RESEARCH REPORT

Institute of Transportation Studies | UNIVERSITY OF CALIFORNIA

# Do Electricity Prices Affect Electric Vehicle Adoption?

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May 2021

ITS UC DAVIS INSTITUTE OF TRANSPORTATION STUDIES

Report No.: UC-ITS-2020-12 | DOI: 10.7922/G2DJ5CX3

# Technical Report Documentation Page

| | | |
|---|---|---|
| **1. Report No.**<br>UC-ITS-2020-12 | **2. Government Accession No.**<br>N/A | **3. Recipient's Catalog No.**<br>N/A |
| **4. Title and Subtitle**<br>Do Electricity Prices Affect Electric Vehicle Adoption? | | **5. Report Date**<br>May 2021<br>**6. Performing Organization Code**<br>ITS-Davis |
| **7. Author(s)**<br>James Bushnell, Ph.D., https://orcid.org/0000-0002-8681-9257<br>Erich Muehlegger, Ph.D., https://orcid.org/0000-0002-5670-7895<br>David Rapson, Ph.D., https://orcid.org/0000-0001-8711-7030 | | **8. Performing Organization Report No.**<br>UCD-ITS-RR-21-24 |
| **9. Performing Organization Name and Address**<br>Institute of Transportation Studies, Davis<br>1605 Tilia Street<br>Davis, CA 95616 | | **10. Work Unit No.**<br>N/A<br>**11. Contract or Grant No.**<br>UC-ITS-2020-12 |
| **12. Sponsoring Agency Name and Address**<br>The University of California Institute of Transportation Studies<br>www.ucits.org | | **13. Type of Report and Period Covered**<br>Final Report (October 2019 – September 2020)<br>**14. Sponsoring Agency Code**<br>UC ITS |
| **15. Supplementary Notes**<br>DOI:10.7922/G2DJ5CX3 | | |
| **16. Abstract**<br>This report presents evidence that gasoline prices have a larger effect on demand for battery electric vehicles (BEVs) than do electricity prices in California. A spatially-disaggregated panel dataset of monthly BEV registration records was matched to detailed records of gasoline and electricity prices in California from 2014-2017, and the matched data was used to estimate the effect of energy prices on BEV demand. Two distinct empirical approaches (panel fixed-effects and a utility-border discontinuity) yield remarkably similar results: a given change in gasoline prices has roughly four times the effect on BEV demand as a similar percentage change in electricity prices. | | |

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|---|---|
| **17. Key Words**<br>Electric vehicles, prices, operating costs, demand, electricity, gasoline, empirical methods, consumer behavior | **18. Distribution Statement**<br>No restrictions. |

| | | | |
|---|---|---|---|
| **19. Security Classification (of this report)**<br>Unclassified | **20. Security Classification (of this page)**<br>Unclassified | **21. No. of Pages**<br>32 | **21. Price**<br>N/A |

Form Dot F 1700.7 (8-72) Reproduction of completed page authorized

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## Acknowledgments

This study was made possible through funding received by the University of California Institute of Transportation Studies from the State of California through the Public Transportation Account and the Road Repair and Accountability Act of 2017 (Senate Bill 1). The authors would like to thank the State of California for its support of university-based research, and especially for the funding received for this project. The authors would also like to thank Sébastien Houde and Katalin Springel for thoughtful comments.


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# Table of Contents

# Table of Contents

# List of Tables

# List of Figures

# Glossary

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| **BEV** | battery electric vehicle |
| **CBG** | Census Block Group |
| **EIA** | U.S. Energy Information Administration |
| **EV** | electric vehicle, including both battery electric and plug-in hybrid |
| **ICE** | internal combustion engine |
| **IOU** | investor-owned utilities |
| **MUD** | multi-unit dwelling |
| **OPIS** | Oil Price Information Service |
| **PGE** | Pacific Gas and Electric |
| **SCE** | Southern California Edison |
| **SDGE** | San Diego Gas and Electric |
| **VMT** | vehicle miles traveled |

# Executive Summary

# Executive Summary

Although the upfront costs of purchasing an electric vehicle (EV) exceed those of a comparable conventional vehicle, the operational costs of an electric vehicle are lower than those of a conventional counterpart. These lower operational costs are often cited by manufacturers, EV advocates, and policy-makers as a significant benefit of driving EVs, and in some cases, sufficient to justify the higher upfront cost. Yet, the question of how consumers value the future operational costs of driving an EV has been largely unexplored.

Most drivers have extensive experience using and purchasing gasoline for conventional vehicles, and the academic literature largely finds that consumers incorporate the future operational costs into their purchase decisions in a rational way. But few drivers have experience with charging and using electricity as a transportation fuel. Research suggests that the typical consumer has a poor understanding of their home electricity bill and the marginal price they face when consuming electricity. And attempts to “educate” prospective EV buyers using savings calculators based on nation-wide electricity costs may provide a poor guide for buyers in parts of the country (like California) where electricity is significantly more costly.

Whether consumers accurately assess the costs (or benefits) of using electricity as a transportation fuel has important implications for EV adoption and plans for deep decarbonization of the transportation sector through electrification. As carbon policy increasingly involves tradeoffs between energy sources, the relative prices of these sources, and consumer responses to them, becomes a critical component of that policy.

