# Driving Change: Assessing the Impact of Electric Vehicle Charging Infrastructure on Gasoline Consumption Across California Counties

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Denison University
2025

**Abstract**

California's rapid electric vehicle (EV) adoption has not yet translated into proportional decreases in gasoline consumption, in part due to uneven charging infrastructure deployment and socioeconomic inequalities. This study examines how variations in charger sufficiency, which are measured by charger to EV ratio, charging capacity per EV and geographical coverage percentage, along with median household income, affect gasoline use per capita across all California counties from 2014 to 2023. We compile a county-year panel dataset merging EV registration counts, charger counts by type (Level 1, Level 2, DC fast chargers), income data, and gasoline sales, then run two-way fixed-effects OLS linear regression models with county and year as fixed effects. We also use faceted scatterplots and county spatial maps as supporting descriptive figures. Our regression results show that within-county increases in Level 2 chargers and higher charger to EV ratios are associated with meaningful declines in gasoline consumption, while raw counts of DC fast chargers see a positive, counterintuitive correlation, which highlights concerns about congestion and inequitable charger deployment. A high overall $R^2$ reflects persistent heterogeneity between counties, but a low within $R^2$ suggests that infrastructure alone only explains a modest amount of year-to-year, within-county changes in fuel use. We conclude that strategically targeted, equity focused charger deployment, along with demand management and consumer incentives, is essential to maximize the environmental benefits of California's transition to EV.

# 1 Introduction

Electric vehicle (EV) adoption in California has surged in recent years, positioning the state as a national leader in the transition away from gasoline-powered transportation. By 2023, California recorded approximately 1.26 million light-duty EV registrations, driven by a combination of state incentives, technological advances, and growing public awareness of climate change impacts (California Energy Commission, 2024; U.S. Department of Energy, n.d.-a). At the same time, gasoline consumption remains a critical environmental concern. Transportation accounts for over 40% of the state's greenhouse gas (GHG) emissions (California Air Resources Board, 2024), and tailpipe pollutants continue to affect air quality in urban and rural communities (Bej & Chattaraj, 2023). This research lies at the intersection of these dual trends, rapid EV uptake on one hand and persistent gasoline reliance on the other, to ask how the effective availability of public charging infrastructure can translate EV presence into significant reductions in gasoline use.

Existing scholarship has demonstrated that both financial incentives and charger density play important roles in fostering EV adoption and in lowering fuel consumption. Simulation studies (Choi et al., 2013) have shown that pairing managed charging with renewable-energy standards can cut gasoline use by more than half, while experimental evidence from California's Enhanced Fleet Modernization Program (EFMP) indicates that each \$1000 in subsidy can boost EV adoption by up to 16% in certain regions (Muehlegger & Rapson, 2018). At the county and zip-code levels, higher public fast-charger density correlates with increased EV adoption (Singh, 2019), and spatial analyses reveal that subsidy programs can yield substantial charger deployment within two years (Luo, 2022). However, simple metrics of charger density often overlook operational factors such as "charging deserts" in peripheral zones or inequities in access that disproportionately affect lower-income communities (Bauer et al., 2021; Hsu & Fingerman, 2021). A growing consensus calls for more measures of infrastructure sufficiency, such as ratios of chargers to EVs, geographical coverage percentage, and charging capacity per EV, to capture the true availability of charging services.

Despite these advances, no study has integrated charger-to-EV ratios, median household income and spatial distribution metrics into a single, county-level model of gasoline consumption. Our paper bridges this gap by examining how variations in infrastructure sufficiency and socioeconomic context mediate gasoline use declines across California's counties from 2014 to 2023. We try to find out how counties should add chargers at rates that keep pace with EV fleet growth, how the chargers should be equitably located to maximize coverage, and to what extent we can see within-county reductions in per-capita gasoline decrease. By incorporating fixed effects to control for unobserved county traits and year shocks, we aim to capture the true impact of infrastructure enhancements on fuel use reduction.

To address these questions, we create a panel dataset merging annual county-level EV registrations, charger counts by type (Level 1, Level 2 and DC fast chargers), calculated charging capacity per EV, geographic area coverage percentages, median household income, and gasoline sales per capita. We then use two-way fixed-effects regression alongside complementary descriptive analyses, which includes scatterplots, correlation matrix, and county maps. Based on them, we discuss policy implications for targeted charger deployment and equity focused incentives. Through this approach, our study contributes to a micro-level understanding of how charging infrastructure sufficiency, not just charger density, drives the transition from gasoline to electric mobility. By foregrounding equity and effectiveness together, we give policymakers an empirical guide on where and how to invest in public charging to maximize both environmental and social benefits.

## 2 Literature Review

California is the leading state in the US in electric vehicle (EV) adoption, with approximately 1.26 million light-duty EV registrations recorded in 2023 (U.S. Department of Energy, n.d.-a). This rapid uptake has been matched by an equally swift expansion of public charging infrastructure: over 24,000 new chargers were installed across the state in the first half of 2024 alone (California Energy Commission, 2024). Despite this growth, significant spatial and socioeconomic disparities exist: people with below household incomes below the median exhibit lower charger availability per EV and continued dependence on gasoline-powered transportation, while higher income areas have greater charging access (Hsu & Fingerman, 2021).

Combining rebates with robust public charging networks can yield substantial EV uptake. Choi et al. (2013) use multiscale electricity system optimization to show that pairing a 33% renewable electricity standard with managed EV charging cuts CO2 emissions by 27% and gasoline consumption by 59%. Using California's Enhanced Fleet Modernization Program (EFMP), Muehlegger and Rapson (2018) estimate that each $1000 in subsidy increases EV adoption by 9% in the South Coast and 16% in the San Joaquin Valley, with complete pass-through of incentives to consumers. Such empirical estimates suggest that meaningful rebates could plausibly yield huge growth in EV adoption, though infrastructure distribution is essential to translate adoption into gasoline reduction.

