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Beyond the Early Era of EVs: Evidence from the Staggered Rollout of the HOV Lane Network in California

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Abstract

Local policies like high-occupancy vehicle (HOV) lane exemptions play an important role in encouraging electric vehicle (EV) adoption, a key component of climate programs. Using tract-level vehicle registrations and detailed data on HOV lane openings from 2012 to 2024, we study the causal effect of HOV policies on EV adoption in California. We find that HOV exemptions significantly increased EV uptake, with effects that were stronger in later years as EV technology and markets advanced. The impact is also greater in more congested areas with longer commutes and concentrated in higher-income tracts, highlighting both the effectiveness and distributional implications of HOV incentives.

Keywords: electric vehicles, transportation policy, environmental subsidy, HOV lane access

JEL codes: H23, Q58, R48

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1 Introduction

The electrification of the transportation sector, especially for passenger vehicles, is widely regarded as a key component of climate policy programs aimed at reducing greenhouse gas (GHG) emissions and local air pollution around the world. Global electric vehicle (EV) sales continue to set new records, with policy support playing a particularly important role in stimulating consumer adoption.[1] In Europe, policymakers continue to pursue ambitious decarbonization targets supported by policies to accelerate the EV transition, while in the U.S., federal support for EVs is being rolled back, including the elimination of the federal tax credit for EV purchases.[2] As a part of this shift, the federal government is terminating California's quarter-century-long Clean Air Vehicle Decal program in September 2025, ending HOV exemptions for EVs.[3] This policy change may have significant implications as access to HOV lanes can make EV adoption especially attractive for consumers commuting in highly congested metropolitan areas such as Los Angeles and the San Francisco Bay Area.[4]

In this paper, we study the causal effect of HOV lane access on EV adoption in California. Using detailed census tract-level data on new vehicle registrations from 2012 to 2024 combined with a panel dataset tracking the opening and closing of each HOV lane over the same time period, we exploit the staggered expansion of the HOV network to identify the impact of HOV lane access on consumer uptake of EVs across the state of California. While prior research has documented sizeable effects of HOV incentives in the early years of the U.S. EV market (DeShazo et al., 2017; Jenn et al., 2018), the EV market and access to the HOV network have evolved substantially in recent years. Coupled with the availability of much longer time-series and census tract–level registration data, these developments highlight the importance of examining the effectiveness of HOV exemptions within the context of a more mature EV market in a rapidly changing policy environment.

The main results demonstrate a strong, positive, and statistically significant impact of HOV lane exemptions on EV adoption in California between 2012 and 2024. Using a two-way fixed-effects (TWFE) estimator, our most conservative estimates indicate that the introduction of a new

[1] In 2024, global EV sales exceeded 17 million, raising EVs as a share of new vehicle sales to over 20% (International Energy Agency, 2025).

[2] See `https://commission.europa.eu/news-and-media/news/eu-climate-law-new-way-reach-2040-targets-2025-07-02_en` and `https://www.edmunds.com/fuel-economy/the-ins-and-outs-of-electric-vehicle-tax-credits.html` for more detail.

[3] `https://www.dmv.ca.gov/portal/vehicle-registration/license-plates-decals-and-placards/clean-air-vehicle-decals-for-using-carpool-lanes`

[4] `https://www.latimes.com/science/la-me-1111-california-commute-20151111-story.html`

HOV lane segment within 5 miles of a census tract population centroid leads to a 1.2 percentage point increase in the tract-level EV market share, which translates to an increase of 16 percent relative to the mean EV share. To address concerns over bias since our setting involves a staggered treatment and potentially heterogeneous treatment effects across cohorts over time, we replicate our findings using a stacked DiD estimator and the Callaway and Sant'Anna (2021) staggered DiD estimator. Both alternative approaches produce statistically significant estimates that are very close in magnitude to our baseline results.

One concern is that our estimates may depend on how we define HOV lane availability and proximity, specifically whether we use population rather than geographic centroids of census tracts and the choice of the distance threshold. To alleviate such concerns, we assess the robustness of our estimates. First, we replace population centroids with geographic centroids. Second, we vary the distance threshold from one to ten miles in one-mile increments. The results indicate that the estimated effect of HOV lanes on EV adoption is stable across these alternative definitions.

Consumers may also be influenced not only by whether they have access to at least one HOV lane within their vicinity, but by the extent of HOV lane availability in their area. We therefore extend our baseline analysis which focuses on the extensive margin of HOV lane access by examining whether EV adoption responds to variation in the number of nearby HOV segments. The results indicate that greater HOV lane availability is associated with a statistically significant increase in consumer EV uptake, suggesting that the intensity of HOV lane access also plays an important role in driving consumer adoption.

A natural question, extending beyond prior research that focused on the early U.S. EV market, is whether and how the impact of HOV lane exemptions has changed over time as the market matured. We address this point by further exploring heterogeneity in the effects of HOV lane exemptions. The estimates indicate that the policy had a larger impact in the later part of the sample period, when EV technology and markets were more advanced. This finding suggests that the effectiveness of HOV exemptions may change with market maturity, reinforcing the importance of broader technological and market conditions for policy design.

The value of HOV lane exemptions is also likely shaped by commuting patterns. In census tracts where residents tend to travel during congested commuting hours or where average commute times are longer, access to HOV lanes is going to be particularly valuable to consumers. Consistent with greater benefits in tracts with such commuting conditions, our estimates show that the effects of HOV policies are stronger in tracts with higher shares of peak-time commuters and in those areas where commutes are more time-intensive. This finding underscores that the benefits of HOV policies are greater where congestion pressures are most acute, making them especially salient for consumers facing time-consuming daily travel.

Finally, the distribution of benefits from HOV exemptions reveals an important equity concern. We find that the estimated impact of HOV lane access is concentrated entirely in higher-income tracts, suggesting that the policy disproportionately encouraged EV adoption among wealthier households. This distributional pattern highlights that while HOV exemptions can be effective, they may also reinforce existing disparities in access to clean technology.

This paper contributes to a growing economics literature on EVs. Prior work has shown that EV adoption responds to several factors, including access to charging infrastructure (Li et al., 2017; Springel, 2021; Li, 2023), subsidies and tax incentives (Yan and Eskeland, 2018; Clinton and Steinberg, 2019; Muehlegger and Rapson, 2022; Haan et al., 2023), household income (Borenstein and Davis, 2016; Gillingham et al., 2023), gasoline prices (Bushnell et al., forthcoming), peer effects (Tebbe, 2023) and local incentives such as exemptions from tolls and congestion pricing (Mersky et al., 2016; Isaksen and Johansen, 2021).[5] In recent work related to this paper, Halse et al. (2025) exploit household-level variation in priority lane access on work travel in Norway to demonstrate that an additional 0.5 kilometers of priority lane access on work commute led a 2.8 percent increase in battery electric vehicles (BEVs) sales between 2015 and 2017. Relative to this literature, our paper contributes by examining the impact of local incentives over a long period of time in a context where the EV market has developed substantially, allowing us to evaluate the evolving role of incentives beyond the early adoption phase.

More specifically, our work contributes to an emerging literature in economics examining the causal effect of HOV lane access policies on EV adoption. While prior research found no significant relationship between HOV policies and hybrid vehicle adoption (Diamond, 2009; Gallagher and Muehlegger, 2011), studies of the early plug-in electric vehicle (PEV) market shows that HOV lane exemptions were strong positive drivers of EV adoption (Sheldon and DeShazo, 2017; Jenn et al., 2018). In particular, Sheldon and DeShazo (2017) use cross-sectional variation to show evidence with a generalized propensity score approach that HOV lane exemptions in California led to a quarter of PEV sales between 2010 and 2013. Our contribution builds on this early evidence by

[5] The broader EV literature also sheds light on how much EVs are driven (Burlig et al., 2021), how EV drivers value refueling time (Dorsey et al., 2025), what an EV replaces (Xing et al., 2021), how EV adoption is associated with political ideology (Davis et al., 2025), how EVs affect emissions and local air quality (Holland et al., 2016, 2020; Gillingham et al., 2025), and how the design of EV subsidies affects disparities in urban air pollution (Jacqz and Johnston, 2024).

examining a more mature U.S. EV market with richer data, which allows us to exploit the staggered expansion of the HOV network for identification. Unlike in the early stages of the market, we study a period in which hundreds of EV models, including larger vehicle classes, are commercially available, battery technology has advanced considerably, charging networks have expanded substantially, and EVs are better understood by consumers. In addition, our empirical setting is particularly well suited for causal analysis: we observe EV adoption and HOV lane availability at the census-tract level, and we construct a panel following the evolution of the HOV lane network over twelve years, during which many new HOV segments opened. This panel structure allows us to implement a staggered DiD design that credibly identifies the impact of HOV access on EV adoption.

The paper proceeds as follows. Section 2 provides an overview of HOV policies in California and describes how HOV lane exemptions apply to EV drivers. Section 3 discusses the data sources and the empirical setup. Section 4 presents the empirical strategy for analyzing the impact of HOV lane exemptions on EV adoption. Section 5 describes the main results, along with additional robustness checks and extensions. Finally, Section 6 concludes.

