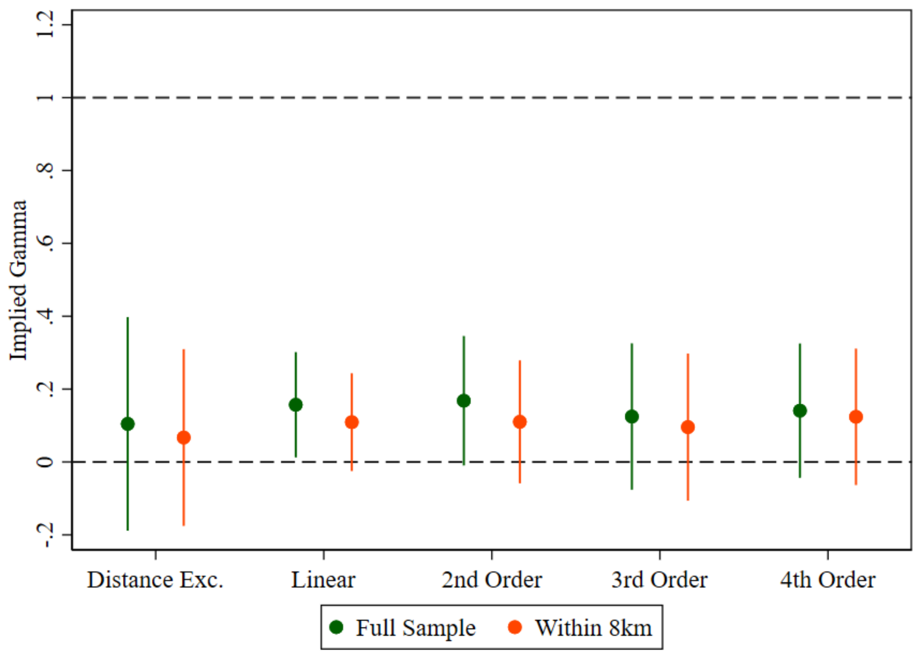
Notes: The figure plots the binned scatter plot of EV adoption against gasoline prices (Panel A) and electricity prices (Panel B) based on the paired RD design in equation 8. All variables are residualized by covariates included in column (3) of Table 3, and binned into twenty quantiles of gasoline price differential or electricity price differential, in panels A and B respectively.

Figure 5: Implied Values of Gamma by Distance Bandwidth



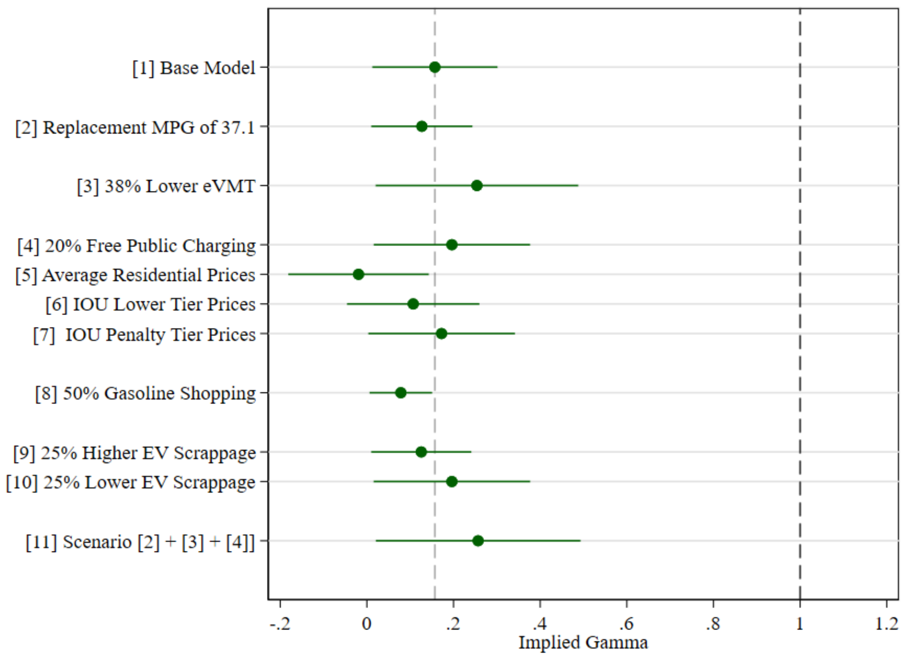
Notes: The figure plots the point estimate (solid line) and the 95 percent confidence interval (shaded region) of gamma, restricting the border discontinuity regression sample to different distance bandwidths. For instance, a bandwidth of 1km only uses pairs of census block groups that are an opposite side of the service territory boundary and are within 1km or less of each other. For reference, the point corresponding to 8km is identical to specification (7) from Table 3. All specifications include demographics characteristics and allow for linear relationship between adoption and distance on either side of the utility boundary. All specifications cluster standard errors by IOU census block group and municipal census block group. The dotted line at a value of 1 corresponds to the value of γ that would imply equivalent treatment of gasoline and electricity prices. Similar graphs for the coefficients on electricity prices and gasoline prices are available in the appendix as Figures A3.

