# The electric vehicle transition exacerbates traffic congestion in California*

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**Abstract**

Electrifying vehicle fleets is central to global climate policy, yet the systemic impact of this transition on urban mobility remains unclear. Using a ZIP code-level panel linking battery electric vehicle (BEV) registrations to highway sensor data from over 40,000 detectors across California (2014–2023), we find that BEV adoption causally degrades peak-hour traffic performance: a doubling of BEV counts reduces average travel speeds by 1.17%, an effect that is robust across specifications, temporal subsets, and spatial spillover tests. We estimate that this congestion externality costs California drivers at least $615 million annually in lost productivity. Three behavioral mechanisms accompany this effect: BEV adoption is associated with net vehicle fleet expansion (1.42–1.86%), induced travel demand (at least 1.16% increase in traffic flow), and declining public transit ridership (23.66%), suggesting that electrification encourages car dependency rather than one-for-one technological substitution. These impacts are spatially unequal—the most severe speed reductions concentrate in socioeconomically disadvantaged and car-dependent communities. Our findings indicate that without integrated land-use, transit, and demand-management policies, vehicle electrification risks intensifying the urban congestion and spatial inequities it is expected to alleviate.

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## Introduction

Global electric vehicle sales surpassed 17 million in 2024[1], yet the systemic impact of this rapid adoption on urban mobility remains largely unexamined. As the cornerstone of transportation decarbonization[2], the shift from internal combustion engine (ICE) vehicles to battery electric vehicles (BEVs) is expected to reduce air pollution, foster green infrastructure, and support cleaner urban environments[3–5]. Vehicle electrification has been regarded as a primary contributor to progress toward the United Nations Sustainable Development Goals—specifically those concerning clean energy, sustainable cities, and climate action[6].

While current scientific consensus recognizes that BEVs are, on average, cleaner than their ICE counterparts[7,8], a growing body of evidence identifies externalities across their life cycle and deployment—from grid-dependent emission reductions[9–13] and energy-intensive battery production[14–18] to socio-environmental costs of mineral extraction[19–21]—that warrant evaluation beyond tailpipe emissions. Within cities, the heterogeneity in adoption behaviors raises concerns about spatial inequality[22], distributional conflicts over charging infrastructure[23], and housing price effects near charging stations[24–26]. Policy-specific distortions have also surfaced: allowing solo BEV drivers to use carpool lanes in Los Angeles worsened congestion for carpoolers[27], and toll exemptions for BEVs in Oslo reduced infrastructure revenue without pricing the congestion they caused[28,29]. These studies, however, treat mobility impacts as secondary outcomes of incentive design and leave unanswered a more fundamental question—whether the adoption of BEVs, independent of specific policies, systemically degrades urban mobility.

The unprecedented scale of the electric vehicle transition necessitates a move beyond isolated policy evaluations toward a comprehensive urban-systems perspective. Unlike conventional vehicles, BEVs introduce unique behavioral drivers—such as lower operating costs and a pro-environmental identity—that could fundamentally reshape ownership and usage patterns. Consequently, a knowledge gap remains regarding how the large-scale electric vehicle transition systemically impacts the efficiency and equity of urban mobility. There are several potential pathways. First, ownership incentives may induce a net expansion of the vehicle fleet by lowering acquisition costs to a level that encourages multi-car households rather than direct vehicle replacement[30,31]. Second, BEV usage could induce increased vehicle travel, thereby amplifying total vehicle miles traveled and congestion[32]. Third, BEVs may substitute rather than complement public transit, as their convenience and perceived sustainability could draw riders away from buses and trains, despite being promoted as a solution for first/last-mile connections and carsharing[33–36]. A systematic evaluation of these pathways is essential to ensure that BEV adoption does not exacerbate the existing urban mobility challenges.

In this study, we seek to examine how the adoption of BEVs has affected traffic congestion in California, U.S. We focus on BEVs in the light-duty vehicle fleet as they represent the most rapidly growing segment of the electric vehicle market and depend more on charging infrastructure than other types of electric vehicles, such as hybrid electric or plug-in hybrid electric vehicles[15]. Traffic congestion is measured by peak-hour travel speed, as a decline in average speed is a direct and widely recognized indicator of increasing traffic flow density and roadway congestion[37]. Based on a set of strictly controlled two-way fixed effects models estimated using a 10-year panel of highway traffic data derived from 40,000+ sensors, we identify a causal relationship between BEV adoption and degraded road performance. Specifically, we find that the electric vehicle transition is not a simple one-for-one technological substitution; rather, it triggers a set of behavioral shifts that increase total vehicle ownership, induce new travel demand, and lead to a significant decline in public transit ridership. By identifying these externalities, our research offers critical insights into the ongoing debate regarding the true costs and benefits of electrifying the transportation sector, suggesting that BEV penetration may intensify urban transportation challenges.