2 Policy Background

California has long been committed to reducing GHG emissions and local air pollution across its industries and economic sectors. Given the dominant role of vehicles and transportation fuels in carbon emissions, the electrification of the state's transportation sector has been an explicit policy priority in order to meet the state's ambitious health-based air quality standards and GHG emissions goals. The California Air Resources Board (CARB) first adopted the Zero-Emission Vehicle (ZEV) requirement in 1990 as part of the Low-Emission Vehicle Regulation, and this requirement has since been modified and amended several time over the last 35 years. In addition, state and local authorities have implemented a variety of incentives and policy programs to support the state's transition to ZEVs, including EV purchase rebates, grants for charging infrastructure and technology, vehicle replacement and upgrade grants, and access to HOV lanes, among other measures.

HOV lanes, defined as lanes requiring a minimum number of vehicle occupants, were introduced in higher population density areas to stimulate and encourage ridesharing on California's highways. Operational practices for HOV lanes vary between Northern and Southern California, reflecting regional differences in traffic and commuting patterns. In Northern California, HOV restriction typically only apply during weekday peak hours and the lanes are otherwise open to all drivers.

By contrast, in Southern California, HOV lanes are generally operated on a continuous basis, with restrictions enforced at all times. The main objective of HOV lanes is to alleviate congestion and to promote ridesharing practices in order to reduce fuel consumption and mitigate air pollution. In alignment with these goals, an exemption was extended to clean-air vehicles with appropriate decals allowing them to use HOV lanes regardless of the number of vehicle occupants.

California's Clean Air Vehicle Decal Program first began granting HOV lane exemptions for qualifying vehicles in 2005 and is scheduled to expire on September 30, 2025. The program went through several changes over the years, including shifts in decal colors, eligible vehicle categories, and income-based provisions. However, we note that during our observed period, qualifying BEVs and plug-in hybrid electric vehicles (PHEVs) were always eligible.[6]

While HOV lane exemption for EVs may encourage EV adoption in California, it is also important to consider the costs of such a program. Granting access to existing HOV lanes for EVs implies relatively low upfront capital investment. However, unintended consequences of such policies may lead to an increase in the total number of vehicles on the highways by incentivizing residents who otherwise may not have purchased a vehicle to buy/lease an EV, or encourage residents who previously may have avoided peak hours to commute during the busiest periods. Such outcomes ultimately can undermine the goal of the program which was to relieve congestion and improving local air quality. In particular, Bento et al. (2014) find that the original yellow decal program, which granted free single-occupant HOV lane access to hybrid vehicles, led to higher congestion costs for carpoolers in the greater Los Angeles metropolitan area.

The HOV lane exemption program has been widely popular among residents of California. The more than two decades old program has issued more than one million decals to eligible low- and

[6]HOV lane exemption for qualifying vehicles first took effect in 2005, granting free single-occupant access and issuing white decals to an unlimited number of qualifying BEVs, hydrogen fuel cell vehicles (FCEVs), and advanced compressed natural gas (CNG) vehicles from 2000 until 2019. The original yellow decals were issued to conventional hybrid vehicles from 2005 to 2011 while the original green decals were issued to plug-in hybrid vehicles from 2012 until 2019. Income-based decals were also made available to new owners of qualifying used vehicles meeting specific requirements from 2020 to 2024. The original green decals for PHEVs were initially only available in limited quantities. This limit was increased multiple times until the statutory limit was eventually removed effective of September 18, 2016 and an unlimited number of decals were available until the program ultimately expired in 2019. With the exception of a few months in the beginning of 2016, the limit on available green decals for PHEVs was never binding. During these months, the California Department of Motor Vehicles continued to accept applications without payment to establish a queue should an additional amount of decals be authorized. Once the additional decals were approved when the limit was removed, individuals in the queue were notified to submit payment. The current program, established in 2019, continues to allow free single-occupant use of HOV lanes for qualifying BEVs, PHEVs, FCEVs and CNG vehicles. The color of decals under the current program has changed every year, beginning with purple for 2019, orange for 2020, blue for 2021, yellow for 2022, green for 2023, burgundy for 2024, and finally teal for 2025. For details on the history of decal programs, see `https://ww2.arb.ca.gov/our-work/programs/carpool-stickers`.

-zero emission vehicles allowing them to drive solo in HOV lanes.[7] In 2013, the California Center for Sustainable Energy conducted a survey of California drivers and found that 59% of the survey respondents stated that HOV lane access was "extremely" or "very important" in their decision to purchase an EV.[8] Bento et al. (2014) estimate that the maximum rent for hybrid vehicles to be able to use the I-10 HOV lane was $743 per year on average. Similarly, Sheldon et al. (2017) find that the average respondent in their California new car buyer survey was willing to pay about $900 for free single-occupant access to HOV lanes.

3 Data and Empirical Setup

3.1 Data

The primary dataset for our analysis is the Experian North American Vehicle Database.[9] This proprietary dataset, compiled by Experian from state department of motor vehicle records and additional sources, covers the universe of new vehicle registrations in the United States. The Experian data are particularly well-suited to our research design for two reasons. First, they record the census tract in which the vehicle was initially registered, regardless of where it was purchased or leased. This ensures that all vehicles are assigned to the census tract where the household resides. Second, the Experian data capture both sales and leases. Leasing is a common practice in the U.S. and is particularly prevalent among EVs. The share of new vehicles leased fluctuates considerably during our sample period, rising from 24.79% in 2012 to 30.64% in 2019 before falling to 17.72% in 2022 and then increasing to 24.49% in 2024.[10] To capture EV adoption, we construct the "EV Share," defined as the share of all new vehicle registrations that are EVs. Our definition of EVs includes both plug-in hybrid EVs (e.g., the Chevrolet Volt) and battery EVs (e.g., the Nissan Leaf). We observe monthly EV shares at the census tract level for the 2012-2024 period. Note that Experian uses the 2020 census tract definitions, which we also adopt.

The EV market has evolved significantly during our observed time period. Figure 1 illustrates the distribution of EV shares at the tract level from the beginning of the sample period (January 2012) to the end (December 2024). EV adoption rates have increased substantially throughout California, yet there remains considerable heterogeneity in adoption rates in 2024. As Figure 1

[7] https://www.sfchronicle.com/california/article/carpool-clean-air-vehicle-decals-19973886.php

[8] February 2014 Survey Results, Center for Sustainable Energy, 2014, https://energycenter.org/sites/default/files/docs/nav/transportation/cvrp/survey-results/California_PEV_Owner_Survey_3.pdf

[9] See https://www.experian.com/automotive/auto-vehicle-data for details.

[10] For details, see the Q4 editions of Experian Automotive's State of the Automotive Finance Market (2012, 2016, 2020, 2023, and 2024).

shows, over 90% of California's census tracts had an EV share below 1% at the beginning of 2012. By contrast, at the end of 2024, 50% of California's census tracts had an EV share higher than 25%.

To construct our measure of HOV lanes, we utilize the California HOV lane inventory compiled by Caltrans.[11] This inventory provides a snapshot of the HOV lanes in California.[12] HOV lanes are defined by district, route, driving direction, endpoint postmiles, and endpoint counties. While the inventory reflects a snapshot HOV lanes as of early 2025, it also includes a description of segment openings and closings, allowing us to recover a monthly panel of HOV lane segments between 2012 and 2024.[13] HOV lane segments are specified based on the definition of the HOV lane inventory and can vary substantially in length from less than 0.1 miles to over 40 miles. An HOV lane segment is defined as an HOV lane (or part of an HOV lane) that became operational on a given date, route, driving direction (Southbound, Northbound, Westbound, or Eastbound), and Caltrans district.[14] GIS shapefiles of California HOV lanes were also obtained from Caltrans.[15]

Figure 2 shows how the total number of HOV lane segments evolved between 2012 and 2024. At the beginning of our sample period, there were already 114 HOV segments available to EV drivers. This number increased substantially over the next 12 years, reaching nearly 200 by the end of 2024. The largest expansions occurred between 2014 and 2017 and again between 2022 and 2023.

While Figure 2 highlights changes in the number of segments over time, Figure 3 illustrates their geographic distribution. The figure maps all HOV lane segments that were operational at some point during our sample period (2012–2024) against California's 2024 road network.[16] The HOV network spans many urban centers in counties including Los Angeles, Sacramento, San Bernardino, San Diego, San Francisco, San Joaquin, San Mateo, and Santa Barbara, among others.

We use the U.S. Census Bureau TIGER/Line Shapefiles to obtain maps of California at the state, county, and tract levels, as well as the geographic centroids of tracts and the network of

[11] See `https://dot.ca.gov/programs/traffic-operations/hov` for details.

[12] This paper uses the snapshot from early 2025.

[13] Missing opening and closing dates were recovered from several sources, including earlier versions of the HOV lane inventory from 2010 and 2013 obtained from the website of Caltrans via the Wayback Machine, via email correspondence with the HOV Program Coordinator in June-July 2025, based on the annual California HOV Facilities Degradation Reports as well as based on annual HOV reports for Districts 4 and 7. All HOV reports were obtained from the website of Caltrans.

[14] Caltrans is divided into 12 districts, each responsible for transportation within a specific geographic region defined by county boundaries. See `https://dot.ca.gov/caltrans-near-me` for details and a map of the Caltrans districts.

[15] The GIS shapefile used in this paper provided by Caltrans is based on a snapshot of the HOV lane inventory from August 21, 2024. HOV lanes that opened between August 21, 2024 and December 31, 2024 were obtained based on the HOV lane description in the HOV lane inventory using OpenStreetMap (`/www.openstreetmap.org`).