Figure 6: Implied Values of Gamma using Alternative Polynomials for Distance



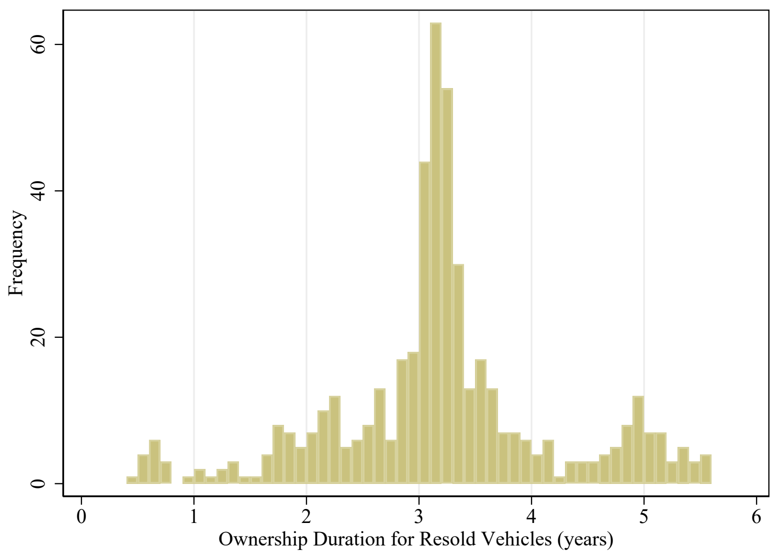
Notes: Graph plots the point estimate and the 95 percent confidence interval of γ allowing for the relationship between distance and adoption to vary on either side of each service territory boundary. The figure presents estimates using the full sample of paired block groups and the subsample of pairs that are within 8km of each other. The first two estimates exclude coefficients on distance. The second estimates recreate the baseline model from Table 3 that allows for a linear relationship between distance and adoption on either side of each boundary. The remaining three pairs of estimates allow for 2nd, 3rd, and 4th order polynomials on distance. All specifications include demographics characteristics and cluster standard errors by IOU census block group and municipal census block group. The dotted line at a value of 1 corresponds to the value of γ that would imply equivalent treatment of gasoline and electricity prices. Similar graphs for the coefficients on electricity prices and gasoline prices are available in the appendix as Appendix Figure A4, and the full table of coefficients is presented in Appendix Table A1.

Figure 7: Implied Values of Gamma using Alternative Assumptions



Notes: Graph plots the point estimate and the 95 percent confidence interval of γ under different sets of assumptions. All values of γ are estimated with demographic covariates, similar to specification in column (3) of Table 3. Row [1] corresponds to the implied γ in column (3) of Table 3. Row [2] uses a fuel economy for the alternative conventional vehicle of 37.1, based on Muehlegger and Rapson (2023). Row [3] assumes that VMT for the electric vehicle is 62% of the VMT of the alternative conventional vehicle, based on Davis (2019). Row [4] assumes that only 80% of electric vehicle charging occurs at home, based on Hardman et al. (2018), and that the remaining 20% occurs at free public charging stations. Row [5] uses the average price for 900 kWh of monthly electricity rather than the marginal price for electricity. Rows [6] and [7] use the marginal prices for electricity based on one lower tier and the highest tier, respectively. Row [8] assumes that conventional vehicle drivers living in a high-price census tract purchase half of their fuel in the nearby low-price census tract. Rows [9] and [10] assume that electric vehicle face a 25% higher or 25% lower scrappage rate than conventional vehicles, respectively. Row [11] combines the assumptions of the three scenarios supported by evidence from the literature, scenarios [2], [3] and [4].

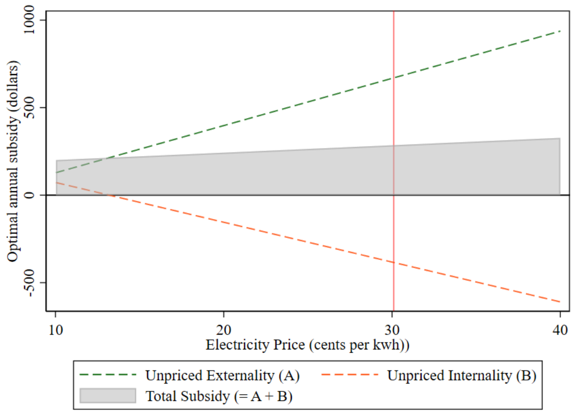
Figure 8: Ownership length, conditional on resale



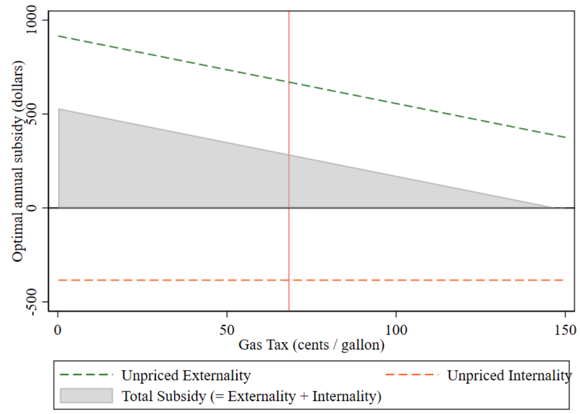
Note: The histogram plots the duration between first and second sales for vehicles purchased in January 2014, conditional on the vehicle being resold and re-registered in California. Because the ownership data ends in October 2019, the maximum length of ownership, conditional on resale, is five years and ten months.