Singh (2019) uses empirical work at the county and zip-code levels to find a significant positive correlation between public fast-charger density and EV registration rates, underscoring infrastructure's critical role in raising EV adoption. Luo (2022) use a difference-in-difference analysis design to reveal that county-level charging station subsidies yield a 36% increase in charger counts within two years. However, conventional density metrics often overlook operational challenges. Pal and Behera (2023) highlight “charging station congestion” in high-density zones, limiting effective charger availability and constraining adoption. Mehditabrizi et al. (2024) adds on this by using spatial analyses that incorporate on-route and destination charging to reveal overestimation of central-city access and underestimation in peripheral zones, calling for equity-focused deployment to prevent underserved “charging deserts”. Moreover, there are socioeconomic equity concerns in EV ownership. Bauer et al. (2021) reveals that among used-vehicle buyers in California, the median household income of EV purchasers is $150,000, while the median household income of gasoline-vehicle buyers is only $90,000. This disparity reflects both the higher upfront cost of many EV models and uneven rebate uptake, highlighting the need for policies that lower barriers in lower-income communities.

While simulation (Choi et al., 2013) and empirical incentive studies (Muehlegger & Rapson, 2018) establish the potency of rebates, and spatial analyses (Mehditabrizi et al., 2024; Singh, 2019) emphasize the necessity of equitable charger deployment, no existing research integrates these dimensions with charger-to-EV ratios and median income to directly model county-level gasoline consumption. Our proposed study will combine county EV registration records, charging-to-EV ratio data, geographical distribution of charging stations at the county level and income data to quantify how variations in infrastructure sufficiency and socioeconomic context mediate gasoline consumption declines, filling a critical gap in the micro-level understanding of EV infrastructure impacts on gasoline reduction.

# 3 Methodology

## 3.1 Data Preparation

After gathering chargers, gasoline consumption, EV fleet population and income data, we merge them into one big data frame and group them by county and by year during the 2014-2023 period, with missing values dropped. We then calculate the variables needed for analysis, which are EV adoption rate, gasoline consumption per capita, number of chargers per 100 EVs, charging capacity per EV and percentage of area for each county within the 5-mile radius of a charger based on the data we collected and from the spatial data provided from R for the geographical coverage percentage.

### 3.2 Models, visualizations and diagnostics

Our study employs a two-way fixed-effects OLS regression model:

$$\begin{aligned}\text{gas\_per\_capita}_{it} = &\ \beta_1 \,\text{level1}_{it} + \beta_2 \,\text{level2}_{it} + \beta_3 \,\text{dc\_fast}_{it} + \beta_4 \,\text{ev\_adoption}_{it} \\ &+ \beta_5 \,\text{income}_{it} + \beta_6 \,\text{charger\_ratio}_{it} + \beta_7 \,\text{capacity\_ratio}_{it} + \beta_8 \,\text{coverage}_{it} \\ &+ \alpha_i + \gamma_t + \epsilon\end{aligned} \tag{1}$$

where $\alpha_i$ and $\gamma_t$ are county and year fixed effects respectively. Standard errors are clustered by county to account for serial correlation.

We also use scatterplots and maps to see the relationships between our metrics and gasoline consumption per capita.

## 4 Data

To build a dataset for assessing how EV infrastructure influences gasoline consumption at the county level in California, I collected data from authoritative sources, such as California Energy Commission (CEC) or US Department of Energy. Each dataset is preprocessed to ensure variable consistency for analysis.

*Data sources and processing steps:*

*EV adoption rate:* Taken from California Energy Commission. I compare the EV fleet population of each year with that of last year and determine the percentage rise in the EV fleet population, which is the EV adoption rate.

*Chargers' data:* Taken from US Department of Energy's Alternative Fuel Data Sources (AFDC). Chargers are classified into three types: Level 1, Level 2 and DC Fast chargers. *Median household income:* Collected from separate data sets for each year, from 2014 to 2023.

*Charging capacity to EV ratio:* Pierce and Slowik (2023) classifies light-duty EV charging infrastructures into three main types: Level 1 chargers provide up to 5 miles per hour of charge, Level 2 chargers provide up to 50 miles per hour of charge, and DC fast chargers provide up to 100 miles per hour of charge. Based on this, the total charging capacity will be calculated as follows:

$$\text{Capacity} = L_1 \cdot 5 + L_2 \cdot 50 + DC \cdot 100$$

where $L_1$, $L_2$, and $DC$ are the number of Level 1, Level 2, and DC fast chargers, respectively.

*Geographical Area Coverage Percentage:* The chargers' data have the latitude and longitude for each charger point, so we loaded the spatial data for California counties from R, prepare the charger locations as points and based on this to calculate area coverage percentage.

The data considered in this analysis are taken during the 10-year period from 2014 to 2023.