[16] The road network is defined to include primary (e.g., Interstate highways) and secondary roads (e.g., U.S. and State highways).

primary and secondary roads.[17] The maps and tract centroids are based on the 2020 TIGER/Line files, while the road network comes from the 2024 release.[18] Since geographic centroids may not accurately represent accessibility when the population is unevenly distributed within a tract, we use population centroids from the IPUMS National Historical Geographic Information System.[19] Population centroids are weighted by the spatial distribution of residents and therefore provide a better approximation of the "average location" of people within tracts. This is particularly relevant for our analysis, where we measure the distance to the nearest HOV lanes in order to assess their impact on EV adoption.

We also include counts of EV charging stations in some specifications. Previous research has shown that charging availability is an important driver of EV adoption as a denser charging network increases the value of owning an EV (Li et al., 2017; Springel, 2021). We compiled tract-by-year counts of Level 2 and Level 3 chargers using data from the U.S. Department of Energy, Alternative Fuels Data Center (AFDC).[20]

Finally, we use data from the 2008-2012 American Community Survey to obtain tract-level demographic, commute, and other characteristics in the baseline period.[21]

3.2 Treatment Assignment

We define treatment based on the entry of HOV lane segments in our empirical design as follows. We record the opening month and year of each HOV segment and intersect each segment with 5-mile radius circles centered on census tract population centroids. A census tract is defined as treated in a given month if at least one HOV lane segment is operational and available to EV drivers within the 5-mile circle during that month.

Figure 4 illustrates staggered treatment over time using San Diego County as a case study, which is the county with the largest number of treated tracts during the sample period. The figure shows how the gradual expansion of the HOV lane network led to more tracts being treated over time. In particular, gray tracts represent areas that are considered always treated during our sample period (2012–2024). These are tracts with one (or more) HOV lane segments within 5 miles of the tract's population centroid that opened before January 2012. The always-treated tracts are not included in our analysis.

[17] https://www.census.gov/programs-surveys/geography.html

[18] Note that the road network is only used for illustration purposes in Figure 3 and it is not used in our analysis.

[19] http://doi.org/10.18128/D050.V19.0

[20] https://afdc.energy.gov/data_download

[21] We obtain these data from the IPUMS National Historical Geographic Information System (http://doi.org/10.18128/D050.V19.0)

Census tracts that are not colored represent never-treated tracts, meaning they did not experience the opening of any HOV lane segments within 5 miles of their population centroid before the end of our sample period in December 2024. These tracts are always included in the control group in our empirical analysis.

Finally, red, orange, blue, and purple tracts represent treated tracts—that is, tracts that experienced the opening of a nearby HOV lane segment during our sample period. Specifically, red tracts became treated in March 2014, orange tracts in June 2016, blue tracts in February 2022, and purple tracts in June 2023.[22] The HOV lane segments themselves are color-coded to match the treatment status of the different tracts.

Figure 5 illustrates the evolution of the total number of census tracts with at least one HOV segment within 5 or 10 miles of their population centroid between 2012 and 2024. Of the 9,129 California census tracts, over 4,500 already had an HOV segment within 5 miles at the beginning of 2012.[23] By the end of 2024, nearly 60% of all census tracts had an HOV segment within 5 miles of their population centroid. When extending the distance to 10 miles, close to 70% of tracts had access to an HOV segment. The number of treated tracts at both distances increased gradually over time, with particularly large expansions between 2014 and 2016 and again in late 2021.

3.3 Summary Statistics

Our estimation sample consists of a panel of 4,323 census tracts in California observed monthly from January 2012 to December 2024. We exclude census tracts that are always treated during the sample period, since they provide no meaningful counterfactual variation. This restriction ensures that identification relies on comparisons between tracts that are eventually treated and those that are never treated.[24]

Appendix Table 1 presents summary statistics comparing our estimation sample to the full population of California census tracts, measured in the baseline year 2012. Overall, the estimation sample is fairly representative across a wide range of demographic variables. One notable difference is population density, which is on average higher in sample tracts, reflecting the fact that HOV lane expansion is concentrated in urban areas. These differences are important when considering

[22] In Section 5, we also consider specifications where the control group includes not-yet-treated tracts. In the San Diego County example, this means that for the red treated tracts, the control group includes not only the never-treated tracts but also the orange, blue, and purple tracts, all of which will be treated at a later date.

[23] As discussed above, we use the 2020 census tract definitions.

[24] We discuss identification in more detail in Section 4.

the external validity of the estimated treatment effects, and in particular with respect to rural and low-density areas.[25]

Table 1 reports 2012 baseline covariates comparing never-treated census tracts to census tracts that are eventually treated in the sample period. Therefore, this table compares observable characteristics of the treatment and control groups prior to the treatment of any tract. There are some important differences across groups. Unsurprisingly, since HOV lanes tend to be opened in metropolitan areas, not-yet-treated tracts (i.e., tracts where HOV lanes opened sometime during our sample period) have higher population densities on average than never treated tracts (i.e., tracts that do not observe any HOV lane openings during our sample period). At the same time, eventually-treated tracts have a lower share of workers who commute by car in the base period, which may reflect differences in public transportation availability. Given the differences in characteristics across treatment groups, our estimation strategy includes a full set of census tract fixed effects, which control for time-invariant differences in both observable and non-observable characteristics between census tracts.

4 Estimation Strategy

Our goal is to estimate the effect of access to HOV lanes on EV adoption. Our empirical approach exploits the staggered expansion of HOV lanes across time and space with a DiD research design.

We begin with the baseline model:

$$Y_{it} = \beta HOV_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{1}$$

where Y_{it} denotes the share of EVs among newly registered vehicles in census tract i and month t. The treatment variable HOV_{it} is a dummy variable equal to 1 if an HOV lane segment is operational and available to EV drivers within 5 miles of the population centroid of tract i in month t, and 0 otherwise. This variable switches from 0 to 1 in the month that an HOV lane segment opens near a census tract and remains 1 thereafter. The control group consists of census tracts in which no HOV lane segments are available within 5 miles of the population centroid during the entire sample period.[26]

[25] We return to this point in Section 5.2 where we assess the robustness of our results to alternative control groups and samples. In particular, we also consider a case where the control group is restricted to tracts in treated counties and a case where low-density tracts are dropped from the sample.

[26] We assess the robustness of the results to alternative treatment definitions in Section 5.2. Specifically, we vary the definition of a nearby HOV lane segment from 1 to 10 miles of a tract's population or geographic centroid. We also consider alternative specifications where the treatment intensity varies, as measured by the number of nearby HOV segments.

To control for time-invariant characteristics that vary across census tracts, such as geography or long-run road networks, we include census tract fixed effects α_i. To control for aggregate factors that vary over time, such as technological progress in EVs, state-level policy changes, or macroeconomic fluctuations, we include year-month fixed effects γ_t. ε_{it} denotes the error term. Standard errors are clustered at the census tract level to allow for serial correlation.

A potential threat to identification is the possibility that HOV lane expansions may correlate with tract-specific, time-varying factors that also influence EV adoption. For example, this could happen if new HOV segments are rolled out specifically in high-density areas with faster potential growth in EV adoption. To mitigate this type of concern, we also augment Equation 1 to include additional control variables. First, we include the tract-level count of charging stations to control for the possibility that the opening of new HOV segments is correlated with changes in charging infrastructure. We also include interactions between baseline tract-level observable characteristics (i.e., population density, household income, and commuting patterns) and time fixed effects. This allows tracts with differing observable characteristics in the baseline period—for example, tracts with high or low population density—to flexibly follow distinct trends in EV adoption over time. In particular, we include median household income, as prior work has shown that higher-income households are more likely to purchase EVs (Borenstein and Davis, 2016; Gillingham et al., 2023), and population density, as EVs tend to be a more practical and cost-efficient vehicle choice in more densely populated areas. We also control for commuting patterns, such as the share of workers who drive alone to work, since these may be correlated with the rollout of new HOV lanes. Finally, we also estimate a specification including tract-specific quadratic time trends.

The baseline model described in Equation 1 employs a TWFE estimator. Recent work highlights limitations of TWFE estimators in settings with staggered treatment adoption and heterogeneous treatment effects across cohorts over time (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021). In particular, the TWFE coefficient can be interpreted as a weighted average of possible two-by-two DiD comparisons, some of which may involve problematic comparisons, such as instances where already-treated units serve as controls for later-treated units. To address these concerns, we complement our TWFE approach with two alternative estimators. First, we implement a stacked DiD estimator, which constructs separate comparisons for each treatment cohort c, pairing treated units with not-yet-treated controls in the corresponding period, and then stacks these comparisons into a single dataset where controls are always untreated.[27] Second, we employ the semi-parametric

[27] For example, see Cengiz et al. (2019) for more detail on this approach.

DiD estimator proposed by Callaway and Sant'Anna (2021), which flexibly accounts for staggered treatment timing and allows for the direct estimation of the average treatment effect on the treated (ATT).

The key identifying assumption of our DiD design is that, in the absence of new HOV lanes, control and treatment census tracts would have parallel trends in EV adoption. While this assumption is not directly testable, we evaluate its plausibility through event study plots which trace dynamic treatment effects before and after the opening of additional HOV lanes. Ideally, the estimated pre-treatment coefficients are statistically indistinguishable from zero, lending credibility to parallel trends assumption. We caution, however, that the absence of significant pre-trends does not necessarily guarantee the validity of the assumption.