In this report, we examine highly disaggregated data on battery electric vehicle (BEV) purchases in California over the period from 2014-2017, when the BEV fleet in California tripled in size, growing by roughly 200,000 vehicles. We exploit a novel identification strategy to measure the degree to which consumers incorporate future electricity costs into their vehicle purchase decisions. We compare the rate of BEV adoption of households that live in census block-groups along the boundaries of the three major investor-owned utilities in California (Pacific Gas and Electric, Southern California Edison and San Diego Gas and Electric). Residential electricity prices from the three utilities in California are amongst the highest in the nation. Yet, in neighboring municipal electric utilities, residential electricity prices are often a fraction of those in the investor-owned utilities. To understand how consumers value electricity prices when purchasing EVs, we compare the purchase decisions of similar households with similar commuting patterns who face very different electricity prices by virtue of falling on one side of the utility area boundary or the other.

We find that fuel prices do indeed influence vehicle technology choice, although not to an equal degree. While consumers appear to be influenced by both gasoline and electricity prices when making adoption decisions, the influence of gasoline prices is roughly four to six times stronger, relative to operating costs, than is the electricity price. This asymmetry could be due to a combination of customer confusion about their marginal electricity price and the translation of that price to vehicle operating costs, relative to conventional vehicles. From a policy perspective, our results suggest that prospective EV buyers have a relatively poor sense of the true operational costs of a BEV, and as a result, may underweight the potential operational cost savings associated with purchasing a BEV.

# Contents

# 1. Introduction

In the areas of environmental and transportation policy, there is an ongoing tension between advocates of price-based mechanisms, such as carbon and congestion pricing, and supporters of more direct interventions into the supply of vehicles through measures such as mileage standards and subsidies for alternative fuel vehicles. Supporters of more direct regulations express skepticism over the ability of price-based incentives to effect sufficient change. This view is partly influenced by a belief that customers do not properly internalize the future savings enjoyed from more fuel-efficient vehicles and, therefore, are less willing to pay for fuel efficiency in new cars. If true, this behavioral bias would partially offset the effects of carbon pricing and create a justification for further regulations (see e.g., Allcott et al. (2014)). However, a string of recent economics studies has largely failed to reject the conventional economic assumption that customers do properly value fuel efficiency in the marketplace (Busse et al. (2013), Allcott and Wozny (2014), Sallee et al. (2016)).

While the question of the interaction of fuel prices with vehicle choice has been extensively studied the context of conventional passenger vehicles, to our knowledge no one has addressed this interaction in the context of electric vehicles (EVs). This is despite the fact that EVs play a central role in policy initiatives that target transportation sector emissions. Federal incentives for EV manufactures total up to $1.5 Billion. In California, an executive order by former Governor Brown calls for 5 million “zero-emissions vehicles” (ZEVs) by 2030 as part of an ambitious goal to reduce transportation emissions by 50% by 2030 (Rapson and Muehlegger (2018)). While there has been considerable attention devoted to the impact of EV subsidies and the deployment of charging networks (Springel (2017), Li (2017), Li et al. (2017)), the more fundamental question of how consumers respond to the relative fuel-cost benefits of EVs has not been examined. On one hand, the literature on conventional vehicles suggests that fuel costs are an important consideration for prospective vehicle buyers and the differential fuel efficiency is, in principle, highlighted on fuel economy stickers on all new passenger vehicles. But there are also reasons to expect that buyers are less sensitive to electricity prices. While vehicle buyers have extensive experience with the link between gasoline prices and vehicle use, they have less experience and, potentially, understanding of the link between home charging and electricity bills. Ito (2014) finds evidence that consumers poorly understand the marginal electricity price they face, and, to the extent there are meaningful differences in electricity prices as documented by Borenstein and Bushnell (2019), Davis and Metcalf (2016) suggest that energy savings calculations performed at the national-level might abstract away from important elements of electricity costs.

The role that relative fuel prices play on the choice of vehicle is particularly important given the fact that most plans for deep decarbonization in developed economies call for a large degree of electrification of transportation and other sectors. While states such as California have devoted substantial resources toward subsidizing both EV purchases and supporting infrastructure, many of these programs, somewhat ironically, are funded directly or indirectly through electric rates. Furthermore, as carbon policy increasingly involves tradeoffs between energy sources, the relative prices of these sources, and consumer responses to them, becomes a critical component of that policy. Currently, however, energy prices do not reflect either private or social costs in symmetric ways. Borenstein and Bushnell (2019) estimate that the average variable electricity price is more than four times the social marginal cost in California. In contrast, they find that gasoline prices in California tend to average slightly below the social marginal cost.

In this report, we study the adoption of battery electric vehicles (BEVs) in California over the period from 2014-2017. During this period, the BEV passenger fleet in California grew by over 200,000 vehicles, roughly tripling in size. There was also considerable variation in gasoline and electricity prices in California over the sample period, as well as geographic variation in these prices. We take advantage of the geographic and temporal variation to examine BEV penetration at the census block group (CBG) level over time. We exploit the discontinuity in electricity prices along the borders of neighboring electric utility service territories to study the interaction of fuel prices with EV adoption amongst geographically proximate CBGs. These CBGs should share comparable unobservable factors, such as commute directions and times, as well as local EV charging infrastructure, that might also influence BEV adoptions.

