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ABSTRACT

Household carbon dioxide emissions have been an increasing function of income and distance from the city. Richer suburbanites drive more and consume more electricity and natural gas at home. In recent years, richer people in California have been more likely to buy electric vehicles and to install solar panels in their homes. The electricity grid has become less carbon intensive over time. Using several California datasets, we document that these ongoing shifts in consumer behavior have flattened household transportation carbon dioxide Engel curves over the years 2018 to 2022. While household electricity emissions as a function of income have flattened, the natural gas Engel curves have not. We explore the political economy implications of the ongoing decarbonization of the private vehicle fleet. Based on voting data from California, we document that communities tend to support higher fuel taxes when their vehicle fleet is more fuel efficient.

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Introduction

The free rider hypothesis predicts that few people will take costly actions to unilaterally reduce their production of greenhouse gas emissions. Empirical studies have documented that richer people and richer nations produce more greenhouse gas emissions (Harbaugh, Levinson, and Wilson 2002; Akbostancı, Türüt-Aşık, and Tunç 2009, Schmalensee, Stoker and Judson 1998). Richer people are more likely to purchase higher quality products such as Tesla electric vehicles. If the private quality of a product is negatively correlated with its emissions, then richer people may provide public goods as they opt to buy higher quality products (Kotchen 2006, Delmas, Kahn and Locke 2017).

A household's production of greenhouse gas emissions also depends on where it lives and works. Most suburban households feature a worker who works in the suburbs and commutes around by private vehicle (Glaeser and Kahn 2004). Urban economic research has documented an association between urban form and household carbon dioxide emissions. When people live in center cities, they live in smaller units and use public transit more (Glaeser and Kahn 2010). In the past, low density living produced greater carbon emissions as spread-out people drove more and lived in larger homes that consumed more energy (Kahn 2000; Glaeser and Kahn 2004; Bento et. al. 2005, Reiss and White 2005). Given that people are not randomly assigned to residential locations, the negative correlation between a household's carbon dioxide production and local population density reflects both a selection effect and a causal treatment effect of urban form on transport demand.

The empirical literature suggests that income growth and suburbanization contribute to the ongoing growth of the US household greenhouse gas production. The household sector contributes to over 20% of the total carbon emissions through its consumption of fossil fuels in personal transportation, and through electricity and gas consumption for other household activities such as heating and cooling (Goldstein, Gounaridis, and Newell 2020).

In this paper, we use California zip code panels to study household carbon emissions from transportation, electricity use, and natural gas. For the first two, we document that the income elasticity of emissions is shrinking. In recent years, richer people are buying electric vehicles and installing solar panels. Meanwhile, the electricity grid has become cleaner as coal fired power plants are retired and as more electricity is generated using renewables. In contrast to the household transportation sector and the household electricity consumption, we find that the income elasticity of household carbon dioxide emissions from natural gas has not shrunk. Our explanation hinges on the continuation of the rise of Work from Home. Richer people are more likely to be working from home for at least a couple of days a week relative to the pre-COVID baseline. As they stay home longer, they consume more natural gas. Unlike the cases of electricity and transportation, traditional homes cannot substitute away from natural gas. The rise of electric heat pump adoption is only taking place slowly, which means that the scale effect associated with being richer is not offset by composition and technique effects that we observe for the other two sectors (Davis 2023).

In our empirical work, we study household Carbon Engel curves using non-parametric and parametric methods. For total emissions and separately for transport, electricity, and natural gas emissions, we explore the association between household income, urban form, local weather, political ideology, and household emissions.

Our paper contributes to the empirical literature on the relationship between pollution, income, and suburbanization. Some studies have documented an Environmental Kuznets Curve between air pollution and income, which posits an inverted-U relationship between the two (Grossman and Krueger 1991; Hilton and Levinson 1998; Schmalensee, Stoker and Judson 1998; Bistline 2022). Other studies have rejected the existence of an EKC between national pollution levels and per-capita income (Harbaugh, Levinson, and Wilson 2002; Akbostancı, Türüt-Aşık, and Tunç 2009). In the transportation sector, Cox et al. (2012) found that richer people own newer vehicles and drive them more. Our paper emphasizes that composition and technique effects (i.e. more efficient vehicles and cleaner electricity) can offset scale effects. Since we have data for five years, we test whether the emissions Engel curve is shifting down (Dasgupta et. al. 2002).

We contribute to the literature on the carbon emissions of the vehicle fleet. Li, Kahn, and Nickelsburg (2015) document that public buses are not becoming more energy-efficient, while private bus agencies own more fuel-efficient buses. Klier and Linn (2010) use monthly vehicle sales data to show that an increase in gasoline prices incentivizes people to purchase fuel-efficient vehicles. Californians adopt EVs in response to the rising gasoline prices (Bushnell, Muehlegger, and Rapson 2022). We build on this work by studying how the nascent electric vehicle market and the take-up of solar panels jointly reduce household emissions.

We discuss the political economy implications of the shifting emissions Engel Curve. The Inflation Reduction Act embraces a green energy subsidy approach rather than raising taxes for mitigating greenhouse gas emissions. A majority of Americans live and work in the suburbs. This group's lifestyle has been carbon intensive. A carbon tax would lower their real incomes, so they tended to oppose gas tax increases (Holian and Kahn 2015). If the trends we document continue, then as the upper-middle class suburbs decarbonize, their opposition to carbon taxes is likely to decline. Using voting data on Proposition 6 in 2018, we find that geographic areas where people drive low emissions cars are more likely to vote in favor of a fuel tax.

This paper is structured as follows. We start by presenting our empirical hypotheses and benchmark California's decarbonization progress against other states. We then present our emissions accounting framework and data sources. Using our panel datasets, we document the shape of the emissions Engel Curve and how it changes over time as households adopt EVs and solar panels. We discuss the political implications of our findings and conclude by commenting on the dynamics between households' pollution production and exposure.

Household Carbon Dioxide Engel Curve Hypotheses

We view a household's carbon footprint to be an emergent byproduct of consumer optimization. An exogenous increase in this household's income traces out a particular household's carbon Engel curve. Households consume fossil fuels such as gasoline and natural gas to achieve their daily goals. Such energy is an intermediate input in commuting and leisure activities (Reiss and White 2005). Together, these utility maximizing choices determine a household's carbon footprint.

Starting with Dubin and McFadden (1984), economic research has studied the interplay between consumer choices at the extensive and intensive margin. In their work, they model the discrete choice of an air conditioner and its utilization. Other studies such as Goldberg (1998) have extended this approach to studying the discrete purchase of a car and the mileage driven. She studies the anticipated rebound effect as people owning fuel-efficient cars face a low price per mile and drive more. Reiss and White (2002) study household electricity consumption using a Becker household production function approach such that households consume electricity as an intermediate input to produce household leisure, cooking, and comfort services.

In this paper, we test a series of hypotheses concerning how household carbon production varies in the cross-section and over time. Most of our data are from California.

Hypothesis I: California's transport and household sectors are consistently less carbon-intensive than the rest of the nation.

For decades, California has been the nation's leader in passing legislation intended to reduce pollution. California's AB32 has focused on a suite of policies to decarbonize the state's economy. In 2022, 19% of all new vehicles sold in California were electric vehicles, and 40% of the nation's electric vehicles were registered in California.[1] In recent years, California has aggressively increased its Renewable Portfolio Standard to 30%. This represents a tripling since 2010.

Hypothesis II: The household level Carbon Engel Curve with respect to income and distance from the city center shifts down and flattens over time.

Technological innovations can reduce the negative environmental impacts of suburbanization. In the case of urban air pollution from vehicles, vehicle emissions control technology has led to a sharp reduction in ambient air pollution during a time when we are driving more miles than ever (Kahn and Schwartz 2008). Since 2010, the fuel efficiency of the average internal combustion engine vehicles (ICEs) in the US has increased by more than 15%. The 2022 EV models are 30% more efficient than the earliest EV models manufactured in early 2010s. Emissions from EVs decline as more power is generated from renewable sources (Holland et al. 2016). Such composition and technique effects imply that households' emissions intensity declines in the transportation and the electricity sector. The Engel Curve will shift down if these emissions reductions emissions are not offset by the rebound effect.