5 Results

5.1 Main Results

Table 2 reports estimates from variations of the TWFE DiD model described in Equation 1. The baseline specification in Column 1 estimates the effect of the introduction of a nearby HOV lane on the EV market share, controlling for census tract and time fixed effects. Column 2 extends this specification by including the number of charging stations as a control variable as well as interactions between base period covariates (population density, median household income, share of workers who drove alone to work, share of commuters leaving home before 6, between 6-8, between 8-10, and after 10) and time fixed effects. Importantly, this specification allows census tracts to have different EV adoption trends based on their initial characteristics. Column 3 extends the baseline specification by including tract-specific quadratic time trends to flexibly allow each tract to have a separate trend in EV adoption. Across all specifications, the estimates suggest that the introduction of new HOV lane segments led to increases in EV market shares. The magnitude of the increase varies from 1.2 to 4.5 percentage points. Our more conservative estimate of 1.2 percentage points translates to an economically significant increase in the EV share of 16 percent (relative to the mean of the variable).

Our definition of EVs include both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). In Table 3, we separately estimate the model on the BEV share (Columns 1–3) and the PHEV share (Columns 4–6). The results suggest that the effect of HOV lanes on EV adoption is almost entirely explained by higher market shares for BEVs, as the impact on PHEVs is close to zero across all specifications.

To address concerns about potential biases in the TWFE estimator, we replicate the analysis with two alternative approaches. First, we consider the stacked DiD estimator (Cengiz et al., 2019). The results reported in Table 4 show that the estimates are consistent with those obtained with the TWFE estimator. For example, in the baseline specification (Column 1), the stacked DiD estimates suggest that the introduction of a nearby HOV lane leads to an increase in the market share of EVs of 4.8 percentage points.

Second, we implement the DiD estimator proposed by Callaway and Sant'Anna (2021). Figure 6 reports the dynamic effects of the introduction of HOV lanes on EV adoption using this approach. The control group consists of never-treated census tracts in Panel A and also includes not-yet-treated tracts in Panel B. We include 12 periods (months) prior to treatment to inspect for pre-trends in EV adoption rates which may predict the rollout of new HOV lanes. We also include 36 months following treatment to compare short- and long-term effects on EV market shares. In Panel A, the pre-treatment average coefficient is 0.00048 ($p = 0.899$), which is economically and statistically indistinguishable from zero. In contrast, the post-treatment average coefficient is 0.018 ($p < 0.001$), implying that the addition of a nearby HOV lane increases EV share by an average of 1.8 percentage points after treatment. Visually inspecting the figure suggests that the effects gradually strengthen in the months following the opening of a new HOV lane, consistent with the idea that households take time to adjust their vehicle purchase decisions. Panel B, where the control group is modified to also include not-yet-treated tracts, depicts a nearly identical set of estimates to Panel A.

5.2 Additional Robustness Checks and Extensions

Alternative Treatment Definitions Our primary treatment variable is a dummy variable indicating whether an HOV lane is located within 5 miles of a census tract population centroid. We believe that this definition is reasonable because the average commute time in our sample is 27 minutes in the 2012 base year. However, it is possible that the results are sensitive to this threshold choice. Therefore, we assess the robustness of our results to the treatment definition in two dimensions. First, we substitute geographic centroids for population centroids to test for the possibility that the use of population centroids skews the results. Second, we vary the distance threshold to assign treatment from 1 to 10 miles in one-mile increments. In this way, we can observe how sensitive EV adoption rates are to the introduction of HOV lanes at different distances.

Figure 7 depicts estimated treatment effects for the alternative treatment definitions under the baseline model. The top panel uses distances to geographic centroids and the bottom panel uses distances to population centroids. Each point depicts the treatment effect for a given definition of closeness to an HOV lane, varying from 1 to 10 miles. The results suggest that the effect of HOV lanes on EV adoption rates is consistent across a wide range of treatment definitions. In particular, the results are strongest for treatment thresholds of 5 to 6 miles from census tract centroids.

Alternative Control Groups and Samples In our baseline specification, we consider all never-treated tracts in California to be in the control group. This implies that the control group contains many census tracts in counties that are less dense and less urban than treatment tracts. These differences in characteristics could potentially lead to violations of the parallel trends assumption.

To mitigate this concern, we re-estimate the model where we restrict the control group to a smaller subset of tracts. In this specification, any county in which no census tract is ever treated is dropped from the sample. Therefore, treated tracts are only compared to other non-treated tracts in treated counties. Appendix Table 2 reports the TWFE results. The estimates are slightly attenuated, but remain highly statistically significant. Appendix Figure 1 replicates the event study estimates using the Callaway and Sant'Anna (2021) estimator. The pre-treatment average coefficient is 0.0019 and it is statistically insignificant ($p = 0.613$) while the post-treatment average coefficient is 0.011 and remains significant ($p = 0.003$), indicating that the EV market share is on average 1.1 percentage points higher in treatment tracts following the introduction of a nearby HOV lane. These results confirm that our findings are not driven by comparisons between untreated and treated counties.

Even within treated counties, some census tracts, especially in the control group, are considerably more rural. To address this concern, we also re-estimate the model for a restricted subsample where each tract has a population density of at least 1000 per square mile. Again, we find qualitatively similar results with the TWFE estimator (see Appendix Table 3) and with the Callaway and Sant'Anna (2021) estimator (see Appendix Figure 2). In this case, the pre-treatment average coefficient is 0.0008 ($p = 0.834$) compared to the post-treatment average of 0.017 ($p < 0.001$). Thus, when restricting the analysis to more urbanized census tracts, we find that HOV lane access is associated with a 1.7 percentage point increase in the EV share.

Treatment Intensity So far, we have focused on the extensive margin of HOV lane access. The main treatment variable HOV_{it} measures whether any HOV lane segment is located close to a census tract; however, in some cases, a single tract may be close to several segments. We next investigate whether consumers respond to the number of HOV lane segments in their vicinity by re-estimating versions of Equation 1 where we replace the treatment dummy with a count variable for the number of HOV lane segments located within 5 miles of a census tract population centroid. In our estimation sample, treated census tracts are close to an average of 2.28 HOV lane segments.

Table 5 reports the results when measuring the treatment as a count variable. The baseline estimates in Column 1 suggest that the average effect of an additional nearby HOV segment is an increase in the EV share by 2.1 percentage points. When we include additional covariates (Column 2) or tract-specific quadratic time trends (Column 3), the estimates of the effect diminish to 0.5 and 0.4 percentage points, respectively.

5.3 Heterogeneous Treatment Effects

The introduction of HOV lanes may have varying effects on the sales of EVs based on heterogeneity across tracts and across time. First, as documented in Figure 1, the market shares of EVs have increased markedly across the state from 2012 to 2024 for a number of reasons such as increased model availability, improved battery technology, higher density of charging stations, among others. In the early stages of the market, very few EV models were widely available for purchase, and those models offered only modest electric range while public charging was sparse. Today, by contrast, consumers can choose from a large variety of EV models, with much longer average electric driving range, and the charging network has substantially expanded, especially in terms of fast chargers. As such, the marginal impact of HOV lane access on EV adoption is likely to be higher in the later years of the sample. Second, commute patterns differ across tracts. HOV lane access is more likely to be beneficial when a higher share of commuters travel at peak congestion hours, especially since in some areas HOV lanes are only operational at such times.[28] In addition, HOV lane access is likely to be more valuable in tracts where commute times are longer and where a greater share of drivers drive alone, and thus cannot access the HOV lane without an EV. Third, the impact of HOV lanes may vary across income levels. Given the relatively higher prices of EVs, it is likely that HOV lane access had a greater effect in census tracts where income levels are higher.

[28]In Northern California, HOV lanes are only operational from 6 a.m. to 10 a.m. and from 3 p.m. to 7 p.m.

In Table 6, we present the results from estimating the TWFE model with an interaction term between the treatment and various binary variables. In Column 1, we interact the treatment with the second half of the time period under study (2018–2024). The results suggest that, as expected, HOV lane access has a larger impact in the second half of the time period when EV technology and the EV market in general are more developed.

In Columns 2 to 4, we interact the treatment with various binary commute variables splitting the sample in half for tracts with values above versus below the median values.[29] Consistent with the idea that HOV lanes have greater benefits during congested commutes, the results suggest that treatment effects are larger in tracts with high shares of peak time commuters and with above-median average commute times. Surprisingly, however, the effect is not larger in tracts with higher shares of solo drivers, contrary to our expectations that HOV lane access would make EV purchases more compelling for these commuters.

Finally, in Column 5, we interact the treatment with a dummy for tracts with above-median household income levels. We find that the treatment effect is entirely driven by high-income tracts. Since we do not observe individual-level purchase decisions, we cannot make definitive conclusions on the distributional impact of the policy due to the possibility of aggregation bias. However, the results are suggestive that the policy may have disproportionately benefited higher-income households, raising important distributional considerations for policymakers.

6 Conclusion

California's Clean Air Vehicle Decal program, which granted EVs single-occupancy access to HOV lanes, is set to expire on September 30, 2025, as the federal authority required to continue the program was not extended. Over the program's long history, California's HOV lane network expanded substantially alongside the significant growth of the EV market. This provides a timely opportunity to evaluate the role of HOV exemptions in influencing EV adoption and to examine heterogeneity in the effects over time as well as across census tracts with differing commute lengths, levels of congestion, and household income.