We find that fuel prices do indeed influence vehicle technology choice, although to a different degree. While consumers appear to be influenced by both gasoline and electricity prices when making BEV adoption decisions, the influence of gasoline prices is roughly four times stronger, relative to operating costs, than is the electricity price. This asymmetry could be due to a combination of customer confusion about their marginal electricity price and the translation of that price to vehicle operating costs, relative to conventional vehicles.

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 section 4 our methodology. Results are presented in section 5, and we conclude in section 6.

# 2. Methodological Framework

The goal of this report is to test whether the marginal BEV 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 a BEV and a conventional vehicle ("ICE," for internal combustion engine).

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.

$$\mathcal{U}_i^{BEV} = \alpha^{BEV} + \sum_{t=0}^{T^{BEV}} \delta^t \left[\gamma E[P_t^e | P_0^e] \left(\frac{kwh}{mile}\right) + (1-\gamma)\theta\right] VMT_i + \in_i^{BEV} \qquad (1)$$

$$\boldsymbol{\mathcal{U}_i^{ICE}} = \boldsymbol{\alpha^{ICE}} + \sum_{\boldsymbol{t=0}}^{\boldsymbol{T^{ICE}}} \boldsymbol{\delta^t E[P_t^g | P_0^g] \left(\frac{gal}{mile}\right) VMT_i} + \in_{\boldsymbol{i}}^{\boldsymbol{ICE}}\mathrm{t} \qquad (2)$$

Since this report focuses on how consumers value energy costs, we abstract away from many of the common elements of the utility of purchasing a particular vehicle. The first term captures the utility a buyer receives from purchasing a particular vehicle—inclusive of observable and unobservable characteristics (including purchase price) unrelated to the costs of operation. The last term reflects the idiosyncratic utility buyer i derives from purchasing an EV (in equation (1)) or a conventional vehicle (in equation (2)).

The second term reflects expected future costs of operation. At the time of purchase, the buyer observes electricity prices,$P_0^e$, and gas prices, $P_0^g$ , and forms expectations of future electricity and gasoline prices. Depending on vehicle miles a buyer will travel ($VMT_i$), the buyer faces future costs of operating the vehicle, which are discounted by a common discount factor ▯. For conventional vehicles, we assume that buyers understand the future operational costs well. Although they might discount future costs at a high rate, they form an accurate assessment of operational costs.

For BEVs, we allow for consumers to imperfectly value future energy costs of a BEV, where $\gamma \in [0, 1]$ reflects the relative weight a consumer places on the true operational costs of operating the BEV, relative to some prior expectation of the per-mile costs of operation, $\theta$. While buyers discount the perceived operational costs of a BEV at a similar discount factor as the future operational costs of a conventional vehicle, the buyer might have an imperfect understanding of the future operational costs. As summarized in Allcott et al. (2014), such an outcome could arise from differences in the salience of gasoline prices and electricity prices, imperfect understanding of one's marginal electricity price (e.g., Ito (2014)), biased beliefs about energy prices, rational inattention, or imperfectly targeted labelling (see e.g., Davis and Metcalf (2016)).[1] We do not take a stand on

[1] To be clear, we do assume a buyer applies a common discount factor to both future electricity and future gasoline costs. If consumers are not forward looking, if they employ high discount rates, or they hyperbolically discount future energy

whether $E\left[P_t^g \middle| P_0^g\right] \frac{gal}{mile}$ is greater than or less than $\theta$, that is, whether consumers under- or over-estimate the true operational costs of an BEV. We further make several simplifying assumptions to link the model above to our empirical specification. We assume that a consumer: (1) plans to own either vehicle for an identical length of time (i.e.,$T^{BEV} = T^{ICE}$ ); (2) would drive either vehicle an identical amount; and (3) forecasts "no-change" in gasoline and electricity prices. With regard to the last assumption, Anderson et al. (2013) finds evidence that use of a "no-change" forecast accurately captures consumer beliefs of future gasoline prices; we are unaware of similar research examining consumer beliefs of future electricity prices. In the discussion of our results, we place our empirical results in a context relative to each of these assumptions.