Rich suburbanites are more likely to buy the expensive low-carbon products including solar panels and EVs. The rise of WFH means that people live further out have more flexible working schedule and higher demand for quality of life. In the emerging WFH economy, more people are choosing to live in the suburb in newer homes (Ranmani and Bloom 2021). California has required

[1]gov.ca.gov/2023/01/20/california-zev-sales-near-19-of-all-new-car-sales-in-2022/

solar panels on all new construction since 2020. If these new homes feature installed solar panels that charge EVs, then carbon emissions could decline at the fringe due to green product bundling (Delmas, Kahn, and Locke 2017). These factors jointly imply that high-income, suburban zip codes decarbonize faster, resulting in a flattening Engel curve.

Hypothesis III: Liberal households consume less energy and are more likely to purchase EVs and solar panels.

Carbon emissions represent a global externality as most people do not internalize the social costs of their privately beneficial actions. Some households do embrace a philosophy of voluntary restraint such that they lose utility from polluting. Kotchen and Moore (2008) have documented that liberal consumers voluntarily conserve on their consumption of dirty electricity and pay a price premium for green electricity.

Hypothesis IV: Opposition to gas taxes is higher in areas where vehicles have a higher carbon emissions factor.

Vehicles are not randomly assigned to people. Those who choose to purchase a “gas guzzler” recognize that higher gasoline taxes will lower their purchasing power. Those who buy these cars may be less likely to embrace voluntary restraint and have fewer concerns about the climate change challenge. Both this selection effect and this treatment effect predict that areas relying on cleaner transport will be more supportive of carbon pricing.

In the recent past, suburban voters were less likely to support California’s efforts to reduce greenhouse gas emissions than urban voters. Holian and Kahn (2015) posit that suburban voters recognized that they would bear more of the economic incidence of regulation that implicitly raises the price of gasoline. If the rise of solar EV bundles are decarbonizing the distant suburbs, then the Holian and Kahn claim should be attenuated over time. A zero-carbon suburban driver does not bear the burden of a carbon tax. We test this political economy hypothesis using voting results from a 2018 California proposition that rejected the overturn of a fuel tax.

Hypothesis V: There is a negative correlation between a zip code's carbon emissions and its resident's exposure to local air pollution.

Environmental justice research has documented that poor residents in center cities are often exposed to more air pollution and live closer to hazardous waste sites (Banzhaf, Ma and Timmins 2019). Although low-income households drive less, their neighborhoods are located in the densely populated urban areas with high pollution levels (Carozzi and Roth 2023). Boeing, Lu, and Pilgram (2023) have documented low-income neighborhoods in Los Angeles are exposed to higher roadside PM2.5 levels. In contrast, high-income people produce more transport emissions but often live farther away from downtown. Low density suburban locations feature less ambient air pollution. These facts suggest that we will observe a negative correlation between a household's carbon dioxide pollution production and local PM2.5 exposure.

Does California Outpace Other States in Decarbonization?

In this section, we benchmark California's decarbonization progress against that in other states. To this end, we calculate households' carbon emissions by state/year for each of the three sectors: transportation, electricity, and gas. We then calculate state i's z-score using the following formula:

$$z_{it} = \frac{Emissions_{it} - \overline{Emissions_t}}{SD(Emissions)_t} \tag{1}$$

In Figure 1, we plot the z-score of California in each sector from 2010 to 2021. In the transportation and the gas sector, the total emissions in California are approximately 0.5 standard deviation below the average. In the electricity sector, California is 1.5 standard deviations below the country average. These results are consistent with Hypothesis I. Emissions from gas consumption have been steadily deviating from the rest of the nation. This could be explained by the adoption of heat pumps so that heating is powered by electricity instead of gas (Davis 2023). In the other two sectors, we find no evidence that California has made larger decarbonization progress. While California has pursued ambitious policy agendas to achieve net-zero, there is mixed evidence on whether environmental regulations can explain the energy savings in the state. Levinson (2014, 2016) has documented that most of such savings could be explained by local demographics and weather.

Estimating Carbon Emissions Engel Curves

Household carbon emissions equal the sum of net emissions from household electricity use, natural gas consumption, and personal transportation. We study the microeconomic determinants of household carbon emissions dynamics. Such emissions depend on choices at the extensive margin (vehicle choice and electricity source choice) and the intensive margin (utilization). We use several datasets from California to tease out scale effects from the fleet's composition and technique effects. Composition effects occur when households substitute ICEs with EVs or substitute grid power with self-generation from solar panels. Technique effects refer to the increasing fuel efficiency of vehicles and the decreasing emissions intensity of the electricity grid. In this section, we present a unified accounting framework of consumers' emissions level that includes both an extensive margin and an intensive margin.

In our empirical work, our geographic unit of analysis is a zip code. The total household emissions in zip code z are given by equation (2):

$$Emissions_z = \sum_{i \in \{transit, electicity, gas\}} r_{iz} x_{iz} \tag{2}$$

where r is the emissions intensity of the sector and x is the total utilization. In the electricity and the gas sector, r refers to the emissions intensity of the grid and the emissions factor of natural gas respectively.

In the transportation sector, r refers to the carbon emissions per mile travelled. The zip code (denoted by z) average emissions per mile is calculated from equation (3). For every transportation choice j (public transit, gasoline vehicles, or electric vehicles), we observe the share of a zip code that chooses this mode (s). Each transit mode has different emission rates (e) across zip codes. For example, emissions per mile of an EV are lower in zip codes with cleaner electric grids. The zip code emissions per mile is the average emission rates weighted by the respective rider share.

$$Emissions\ per\ mile_z = \sum_{j \in J} s_{jz}\, e_{jz} \tag{3}$$

Using the output from equation (2) as a dependent variable, we will study the gradient of emissions with respect to income and urban form. $X_{transit}$ is an increasing function of income and distance to the city center since richer, suburban people travel more miles (Bemto et al. 2005). In the recent past, $r_{transit}$ is also an increasing function of income. When poor people grow richer, they substitute away from public transit to a dirtier technology (e.g. an old car) (Glaeser, Kahn and Rappaport 2008). As middle-class people become richer, they choose to drive a large, comfortable vehicles (i.e. SUVs) that produce more carbon dioxide emissions (Knittel 2011; Anderson and Auffhammer 2014). Today, this gradient of $r_{transit}$ can flatten or become negative as rich people opt into EVs and solar panels (Holland et al. 2016; Delmas et al. 2017). If they charge EVs using solar panels, $r_{transit}$ can equal zero.

In the electricity and the gas sector, the total consumption increases as households become richer and suburbanize, living in bigger houses with more emissions-intensive features. The emissions intensity in the electricity sector ($r_{electicity}$) can be lower in rich, suburban households as they generate their own power using solar panels. In the gas sector, r_{gas} can have a negative gradient with respect to income if households adopt electric heat pumps (Davis 2023). The gradient of total emissions from these two sectors hinge upon a race between the scale effect versus the composition and technique effects.

California Data

To test our hypotheses, we use multiple California datasets to construct a zip/year panel dataset from 2018 to 2022. There are 1760 zip codes in our data based on the 2010 census boundaries. In our analysis, we focus on the 1677 zip codes within 75 miles from the city center.

The first component of our data is the count of EVs, solar homes, and EV and solar bundles (homes with solar panels and at least one EV vehicle). We obtain the EV sales data from the California Energy Commission.[2] Based on the annual sales data by zip code, we calculate the cumulative EV counts. Our data on solar homes and solar EV bundles are gathered from the California Solar Initiative (CSI) datasets provided by SCE, SG&E, and PG&E.[3] Each of these investor-owned utilities report every installation of home solar panels within its service territory and whether the installed panels will be used to charge EVs. We aggregate the household installation data to obtain the count of solar homes and EV/Solar bundles by zip/year.

[2] https://www.energy.ca.gov/files/zev-and-infrastructure-stats-data

[3] https://www.californiadgstats.ca.gov/downloads/

Note that this dataset may underestimate the solar and bundle counts because roughly 30% of the consumers in California are served by neither of these three utilities.