*Variables:*

**Table 1:** Variable definitions, descriptions, measurements, and sources

| **Variable** | **Description** | **Measurement** | **Source** |
|---|---|---|---|
| EV Adoption Rate | Percentage growth in EV population over time | (EV population this year − EV population last year)/EV population last year × 100 | California Energy Commission, 2025d |
| Number of Level 1 chargers | Number of Level 1 chargers in each county by year | Count of Level 1 chargers | U.S. Department of Energy, n.d.-b |
| Number of Level 2 chargers | Number of Level 2 chargers in each county by year | Count of Level 2 chargers | U.S. Department of Energy, n.d.-b |
| Number of DC fast chargers | Number of DC fast chargers in each county by year | Count of DC fast chargers | U.S. Department of Energy, n.d.-b |
| Median Household Income | Median income per capita for each county by year | Median income, taken from data | U.S. Census Bureau, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024 |

| Variable | Description | Measurement | Source |
|---|---|---|---|
| Number of chargers per 100 EV | Aggregate number of chargers per 100 EV | $100 \times \frac{\text{number of chargers}}{\text{number of EVs}}$ | California Energy Commission, 2025d; U.S. Department of Energy, n.d.-b |
| Charging capacity to EV ratio | Aggregate charging capacity per hour per EV | $\frac{\text{Total charging capacity (in miles per hour)}}{\text{number of EVs}}$ | California Energy Commission, 2025d; U.S. Department of Energy, n.d.-b |
| Geographical coverage percentage | Percentage of area within 5-mile radius of a charger for each county by year | $\frac{\text{Total area covered by chargers}}{\text{County area}}$, calculated from chargers' data | U.S. Department of Energy, n.d.-b |
| Gasoline Consumption | Amount of gasoline consumed per capita per year | $\frac{\text{Total gasoline sales}}{\text{Population}}$, taken from gasoline sales and population data | California Department of Finance, 2023; California Energy Commission, 2025a |

# 5 Results

## 5.1 OLS Model

These are the coefficient estimates of our OLS model:

**Table 2:** OLS Regression Coefficient Estimates

| **Predictor** | **Estimate** | **Standard Error** | **p-value** |
|---|---|---|---|
| Level 1 chargers | +0.0967 | 0.1046 | 0.3599 |
| Level 2 chargers | −0.0225 | 0.0130 | 0.0902 |
| DC fast chargers | +0.1237 | 0.0667 | 0.0695 |
| EV adoption rate | −0.0330 | 0.1391 | 0.8132 |
| Median household income (USD) | −0.00045 | 0.0006 | 0.4569 |
| Chargers per 100 EVs | −0.4899 | 0.3650 | 0.1854 |
| Charging capacity (mi/EV) | +1.0383 | 0.7934 | 0.1965 |
| Geographic coverage (%) | +0.3679 | 0.7454 | 0.6237 |

*Notes*: Number of observations: 483. Fixed effects: County, Year.

Adjusted $R^2 = 0.8911$. Within $R^2 = 0.0465$.

Within a county, growth in Level 2 chargers is associated with lower gasoline use. This is consistent with Singh (2019), who shows charger availability spurs EV uptake, and with Choi et al. (2013) and Muehlegger and Rapson (2018), who demonstrate that infrastructure paired with incentives can reduce fuel consumption. This result suggests that everyday accessible charging can help translate EV presence into actual gasoline displacement. Although the coefficient for the number of DC fast chargers implies a counterintuitive relation that more DC fast chargers lead to higher gasoline use, this relation actually aligns with Pal and Behera (2023) and Mehditabrizi et al. (2024)'s findings that only considering raw charger counts may overlook congestion, corridor clustering, or building chargers in areas that already has a high usage of vehicles using gasoline. This implies that simply adding fast chargers, without attention to equitable locating or effective availability, may not immediately lower gasoline consumption. As for number of Level 1 chargers, we do not see any reliable relationship. Since Level 1 chargers have low charging speed and the fact that they are more likely to be built in places where drivers rely heavily on gasoline, this relationship is of no surprise. It only reinforces Hsu and Fingerman (2021) and Singh (2019)'s emphasis on higher capacity public networks.

Moving beyond raw charger counts, the model suggests that a higher charger-to-EV ratio points toward lower gasoline use, which aligns with Hsu and Fingerman (2021) and Mehditabrizi et al. (2024)'s insights that when access scales with demand, EV owners are less forced back to gasoline. The coefficients of charging capacity and geographic coverage are not significant. The geographic coverage percentage can over-credit areas with long road networks or scattered chargers that remain inconvenient Mehditabrizi et al. (2024). These results suggest refining the way to operationalize "capacity" and "coverage" to capture effective charger availability more accurately.

After controlling for infrastructure and income, increments in EV adoption alone do not show a clear within-county gasoline decline. This supports the argument that adoption is necessary but not sufficient. Without adequate, well-sited infrastructure, households may still rely on gasoline for part of their travel. Similarly, short-run income changes are not tightly connected to gasoline use once fixed effects remove persistent cross-county income gaps. Although Bauer et al. (2021) mentions about large cross-county income inequities in EV ownership, our fixed-effect model filters those out when talk about within-county income inequities. We suggest that equity may operate through who gets chargers and incentives rather than through small annual income changes.

The adjusted $R^2$ of 0.89 indicates that most variance is captured by our county and years fixed effect model. However, the within $R^2$ of 0.047 shows that our time-varying predictors only explain a marginal proportion of the other factors' variations in year-to-year changes within counties. The negative coefficients for the number of Level 2 chargers and the charger-to-EV ratio support strategies that ensure sufficient infrastructure with everyday accessibility rather than just planting more chargers. The positive coefficient in the number of DC fast chargers underscores the warning that raw counts can mislead policymakers if they ignore other factors such as congestion, distribution, and income equity (Hsu & Fingerman, 2021; Mehditabrizi et al., 2024; Pal & Behera, 2023).