Figure 9: Decomposition of optimal subsidy

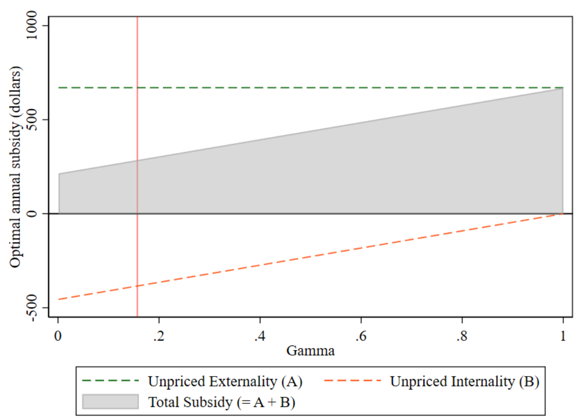
(a) Electricity Prices



(b) Gasoline Taxes



(c) Gamma



The figures present how the optimal subsidy per year of ownership (shaded region), unpriced externality (green dashed line) and unpriced internality (red dashed line) change with the residential electricity price (Panel A), gasoline tax (Panel B) and degree of undervaluation of electricity prices (Panel C). All figures assume that annual VMT is equal to mean, self-reported VMT from 2017 NHTS for California (10793), fuel efficiency for electric vehicles and conventional vehicles of 4 miles/kWh and 30 miles/gallon, respectively, damages per mile for EVs and CVs based on Holland et al. (2016), and marginal private cost of electricity based on Borenstein and Bushnell (2022) and a reference electricity price of 13.2 cents / kWh based on the assumptions of the EPA fuel economy calculator for electric vehicles. For reference, the red vertical lines correspond to the average marginal electricity price for investor owned utilities in panel (a), the combined state and federal gasoline taxes in 2017 in California in panel (b) and our estimate of γ from Table 3, Column (3) in panel (c).

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: The table reports the mean and standard deviation (in parentheses) of the variables. 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 Regression Results

	Monthly Sales Per Cap			Annual Sales Per Cap		
	(1)	(2)	(3)	(4)	(5)	(6)
Marg. Price (cents/kwh)	0.0036***	-0.0035**	-0.0029*	0.030**	-0.061***	-0.056**
	(0.00096)	(0.0015)	(0.0015)	(0.012)	(0.023)	(0.023)
Gas Price (cpg)	-0.0011***	0.0041***	0.0037***	-0.022***	0.16***	0.14***
	(0.000078)	(0.00060)	(0.00059)	(0.0013)	(0.013)	(0.012)
CBG FE		X	X		X	X
Time FE		X	X		X	X
Demographics			X			X
Implied γ		.114	.106		.052	.053
		(.052)	(.056)		(.02)	(.022)
Observations	872314	872314	861370	73351	73336	72364
R-Squared	0.00030	0.15	0.15	0.0020	0.61	0.60

The table reports the coefficients from the panel regression from Section 4. Columns (1) through (3) conduct the analysis at the monthly level, while columns (4) through (6) conduct the analysis at the annual level. Columns (3) and (6) include median household income, median age, fraction of the population with a bachelor's degree, and the white fraction of the population. The 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. The implied values of γ assume fuel efficiencies of 4 miles / kWh for EVs and 30 miles / gallon for the alternative conventional vehicle.

Table 3: Border Discontinuity Results

	Full Sample				CBG dist < 8km			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Marg. Price (cents/kwh)	-0.11	-0.16***	-0.20***	-0.070	-0.14*	-0.16**	-0.17**	-0.043
	(0.079)	(0.060)	(0.064)	(0.15)	(0.087)	(0.074)	(0.074)	(0.16)
Δ Gas Price (cpg)	0.35***	0.39***	0.17***	0.16***	0.51***	0.57***	0.21**	0.19**
	(0.10)	(0.10)	(0.054)	(0.054)	(0.16)	(0.15)	(0.084)	(0.085)
Δ Pop Density (000s ppl/sqm)		-0.50***	-0.15***	-0.16***		-0.49***	-0.13***	-0.14***
		(0.062)	(0.041)	(0.043)		(0.061)	(0.042)	(0.043)
Δ MUD HH share (2013)		-10.9***	-3.45**	-3.49***		-11.3***	-2.74**	-2.85**
		(1.73)	(1.34)	(1.34)		(1.78)	(1.39)	(1.38)
Δ Mean Fuel Econ (mpg, 2013)			2.53***	2.55***			2.31**	2.34**
			(0.94)	(0.94)			(0.94)	(0.94)
Δ Hybrid Fleet Share (2013)			-12.4	-11.2			-5.34	-2.23
			(30.1)	(29.9)			(31.0)	(30.6)
Δ Luxury Fleet Share (2013)			127.8***	128.5***			136.3***	137.9***
			(20.4)	(20.3)			(20.9)	(20.6)
Δ Income ($000)			0.084***	0.083***			0.090***	0.087***
			(0.020)	(0.020)			(0.021)	(0.021)
Δ Population (000s)			-1.08***	-1.05***			-1.35***	-1.30***
			(0.34)	(0.34)			(0.41)	(0.40)
IOU FE				X				X
Implied γ	.042	.055	.157	.058	.037	.037	.109	.03
	(.033)	(.026)	(.074)	(.124)	(.026)	(.02)	(.068)	(.115)
Observations	7179	7167	6759	6759	6156	6144	5838	5838
R-Squared	0.097	0.19	0.33	0.33	0.092	0.19	0.34	0.34

The table reports the coefficients from the geographic regression discontinuity analysis from Section 5. Columns (1) - (4) include all census block-group pairs separated by the utility service territory boundary. Columns (5) - (8) only include block-group pairs separated by the utility service territory boundary that are within 8km of each other. The 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 for a linear function of distance that varies on either side of every utility boundary.