We find that HOV exemptions significantly increased EV uptake in California between 2012 and 2024. The effects were larger in the later part of the sample period when EV technology and

[29] All commute variables are measured in the baseline period, prior to treatment. The share of peak time commuters refers to the share of commuters from 6 to 10 a.m. in a given census tract. The average commute time is measured at the county-level due to data constraints. The share driving alone refers to the share of commuters who drive alone as a means of transportation, measured at the tract-level.

markets were more developed. We also show that the impact was greater in areas with longer commutes and heavier congestion, and that the benefits were concentrated in higher-income tracts. These findings highlight both the effectiveness of HOV access in stimulating adoption and the uneven distribution of benefits across households.

The termination of the HOV exemption program in 2025 will make it possible to measure the extent to which the benefits of HOV access continue to matter for EV adoption in a more mature market. Future work can examine the magnitude of any reduction in uptake once the program ends and whether the adjustment differs across areas and income groups. The policy implications will also be important for other even more advanced markets such as Norway where policymakers have started to scale back or eliminate incentives but have not yet ended preferential access to bus lanes.

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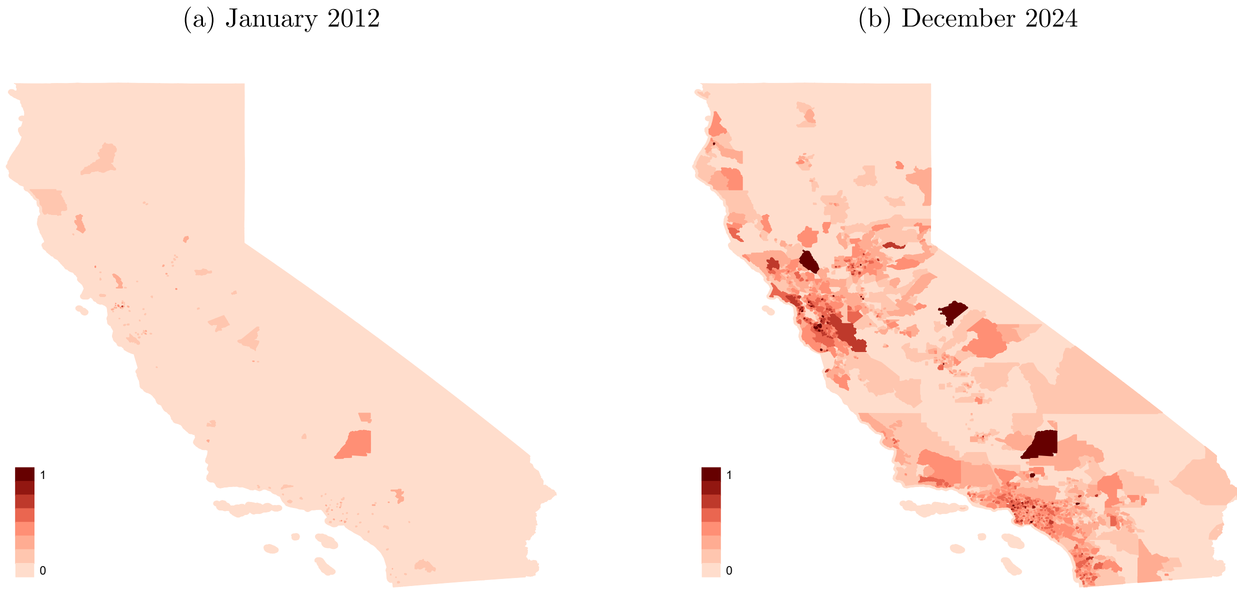
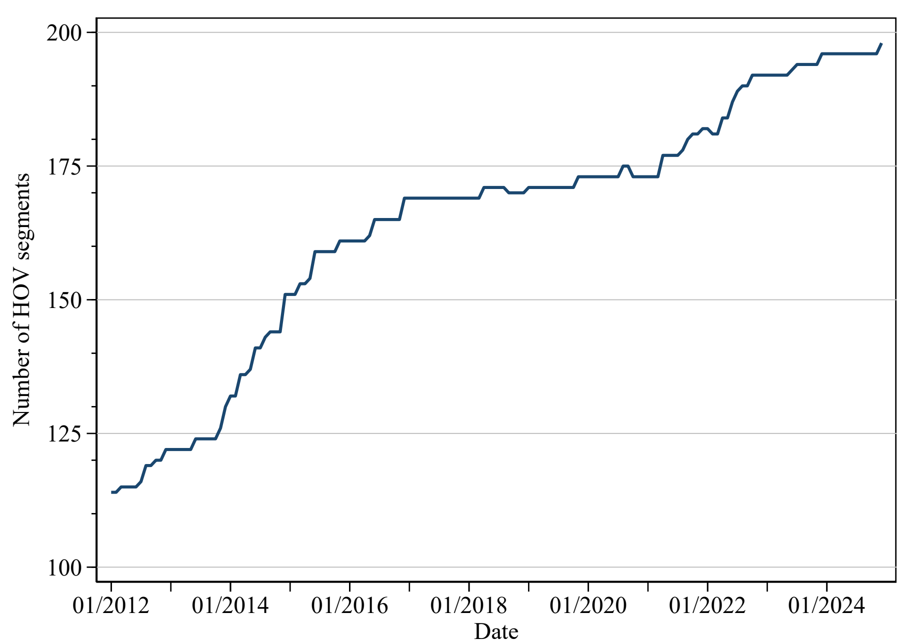
Figure 1: EV Adoption by Census Tract in California



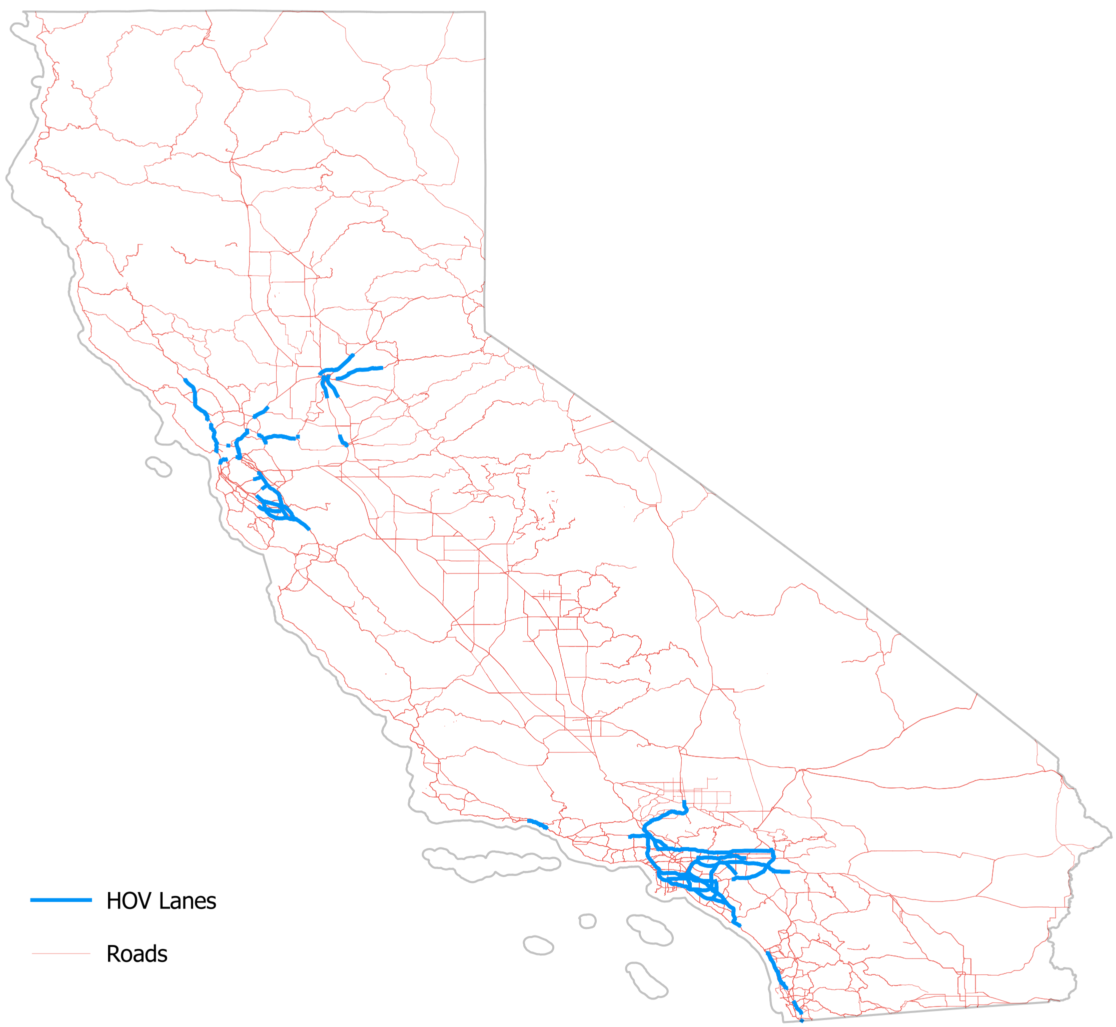
Notes: The two maps show EV shares at the census tract level in California in the beginning (January 2012) and at the end (December 2024) of our observed time period. Darker colors represent census tract with higher EV adoption rates while lighter colors show tracts with lower EV shares.