The second component is each zip code's vehicle fleet emissions intensity by year. This allows us to measure the cross-sectional and time series variation in the carbon emissions per mile of driving. We obtain the California vehicle stock data from the state DMV.[4] We exclude heavy-duty vehicles (e.g. delivery trucks) from our analysis. For each zip/year, the DMV dataset breaks down the vehicle fleet by brand/fuel type/model year. For example, the dataset informs us how many fully electric (fuel type) Tesla (brand) manufactured in 2015 (model year) are registered in zip code 90024 in the year 2018.

The EPA provides data on the MPG or kWh/mile for each brand/fuel type/model/model year.[5] One limitation of the DMV vehicle stock is that we do not know the share of each model within each brand, so we assume that within each brand/fuel type/model year, consumers purchase the newest released compact car model.[6] Based on this assumption, we calculate the emissions/mile by brand/fuel type/model year using the EPA fuel economy data and the emissions factors data.[7]

We then merge in the emissions per mile to the DMV vehicle stock dataset by brand/fuel type/model year. For example, we merge in the fuel efficiency of a fully electric Tesla (brand and fuel) with model year 2015. Based on the merged dataset, we calculate the emissions/mile for each of the three fuel types (gasoline, hybrid, or fully electric) in each zip/year. Using our data on solar EV bundles, we calculate the percentage of EVs charged by solar power, denoted as $solar_{it}$. These vehicles have zero emission per mile. Then the emissions/private mile of zip code i in year t is given as:

$$E_{it} = \sum_{f \in F} e_{itf} * p_{itf} - \sum_{f \in \{electric, hybrid\}} e_{itf} * p_{itf} * solar_{it} \qquad (4)$$

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[4] https://data.ca.gov/dataset/vehicle-fuel-type-count-by-zip-code
[5] https://www.fueleconomy.gov/feg/download.shtml
[6] For example, in 2019, Tesla manufactured the Model S, Model X, and Model 3. We use the fuel efficiency of Model 3 as the fuel efficiency of all Tesla vehicles with model year 2019, because (1) Model X is an SUV, not a compact car; and (2) Model 3 was released in 2017, later than Model S released in 2012. We acknowledge that this is an optimistic assumption because Americans are buying more large cars.
[7] Emission factors: https://www.epa.gov/sites/default/files/2015-07/documents/emission-factors_2014.pdf
EGRID: https://www.epa.gov/egrid
For each zip code, emissions/kWh is calculated as the average emissions/kWh of all utilities serving that zip code.
The emissions from gasoline consumption is 8.78kg/gallon. Thus, emissions/mile=8.78kg/MPG. For BEVs, we use the emissions/kWh generation data for each zip code (based on the EIA utility dataset) to convert kWh/mile into emissions/mile. For hybrid vehicles, both MPG and kWh/mile are reported in the fuel efficiency dataset, and we just average the emissions/mile when driven with gas and with electricity. We assume that they drive with electricity half of the time). As chargers become more accessible, they may use electricity more often.

F is the set of three fuel types, e is the emissions/mile, and p is the percentage of vehicles of fuel type f in zip i in year t. In words, the zip/year emissions/mile is the weighted average of emissions/private of different fuel types on the count of the vehicles of the corresponding fuel type in zip i in year t, where the emissions from vehicles charged by solar are coded as 0.

To account for public transit, we use data from the American Community Survey (ACS) and the National Transit Database (NTD). The ACS data includes the percentage of people commuting by public transit in each zip/year. From the NTD data, we calculate the public transit emissions per passenger mile.[8] Using data from the National Household Travel Survey (NHTS), we interpolate each zip code's household annual mileage (m) based on its income level and population density.[9] The total personal transit emissions in zip i in year t is:

$$Total_{it} = m_i * E_{it} * (1 - public_{it}) + m_i * TE_{it} * Public_{it} \qquad (5)$$

Public is the proportion of people using public transit, and TE is the public transit emissions per passenger mile. We assume that within a zip code that miles travelled is equal for those who commute by public transit and by private vehicle. We also assume each individual only owns one vehicle and use it to commute all the time. Equation (5) embodies the first component of household carbon emissions, namely the transportation emissions.

We obtain the electricity and gas consumption data by zip/month/year from the websites of the three investor-owned electric utilities. We calculate each county's grid emissions factor in each year based on the generator level data provided by the EIA.[10] The carbon emissions factor of natural gas is 53.06 kg/mmBtu.[11] We aggregate the monthly data by zip/year, multiplying the annual electricity and gas consumption by the respective emissions factor to get the total emissions from these two sectors (see equation (2)). We add them to the personal transit emissions to get the total household emissions by year. Note that we also calculate the emissions from electricity and

[8] See Huang and Kahn (2023) for more details.
[9] The specification is similar to that in Bento et al. (2005), but we use up-to-date survey data from 2017. The regression results are available on request. We assume the zip vehicle mileage is constant over 2018 to 2022. This may underestimate the emissions as Californians drive more over time.
Using annual private vehicle mileage data in California from 1972 to 2019, we find that vehicle miles travelled increase by 2% per year. When we restrict the sample to years since 2000, the annual increase is 0.7%. Both are statistically significant at the 1% level. Data source: https://dot.ca.gov/programs/traffic-operations/census/mvmt
[10] https://www.eia.gov/electricity/data/eia860/
[11] https://www.epa.gov/system/files/documents/2023-03/ghg_emission_factors_hub.pdf

gas consumption using the original data at the zip/year/month level (i.e. without annual aggregation). The zip/year/month panels are used in Table 3.

In the regressions we report below, we include demographic variables. The 2018 American Community Survey data provides us with census tract information including median household income and population density. We aggregate them by zip code. In addition, we calculate the percentage of liberal voters (i.e. Democrat or Green) in each zip code using the 2018 voting data from the California State Database.[12] We use GIS to convert the original precinct level data to zip level data. We calculate each zip code's summer temperature using the spatial files from the PRISM climate data.[13]

Carbon Emissions Engel Curve Estimates

In this section, we present evidence on how household carbon emissions vary across space and over time (see Hypothesis II). Total emissions increase monotonically as energy consumption rises. In Figure 2, we plot the monthly personal transport mileage and electricity and gas consumption in California. Transit mileage has recovered from the sharp drop in 2020 but has not returned to the pre-pandemic level. In the emerging WFH economy, the need for commuting decreases. If people suburbanize but commute less often, their total distance traveled can drop, even though each trip gets longer. Both electricity and natural gas use exhibit clear seasonal patterns. Electricity consumption peaks in summer, while gas consumption is higher in winter. The plot indicates that households have been using more electricity in the WFH economy since 2020 (Cicala 2023).

Household emissions are jointly determined by the intensive margin and the extensive margin. The adoption of green products can offset the emissions from the increasing use of vehicles and electricity. Using our zip/year panel data, we report the empirical distribution of zip code average household carbon emissions by year in Table 1. The average emissions declined by approximately 4% from 2018 to 2022. At the 25th, 50th, and 75th percentile, emissions dropped by a similar percentage, both when weighted and unweighted by the zip code population.

[12] https://statewidedatabase.org/d10/g18.html
[13] https://prism.oregonstate.edu/

Building on the summary statistics, we estimate the following cross-sectional specification for zip code i in each year:

$$\log(E_i) = \alpha' \mathrm{X}_i + \beta_1 \log(\mathrm{Income}_i) + \beta_2 \log(\mathrm{Distance}_i) + \delta_c + \varepsilon_{it} \qquad (6)$$

where E refers to total emissions, and X is a covariate vector including the percentage of liberal voters, and the average temperature. βs are the coefficients of interest. We test whether the gradients are declining due to composition and technique effects. We include county fixed effects (δ_c). The regressions are weighted by the total zip code population.[14] Standard errors are clustered by zip codes in this and later equations. The results are presented in Table 2.

In all years, emissions are positively associated with income. The income elasticity was higher during the pandemic as upper-middle class were more likely to have jobs that allowed them to work from home. In 2022, the income elasticity had dropped to its pre-pandemic level in 2019. We find that emissions are also positively corelated with the distance from the city. This positive association does not shrink over time, inconsistent with the prediction by Hypothesis II.