California offers an ideal context for our investigation as the national leader in BEV adoption, accounting for more than one-third of the U.S. BEV market[38] and having set a target of 100% zero-emission light-duty vehicle sales by 2035[39]. Meanwhile, it consistently experiences some of the nation's most severe traffic congestion[40]. This combination of high penetration of the BEV and significant congestion provides a unique setting for analyzing the mobility impacts of the electric transition. As illustrated in Figure 1, BEV adoption has been spatially heterogeneous throughout the state, with the most substantial growth concentrated in the San Francisco Bay Area and the Los Angeles Metropolitan Area. This geographic and temporal variation provides the necessary identification power to evaluate how the electric vehicle transition influences the collective performance of the urban mobility system.

## Results

We examine the effects and underlying mechanisms of BEV adoption on traffic congestion in California. Our identification strategy leverages the heterogeneity in BEV adoption across spatial units (ZIP codes) and over time (years), as illustrated in Figure 1. Using ZIP code-level panel data, we estimate two-way fixed effects models to isolate the causal impact of BEV penetration on traffic congestion. Our identification exploits within-ZIP code variation in BEV adoption over time, after netting out time-invariant local characteristics through unit fixed effects and common macro trends and policy shocks through year fixed effects. Our primary dependent variable is the log of average peak-hour weekday travel speed. To ensure the stability of our estimates, we further test travel speeds under alternative conditions, including midweek (Tuesday, Wednesday, and Thursday) peaks and weekend midnight baselines, as robustness checks. To unpack the mechanisms under this effect, we analyze additional dependent variables in log form, including total vehicle ownership, hourly travel flow, and transit ridership.

The first set of models (Table 1) quantifies the causal effect of BEV adoption on traffic congestion levels. The second set (Table 2) explores three potential channels through which these effects manifest: first is ownership expansion—determining if BEVs increase total fleet size rather than displacing ICE vehicles; the second is induced demand—testing for a rebound effect in travel flow due to lower marginal driving costs; and the third is modal substitution—examining whether BEV adoption affects public transit ridership, estimated at the Urbanized Area (UA) level to match the most granular data availability. All specifications include year and unit (ZIP code or UA) fixed effects to account for time-invariant and unit-specific unobserved factors. We further control for time-varying ZIP code-level covariates, including median household income, population, population density, the share of public transit commuters, the share of long commuters (>45 mins), educational attainment (bachelor's degree or higher), and charging infrastructure density (both Level 2 and DC fast chargers). We employ county-by-year fixed effects to control for regional time-varying shocks, serving as a robustness test for our primary two-way fixed effects model estimates. To rule out potential reverse causality, we also run the main specifications using a lagged independent variable.

Our analysis reveals that BEV adoption in California is accompanied by significant, previously overlooked negative externalities, where a doubling of the BEV fleet results in a 1.17% reduction in peak-hour highway travel speeds. This degradation of road performance is accompanied by three behavioral patterns: a net increase in total vehicle ownership (1.42–1.86%), a rebound effect in hourly traffic flow (at least 1.16%), and a decline in public transit ridership (23.66%). These impacts are spatially heterogeneous, with the most acute speed reductions concentrated in socioeconomically disadvantaged and car-dependent communities. While electrification is a cornerstone of decarbonization, these results demonstrate that without integrated transit and infrastructure planning, BEV penetration can intensify urban mobility challenges and exacerbate spatial inequities.

***Electric vehicle adoption and traffic congestion***

The first set of models in Table 1 presents the effects of BEV adoption on traffic congestion as measured by annual weighted (by flow) average vehicle travel speed on highways from 2014 to 2023. A central empirical concern is that BEV adoption may be endogenous to local traffic conditions. For example, areas with relatively congested traffic conditions may simultaneously experience greater demand for electric vehicles due to environmental preferences, income growth, or unobserved urban development trends. Our identification strategy addresses these concerns by leveraging within-ZIP code changes in BEV adoption over time, conditional on a rich set of fixed effects and controls. This allows for a causal interpretation of these estimates, the formal details of which are elaborated upon in the Methods section.

The speeds are measured using hourly speed sensor data derived from the California Performance Measurement System (PeMS) and aggregated at the ZIP code level. Our primary specification (Column 1) yields an elasticity of −0.0117, indicating that a doubling of the BEV fleet leads to a 1.17% reduction in peak-hour travel speeds. This negative effect is robust to the inclusion of county-by-year fixed effects (Column 2), which absorb localized, time-varying shocks. We find consistent results for midweek peak hours (Columns 3 and 4), where the estimated impact remains statistically significant and quantitatively stable. While a 1.17% reduction in speed may appear marginal at the local scale, it represents a substantial aggregate increase in travel delay and social costs when scaled across California's high-volume road networks. Given that these estimates capture the early stages of the transition, the marginal impact on congestion may non-linearly intensify as BEV market share grows, posing a significant challenge to urban sustainability goals. To test whether our results reflect general traffic trends or unobserved spatial confounders, we examine midnight travel speeds as a placebo test. As shown in Columns (5) and (6), the coefficients for the midnight period are either statistically indistinguishable from zero or positive and negligible in magnitude (0.0025 in Column 6). This sharp divergence shows that BEV adoption is associated with speed reductions only during high-demand peak hours. Also, we use a lagged BEV adoption count to run the main specification to rule out potential reverse causalities. As shown in Table A.1, our findings remain robust and significant compared to results in Table 1. This pattern suggests that the congestion effect operates through active vehicle usage and increased pressure on road capacity, rather than reflecting spurious correlations or broad trends in traffic conditions.