## 5.2 Scatterplots and Correlation Matrix

Across all years, the faceted scatterplots (Figure 1) show that counties with higher number of chargers per 100 EVs tend to report higher gasoline consumption per capita. High-income counties consistently sit in the lower-left part of the plots, combining relatively low charger-to-EV ratio with low gasoline consumption. This is an evidence of rapid EV adoption in affluent regions outpacing charger deployment (Bauer et al., 2021; Hsu & Fingerman, 2021). In contrast, mid-income and low-income counties exhibit both higher ratios and higher fuel use, suggesting that charger sufficiency alone does not directly translate into immediate gasoline reduction. This pattern aligns with Pal and Behera (2023) and Mehditabrizi et al. (2024)'s findings: simple sufficiency ratios can overlook "charging deserts" and congestion hotspots. In fast-growing EV markets, chargers may cluster in convenient urban centers or along major corridors, leaving peripheral and lower-income areas underserved even when overall sufficiency appears high. This trend contrasts with the coefficient for number of chargers per 100 EVs in our fixed effects OLS model, where persistent county traits, year shocks and income fluctuations are controlled to isolate the genuine impact of actual increases in charger sufficiency on gasoline use. This discrepancy shows that our OLS model is needed to measure the true effect of expanding charging infrastructure. Our findings further support the argument that reliable gasoline decreases require not just more chargers, but sufficiency increases relative to growing EV demand within counties, especially when paired with equitable charger distribution and operation.

**Figure 1:** Correlation between number of chargers and gasoline consumption per capita, faceted by year and median income.

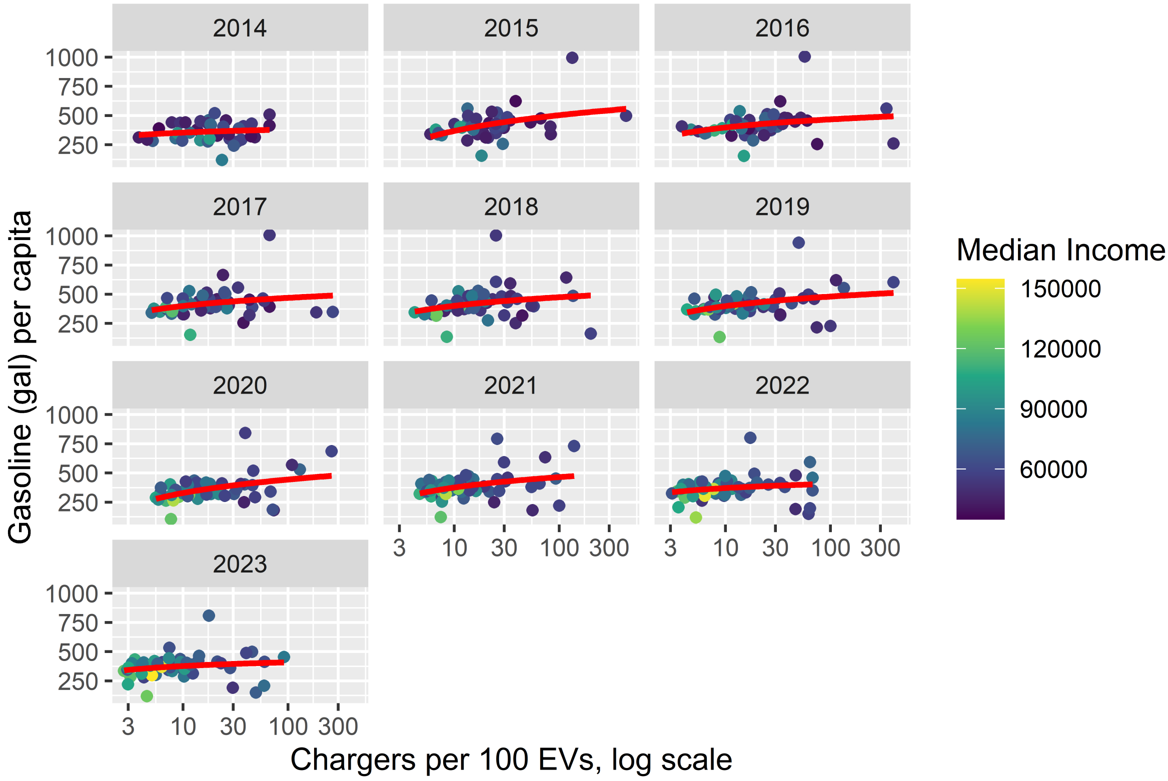



Figure 2 shows a positive raw association: counties reporting greater miles of charging infrastructure per EV also tend to consume more gasoline. This aligns with Mehditabrizi et al. (2024), who demonstrate that aggregate capacity measures can overstate accessibility in central or urban areas and understate accessibility limitations in rural areas, and with Pal and Behera (2023), who describe operational bottlenecks that limit effective use despite nominal capacity. Visually, counties with exceptionally high capacity span a wide range of gasoline use, highlighting that raw charging capacity does not uniformly imply substitution away from gasoline. Counties with medium capacity range cluster tightly around the upward sloping trend, suggesting that nominal increase in charging capacity may accompany travel patterns where gasoline use remains high, such as long rural commutes. The pattern we see in this plot is consistent with the charging capacity coefficient in Model 1, which is positive but lacks sufficient statistical evidence ($p = 0.1965$). This indicates that nominal charging capacity alone does not reliably predict fuel reductions once we net out income, county fixed effects and year shocks.