Under these assumptions and standard logit assumptions for the idiosyncratic utility, we can represent the change in probability of purchasing a BEV with respect to electricity and gasoline prices as:

$$\boldsymbol{\frac{dPr(BEV)}{dP_0^e} = \gamma \left(\frac{kwh}{mile}\right) VMT_i \sum_{t=0}^{T} \delta^t * A} \tag{3}$$

$$\frac{dPr(BEV)}{dP_0^g} = -\left(\frac{gal}{mile}\right) VMT_i \sum_{t=0}^{T} \delta^t * A$$

where $A = Pr(BEV) * Pr(\ ICE)$. In our empirical specification, we will estimate the effect of electricity and gasoline prices on BEV sales. Equations (3) and (4) correspond roughly to the response of sales to electricity and gasoline prices, respectively. Denoting the estimated coefficients as $\hat{\beta}^e$ and$\hat{\beta}^g$, we can derive an estimate of $\gamma$ as:

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

Intuitively, the numerator of $\hat{\gamma}$ reflects the impact of per-mile electricity costs of the BEV and the denominator reflects the impact of per-mile gasoline costs of the conventional vehicle. In both cases the impact of electricity prices and gasoline prices, $\hat{\beta}^e$ and$\hat{\beta}^g$, are scaled by the relative fuel efficiencies of the two vehicles (in terms of kwh-per-mile for BEVs and gallons-per-mile for conventional vehicles). Although, ultimately, we will have to take a stand on the relative fuel efficiencies of the electric and conventional vehicles, the comparison of the response to electricity and gasoline prices allows us to side-step the question of whether consumers are myopic with respect to the operational costs of the vehicle. Not only is this question still under debate in the context of conventional vehicles (e.g., Sallee et al. (2016), Allcott and Wozny (2014), Busse et al. (2013), Gillingham et al. (2019), to name a few), but it is easier to estimate in the context of conventional vehicles, for which fuel prices fluctuate at high frequency, in a setting where consumers have ample experience with fueling and operational costs, and where a robust market for used vehicles exists.

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costs, we assume that these distortions are present for both gasoline and electricity. If a buyer discounts future electricity prices or gasoline prices in a fundamentally different way, it would be nested in the parameter γ.

# 3. Empirical Setting and Data

There are roughly 23,000 Census Block Groups (CBGs) in California, each consisting of approximately 600 to 3,000 people, or 200 to 1,000 households. Each of our empirical approaches exploits temporal and cross-sectional variation in gasoline and electricity prices across CBGs. Our preferred approach focuses only on CBGs that are close to electric utility boundaries, allowing for a border discontinuity study design that compares BEV purchase behavior in CBGs on one side of a utility boundary to purchase behavior in CBGs on the other side. But, as an alternative, we also consider a panel model with fixed effects that uses data from all of California. Each of these approaches requires making use of three main datasets: for EV purchases, retail electricity prices, and retail gasoline prices—each from the period 2014-2017.

The vehicle purchase data originates from the California Department of Motor Vehicles (DMV) and was purchased through a third party data provider. The data include a vehicle identification number (VIN), purchase date and location (CBG) for the universe of EVs purchased in California from 2014-2017. We are thus able to identify the make, model and model-year of every EV car in the dataset and, importantly, when the purchase occurred and in which CBG the registered owner lives. We aggregate these purchases up to the CBG-by-month. Although we observe sales of plug-in hybrid vehicles and fuel cell vehicles in the data, our empirical analysis focuses on BEVs, for which electricity prices are most important.

In California during this period, there were two main types of electric utility companies: investor-owned utilities (IOUs), such as Pacific Gas & Electric and Southern California Edison, and municipal utilities, such as Sacramento Municipal Utility District (SMUD) and City of Palo Alto. The electricity prices faced by customers in different service territories vary immensely, and they often increase in a stepwise fashion with total monthly usage. In such cases of increasing block rates, households charging vehicles at home will likely find themselves on the top tier of the residential rate schedule. Figure 1 and Figure 2 display the rates for households on the top rate tier for utilities in the San Francisco Bay Area and greater Los Angeles, where the “top tier rate” for flat rate customers is simply the flat rate.