Figure 2: HOV Lane Segments in California (2012-2024)



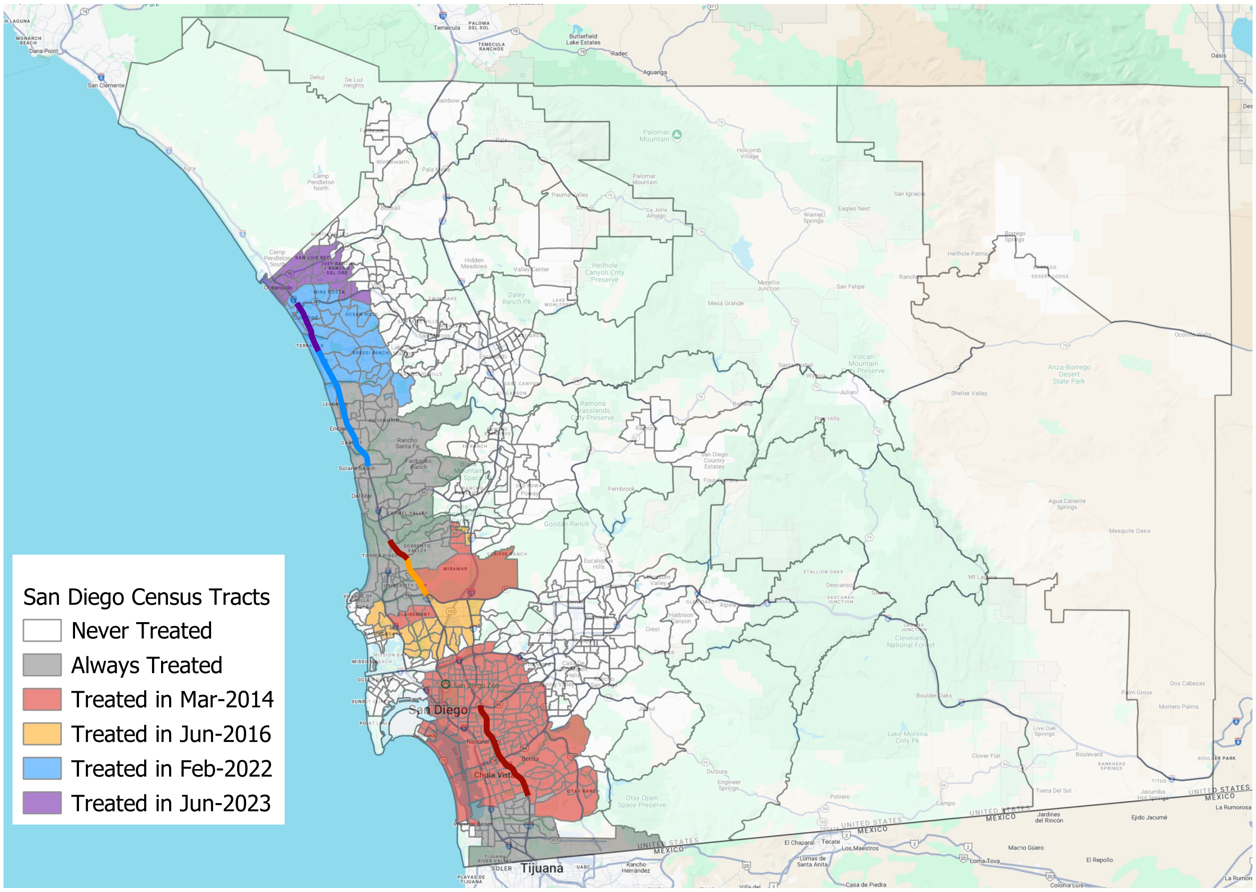
Notes: This figure plots the cumulative number of HOV lane segments in California between January 2012 and December 2024. The figure highlights two periods of rapid expansion: 2014–2017 and 2022–2023.

Figure 3: Inventory of Operational HOV Lanes in California (2012-2024)



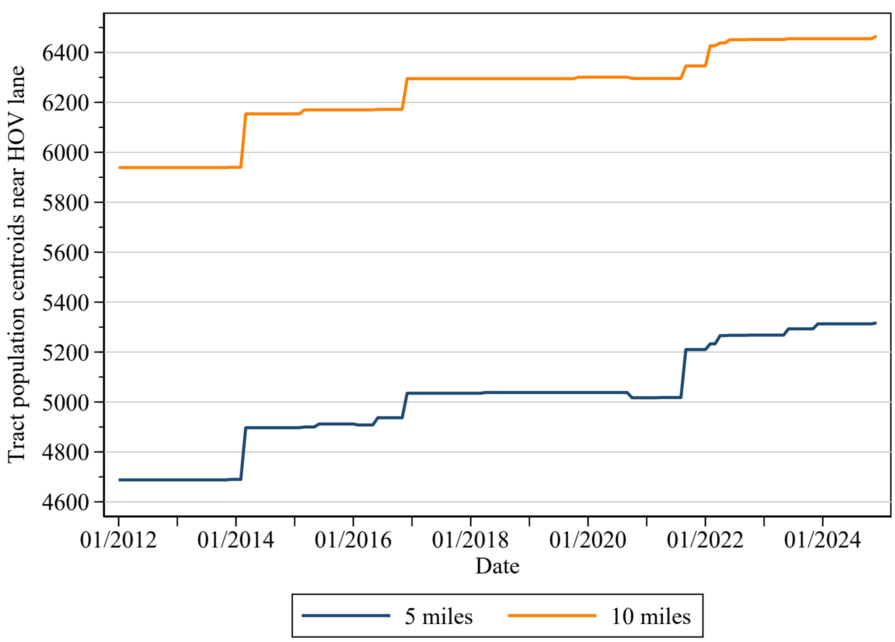
Notes: This map shows all operational HOV lanes from 2012 to 2024 (in blue) along with the primary and secondary road network (in red) of California in 2024.

Figure 4: Illustration of HOV Treatment of Census Tracts in San Diego County



Notes: This figure provides an example of how we define the treatment of census tracts based on the addition of new HOV lane segments within 5 miles of the population centroid of a tract. The map shows all the census tracts of San Diego County, color coded based on their treatment status. Census tracts that are not colored represent tracts that are never treated since there are never any operational HOV lanes within 5 miles of their population centroid between 2012 and 2024. Grey tracts are always treated as there were operation HOV lanes within 5 miles of their centroids before our observed time period began in 2012. Red tracts represent tracts that gained access to an HOV lane within 5 miles of their population centroid when new HOV segments were added to the HOV lane network in March 2014. In a similar way, other tracts are treated following the addition of new HOV lanes as follows: yellow tracts in June 2016; blue tracts in February 2022; and purple tracts in June 2023. The map also includes the HOV lanes added to the road network during our sample and it is color-coded to match the treatment of tracts. For example, the HOV lane segments in red represent HOV lanes that became operational in March 2014.

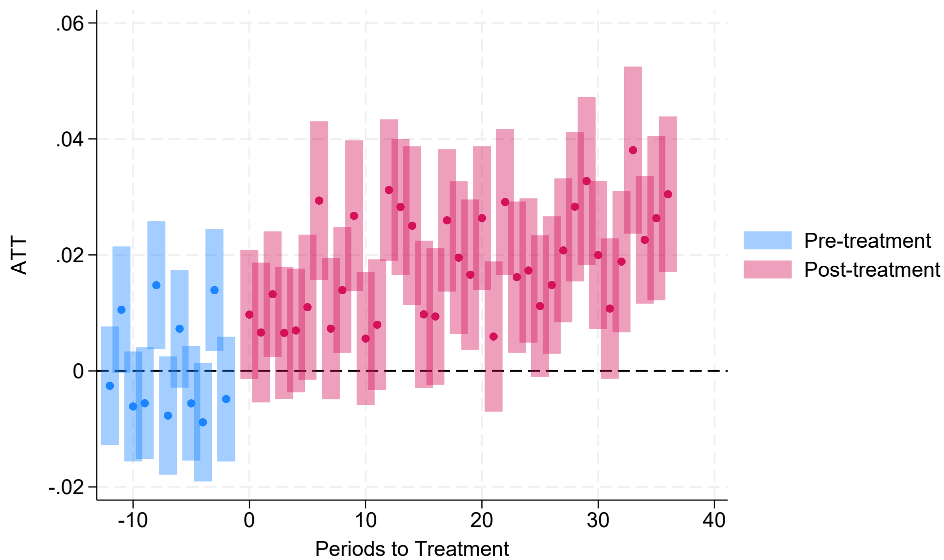
Figure 5: Census Tract (Population) Centroids within 5/10 Miles of an HOV Lane



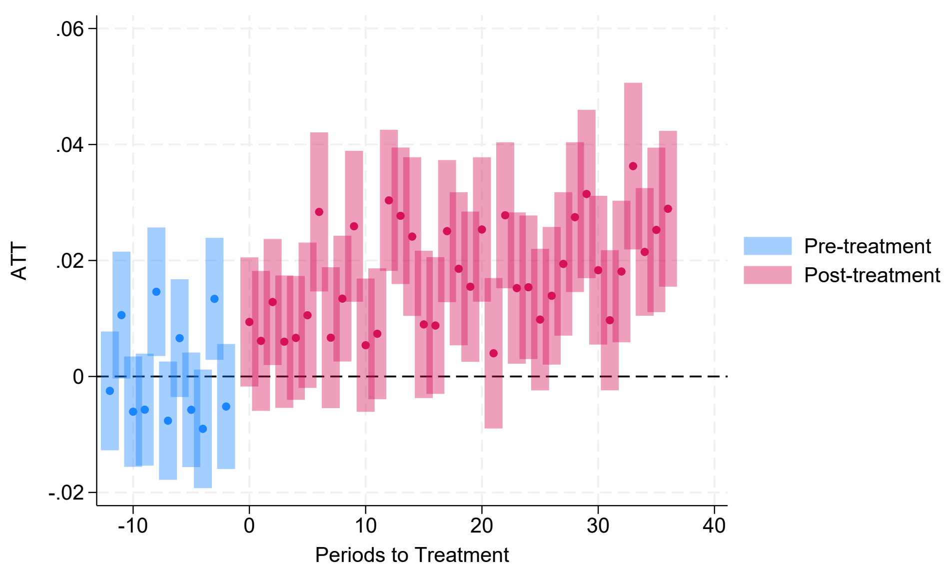
Notes: This figure shows the cumulative number of California census tract population centroids located within 5 miles (blue) and 10 miles (orange) of an HOV lane segment between January 2012 and December 2024. The coverage of tracts increased gradually over time, with especially notable expansions around 2014–2016 and again in late 2021.