The liberal variable has a significantly negative coefficient in some years. We find some support for Hypothesis III based on the measure of total emissions. The liberal coefficient could shrink toward zero going forward as Republicans opt into high-quality EVs and purchase solar panels (Delmas, Kahn, and Locke 2017). Temperature has a statistically insignificant coefficient. While households in colder zip codes use more natural gas for heating, they rely less on air conditioners for cooling over the summer. We will explore such heterogeneities across sectors in the next section.

[14] We recognize that relying on zip code level data raises the ecological inference issue. We use weighted least square to partially address this. In our setting, we do not believe that individual level data would yield very different insights. Our two explanatory variables are median household income and distance to the city center. Population sorting into school districts due to local amenities means that the population's income in zip code level neighborhoods features less variation than across a metropolitan area as a whole (Tiebout 1956). Structural research has documented that preference heterogeneity for local public goods is the major source of how within neighborhood income heterogeneity can arise in spatial equilibrium (Epple and Sieg 1999). Meanwhile, a zip code's centroid's distance to the city center proxies well for each household's distance to the city center. We are confident the cross-zip code variation in these two variables swamps the within-zip code variation. Studies such as Thomas et al. (2008) have documented that zip code estimates yield similar coefficients as census tract level estimates, and tracts are small levels of a unit of analysis.

The IRS tax data includes the number of tax returns in each of the six income categories in each zip code. The median income is negatively correlated low-income categories and positively correlated with high-income ones. The correlation is -0.74 (income<$25000), -0.78 ($25000 to $50000), -0.42 ($50000 to $75000), 0.1 ($75000 to $100000), 0.6 ($100000 to $200000), and 0.89 (>$200000).

Sectoral Variation in the Carbon Dioxide Engel Curves

Environmental economists emphasize that total emissions depend on scale, composition, and technique effects. If a driver drives many miles (scale) but drives a low emissions vehicle (technique), then the total emissions can be low. In the case of household transportation and electricity consumption, technique effects (i.e. high fuel economy vehicles and a green grid) can offset scale effects. In the case of natural gas consumption for home heating, we do not expect to observe an offsetting scale effect. While starting in 2026 new California homes are required to be electric homes, the vast majority of California's homes were built decades ago.[15]

In Figure 3, we plot the nonparametric graphs of transportation and electricity emissions against income and distance to the city center. These two sectors jointly contribute to 75% of the total emissions.[16] When creating these plots, we control for zip codes' political ideology and temperature nonparametrically. In both sectors, emissions are an increasing function of income, but the relationship is becoming more concave over time. The Engel Curves are flattening at high-income levels and shifting down over time, except for a rebound in electricity emissions in 2020. Households' use of electricity increases when people work from home (Kahn 2022; Cicala 2023). This supports Hypothesis II.

Transportation emissions and the distance to the CBD have a U-shape relationship. They decline in the urban areas (within 10 miles from downtown) but then rise as suburbanites move further out. This is consistent with the evidence from Baum-Snow and Kahn (2005). New rail lines incentivize urban households to drive less, yet suburban people do not substitute from private cars to public transit. So far, we have not observed a flattening tail of the emissions curves with respect to distance. Our explanation is that vehicles are durable capital. In the electricity sector, the gradient of emissions is flattening in suburban areas.

To complement our nonparametric plots, in Table 3, we estimate equation (6) using emissions from each of the three sectors. The transportation regression is based on the zip/year

[15] https://www.energy.ca.gov/programs-and-topics/programs/california-electric-homes-program-calehp

[16] We omit the gas sector because relatively few people have adopted electric heat pumps, indicating emissions from this sector are primarily driven by scale effects. When we plot the emissions from gas use, they have a monotonic increasing relationship with both income and urban form, and the curves have shifted little over time.

panel, and the electricity and gas regressions are based on the zip/year/month panels (see the data section.

The income elasticity of emissions has shrunk by more than 30% in the transportation and the electricity sector over the years 2018 to 2022, but it has increased in the gas sector. The elasticity is also the largest in magnitude in the gas sector (0.25), while it is the smallest in the transportation sector (0.05). These results are consistent with the trend in green products adoption and WFH. Relatively few households are using electric heat pumps, whereas EVs and solar panels have grown faster in popularity in recent years. Also, richer households consume more electricity and natural gas as they are home more often. The income elasticity of emissions from these sectors rise if such scale effect is not offset by the technique effect.

In the transportation sector, the coefficient on the distance to the city is declining in statistical significance and slightly in magnitude. This suggests that EVs and a cleaner electric grid is offsetting the scale effects associated with suburban drivers documented in previous studies such as Bento et al. (2005) and Cox et al. (2012). This is overall consistent with Figure 3. In the electricity sector, unlike in the figure, we find no clear pattern of the distance coefficient. While EVs reduce emissions in the transportation sector, they increase electricity consumption, offsetting the technique effects induced by renewable generation. In the gas sector, the emissions gradient with respect to distance is flattening. These results provide mixed evidence on Hypothesis II.

In the transportation table, the liberal coefficient is significantly negative in all columns. As documented by studies such as Kahn (2007), liberal households ae more likely to adopt low-carbon vehicles, but non-environmentalists may catch up on EV adoption as the product quality increases (Delmas, Kahn, and Locke 2017). In the electricity sector, we find that liberal zip codes are associated with lower emissions. Kotchen and Moore (2008) have found that liberal households conserve electricity and are more likely to opt into renewable power. Our results are consistent with their finding and Hypothesis III. We find little evidence that liberal and conservative households differ in gas consumption. As discussed, there is less technique effect is the gas sector, and liberals tend to live in older housing in the city center.

In all years, higher temperature is associated with higher electricity emissions and lower emissions from natural gas. In warmer zip codes, households use air conditioners more in summer, but they need less heating in winter.

The Declining Emissions Intensity of Transportation and Electricity Generation

Our figures and tables have shown that the intercept in the Carbon Engel Curves is shrinking in recent years. To explain this pattern, we focus on the transport capital stock's emissions intensity and trends in the electricity grid's carbon intensity.

Using California's vehicle stock data from 2022, we plot the emissions per mile by fuel type and model year in Figure 4. Among the existing ICE vehicles in California, those manufactured in 2007 are 24% less efficient than those produced in 2022. The emissions of PHEVs fluctuate by model year, while those of BEVs steadily trend down, with the new models from 2022 roughly 30% more efficient than the earliest EV models from 2013. These reductions demonstrate the technique effects as vehicles' fuel use per mile and the emission intensity of the grid declines.

Public transit's emissions per mile have also been decreasing as transit agencies invest in energy-efficient buses (Huang and Kahn 2023). The IRA in 2022 provides new funding for these agencies to upgrade their fleet, with an intention to electrify public transit buses. Together with efforts to decarbonize the grid, these investments accelerate the emissions reductions in the public transit sector (Holland et al. 2021).

In the electricity sector, the federal government has initiated a push to decarbonize the grid. While the amount of gas and hydro capacity remains almost constant since 2018, wind and solar capacity has risen by 50% over the same time in California. In 2022, half of the in-state generation was supplied by renewable sources and 42% by natural gas.[17] Although there is still more natural gas capacity, it is utilized less often than in the past. The average emissions go down as more power comes from renewable sources.

Determinants of Green Products Adoption

Outside of major center cities, relatively few affluent Americans commute by public transit (Baum-Snow and Kahn 2005). This point highlights why the key discrete substitution mode for drivers of ICE vehicles is to substitute to EVs as these households are unlikely to substitute to

[17] https://www.eia.gov/state/?sid=CA

public transit. As people replace ICEs with EVs, more passenger miles are run on electricity rather than fossil fuels. If households charge their EVs using power generated from solar panels at home, the composition shift would lead to an even larger emissions reduction. The increasing fuel efficiency of EVs can also contribute to lowering household emissions (see Figure 4).

We use a negative binomial regression to study the adoption of EVs, solar homes, and solar EV bundles across zip codes as a function of community demographics. We choose a negative binomial model since the adoption pattern of these technologies are right-skewed. For zip code i in year t, the negative binomial model can be written as:

$$P(Y = y_{it}|X_{it}) = {\Gamma(\theta + y_{it}) {r_{it}}^{\theta} (1 - r_{it})^{y_{it}}} \Big/ {\Gamma(1 + y_{it}) \Gamma(\theta)}$$

$$with \quad r_{it} = {\theta} \Big/ {(\theta + \exp(\alpha + \beta' X_{it} + \delta_c))} \tag{7}$$

where y is the count of EVs, solar homes, or the bundles, $\Gamma(.)$ is the gamma function, and X is a vector including income, distance, and proportion of liberal households. δ_c represents the county fixed effects. This controls for the county-level policy incentives such as EV rebates. θ is the dispersion parameter. The regression results are reported in Table 4. Our choice of the negative binomial model is justified by the significantly positive overdispersion parameter reported in each column.