**Figure 2:** Correlation between charging capacity (miles/EV) and gasoline consumption per capita.

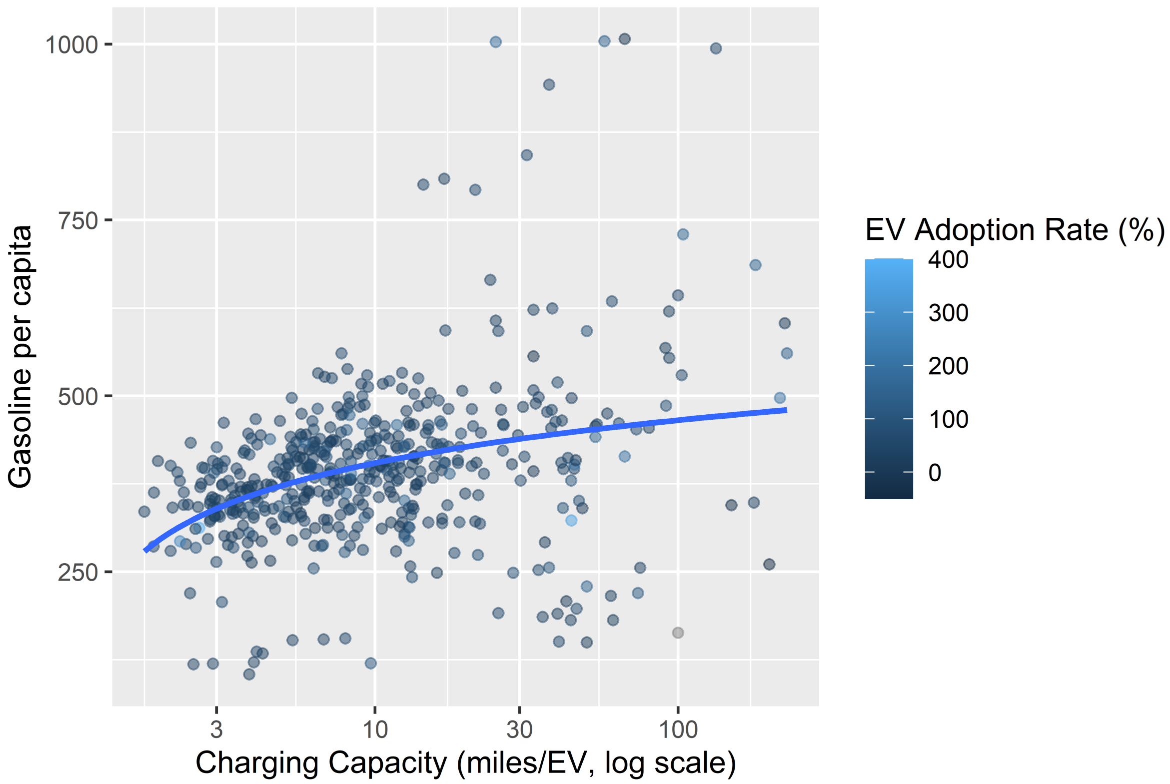
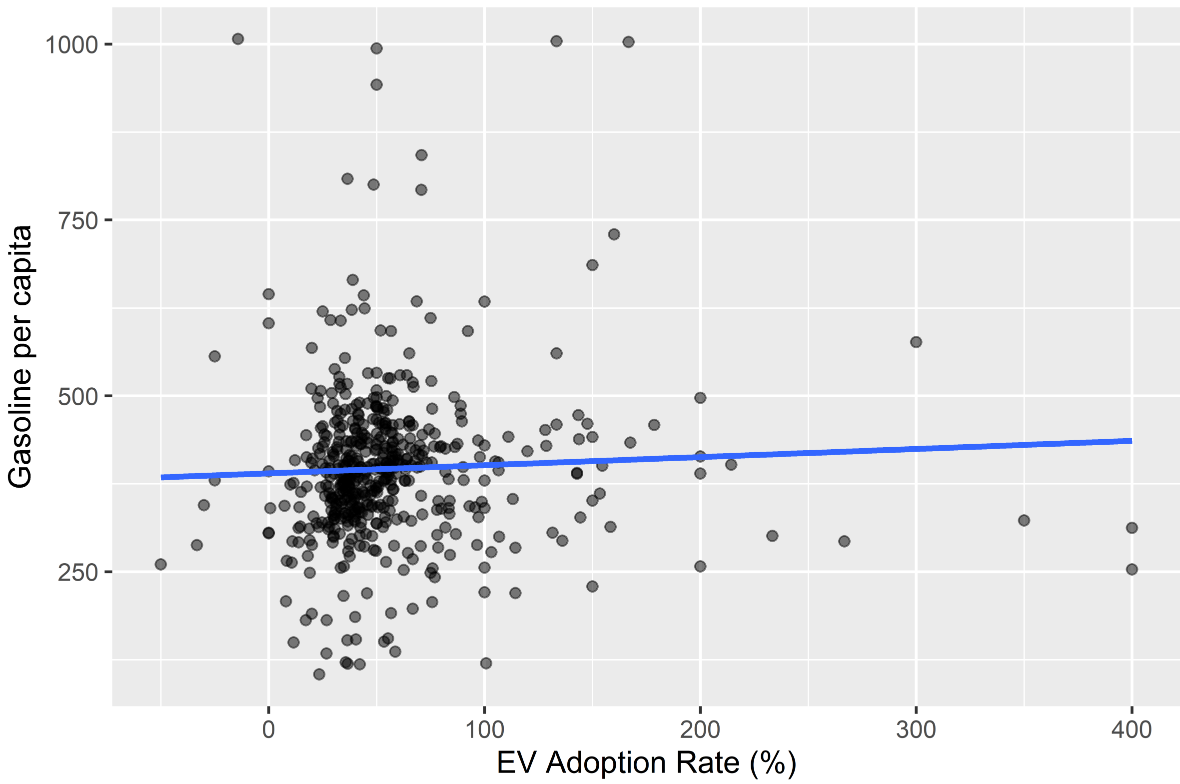