Figure 6: The Effects of HOV Lanes on EV Adoption

(a) Control: Never Treated

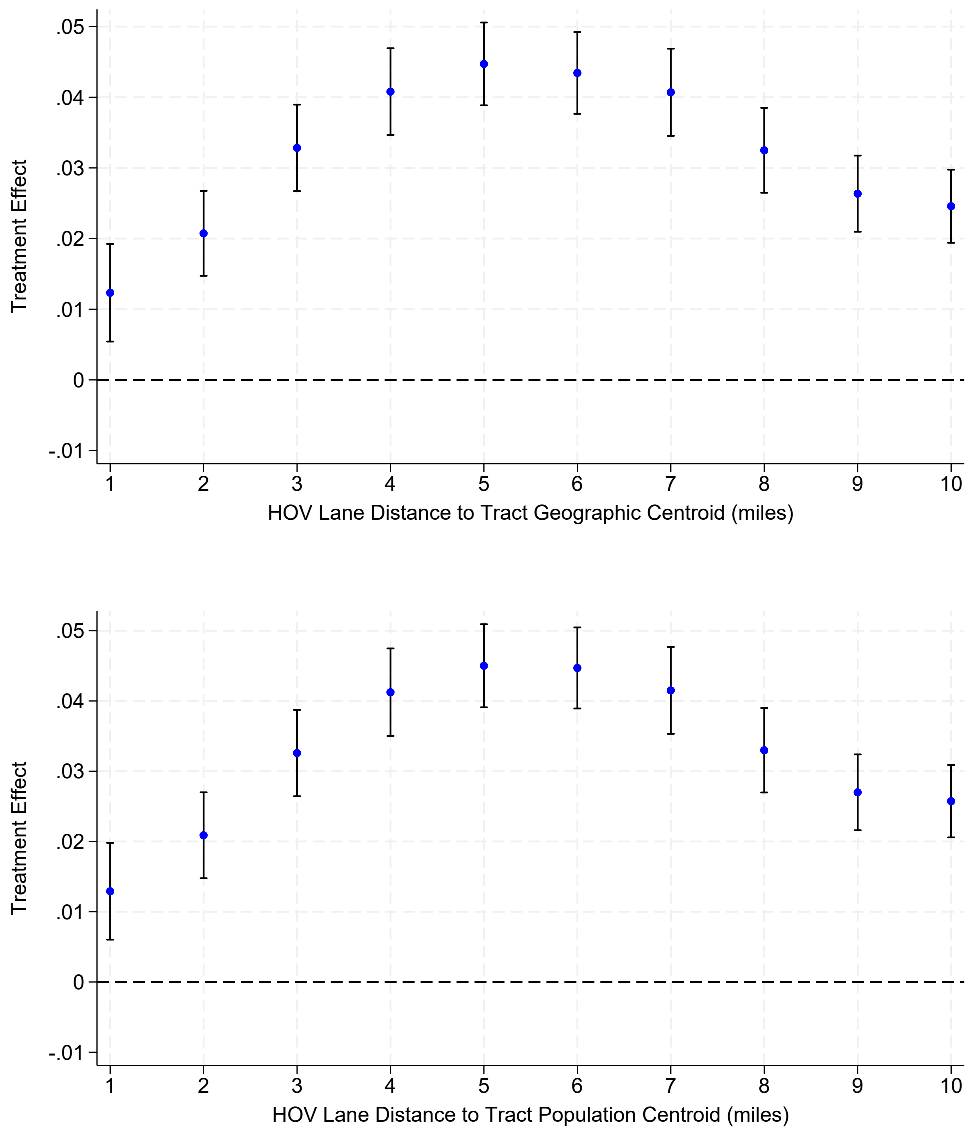


(b) Control: Never Treated and Not-Yet Treated



Notes: This figure displays event-study coefficients and 95 percent confidence intervals following the Callaway and Sant'Anna (2021) estimation approach. The dependent variable is the EV share in a tract-month. Treatment is defined as the presence of an HOV lane segment located within 5 miles of the population centroid of a census tract. The control group in the top panel are never-treated tracts. The control group in the bottom panel also includes not-yet-treated tracts. The base period is -1 (i.e., one month before treatment). Standard errors are clustered at the census tract level.

Figure 7: Effects of HOV Lanes on EV Adoption for Alternative Treatment Definitions



Notes: Each point depicts the estimated treatment effect and confidence interval for a separate specification of Equation 1. In the top panel, the treatment variable is equal to 1 if the geographic centroid of a census tract is located within 1 (to 10) miles of a HOV lane. In the bottom panel, the treatment variable is equal to 1 if the population centroid of a census tract is located within 1 (to 10) miles of a HOV lane. All specifications includes census tract and time fixed effects, and standard errors are clustered by census tract.

Table 1: Baseline Summary Statistics by Treatment Group

	Never Treated	Not Yet Treated	Full Sample
Population	3925.97	3907.08	3923.15
Population density (per sq mile)	5569.47	16411.51	7190.51
Female	0.50	0.49	0.50
White	0.71	0.60	0.70
Black	0.04	0.07	0.05
Hispanic	0.36	0.29	0.35
Less than high school	0.20	0.17	0.20
High school graduate	0.22	0.18	0.22
Some college	0.32	0.28	0.31
BA or more	0.26	0.37	0.27
Labor force	0.62	0.67	0.63
Car	0.85	0.71	0.83
Car: drove alone	0.73	0.61	0.71
Car: carpooled	0.12	0.10	0.12
Public transportation	0.04	0.13	0.05
Other form of transportation	0.04	0.08	0.05
Worked at Home	0.06	0.06	0.06
Commute before 6	0.16	0.12	0.15
Commute between 6 and 8	0.44	0.41	0.43
Commute between 8 and 10	0.23	0.29	0.24
Commute after 10	0.17	0.18	0.17
Renter	0.41	0.55	0.43
Median age (approx.)	37.26	36.73	37.18
Median income (approx.)	62699.92	67019.96	63348.81
Average commute (minutes)	25.71	26.89	25.89
Observations	3779	662	4441

Notes: This table reports summary statistics for census tracts during the baseline period (2012). "Never Treated" are census tracts which are never treated in the sample period (January 2012 to December 2024). "Not Yet Treated" are census tracts which begin as untreated in January 2012 and become treated at any time before December 2024. Always-treated tracts are not including in the sample. See Section 3 for more details.

Table 2: The Effect of HOV Lanes on EV Adoption

	EV Share		
	(1)	(2)	(3)
Treatment	0.045***	0.013***	0.012***
	(0.003)	(0.002)	(0.002)
Observations	679535	678194	679535
Mean of Dependent Variable	0.072	0.072	0.072
Census-Tract FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Covariates	No	Yes	No
Tract-Specific Quadratic Time	No	No	Yes

Notes: This table reports TWFE estimates. Treatment is defined as the presence of an HOV lane within 5 miles of the population centroid of a census tract. Covariates include charging stations and interactions of time fixed effects with the following baseline census tract demographics: median household income (approximated), population density, share of workers who drove alone to work, and shares of commuters leaving home before 6, between 6-8, 8-10, and after 10. Standard errors are clustered at the census tract level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: The Effect of HOV Lanes on BEV and PHEV Adoption

	BEV Share			PHEV Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.041***	0.011***	0.014***	0.004***	0.002***	-0.002***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)
Observations	679535	678194	679535	679535	678194	679535
Mean of Dependent Variable	0.054	0.054	0.054	0.018	0.018	0.018
Census-Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	No	No	Yes	No
Tract-Specific Quadratic Time	No	No	Yes	No	No	Yes

Notes: This table reports TWFE estimates. Treatment is defined as the presence of an HOV lane within 5 miles of the population centroid of a census tract. Covariates include charging stations and interactions of time fixed effects with the following baseline census tract demographics: median household income (approximated), population density, share of workers who drove alone to work, and shares of commuters leaving home before 6, between 6-8, 8-10, and after 10. Standard errors are clustered at the census tract level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Stacked DiD Estimates for the Effect of HOV Lanes on EV Adoption