The deployment of these three technologies exhibits similar patterns. All of them have a positive time trend, and the EV and solar bundle has the fastest growth rate. Richer zip codes have adopted more such technologies. Yet, from 2018 to 2022, the zip code median income weighted by EV counts has declined from \$141,000 to \$134,000. This implies that new adoption is taking place in upper-middle class zip codes instead of the richest neighborhoods. This is consistent with the increasingly concave transport emissions Engel curve we report.

The negative coefficient on distance in column (1) indicates that suburban households have purchased fewer EVs than have urban households, but this pattern is likely changing. In Figure 5, we examine where new vehicles are registered in California. We weight each zip code's vehicle counts by its distance from the city center and calculate the average distance. For gas and hybrid vehicles, this average distance stayed relatively stable from 2018 to 2022. EVs were on average owned by households living 15.8 miles from downtown in 2018 but 16.4 miles in 2022, implying that suburban people have registered more EVs in recent years.

We find no evidence that solar panel adoption varies as a function of the distance from the city center. Going forward, solar take-up is likely to rise in the suburbs. The California Solar Mandate requires all homes built after 2020 to include a solar photovoltaic (PV) system. New residential developments tend to take place at the fringe of the city. Although suburban families tend to consume more resources, the presence of newer capital stock can partially offset this impact. In the urban core, it is costly to retrofit older housing, and obtaining the necessary political mandate for such transformations can be challenging. The distance coefficients in columns (1) to (3) are consistent with the distance gradients in Table 3.

We document that liberal households have adopted more EVs but fewer solar homes. Liberal people are more likely to live in older center cities. For example, the majority of Berkeley, California homes were built over 50 years ago. Republicans are more likely to live in areas featuring newer homes. Also, households are paid for their self-generated electricity fed back to the grid, which incentivizes Republicans to purchase solar panels despite their political ideology.

Emissions per mile differ across EV brands. The aggregate transportation emissions will decline if low-emission EVs are replacing high-emission ones as the green cars. For example, emissions per mile from Toyota Prius are approximately 0.1 pounds (or 40%) higher than Tesla. Environmentalists have purchased Prius as a symbol of their environmental consciousness (Sexton and Sexton 2014). We test this claim based on the results reported in column (4). The dependent variable is a zip code's share of EVs that are Teslas. Tesla adoption appears to be more prevalent in rich, urban, and Republican neighborhoods. The negative coefficient on liberal can be explained by the technological improvements in the EV industry. Rich, non-environmentalists are purchasing high-quality EVs such as Tesla (Delmas, Kahn, and Locke 2017). As they purchase the Tesla instead of the Prius, their emissions footprints could decline faster.

Public transit produces lower emissions than do private vehicles. In column (5), we show that public transit use has a negative time trend. In rich, suburban, and Republican zip codes, fewer people ride public transit. In column (6), we test the joint effect of households' transport mode choice on their emissions footprint. The dependent variable is the log of transport carbon dioxide emissions per mile. Largely consistent with previous columns, high-income, urban, and liberal households own more fuel-efficient vehicles, and the time trend on emissions per mile is significantly negative.

We end this section by briefly commenting on the electric heat pump adoption. Currently, 14% of American households use it for heating, but heat pumps are rare in Western states. Davis (2023) documents that heat pump adoption does not correlate with income, unlike what we have shown for EVs and solar panels. If the use of heat pumps is more uniform across the income distribution, the adoption will shift down the carbon Engel curve associated with natural gas consumption, but it may not flatten the curve.

The Political Economy Consequences of Decarbonizing the Suburbs

Suburbanites tend to be richer, live in larger homes, and are more likely to be Republicans than center city residents. In the recent past, when there were not low carbon products such as high quality EVs and solar panels, such suburbanites produced more household greenhouse gas emissions. Holian and Kahn (2015) have documented that California voting precincts in the suburb tend to vote against a carbon tax. These voters realize they will bear the tax incidence because they drive more and own emission-intensive vehicles. However, as these suburban residents purchase EVs, their emissions per mile trend down. This could motivate them to support carbon dioxide mitigation legislation.

In 2018, Californians voted on Proposition 6 that proposed to repeal the Road Repair and Accountability Act that raised a fuel tax to fund road maintenance.[18] A "No" vote meant the fuel tax would continue to be in effect and the state legislature could increase state fuel and vehicle tax without further approval from voters in the future. 57% of the voters voted no. We test whether zip codes with lower emissions per mile are more likely to vote in favor of a fuel tax (Hypothesis IV).

We use cross-sectional data from 2018 to estimate the following equation for zip code i:

$$Y_i = \beta_0 + \beta_1 Emissions\ per\ mile_i + \beta_2' Z + \delta_c + \varepsilon_i \tag{8}$$

[18] https://lao.ca.gov/BallotAnalysis/Proposition?number=6&year=2018
At the time of voting, fuel and vehicle taxes provided $5.1 billion revenues to the state.

where Y is the proportion of voters who supported a fuel tax, and Z is a vector of covariates including income and the percentage of liberal voters. We include CBSA fixed effects (δ_c). The regression results are reported in Table 5.

In column (1), the coefficient on emissions per mile is significantly negative as expected. A 1% increase in emissions per mile is associated with a 0.8% decrease in the support for fuel tax, and the overall support rate is 53%. Voters' attitudes toward a carbon tax is sensitive to their own emission levels. All covariates have expected coefficients. Liberal and educated people vote for a tax as posited by the voluntary restraint hypothesis (Kotchen and Moore 2008).

We acknowledge that our results could reflect selection effects as households choose which vehicles they drive. Households' unobserved tastes for fuel efficient vehicles may explain both purchase decisions and voting outcomes. We partially address this concern by conducting a placebo test using Proposition 2 from the same election. Proposition 2 proposed to use the state's mental health funds to provide free housing to unhoused people.[19] As the fuel tax, this was supported by liberal voters. It was passed with 63% of voters voting yes. In column (2), the coefficient of emissions per mile is insignificant and has a magnitude close to 0. All other covariates have the same sign and similar significance level as in column (1). This boosts our confidence that column (1) indicates that people driving fuel efficient vehicles are more incentivized to support a higher fuel tax.[20]

Shifts in the Negative Correlation Between Local Air Pollution Exposure and GHG Emissions Production

Consider an economy featuring no electric vehicles and where most people live close to the city center. These center city residents live in dense areas and a large share use public transit. In this case, a negative correlation between outdoor air pollution exposure as measured by PM2.5 and per-capita carbon dioxide will emerge. Urban residents are exposed to more pollution due to local scale effects, but each of them produces less of the global externality (carbon dioxide).

[19] https://lao.ca.gov/BallotAnalysis/Proposition?number=6&year=2018

[20] When we use total emissions instead of emissions per mile as the explanatory variable, the coefficients reported in both columns have the same sign and significance and are numerically close to the corresponding coefficients in Table 5.

Boeing, Lu, and Pilgram (2023) have found that low-income people are disproportionally affected by urban pollution, even though they rarely drive. Many low-income neighborhoods are located near highway entrances where higher-income people drive through. In contrast, those who live far from the cities generate more carbon emissions but are exposed to less air pollution (Carozzi and Roth 2023). Pollution gets diluted in low-density suburbs.

As rich suburbanites opt to drive EVs, this will simultaneously reduce the global GHG externality and the smog externality that urban dwellers bear the incidence of. We present some descriptive evidence based on this point. For each zip code's daily air pollution data in 2020 and 2022, we calculate the 95th, 90th, 75th, median, and mean pollution of each zip code, plotting them as a function of the distance to the city center in Figure 6.[21] In 2020, wildfires caused more than $12 billion in damages in California, whereas 2022 was a "quiet" year for fires. We compare these two years to study the differential impact of wildfires on urban and suburban households' exposure to PM2.5 pollution.