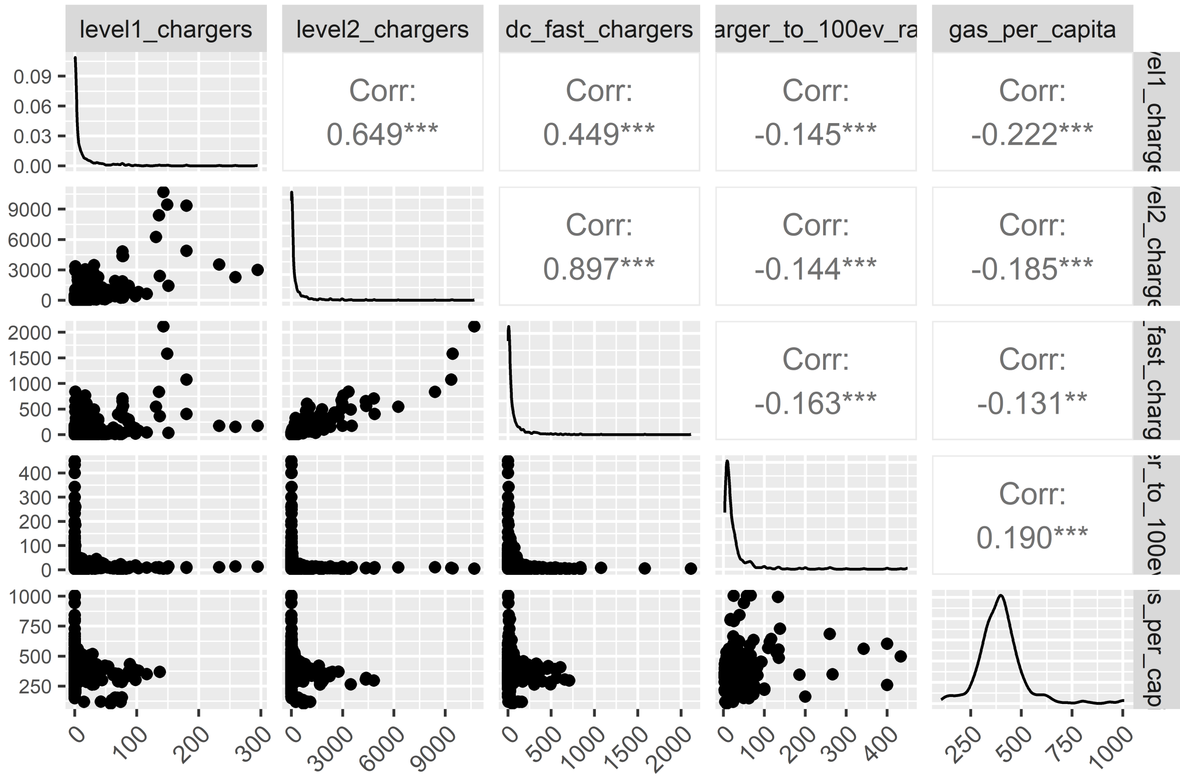

Figure 3 shows a slight upward slope: counties with higher EV adoption rate often report higher gasoline use per person. This reflects the early-adopter phenomenon documented by Choi et al. (2013) and Muehlegger and Rapson (2018), in which wealthier regions with higher amount of transportation are the first to adopt EVs but still have high travel distances. On the plot, counties with high EV adoption rates see a broad range of gasoline consumption, suggesting that adoption alone does not guarantee lower fuel use. Counties with lower EV adoption, likewise, display varied gasoline use, implying that EV adoption alone does not capture the full dynamics of gasoline usage behavior. The trend seen in this plot contrasts with the near zero and statistically insignificant within-county coefficient on EV adoption in the two-way fixed effects OLS model we mentioned above ($\beta$ = -0.03, p = 0.81). This illustrates that EV adoption by itself does not drive gasoline displacement without concurrent improvements in infrastructure sufficiency and equitable access. These results validate our argument that fostering gasoline reductions requires a simultaneous focus on both EV adoption and charging infrastructure, rather than merely treating adoption as a standalone policy lever.

**Figure 3:** Correlation between EV adoption rate and gasoline consumption per capita.




The correlation matrix in Figure 4 reveals mixed raw associations. Level 1, Level 2 and DC fast charger counts each correlate negatively with gasoline use, while number of chargers per 100 EVs correlates positively. These patterns reflect Singh (2019)'s density-driven adoption insights alongside cross-county confounding by socioeconomic and spatial factors (Bauer et al., 2021; Hsu & Fingerman, 2021). This result aligns with the negative coefficient of number of Level 2 chargers but contrasts with the positive coefficient of number of Level 1 and DC fast chargers in our fixed-effect OLS model, which illustrates how fixed effects and income controls can dramatically alter the apparent impact of infrastructure changes and reveal the true direction of the effects on gasoline consumption.