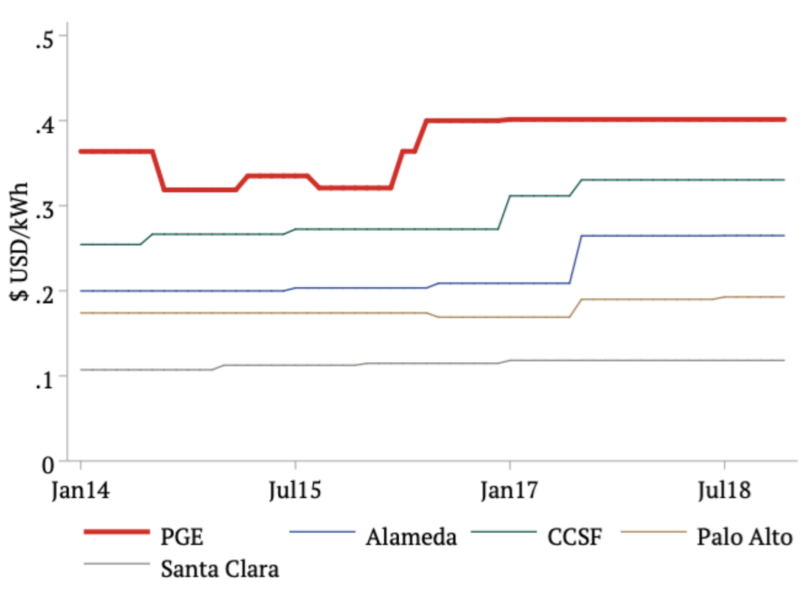


**Figure 1. Residential Retail Electric Prices in the San Francisco Bay Area (Top Tier, 2014-2017)**

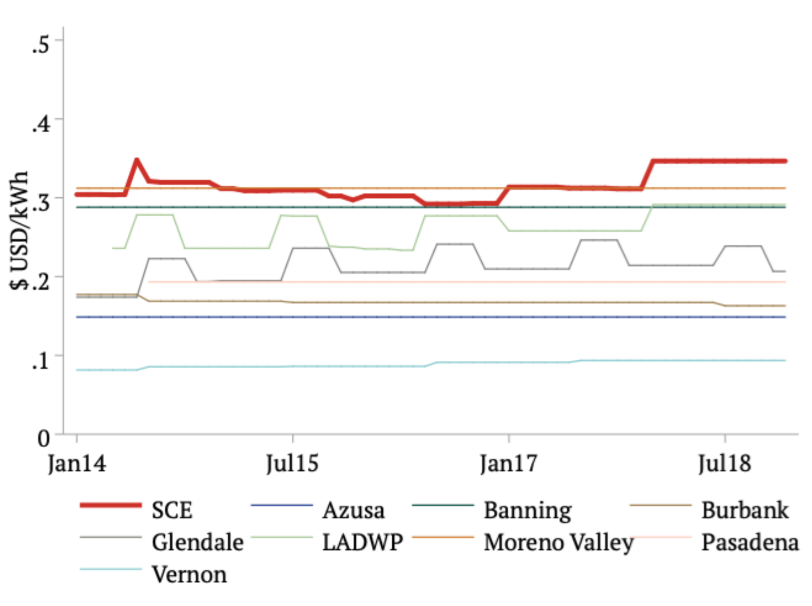


**Figure 2. Residential Retail Electric Prices Los Angeles (Top Tier, 2014-2017)**

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

Retail electricity price data are collected as part of the Form EIA-861 survey published by the US Energy Information Administration (EIA). The survey is administered to electric utilities, and the resulting dataset provides information on electricity sales, prices, customer counts by type, and a variety of other information about the utility companies and regulatory regimes. Here we focus on the residential electricity price. The EIA-861 data provide rate schedules for IOUs but not for municipal utilities. Since a major source of cross-sectional variation in this study comes from municipal utilities, we augment the EIA data with rates retrieved directly from the municipal utility websites or service representatives.

Retail gasoline prices come from the Oil Price Information Service (OPIS) which tracks daily prices of fuels at the station-level. In addition, the data provide the geocoordinates for each station. For each zip code, we construct the monthly average gasoline prices for all stations within 3 miles of the zip code centroid, reflective of the set of stations that might serve a particular community.[2] We merge gasoline prices to the vehicle data (at the CBG-by-month level) by matching each CBG to prices from the zip code with the greatest geographic overlap with the CBG. Perhaps surprisingly, there is a substantial amount of cross-sectional variation in gasoline prices between adjacent CBGs across utility boundaries.

We summarize the relevant data in Table 1. As our primary source of electricity price variation comes from differences between locations served by investor-owned utilities and municipal utilities, we report the summary statistics separately for areas served by the two types of electricity providers. In columns (1) and (2), we report summary statistics for all locations in California. In Columns (3) and (4), we limit the sample of locations to those used to estimate the border discontinuity regressions.

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

**Table 1. Summary Statistics**

| | Full Sample | | Border Discontinuity Subsample | |
|---|---|---|---|---|
| | **IOU** | **Municipal Utility** | **IOU** | **Municipal Utility** |
| BEV Sales per 10000 pop | 0.912<br>(3.288) | 0.734<br>(3.046) | 14.26<br>(22.50) | 12.44<br>(20.37) |
| Marg. Price, cents/kwh | 31.74<br>(4.979) | 21.54<br>(5.621) | 30.01<br>(3.577) | 22.03<br>(5.384) |
| Population, × 1000 | 1.720<br>(1.087) | 1.631<br>(0.872) | 1.766<br>(1.107) | 1.667<br>(0.773) |
| Pop Density, × 1000 ppl/sqm | 8.878<br>(9.088) | 12.86<br>(12.70) | 8.604<br>(7.847) | 10.71<br>(9.418) |
| Income × $1000 | 79.10<br>(40.97) | 64.67<br>(36.01) | 86.98<br>(45.16) | 77.71<br>(44.17) |
| Hybrid Fleet Share (2013) | 0.0609<br>(0.0420) | 0.0559<br>(0.0419) | 0.0648<br>(0.0452) | 0.0657<br>(0.0489) |
| Luxury Fleet Share (2013) | 0.0421<br>(0.0486) | 0.0408<br>(0.0470) | 0.0596<br>(0.0670) | 0.0549<br>(0.0647) |
| MUD HH share (2013) | 0.326<br>(0.310) | 0.430<br>(0.334) | 0.316<br>(0.308) | 0.403<br>(0.322) |
| Mean Fuel Econ, mpg (2013) | 23.09<br>(1.233) | 23.07<br>(1.160) | 23.03<br>(1.249) | 23.11<br>(1.257) |
| Fraction in PGE | 0.458<br>(0.498) | 0<br>(0) | 0.256<br>(0.437) | 0<br>(0) |
| Fraction in SCE | 0.424<br>(0.494) | 0<br>(0) | 0.742<br>(0.437) | 0<br>(0) |
| Fraction in SDGE | 0.117<br>(0.321) | 0<br>(0) | 0.00123<br>(0.0350) | 0<br>(0) |
| Dist. to Util. Boundary, km | N/A | N/A | 0.610<br>(1.391) | 0.776<br>(1.680) |