Table 4: Border Discontinuity Checks

	(1) Full Sample	(2) Excl. PGE CBGs	(3) Exc. Urban/Rural Boundaries
Δ Marg. Price (cents/kwh)	-0.20***	-0.33***	-0.19***
	(0.064)	(0.088)	(0.067)
Δ Gas Price (cpg)	0.17***	0.23***	0.17***
	(0.054)	(0.072)	(0.058)
Δ Pop Density (000s ppl/sqm)	-0.15***	-0.18***	-0.15***
	(0.041)	(0.040)	(0.042)
Δ MUD HH share (2013)	-3.45**	-3.45**	-3.73***
	(1.34)	(1.45)	(1.39)
Δ Mean Fuel Econ (mpg, 2013)	2.53***	1.82**	2.75***
	(0.94)	(0.85)	(0.98)
Δ Hybrid Fleet Share (2013)	-12.4	-29.1	-17.9
	(30.1)	(36.2)	(31.0)
Δ Luxury Fleet Share (2013)	127.8***	114.4***	123.8***
	(20.4)	(19.5)	(22.1)
Δ Income ($000)	0.084***	0.062**	0.083***
	(0.020)	(0.025)	(0.021)
Δ Population (000s)	-1.08***	-1.03**	-1.02***
	(0.34)	(0.41)	(0.36)
Implied γ	.157	.19	.146
	(.074)	(.08)	(.072)
Observations	6759	4956	6036
R-Squared	0.33	0.28	0.31

The table reports robustness checks for the border discontinuity analysis from Section 5. Column (1) replicates column (3) from Table 3. Column (2) restricts the sample to census block group pairs that do not involve PGE. Column (3) excludes block-pairs for which the municipal-IOU difference in either population density or the share of multi-unit housing is the top quartile. A diagram illustrating the excluded municipal-IOU boundaries can be found in Appendix Table A5. 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 for a linear function of distance that varies on either side of every utility boundary.

Table 5: 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

The table presents the estimates of the six placebo treatment effects along municipal boundaries across which there is no price change for the border, as described in section 5.3. 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. For instance, the top-left point estimate reflects the estimated discontinuity when comparing low-income and high-income CBGs in two different municipalities that have the same electricity price. The standard errors for each of the placebo treatment effects (in parentheses) are two-way clustered by IOU census block group and municipal census block group. All specifications allow for a linear function of distance that varies on either side of every municipal boundary.

Table 6: Energy Prices and Vehicle Retention

	(1)	(2)	(3)	(4)
Marg. Elec. Price	0.0027*	0.0029**	0.0030**	0.0042**
	(0.0014)	(0.0014)	(0.0014)	(0.0017)
Gas Price		0.00056***	0.00050**	0.00041
		(0.00021)	(0.00022)	(0.00036)
Observations	33946	31514	31500	27790
R-Squared	0.020	0.020	0.021	0.23
Make-Model FE	X	X	X	X
Purchase Mon-YR FE	X	X	X	X
Utility FE	X	X	X	
Demographics			X	
CBG FE				X

The table presents the results from the resale analysis performed in section 6. The dependent variable is a dummy variable equal to one if the vehicle is resold within four years. Observations are at the vehicle transaction level. The sample is restricted to vehicles that were purchased between Jan 2014 and Oct 2015 and were only registered at a single address during the four-year window. All specifications allow coefficients on distance to the utility boundary to vary on either side of every utility boundary. Standard errors clustered by census block group.

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 EV 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

$$\begin{aligned}
\frac{dPr(EV)}{dP_0^e} &= \gamma_e\left(\sum_k \frac{Pr(EV_k)}{Pr(EV)}(\frac{kWh}{mile})_k VMT\sum_{t=0}^{\infty}(\delta^t S^{EV}(t))\right) * Pr(EV) * (1 - Pr(EV)) \quad (15)\\
\frac{dPr(EV)}{dP_0^g} &= -\gamma_g\left(\sum_j \frac{Pr(CV_j)}{Pr(CV)}(\frac{gal}{mile})_j VMT\sum_{t=0}^{\infty}(\delta^t S^{CV}(t))\right) * Pr(EV) * Pr(CV)
\end{aligned}$$

where $Pr(EV)$ denotes the probability of purchasing any one of the electric vehicles denoted by k and $Pr(EV_k)$ 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 General Expression for Implied Gamma

To derive the general expression for γ used for the robustness checks in Figure 7, we modify our expressions for the utility of a risk-neutral prospective vehicle buyer in two ways. First, we allow for electric vehicles and conventional vehicles to be driven different amounts at baseline, where η reflects the degree to which an electric vehicle would be driven less than a conventional vehicle when both faced the same operational costs price per mile, $VMT_{EV}(p) = \eta VMT_{CV}(p)$, respectively Second, we allow the price of electricity and gasoline to be P^e and P^g which is a function of "local" prices, where local prices for electricity are captured by the residential electricity price for the household and the local price for gasoline is captured by the price of gasoline in a neighborhood around the household. We maintain the assumption that potential vehicle buyers have "no-change" forecasts for electricity and gasoline prices, consistent with Anderson et al. (2013).

$$U_i^{EV} = \alpha^{EV} + \gamma_e \sum_{t=0}^{\infty}\delta^t\left[E[P_t^e]\left(\frac{kWh}{mile}\right)\right] VMT_{EV}(P_0^e)S^{EV}(t) + \epsilon_i^{EV} \quad (16)$$

$$U_i^{CV} = \alpha^{CV} + \gamma_g \sum_{t=0}^{\infty}\delta^t\left[E[P_t^g]\left(\frac{gal}{mile}\right)\right] VMT_{CV}(P_0^g)S^{CV}(t) + \epsilon_i^{CV} \quad (17)$$