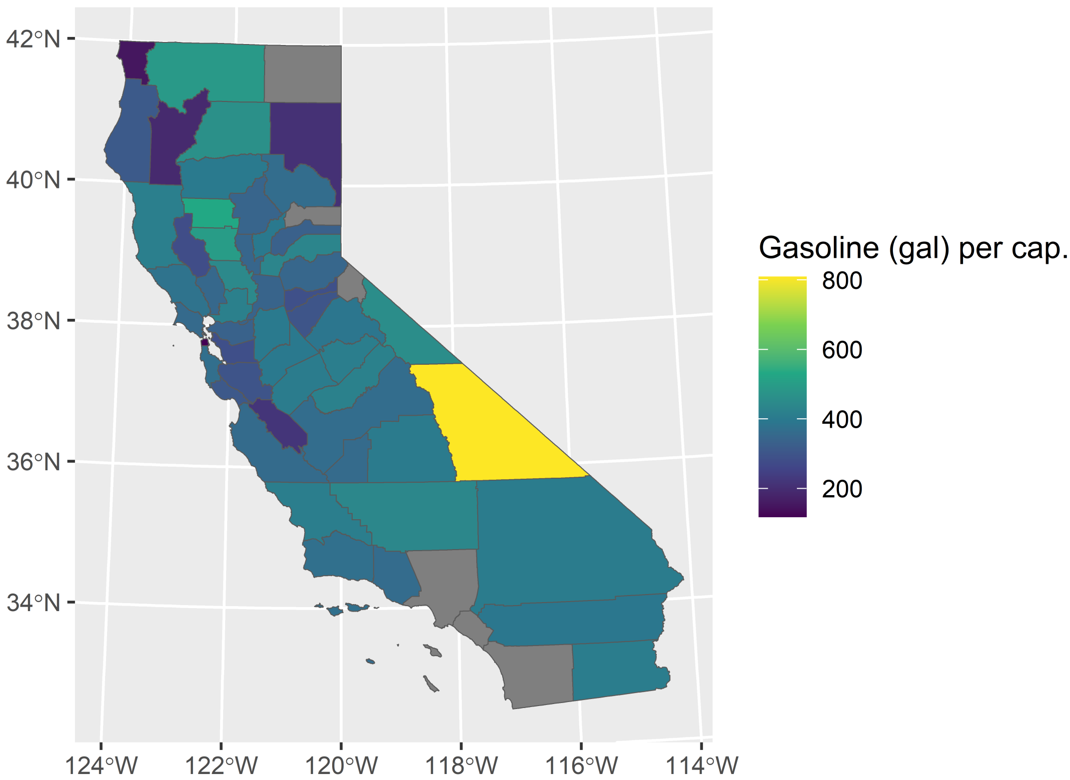
**Figure 4:** Correlation matrix of charger counts, charger-to-EV ratio, and gasoline consumption per capita.




## 5.3 Maps

Figure 5 reveals noticeable coast-inland and north-south divides: remote interiors (Inyo, Imperial, Modoc) have high gasoline consumption, while those of coastal metropolitan areas (San Francisco, Marin, Santa Clara) remain low. This mirrors Hsu and Fingerman (2021), who find that rural, lower-income areas rely more on gasoline due to limited charging and long travel, and aligns with Choi et al. (2013) and Muehlegger and Rapson (2018) on how infrastructure gaps limit fuel use reductions. This contrasts with our two-way fixed-effects model, which reveals a negative within-county effect of charger sufficiency ($\beta = -0.49$). Despite some counties having high gasoline use as shown in the map, our model illustrates that when counties add more chargers relative to their EV fleets, their gasoline consumption falls, which the map does not reveal. Combined together, the map and the model imply that targeted sufficiency expansions in high gasoline use regions can yield substantial fuel reductions, reinforcing the value of county-specific, time-series policy evaluation rather than one-size-fits-all approaches.

**Figure 5:** Gasoline consumption per capita by county, 2023.




The map in figure 6 shows that the majority of counties have fewer than 50 chargers per 100 EVs, with only a few sparsely populated counties (Modoc, Lassen, Mono) having noticeably high number of chargers relative to EVs. Major metropolitan areas also appear under-served relative to fleet size, illustrating the "charging deserts" Pal and Behera (2023) and Mehditabrizi et al. (2024) describe. Cross-sectionally, our two-way fixed-effects model uncovers a negative within-county relationship, in which as counties boost their charger to EV ratios over time, gasoline consumption per capita declines. While the map points out persistent under-sufficiency counties, the fixed-effect OLS model estimates demonstrate that targeted investments in charger sufficiency translates into real fuel-use reductions, even in counties with low charger to EV ratios.