Notes: Standard errors are shown in parentheses. 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) or municipal utility. Columns 3 and 4 summarize variables for census block groups located on either side of the IOU / Municipal utility boundaries. (PGE, Pacific Gas and Electric; SCE, Southern California Edison; SDGE, San Diego Gas and Electric, MUD, multi-unit dwelling).:'N/A, "not applicable."

# 4. Empirical Approach

## Panel Regression

We implement two different empirical strategies to estimate the coefficients $\widehat{\boldsymbol{\beta}}^{e}$ and $\widehat{\boldsymbol{\beta}}^{g}$ from which we can back out estimates of our parameter of interest,$\boldsymbol{\gamma}$.

As a starting point, consider a panel regression given by:

$$\boldsymbol{BEVSalesPerCapita_{ct} = \beta^e P^e_{ct} + \beta^e P^g_{ct} + \gamma_c + \lambda_t + \in_{ct}}\,, \tag{5}$$

where c denotes census block-group and t denotes time. Here, identification follows from differential changes in electricity prices and gasoline prices across CBGs over time. Most of the longer-term variation in the data arises from the regulatory price setting process—for instance, from the resetting of residential rates for California investor-owned utilities in response to changes in capital investments. In addition, a subset of utilities (both investor-owned and municipal) has rates that vary seasonally. We estimate versions of Equations (5) at both the month level and at the annual level, the latter averages out seasonal rates over the course of the year and primarily estimates the effect of longer-term variation in residential electricity prices.

## Regression Discontinuity on Utility Boundaries

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

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

$$\boldsymbol{BEVSalesPerCapita_{ct} = \Theta X_c + v_1 Dist * 1[IO\mathcal{U}_c] + \beta^e \Delta P^e_t[IO\mathcal{U}_c] + \beta^g \Delta P^g_{ct} + \in_{ct}}\,, \tag{6}$$

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

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

$$\Delta \boldsymbol{BEVSalesPerCapita_{it}} = \boldsymbol{\beta^e} \Delta \boldsymbol{P^e_{it}} + \boldsymbol{\beta^e} \Delta \boldsymbol{P^g_{it}} + \boldsymbol{\Theta} \Delta \boldsymbol{X_{it}} + \boldsymbol{v_{1b} D_c} + \boldsymbol{v_{2b} D_{c'}} + \boldsymbol{\in_{it}}, \tag{7}$$

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

# 5. Results

We hypothesize that, with all else equal, an increase in the price of electricity decreases demand for EVs, and that an increase in gasoline prices, which raises the cost of operating a close substitute to EVs, will increase demand for EVs. In this section we describe results from the panel fixed-effect and border discontinuity approaches described in Section 2 Methodological Framework.

## Panel Fixed Effects Results

Table 2 presents results corresponding to Equation 5, which regresses BEV sales per capita in a given CBG on the price of electricity, price of gasoline, and control variables. Columns 1 and 2 are aggregated by month, allowing for higher-frequency fluctuations in energy prices to be reflected in changes in BEV demand; columns 3 and 4 are aggregated annually. The coefficient estimates in columns 1 and 3 have the opposite signs of what one would expect—the electricity price coefficient is positive and the gas price coefficient negative. This reflects underlying correlations between unobservable patterns in the demand for EVs and energy prices across CBGs. Demand for EVs is high in areas with high electricity prices. This aligns with a narrative whereby the vast majority of EVs are purchased in IOU territories, which also happen to be where electricity prices are high. However, the signs reverse in columns 2 and 4 after isolating variation within CBGs, thus overcoming the sorting concerns, and controlling for aggregate factors that change with time.

**Table 2. Panel Results**

| | Monthly Sales Per Cap | | Annual Sales Per Cap | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Marg. Price, cents/kwh | 0.0036*** (0.00096) | -0.0035** (0.0015) | 0.030** (0.012) | -0.062*** (0.023) |
| Gas Price, cpg | -0.0011*** (0.000078) | 0.0041*** (0.00060) | -0.022*** (0.0013) | 0.16*** (0.013) |
| Time fixed-effects | NO | YES | NO | YES |
| CBG fixed-effects | NO | YES | NO | YES |
| Implied $\gamma$ | | .113 (.052) | | .052 (.02) |
| Observations | 872314 | 870564 | 73351 | 73160 |
| R-Squared | 0.00030 | 0.15 | 0.0020 | 0.61 |

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

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

Recall from equation 4 that $\hat{\gamma}$ reflects the weight that the consumer places on electricity costs relative to gasoline costs. Consider a consumer whose preferences reflect the panel results in column 2 of Table 2. In a case where a consumer is deciding between a Toyota Camry, an ICE that gets 30 miles-per-gallon, and a Tesla Model 3, which gets 4 miles-per-kWh, $\hat{\gamma} = \frac{.0035*4}{0.0041*30} \approx 0.113$. The interpretation is that this customer places roughly one eighth the weight on electricity prices than on the price of gasoline. As the comparison BEV gets more efficient, or the comparison ICE less efficient, $\hat{\gamma}$ increases and the behavioral interpretation would shift towards the consumer appearing to care more about the price of electricity.