Under the standard logit parameterization for the idiosyncratic utility, we can represent the represent the change in probability of purchasing an EV with respect to the current, local price of electricity and gasoline, $P_0^{\prime e}$ and $P_0^{\prime g}$ as:

$$\frac{dPr(EV)}{dP_0^{\prime e}} = \gamma_e \left(\frac{dP_0^e}{dP_0^{\prime e}} * (1 + \varepsilon_{VMT}) \frac{kWh}{mile} \right) VMT_{EV}(P_0^e) \sum_{t=0}^{\infty} \delta^t S^{EV}(t) Pr(EV)(1 - Pr(EV)) \quad (18)$$

$$\frac{dPr(EV)}{dP_0^{\prime g}} = -\gamma_g \left(\frac{dP_0^g}{dP_0^{\prime g}} * (1 + \varepsilon_{VMT}) \frac{gal}{mile} \right) VMT_{CV}(P_0^g) \sum_{t=0}^{\infty} \delta^t S^{CV}(t) Pr(EV) Pr(CV) \quad (19)$$

where $Pr(EV)$ and $Pr(CV)$ denote the probabilities with which the buyer purchases the EV or the CV, respectively. Denoting the estimated coefficients as $\hat{\beta}^e$ and $\hat{\beta}^g$, we can manipulate the expression for γ to obtain:

$$\bar{\gamma} = \frac{-\hat{\beta}^e * \left(\frac{miles}{kWh}\right)}{\hat{\beta}^g * \left(\frac{miles}{gal}\right)} \frac{dPr(P_0^g)/dP_0^{\prime g}}{dPr(P_0^e)/dP_0^{\prime e}} \frac{Pr(CV)}{1 - Pr(EV)} \eta \sum_{t=0}^{\infty} \delta^t \frac{S^{CV}(t)}{S^{EV}(t)}. \quad (20)$$

A.3 Social Planner Problem

The social planner maximizes

$$\begin{aligned} W = \sum_i \eta_i [\quad & \left(\alpha_{CV} + Y - p_{CV} - V\bar{M}T_i(c_g + \tau_g)\right) + \quad (21) \\ & \int_{\hat{\epsilon}_i}^{\bar{\epsilon}} \left(\alpha_{EV} - \alpha_{CV} - (p_{EV} + S - pCV) - V\bar{M}T_i(c_e + \tau_e - (c_g + \tau_g)) + \epsilon\right) dG(\epsilon) \\ & \left(\tau_g(1 - \lambda_i) V\bar{M}T_i + \tau_e V\bar{M}T_i \lambda_i - S\lambda_i\right) + \\ & \left(-\phi_g V\bar{M}T_i(1 - \lambda_i) - \phi_e V\bar{M}T_i \lambda_i\right) \quad] \end{aligned}$$

where

$$\hat{\epsilon}_i = \alpha_{CV} - \alpha_{EV} - (p_{CV} - p_{EV} - S) - V\bar{M}T_i(c_g + \tau_g - \gamma(c_e + \tau_e) - (1 - \gamma)\theta) \quad (22)$$

, $G(\epsilon)$ 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.3.1 Optimal subsidy design

The optimal 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:

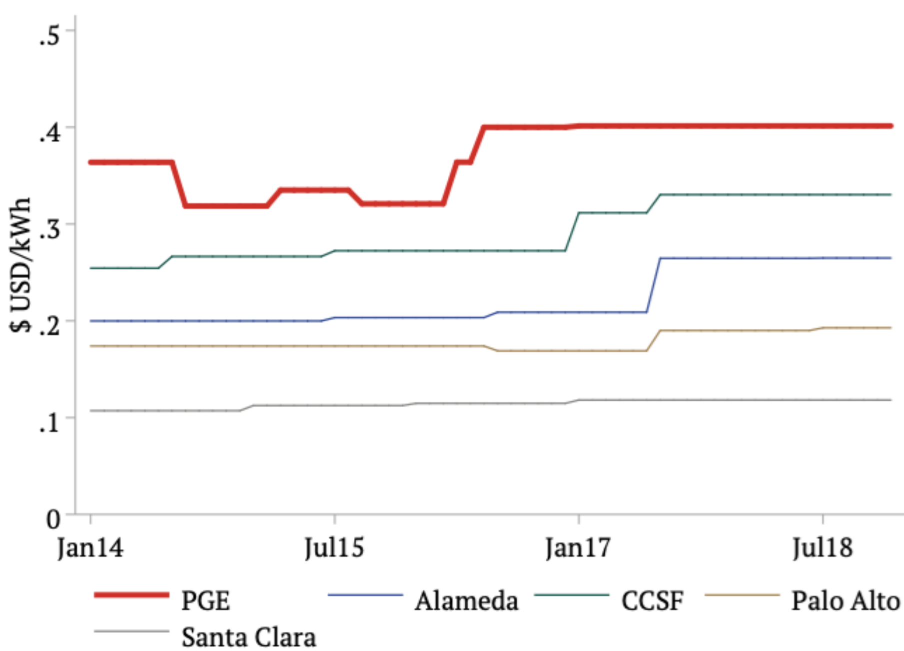
$$\begin{aligned}\frac{dW_i}{dS} &= \int_{\hat{\epsilon}_i}^{\bar{\epsilon}} G(\epsilon)d\epsilon - \frac{d\hat{\epsilon}_i}{dS}G(\hat{\epsilon}_i)[V\bar{M}T_i((1-\gamma)(c_e+\tau_e)+(1-\gamma)\theta)] \\ &\quad -\frac{d\lambda_i}{dS}V\bar{M}T_i(\tau_g-\tau_e) - S\frac{d\lambda_i}{dS} - \lambda_i \\ &\quad +\frac{d\lambda_i}{dS}V\bar{M}T_i(\phi_g-\phi_e)\end{aligned} \tag{23}$$