	EV Share		
	(1)	(2)	(3)
Treatment	0.048***	0.011***	0.012***
	(0.003)	(0.002)	(0.002)
Observations	9921039	9898754	9921039
Mean of Dependent Variable	0.068	0.068	0.068
Tract x Cohort FE	Yes	Yes	Yes
Time x Cohort FE	Yes	Yes	Yes
Covariates	No	Yes	No
Tract-Specific Quadratic Time	No	No	Yes

Notes: This table reports Stacked DiD estimates. Treatment is defined as the presence of an HOV lane within 5 miles of the population centroid of a census tract. Covariates include charging stations and interactions of time fixed effects with the following baseline census tract demographics: median household income (approximated), population density, share of workers who drove alone to work, and shares of commuters leaving home before 6, between 6-8, 8-10, and after 10. Standard errors are clustered at the census tract level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: The Effect of the Number of HOV Segments on Adoption

	EV Share		
	(1)	(2)	(3)
Number of HOV Segments	0.021***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)
Observations	679535	678194	679535
Mean of Dependent Variable	0.072	0.072	0.072
Census-Tract FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Covariates	No	Yes	No
Tract-Specific Quadratic Time	No	No	Yes

Notes: This table reports TWFE estimates. The treatment variable is the count of HOV lane segments within 5 miles of the population centroid of a census tract. Covariates include charging stations and interactions of time fixed effects with the following baseline census tract demographics: median household income (approximated), population density, share of workers who drove alone to work, and shares of commuters leaving home before 6, between 6-8, 8-10, and after 10. Standard errors are clustered at the census tract level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: The Effect of HOV Lanes on EV Adoption–Heterogeneity

	(1)	(2)	(3)	(4)	(5)
Treatment	0.027***	-0.005*	0.018***	0.061***	-0.005*
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
Treatment x Years 2018-2024	0.021***				
	(0.002)				
Treatment x High Share Peak Time Commuters		0.086***			
		(0.005)			
Treatment x Long Commute Time			0.044***		
			(0.005)		
Treatment x High Share Drove Alone				-0.042***	
				(0.005)	
Treatment x High Median Income					0.086***
					(0.005)
Observations	679535	679535	679535	679535	679535
Mean of Dependent Variable	0.072	0.072	0.072	0.072	0.072
Census-Tract FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	No	No	No
Tract-Specific Quadratic Time	No	No	No	No	No

Notes: This table reports TWFE estimates. Treatment is defined as the presence of an HOV lane within 5 miles of the population centroid of a census tract. High Share Peak Time Commuters, Long Commute Time, High Share Drove Alone and High Median Income are dummy variables for above-median levels of the share of commuters from 6 to 10 a.m, average commute time, the share of commuters driving alone and median household income, respectively. Standard errors are clustered at the census tract level. * p < 0.1, ** p < 0.05, *** p < 0.01.

Appendix Table 1: Baseline Summary Statistics for Sample versus Population

	Sample	Population
Population	3923.15	4088.10
Population density (per sq mile)	7190.51	8408.29
Female	0.50	0.50
White	0.70	0.63
Black	0.05	0.06
Hispanic	0.35	0.36
Less than high school	0.20	0.20
High school graduate	0.22	0.21
Some college	0.31	0.30
BA or more	0.27	0.30
Labor force	0.63	0.64
Car	0.83	0.84
Car: drove alone	0.71	0.72
Car: carpooled	0.12	0.12
Public transportation	0.05	0.05
Other form of transportation	0.05	0.04
Worked at Home	0.06	0.05
Commute before 6	0.15	0.14
Commute between 6 and 8	0.43	0.42
Commute between 8 and 10	0.24	0.26
Commute after 10	0.17	0.18
Renter	0.43	0.44
Median age (approx.)	37.18	36.66
Median income (approx.)	63348.81	67140.32
Average commute (minutes)	25.89	27.03
Observations	4441	9129

Notes: This table reports summary statistics for census tracts during the baseline period (2012). "Sample" are census tracts which are never treated or treated in the sample period (January 2012 to December 2024). "Population" are all census tracts within California. See Section 3 for more details.

Appendix Table 2: The Effect of HOV Lanes on EV Adoption–Treated Counties Only

	EV Share		
	(1)	(2)	(3)
Treatment	0.023***	0.009***	0.010***
	(0.003)	(0.002)	(0.002)
Observations	452813	451682	452813
Mean of Dependent Variable	0.087	0.087	0.087
Census-Tract FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Covariates	No	Yes	No
Tract-Specific Quadratic Time	No	No	Yes

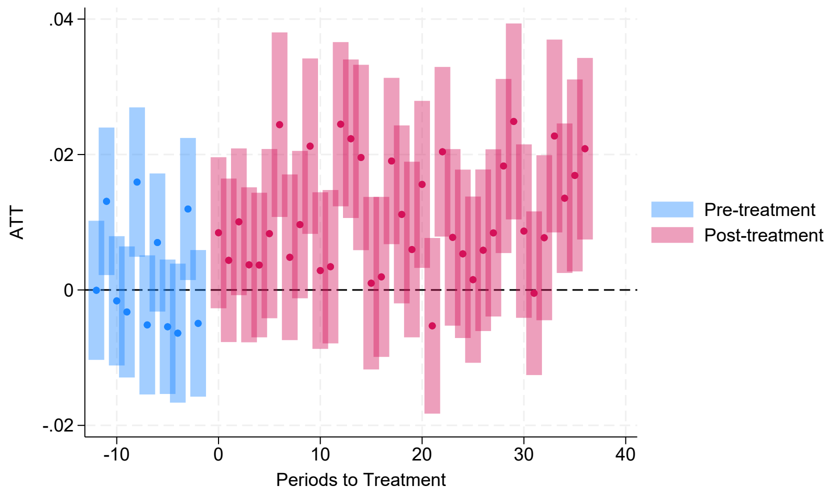
Notes: This table reports TWFE estimates. Treatment is defined as the presence of an HOV lane within 5 miles of the population centroid of a census tract. Covariates include charging stations and interactions of time fixed effects with the following baseline census tract demographics: median household income (approximated), population density, share of workers who drove alone to work, and shares of commuters leaving home before 6, between 6-8, 8-10, and after 10. Standard errors are clustered at the census tract level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table 3: The Effect of HOV Lanes on EV Adoption–High Density Tracts Only

	EV Share		
	(1)	(2)	(3)
Treatment	0.041***	0.010***	0.012***
	(0.003)	(0.002)	(0.002)
Observations	503047	502593	503047
Mean of Dependent Variable	0.075	0.075	0.075
Census-Tract FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Covariates	No	Yes	No
Tract-Specific Quadratic Time	No	No	Yes

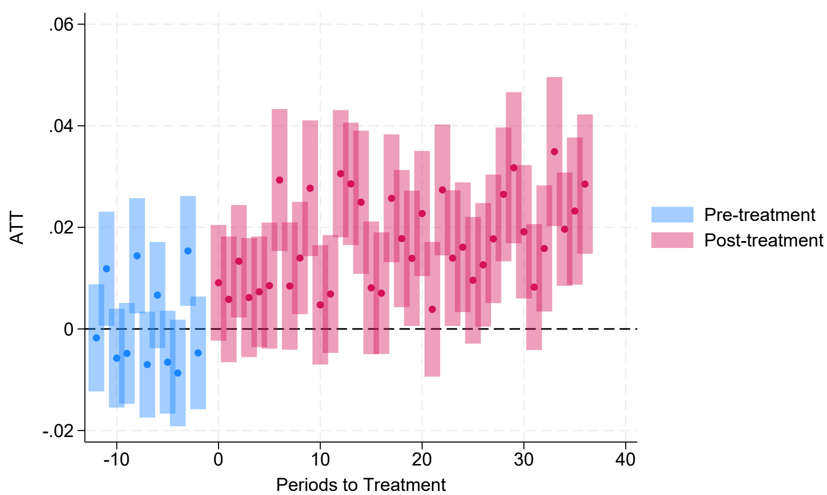
Notes: This table reports TWFE estimates. The sample is restricted to tracts with a population density of at least 1000 per square mile. Treatment is defined as the presence of an HOV lane within 5 miles of the population centroid of a census tract. Covariates include charging stations and interactions of time fixed effects with the following baseline census tract demographics: median household income (approximated), population density, share of workers who drove alone to work, and shares of commuters leaving home before 6, between 6-8, 8-10, and after 10. Standard errors are clustered at the census tract level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Figure 1: The Effects of HOV Lanes on EV Adoption–Treated Counties Only



Notes: This figure displays event-study coefficients and 95 percent confidence intervals following the Callaway and Sant'Anna (2021) estimation approach. The dependent variable is the EV share in a tract-month. Treatment is defined as the presence of an HOV lane segment located within 5 miles of the population centroid of a census tract. The control group consists of never-treated census tracts located in treated counties only. The base period is -1 (i.e., one month before treatment). Standard errors are clustered at the census tract level.

Appendix Figure 2: The Effects of HOV Lanes on EV Adoption–High Density Tracts Only



Notes: This figure displays event-study coefficients and 95 percent confidence intervals following the Callaway and Sant'Anna (2021) estimation approach. The dependent variable is the EV share in a tract-month. Treatment is defined as the presence of an HOV lane segment located within 5 miles of the population centroid of a census tract. The sample is restricted to tracts with a population of at least 1000 in 2012. The control group consists of never-treated tracts. The base period is -1 (i.e., one month before treatment). Standard errors are clustered at the census tract level.

Contact.

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