Panel identification relies on the assumption that there are no unobservables correlated with both the electric vehicle adoption and electricity or gasoline prices, after conditioning on block-group and time fixed effects. If unobservables affecting BEV demand are correlated with changes in electricity prices, our coefficients will subsume the effect of the unobservable. For instance, if electricity prices rise in areas for which the charging station network is expanding quickly, we might mis-attribute the effect of the charging station network to electricity prices and underestimate the amount to which demand for EVs would respond to prices. To address this concern, we examine an alternative estimation strategy that relies on utility service territory borders.

## Border Discontinuity Results

Our alternative empirical approach, the border discontinuity, refines the comparison group to a narrow band around utility district boundaries. In our application of the regression discontinuity, CBGs on one side of the border may differ on average from CBGs on the other on any number of variables that enter the demand equation. The treatment effect of discontinuous differences in energy prices on BEV purchases will be identified so long as unobserved non-energy price determinants of demand vary continuously across the border.

We allow BEV sales to vary linearly on either side of each service territory boundary and identify the coefficient on electricity price from the discrete change in BEV sales crossing from one service territory to another. In contrast, the coefficient on gasoline prices is identified from panel variation within the zip codes in which each

CBG are located. To illustrate the variation, we plot the distributions of the difference in electricity prices and gasoline prices between pairs of block-groups in our data in Figure 3 and 4, respectively.