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:

$$S^*(V\bar{M}T_i) = V\bar{M}T_i[(\phi_g-\tau_g)-(\phi_e-\tau_e)] - [1-\gamma]V\bar{M}T_i[(c_e+\tau_e)-\theta)] \tag{24}$$

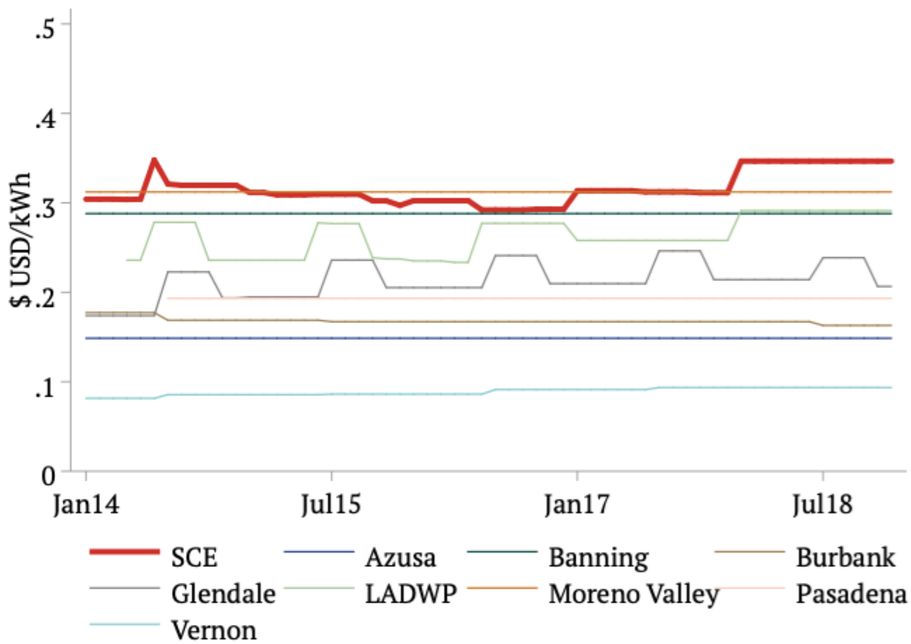
A.4 Supplementary Figures

Figure A1: Residential Retail Electric Prices
Bay Area (Top Tier, 2014-2017)



Notes: The figure plots the top tier of residential electricity prices for PGE (dark red) and municipal utilities in the Bay Area over 2014 - 2017.

Figure A2: Residential Retail Electric Prices
Los Angeles (Top Tier, 2014-2017)

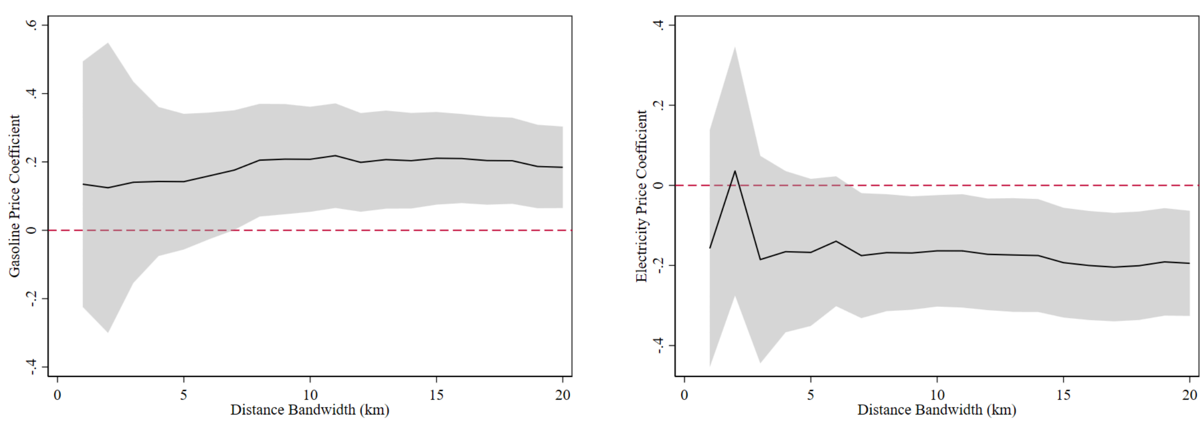


Notes: The figure plots the top tier of residential electricity prices for SCE (dark red) and municipal utilities in the Los Angeles metro area over 2014 - 2017.