In 2022, households farther away from downtown were exposed to less local air pollution. The pollution flattens at 40 miles onward, except at the 95th percentile, where emissions exposure exhibits an inverted-U shape. We interpret this as the PM2.5 spike on wildfire days that primarily affected exurban and rural residents. Low-emission households often live in the downtown where pollutants concentrate. As they move farther out, their own transport externality increases because they drive dirty vehicles more miles, but their PM2.5 exposure declines. The introduction of EVs shifts the pollution exposure function down, especially in urban neighborhoods.

In 2020, for all households, due to wildfire smoke, emissions at every percentile were higher than those in 2022. The median and mean exposure was 7.9 and 12 $\mu g/m^3$ respectively, in comparison to 6.9 and 8.1 $\mu g/m^3$ in 2022. The median and the 75th percentile pollution declined as the distance from the city increases, but emissions at other percentiles had an inverted-U shape. At the 90th and the 95th percentile, emissions shot up in areas beyond 60 miles from the city. The peak emissions in these exurban areas could reach over 70 $\mu g/m^3$. Intertemporally, this level was five times higher than the peak pollution in the same areas in 2022. Cross-sectionally, it was twice as much as the peak pollution in urban areas in 2020. As wildfires grow in frequency and severity,

[21] The original data is from the EPA: https://www.epa.gov/outdoor-air-quality-data/download-daily-data

households face a tradeoff in choosing their residential locations. While suburban areas feature lower pollution in normal years, local pollution would spike in wildfire years.

Going forward, WFH-induced suburbanization could accelerate environmental gains. The traditional view is that emissions increase as cities become more spread out (Glaeser and Kahn 2004; Bento et al. 2005). Yet, because suburban households are more likely to own solar panels and EVs, such technique effects offset the emissions induced by scale effects (Kahn 2008). Suburbanization can also attenuate the equity concerns as low-income households in the city would be exposed to less pollution from driving when suburban households drive EVs and commute less in the WFH economy.

Conclusion

California has been the nation's leader on environmental policy (Fredriksson and Millimet 2002). The state is wealthy and educated and is home to many environmentalists who are willing to be the "green" policy guinea pig. It is no accident that California features the largest share of registered electric vehicles in the nation. We have used several California datasets to describe the relationship between household carbon emissions, income, and suburbanization.

Richer people used to create more carbon emissions as they drive more and consume more energy. The rise of EVs, especially high-end products such as Tesla, and the rise of the bundle of EV and solar chip away at this logic. The growing menu of EVs offers the possibility of accelerated "green progress". Using recent data, we document that the carbon emissions Engel Curve for the household transportation and electricity sector is shifting down. These emissions gradients with respect to income are also shrinking. We show that upper-middle class people have purchased more EVs and installed more solar panels. Even though these households drive more and use more energy, their emissions can decline as technique and composition effects offset the scale effect. The ownership of EVs will continue its upward trajectory leading up to California's mandated ban on the sale of gas cars by 2035. At the same time, we have documented that the income elasticity of natural gas consumption has increased in recent years as more people are working from home. This diverging pattern across sectors highlights the importance of giving households a larger menu of products such as electric heat pumps for encouraging each household sector to decarbonize.

While the transportation sector is decarbonizing, its GHG emissions could remain high for years because the vehicle fleets are highly durable (Davis and Kahn 2010). Given that people can own and operate a vehicle for decades, it can take a long time for the average fleet fuel efficiency to increase even when new models have much lower emissions (Gruenspecht 1982; Kahn and Schwartz 2008; Jacobsen et. al. 2022). Meanwhile, going forward, suburban WFH workers are even less likely to use public transit as they make fewer trips to the center city and often travel by car (Glaeser and Kahn 2004; Ramani and Bloom 2021; Kahn 2022).

Studies such as Levinson (2016) have shown that environmental regulations contribute to only a small proportion of the observed emissions reductions in California. In this paper, we do not examine the causal role of government policies such as EV subsidies and RPS in flattening the emissions Engel curves. Future research could study this issue by using subsidy dynamics as an instrumental variable for green product prices. This approach would yield a structural estimate of the demand for green products, which could be used to predict how subsidies accelerate the pace of green product adoption.

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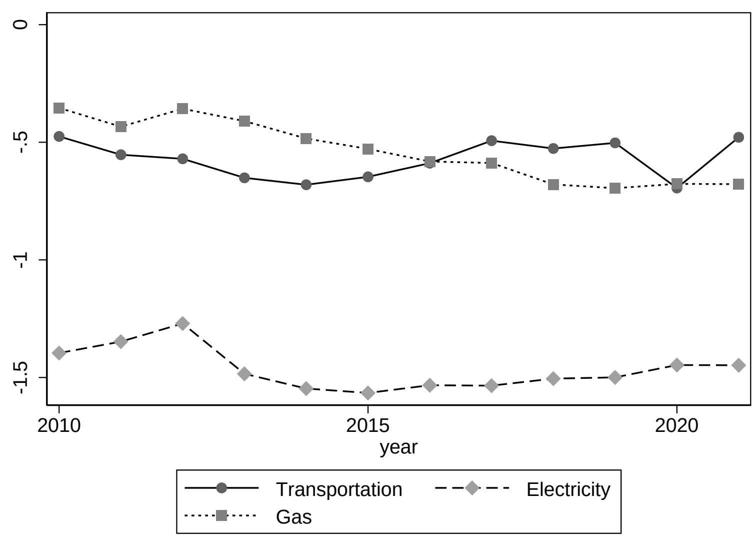
Figure 1

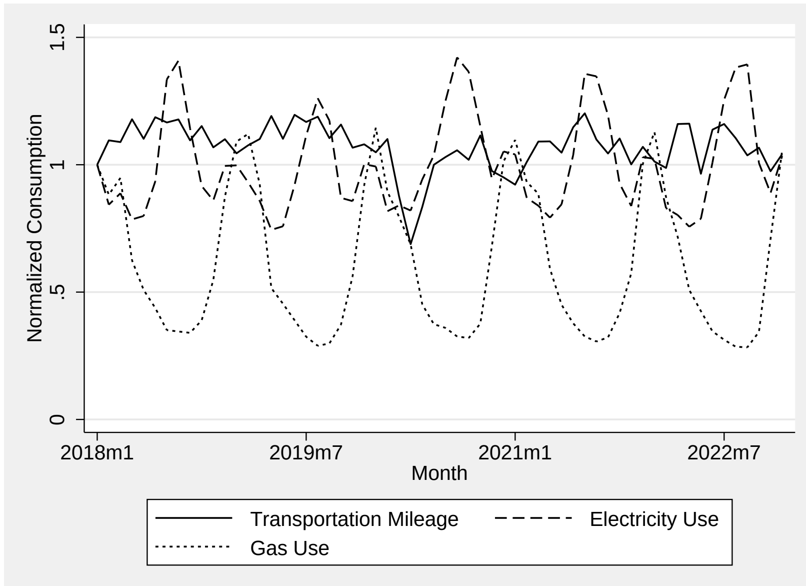
Benchmarking Energy Consumption in California against the Rest of the Nation



We calculate the mean and standard deviation unweighted by state population. The trends are similar.

Figure 2

Time Series of Energy Consumption

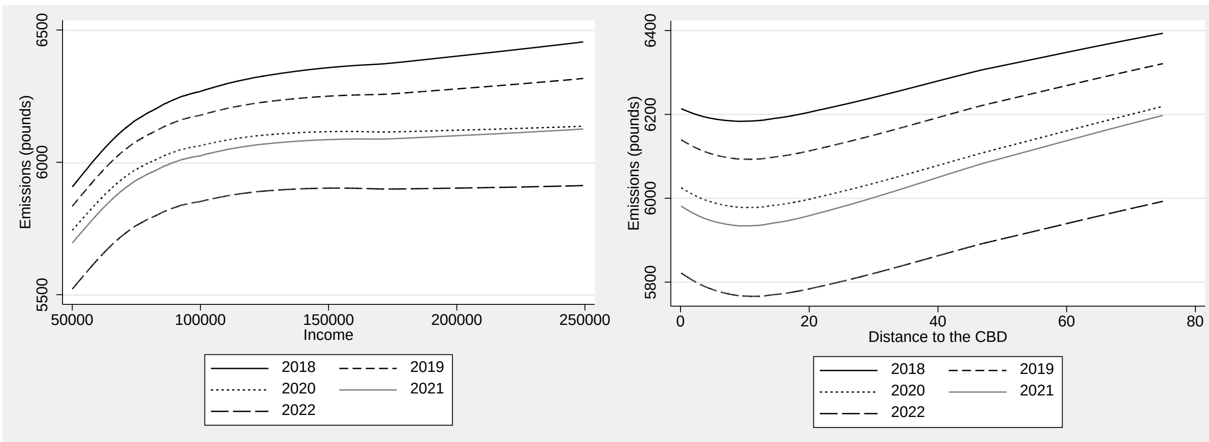


We normalize the three variables to their values in January 2018.