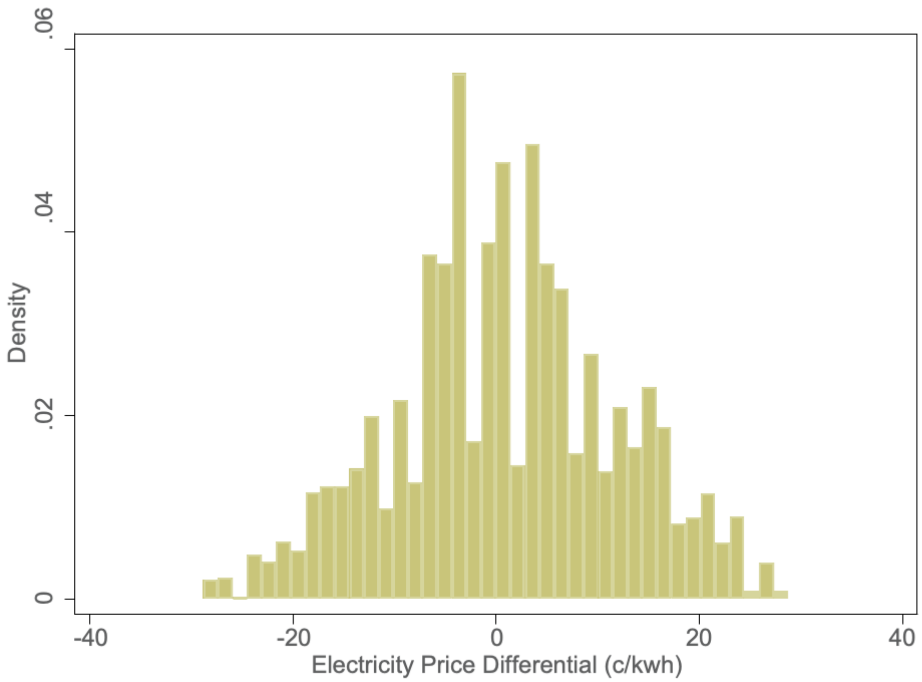


**Figure 3. Electricity Price Differences between Block-Group Pairs**

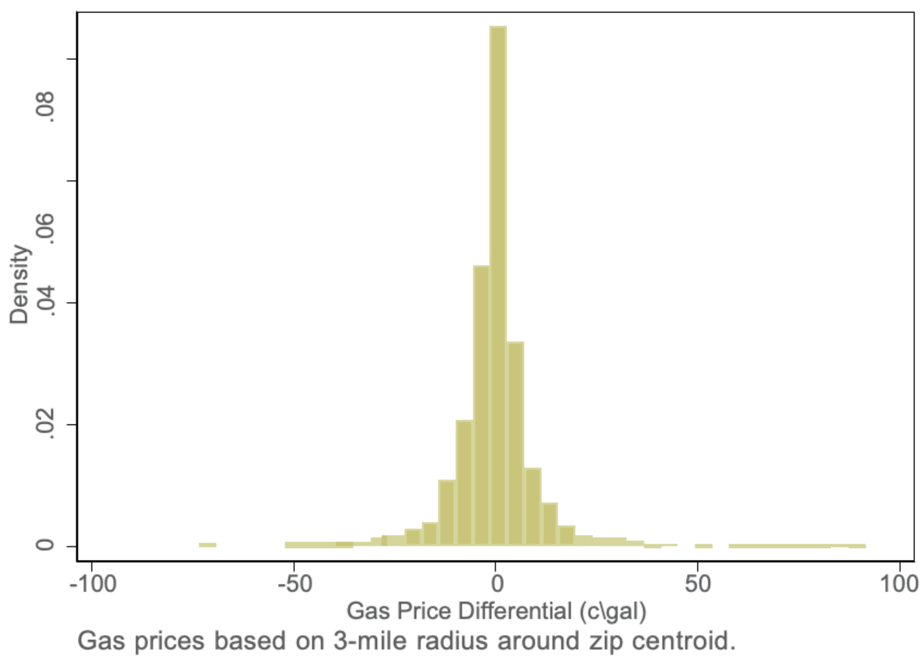


**Figure 4. Gasoline Price Differences between Block-Group Pairs**

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

**Table 3. Border Discontinuity Results**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Δ Marg. Price, cents/kwh | -0.11<br>(0.079) | -0.17*<br>(0.058) | -0.20*<br>(0.064) | -0.070<br>(0.15) |
| Δ Gas Price, cpg | 0.35*(0.10) | 0.32*<br>(0.096) | 0.17*<br>(0.054) | 0.16*<br>(0.054) |
| Δ Population, × 1000 | | -1.23*<br>(0.35) | -1.08*<br>(0.34) | -1.05*<br>(0.34) |
| Δ Pop Density, × 1000 ppl/sqm) | | -0.31*<br>(0,047) | -0.15*<br>(0.041) | -0.16*<br>(0.043) |
| Δ Income, × $1000 | | 0.17*<br>(0.023) | 0.084*<br>(0.020) | 0.083*<br>(0.020) |
| Δ Mean Fuel Econ, mpg (2013) | | | 2.53*<br>(0.94) | 2.55*<br>(0.94) |
| Δ Hybrid Fleet Share (2013) | | | -12.4<br>(30.1) | -11.2<br>(29.9) |
| Δ Luxury Fleet Share (2013) | | | 127.8*<br>(20.4) | 128.5*<br>(20.3) |
| Δ MUD HH Share (2013) | | | -3.45*<br>(1.34) | -3.49*<br>(1.34) |
| IOU fixed-effects | NO | NO | NO | YES |

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Implied $\gamma$ | .042<br>(.033) | .071<br>(.034) | .157<br>(.074) | .058<br>(.124) |
| Observations | 7179 | 6779 | 6759 | 6759 |
| R-Squared | 0.097 | 0.27 | 0.33 | 0.33 |

Dependent variable is BEV 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 value of $\gamma$ assumes fuel efficiencies of 4 miles/kwh for EVs and 30 miles/gallon for the alternative conventional vehicle. All specifications allow coefficients on distance to the utility boundary to vary on either side of every utility boundary. * denotes statistical significance at the 1% level.

Across the four specifications, we estimate negative relationships between electricity price and BEV 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 census block group, we estimate a negative and significant relationship between electricity prices and BEV sales.

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

Following a similar approach to that in the panel regressions, we can back out an estimate of $\hat{\gamma}$ , the weight that the consumer places on electricity costs relative to gasoline costs, from the coefficients on electricity and gasoline prices. Again using a Toyota Camry and Tesla Model 3 as the reference vehicles, our estimates in column 3 imply a $\hat{\gamma} = \frac{.20*4}{0.17*30} \approx 0.157$, remarkably similar to the estimate from the panel specification.

# 6. Conclusion

The prominence of gasoline prices in car purchase decisions aligns with existing evidence in the literature on vehicle choice and consumer behavior in electricity markets. Buyers of conventional vehicles exhibit awareness of differences in the ongoing operational costs of gasoline-powered cars based on their fuel efficiency. This makes sense for several reasons. Gasoline prices are prominently displayed along roadways and gasoline expenditures constitute a significant share of the household budget. Thus, consumers would likely be attentive to any changes in incentives on this margin, and the introduction of alternative modes of transportation interact in the way economics would predict.

Consumers know far less about electricity prices. Again, there are several potential reasons for this. Electricity prices are very different from place-to-place and not prominently displayed like gasoline prices. The consumption expenditure share of electricity is smaller than that of gasoline, and this diminishes the incentive for consumers to inform themselves about how to optimize on this margin. Of course, this expenditure share will increase dramatically for most BEV drivers, and so one might also suspect that their awareness of electricity prices would increase around a BEV purchase event.

While the results presented in this report are consistent with what we know about how consumers relate to gasoline and electricity prices, there are reasons to believe that a shift towards EVs would change the way consumers relate to these input prices. If and when that change occurs, the present electricity price schedules in California would create dramatically different incentives for vehicle choice in some utility districts than in others. The difference in prices between investor-owned and municipally-owned utilities has clear efficiency considerations since the marginal benefit of BEV adoption, and use is likely continuous across utility boundaries, whereas prices are not. In addition, prices that vary dramatically across utilities might stimulate electric vehicle adoption in some locations while (potentially) slowing adoption in other locations where electricity prices are much higher.

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