Figure A3: Electricity and Gasoline Price Coefficients by Distance Bandwidth

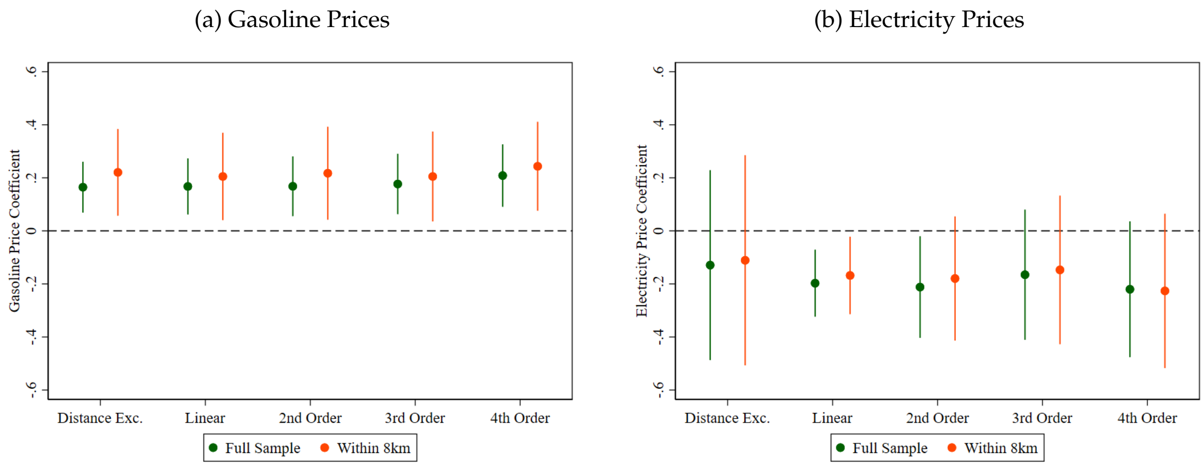
(a) Gasoline Prices

(b) Electricity Prices



Notes: The figure plots the point estimate (solid line) and the 95 percent confidence interval (shaded region) of the coefficient on the difference in gasoline prices (panel A) and the difference in electricity prices (Panel B), restricting the border discontinuity regression sample to different distance bandwidths. For instance, a bandwidth of 1km only uses pairs of census block groups that are on opposite sides of the service territory boundary and are within 1km or less of each other. For reference, the point corresponding to 8km is identical to specification (7) from Table 3. All specifications include demographics characteristics and allow for linear relationship between adoption and distance on either side of the utility boundary. All specifications cluster standard errors by IOU census block group and municipal census block group.

Figure A4: Electricity and Gasoline Price Coefficients for Alternative Distance Polynomials



Notes: Graph plots the point estimate and the 95 percent confidence interval of the difference in gasoline price (Panel A) and the difference in electricity price (Panel B) allowing for the relationship between distance and adoption to vary on either side of each service territory boundary. The figure presents estimates using the full sample of paired block groups and the subsample of pairs that are within 8km of each other. The first two estimates exclude coefficients on distance. The second estimates recreate the baseline model from Table 3 that allows for a linear relationship between distance and adoption on either side of each boundary. The remaining three pairs of estimates allow for 2nd, 3rd, and 4th order polynomials on distance. All specifications include demographics characteristics and cluster standard errors by IOU census block group and municipal census block group.

Figure A5: Population Density and MUD Share Differences
by Service Territory Boundary

Notes: The scatter plot graphs the difference in the share of multi-unit dwellings (x-axis) and the population density (y-axis) between the municipal utility (point labels) and the relevant neighboring investor-owned utility. The dashed grey line corresponds to the 75th percentiles of the difference in the multi-unit dwelling share and the 75th percentile of population density. Only the census-block groups in red are used in the robustness check in column (3) of Table 4.

A.5 Supplementary Tables

Table A1: RD robustness to alternative polynomials

	Full RD Sample					CBG dist < 8km				
	(1) Dist Exc.	(2) Linear	(3) 2nd Degree	(4) 3rd Degree	(5) 4th Degree	(6) Dist Exc.	(7) Linear	(8) 2nd Degree	(9) 3rd Degree	(10) 4th Degree
Δ Marg. Price (cents/kwh)	-0.13	-0.20***	-0.21**	-0.17	-0.22*	-0.11	-0.17**	-0.18	-0.15	-0.23
	(0.18)	(0.064)	(0.098)	(0.13)	(0.13)	(0.20)	(0.074)	(0.12)	(0.14)	(0.15)
Δ Gas Price (cpg)	0.16***	0.17***	0.17***	0.18***	0.21***	0.22***	0.21**	0.22**	0.20**	0.24***
	(0.049)	(0.054)	(0.058)	(0.058)	(0.060)	(0.083)	(0.084)	(0.089)	(0.086)	(0.086)
Δ Pop Density (000s ppl/sqm)	-0.15***	-0.15***	-0.15***	-0.13***	-0.14***	-0.13***	-0.13***	-0.13***	-0.10**	-0.11***
	(0.043)	(0.041)	(0.042)	(0.041)	(0.040)	(0.043)	(0.042)	(0.041)	(0.041)	(0.039)
Δ MUD HH share (2013)	-3.56**	-3.45**	-2.79*	-1.86	-2.18	-2.64*	-2.74**	-2.01	-1.01	-1.14
	(1.54)	(1.34)	(1.42)	(1.41)	(1.37)	(1.56)	(1.39)	(1.46)	(1.47)	(1.46)
Δ Mean Fuel Econ (mpg, 2013)	2.94***	2.53***	2.13***	2.47***	2.16***	2.44***	2.31**	2.08**	2.38***	2.06**
	(0.99)	(0.94)	(0.77)	(0.81)	(0.80)	(0.93)	(0.94)	(0.81)	(0.84)	(0.82)
Δ Hybrid Fleet Share (2013)	-25.9	-12.4	-12.6	-24.5	-21.3	-10.8	-5.34	-8.56	-21.5	-16.5
	(30.1)	(30.1)	(30.0)	(31.0)	(32.3)	(30.4)	(31.0)	(31.0)	(32.1)	(32.7)
Δ Luxury Fleet Share (2013)	136.3***	127.8***	122.7***	132.7***	127.5***	138.7***	136.3***	130.9***	142.1***	134.3***
	(22.1)	(20.4)	(18.5)	(19.6)	(20.6)	(21.3)	(20.9)	(19.3)	(20.4)	(21.7)
Δ Income ($000)	0.084***	0.084***	0.099***	0.11***	0.099***	0.090***	0.090***	0.10***	0.11***	0.10***
	(0.020)	(0.020)	(0.023)	(0.023)	(0.021)	(0.021)	(0.021)	(0.024)	(0.023)	(0.021)
Δ Population (000s)	-1.23***	-1.08***	-1.22***	-1.39***	-1.64***	-1.60***	-1.35***	-1.59***	-2.13***	-2.26***
	(0.37)	(0.34)	(0.34)	(0.36)	(0.40)	(0.44)	(0.41)	(0.42)	(0.46)	(0.50)
Implied γ	.105	.157	.168	.125	.141	.067	.109	.11	.096	.124
	(.15)	(.074)	(.091)	(.102)	(.094)	(.124)	(.068)	(.086)	(.103)	(.096)
Observations	6759	6759	6759	6759	6759	5838	5838	5838	5838	5838
R-Squared	0.32	0.33	0.34	0.36	0.37	0.33	0.34	0.35	0.36	0.38