Figure 3

Carbon Emissions Engel Curves in the Transportation and the Electricity Sector

(a) Transportation



(b) Electricity

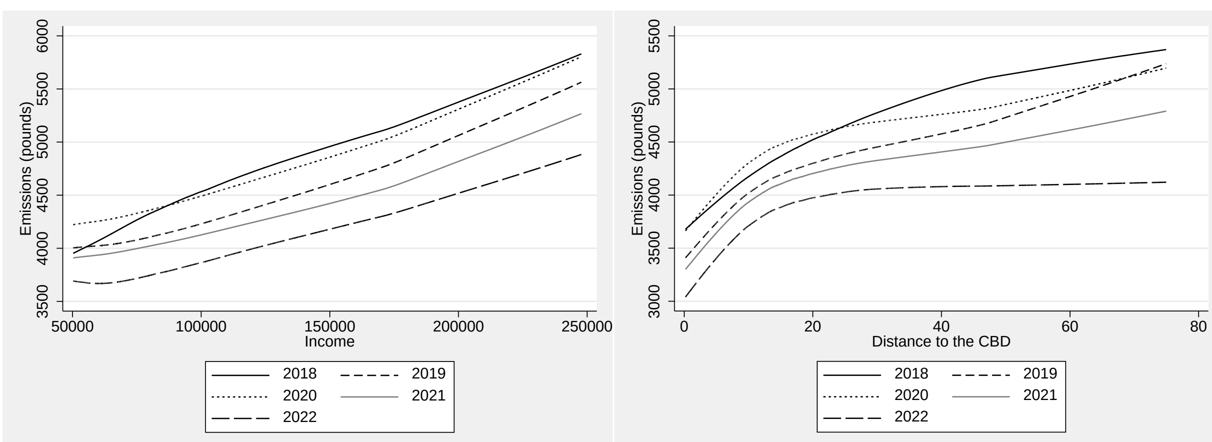
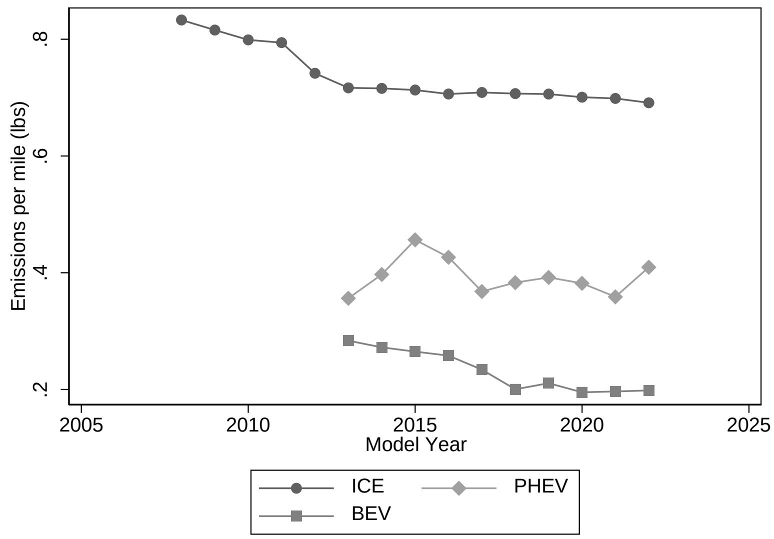


Figure 4

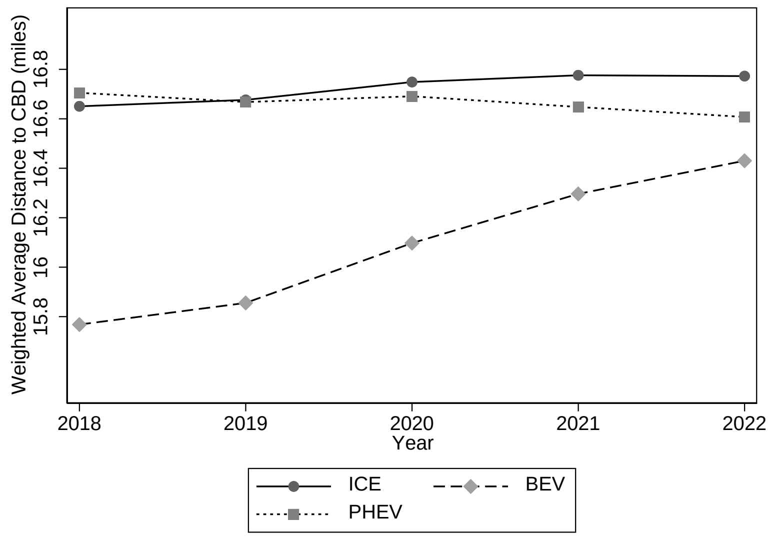
California Private Vehicle Emissions Per Mile by Model Year and Fuel Type



BEVs are fully electric vehicles. To calculate the emissions/mile of PHEVs, we assume it is driven on gasoline and electricity each half of the total mileage.

Figure 5

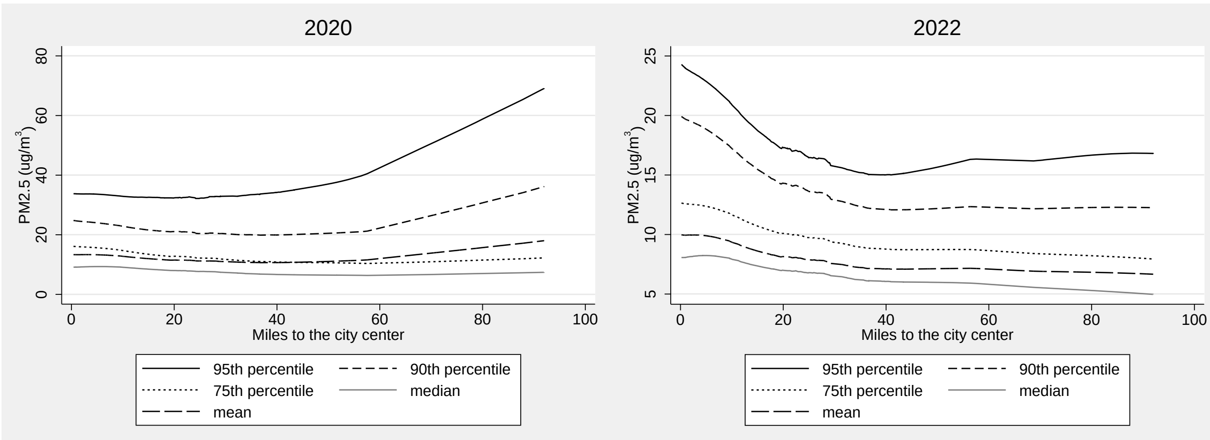
The Geography of New Vehicle Registration



To calculate the weighted average, we weight each zip code's distance to the CBD by the count of EVs in the zip code.

Figure 6

Air Pollution Exposure



Using each zip code's daily air pollution data in 2020 and 2022, we calculate its 99th, 90th, 75th, median, and mean pollution level and plot it against distance.

Table 1

Annual Carbon Dioxide Emissions Summary Statistics

Year	Weighted by population	Mean	25th	Median	75th
2018	No	14637	13112	14028	15208
	Yes	14316	13007	13791	14723
2019	No	14144	12885	13766	14843
	Yes	13671	12716	13481	14350
2020	No	14795	13416	14445	15542
	Yes	14329	13285	14182	15107
2021	No	14671	13270	14271	15437
	Yes	14137	13253	14022	15706
2022	No	14012	12960	14357	15256
	Yes	13797	12763	13760	14670

Our zip code panel dataset includes the annual carbon emissions per household. This table shows their distribution by year. The amount of emissions is in pounds.