**Figure 6:** Chargers per 100 EVs by county, 2023.

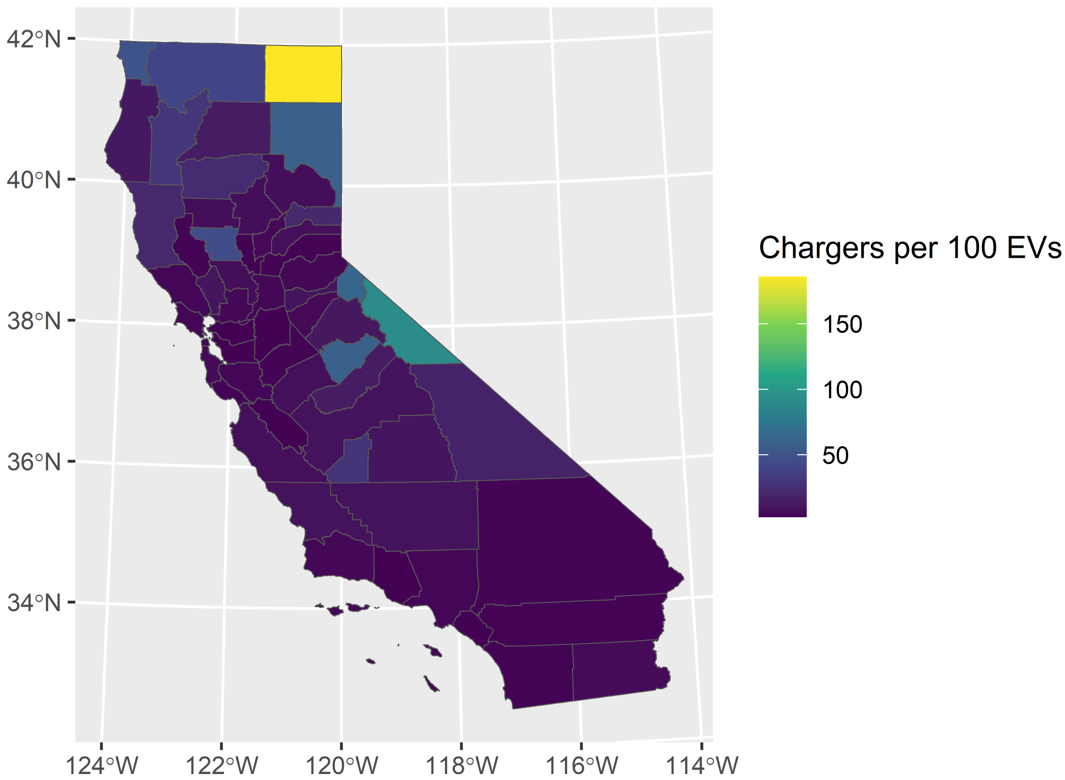
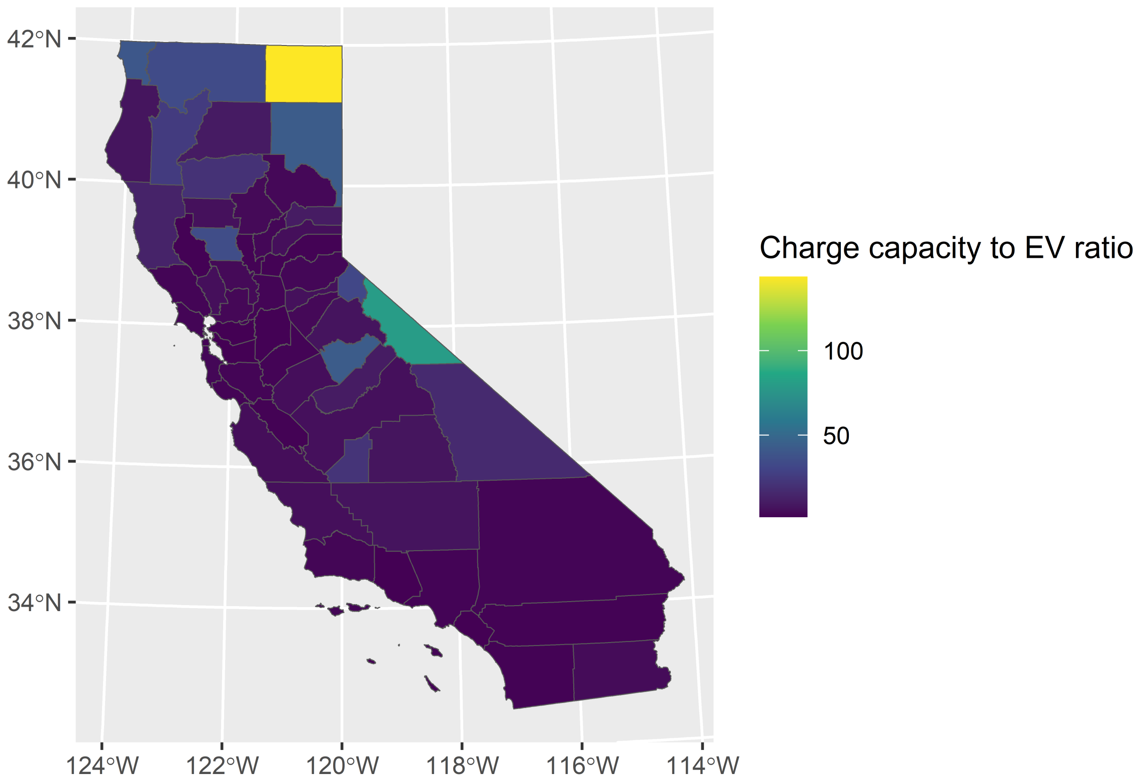



Figure 7 illustrates that most counties have lower than 50 miles per hour of charging per EV, with only a handful of counties having noticeably high charging capacity relative to EV population. Coastal and Central Valley counties show low charging capacity per EV, highlighting potential overestimation of charging access in urban centers (Mehditabrizi et al., 2024). Consistent with the map, the coefficient for charging capacity per EV in our fixed-effects model is positive though not statistically significant, indicating that nominal capacity growth without operational refinements like congestion adjustments does not reliably reduce gasoline consumption.

**Figure 7:** Charging capacity to EV ratio by county, 2023.




## 6 Conclusion

Our fixed-effects regression captures nearly 90% of the cross-county variation in gasoline consumption per capita but merely less than 5% of the year-to-year shifts within counties. Moreover, none of the infrastructure or socioeconomic predictors we used in our model achieves statistical significance, indicating that year-over-year changes in these factors have only minimal effects on gasoline use within a county.

These findings suggest that infrastructure expansion alone may not immediately translate intro reduced gasoline consumption. Complementary strategies, such as targeted incentives for low-income communities, managed charging programs, and consumer education, play important roles in converting charger availability into change in behavior and, in turn, gasoline use. Furthermore, the inequalities in EV uptake and number of chargers highlight the importance of equity-focused charging infrastructure deployment to bridge accessibility gaps and support EV adoption at a broader scale.

By integrating charger-to-EV ratios, charging capacity, geographical coverage, and income data in a fixed-effects model, this study fills a gap in understanding how infrastructure sufficiency and socioeconomic context mediate gasoline use reductions. In the future, we can use station-level utilization data, policy rollouts and integrate travel behavior models to further capture how charger deployment and trends in EV uptake shape patterns in gasoline consumption. These will better inform policies to accelerate equitable EV adoption and achieve higher cuts in GHG emissions in California.

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