Notes: The table presents the coefficients of the border discontinuity regression allowing for the relationship between distance and adoption to vary on either side of each service territory boundary. The figure presents estimates using the full sample of paired block groups and the subsample of pairs that are within 8km of each other. The first two estimates exclude coefficients on distance. The second estimates recreate the baseline model from Table 3 that allows for a linear relationship between distance and adoption on either side of each boundary. The remaining three pairs of estimates allow for 2nd, 3rd, and 4th order polynomials on distance. All specifications include demographics characteristics and cluster standard errors by IOU census block group and municipal census block group.

Table A2: Panel Regression Results - 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)	-0.0030**	-0.00095	-0.0029*	-0.0032**	-0.0028**	-0.0010	-0.0029**	-0.0032**	-0.0028**
	(0.0014)	(0.0018)	(0.0015)	(0.0014)	(0.0014)	(0.0018)	(0.0015)	(0.0014)	(0.0014)
Gas Price (cpg)	0.0023***	0.0040***	0.0037***	0.0028***	0.0029***	0.0040***	0.0034***	0.0028***	0.0028***
	(0.00061)	(0.00058)	(0.00059)	(0.00058)	(0.00080)	(0.00056)	(0.00057)	(0.00056)	(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	.17	.032	.106	.154	.127	.033	.114	.15	.132
	(.089)	(.059)	(.056)	(.075)	(.072)	(.059)	(.06)	(.073)	(.074)
Observations	950486	663832	861370	917046	959022	663832	861370	917046	959022
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)	-0.056***	-0.025	-0.056**	-0.056***	-0.045**	-0.027	-0.057**	-0.055**	-0.045**
	(0.021)	(0.028)	(0.023)	(0.022)	(0.021)	(0.028)	(0.023)	(0.022)	(0.021)
Gas Price (cpg)	0.100***	0.14***	0.14***	0.13***	0.13***	0.14***	0.13***	0.13***	0.12***
	(0.010)	(0.012)	(0.012)	(0.012)	(0.014)	(0.012)	(0.012)	(0.012)	(0.013)
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	.025	.053	.056	.047	.027	.056	.054	.048
	(.029)	(.027)	(.022)	(.022)	(.022)	(.027)	(.023)	(.022)	(.023)
Observations	79894	55848	72364	77095	80560	55848	72364	77095	80560
R-Squared	0.59	0.59	0.60	0.60	0.60	0.59	0.60	0.60	0.60

Notes: The table presents the coefficients of the border discontinuity regression allowing for the relationship between distance and adoption to vary on either side of each service territory boundary. The figure presents estimates using the full sample of paired block groups and the subsample of pairs that are within 8km of each other. The first two estimates exclude coefficients on distance. The second estimates recreate the baseline model from Table 3 that allows for a linear relationship between distance and adoption on either side of each boundary. The remaining three pairs of estimates allow for 2nd, 3rd, and 4th order polynomials on distance. All specifications include demographics characteristics and cluster standard errors by IOU census block group and municipal census block group.

Table A3: Border Discontinuity Results - 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 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 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)
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 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 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)
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

The table reports the coefficients from the border discontinuity regression from Section under alternative measures of local gasoline prices. 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 for a linear function of distance that varies on either side of every utility boundary.

Table A4: Energy Prices and Vehicle Retention

	(1)	(2)	(3)	(4)
Marg. Elec. Price	0.026***	0.027***	0.028***	0.022*
	(0.0090)	(0.0091)	(0.0091)	(0.012)
Gas Price		0.00056**	0.00049	0.00047
		(0.00028)	(0.00031)	(0.0044)
Observations	34218	31796	31781	28065
R-Squared	0.020	0.020	0.022	0.23
Make-Model FE	X	X	X	X
Purchase Mon-YR FE	X	X	X	X
Utility FE	X	X	X	
Demographics			X	
CBG FE				X

The table presents the results from the resale analysis performed in section 6. The dependent variable is a dummy variable equal to one if the vehicle is resold within four years. In this table, electricity and gasoline prices are averaged over a four-year vehicle ownership window. Observations are at the vehicle-transaction level. The sample is restricted to vehicles that were purchased between Jan 2014 and Oct 2015 and were only registered at a single address during the four-year window. All specifications allow coefficients on distance to the utility boundary to vary on either side of every utility boundary. Standard errors clustered by census block group.