Table 2

Household Carbon Engel Curve Regressions

	(1) 2018	(2) 2019	(3) 2020	(4) 2021	(5) 2022
	log(Total emissions)				
log(Income)	0.156***	0.174***	0.173***	0.171***	0.153***
	(0.0259)	(0.0218)	(0.0227)	(0.0225)	(0.0209)
log(Distance)	0.0279*	0.0386***	0.0358***	0.0343***	0.0325***
	(0.0148)	(0.00920)	(0.00920)	(0.00943)	(0.00843)
Liberal	-0.168*	-0.125	-0.163**	-0.120	-0.165**
	(0.0928)	(0.0782)	(0.0794)	(0.0783)	(0.0683)
log(Temperature)	0.201	0.152	0.334	0.183	0.257
	(0.313)	(0.303)	(0.304)	(0.293)	(0.232)
Constant	7.033***	6.955***	6.257***	6.851***	6.696***
	(1.390)	(1.350)	(1.357)	(1.319)	(1.053)
County FE	Yes	Yes	Yes	Yes	Yes
Observations	994	994	993	993	993
R-squared	0.431	0.549	0.552	0.527	0.525

Standard errors are clustered by zip code.
*** p<0.01, ** p<0.05, * p<0.1

This table shows the estimation from equation (6). Total emissions refer to the average household emissions across all sectors (transportation, gas, and electricity).

The sample includes zip codes that (1) is within 75 miles from the city; (2) within the territory of PGE, SCE, and SDGE where electricity and gas consumption data is available.

Table 3

Carbon Engel Curves by Sector

(a) Transportation

	(1) 2018	(2) 2019	(3) 2020	(4) 2021	(5) 2022
	log(Total emissions)				
log(Income)	0.0700***	0.0647***	0.0549***	0.0561***	0.0490***
	(0.00456)	(0.00464)	(0.00463)	(0.00472)	(0.00475)
log(Distance)	0.00407**	0.00389**	0.00397**	0.00391*	0.00294
	(0.00198)	(0.00198)	(0.00200)	(0.00202)	(0.00204)
Liberal	-0.0363*	-0.0386**	-0.0450**	-0.0437**	-0.0406**
	(0.0187)	(0.0191)	(0.0189)	(0.0192)	(0.0194)
Constant	7.914***	7.959***	8.054***	8.032***	8.088***
	(0.0592)	(0.0600)	(0.0599)	(0.0610)	(0.0612)
County FE	Yes	Yes	Yes	Yes	Yes
Observations	1,635	1,634	1,634	1,632	1,627
R-squared	0.502	0.497	0.460	0.448	0.403

Standard errors are clustered by zip code.
*** p<0.01, ** p<0.05, * p<0.1

(b) Electricity

	(1) 2018	(2) 2019	(3) 2020	(4) 2021	(5) 2022
	log(Total emissions)				
log(Income)	0.112***	0.118***	0.0970***	0.0988***	0.0759**
	(0.0279)	(0.0299)	(0.0297)	(0.0298)	(0.0309)
log(Distance)	0.0511***	0.0520***	0.0491***	0.0493***	0.0672***
	(0.00964)	(0.01000)	(0.00980)	(0.00981)	(0.0118)
Liberal	-0.570***	-0.588***	-0.602***	-0.558***	-0.813***
	(0.105)	(0.117)	(0.115)	(0.115)	(0.108)
log(Temperature)	0.594***	0.613***	0.753***	0.834***	0.886***
	(0.129)	(0.142)	(0.145)	(0.141)	(0.159)
Constant	2.936***	2.798***	2.710***	2.355***	2.402***
	(0.477)	(0.511)	(0.522)	(0.512)	(0.595)
County FE	Yes	Yes	Yes	Yes	Yes
Observations	14,451	14,767	14,657	14,840	15,130
R-squared	0.553	0.585	0.552	0.523	0.372

Standard errors are clustered by zip code.
*** p<0.01, ** p<0.05, * p<0.1

(c) Gas

	(1) 2018	(2) 2019	(3) 2020	(4) 2021	(5) 2022
	log(Total emissions)				
log(Income)	0.187***	0.213***	0.248***	0.253***	0.219***
	(0.0279)	(0.0243)	(0.0259)	(0.0263)	(0.0255)
log(Distance)	0.0257***	0.0258***	0.0204**	0.0155	0.0173
	(0.00881)	(0.00922)	(0.00939)	(0.0107)	(0.0107)
Liberal	0.199**	0.0893	0.0535	0.138	0.120
	(0.0895)	(0.0814)	(0.0833)	(0.0864)	(0.0843)
log(Temperature)	-0.662***	-0.700***	-0.655***	-0.731***	-0.686***
	(0.115)	(0.110)	(0.109)	(0.112)	(0.108)
Constant	5.399***	5.297***	4.831***	4.939***	5.155***
	(0.476)	(0.447)	(0.461)	(0.472)	(0.462)
County FE	Yes	Yes	Yes	Yes	Yes
Observations	13,945	14,047	14,028	14,027	13,941
R-squared	0.056	0.055	0.070	0.073	0.054

Standard errors are clustered by zip code.
*** p<0.01, ** p<0.05, * p<0.1

This table shows the estimation from equation (6).

The transportation regression is estimated using all zip codes within 75 miles from the city. The electricity and gas regressions are estimated on zip codes meeting criteria (1) and (2) in Table 2 notes.

Table 4

The Correlates of Green Product Utilization by California Zip Code

	(1) EV	(2) Solar	(3) Bundle	(4) Tesla%	(5) Public transit%	(6) log(Emissions per mile)
Trend	0.283***	0.158***	0.333***	0.0716***	-0.00301***	-0.0168***
	(0.00229)	(0.00187)	(0.00507)	(0.000742)	(0.000241)	(0.000110)
log(Income)	2.275***	0.623***	2.254***	0.248***	-0.0213***	-0.0218***
	(0.114)	(0.170)	(0.165)	(0.00810)	(0.00571)	(0.00313)
log(Distance)	-0.477***	0.107	-0.0449	-0.00652*	-0.0117***	0.00593***
	(0.0470)	(0.0746)	(0.0730)	(0.00363)	(0.00261)	(0.00104)
Liberal	1.047**	-1.707***	-1.127*	-0.110***	0.0941***	-0.0372***
	(0.483)	(0.624)	(0.638)	(0.0359)	(0.0212)	(0.0126)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Model	NB	NB	NB	OLS	OLS	OLS
Dispersion parameter	0.365***	1.28***	0.885***	/	/	/
Observations	8,345	8,345	8,345	4,603	8,310	8,162
R-squared	/	/	/	0.747	0.746	0.719

Standard errors are clustered by zip code.
*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates based on equation (7). In columns except column (4), the sample includes all zip codes within 75 miles from the city. The dependent variable is the count of each type of "green" product, the percentage of population commuting using public transit in each zip code, and emissions per mile. In column (4), the sample includes zip code with at least one EV, and the dependent variable is the count of Tesla as a percentage of all EVs.

Table 5

The Correlates of Support for Raising the Fuel Tax in California

	(1) Proposition 6 in 2018: No	(2) Proposition 2 in 2018: Yes
log(Emissions per mile)	-0.0776***	0.0202
	(0.0246)	(0.0221)
log(Distance)	-0.0115***	-0.0136***
	(0.00143)	(0.00151)
log(Income)	-0.0462***	-0.0586***
	(0.00590)	(0.00553)
Liberal	0.839***	0.758***
	(0.0216)	(0.0151)
Education	0.257***	0.166***
	(0.00949)	(0.0102)
CBSA FE	Yes	Yes
Observations	1,643	1,643
R-squared	0.935	0.927

Standard errors are clustered by zip code.
*** p<0.01, ** p<0.05, * p<0.1

This table shows the estimation from equation (8). The dependent variable is the proportion of the zip code population who vote against Proposition 6 (column 1) and who vote for Proposition 2 (column 2).