Because urban mobility patterns transcend the spatial boundaries of ZIP codes, we test the sensitivity of our findings to the geographic scale of measurement. Figure 2 illustrates the estimated coefficients for both peak-hour and midnight travel speeds as the analysis expands from the ZIP code centroid across increasing radii (1 15 kilometers). This spatial decay analysis serves to detect potential spillover effects and ensures our results are not an artifact of specific spatial aggregations. In Panel (a), the impact of BEV adoption on peak-hour speeds remains remarkably stable, with coefficients consistently clustering around $-0.01$ across all spatial scales. This persistence indicates that the congestion externality is a localized but resilient phenomenon detectable beyond immediate ZIP code boundaries. In contrast, the coefficients for midnight speeds in Panel (b) remain tightly distributed around zero and statistically insignificant across the entire 15 km range. The stark divergence between peak and off-peak scales reinforces our primary identification that BEV adoption specifically degrades road performance when demand is high, regardless of the geographic unit of analysis.

***Mechanisms: ownership expansion, induced demand, and modal substitution***

To uncover the behavioral drivers behind the tested congestion effects, we evaluate three primary channels: ownership expansion, induced demand, and modal substitution (Table 2). Our results suggest that BEV adoption does not merely swap the powertrain of the existing fleet but alters travel behavior. First, we find that BEV adoption is correlated with a net increase in total vehicle ownership, indicating that BEVs often serve as supplementary additions to household fleets rather than direct replacements for existing vehicles. A doubling of the BEV count increases total vehicle ownership by 1.42% (Column 1) to 1.86% (Column 2). Second, BEV adoption is associated with significantly higher vehicle usage. The two-way fixed effects model (Column 3) shows a positive elasticity of 0.0116, and the county-by-year fixed effects model with larger degrees of freedom (Column 4) reveals an elasticity of 0.1754. The first model is more stringent so it is reasonable for it to have a larger confidence interval, and the effect estimated by the second model is larger possibly due to its capturing the larger regional variations in traffic flows. This suggests that a doubling of BEVs is associated with at least a 1.16% rise in hourly traffic flow, likely related to the lower marginal operating costs of electric propulsion—a classic rebound effect that intensifies road network pressure. Third, we find evidence that BEV adoption is associated with reduced ridership of other sustainable transportation modes. As shown in Column (5), BEV penetration is associated with a marked decline in public transit ridership at the UA level, with an elasticity of $-0.2366$. This indicates that a doubling of BEVs correlates with a 23.66% reduction in transit use. Together, these mechanisms reveal a multifaceted negative externality: the transition to BEVs appears to stimulate private vehicle dependency and usage while simultaneously eroding the viability of public transit. This behavioral shift concentrates travel demand back onto road infrastructure, neutralizing the spatial efficiency gains typically associated with sustainable urban planning and development.

***Heterogeneity across different communities***

To further explore the robustness and nuance of our findings, we examine heterogeneity of the effects of BEV adoption on weekday peak-hour traffic speed across different communities. Figure 3 presents the varying coefficients from the two-way fixed effects models, stratified by quintiles of observed ZIP code-level characteristics. Overall, the results support our main finding that BEV adoption leads peak-hour congestion, by showing stable negative coefficients across all quintiles and characteristics, At the same time, the magnitude of this externality varies systematically with community characteristics

Generally, the congestion effect is more significant in socioeconomically disadvantaged communities. In Panels (a) and (f), the effect is the most pronounced in lower-income areas and those with lower educational attainment, where vehicle dependency is often high due to limited access to alternatives such as high-quality public transit. This is also geographically mirrored in less densely populated areas as shown in Panel (b), where the built environment necessitates private vehicle use. In these settings, the addition of BEVs to the fleet directly intensifies demand on road networks that already lack robust sustainable transportation options. This interpretation is directly corroborated by the commuting-pattern results. The effect is strongest precisely where public transit use share is low and where long car commutes are more common, as shown in Panels (c) and (d). Combined, this confirms that the BEV-congestion link is powerfully mediated by a community's baseline reliance on private vehicles. Finally, infrastructure plays a critical moderating role. In Panel (e), the effect is greater in areas with fewer BEV chargers per capita. Limited charging access may not only reflect general under-investment but can also induce peak-concentrated charging behavior and congestion.

## Discussion

While the transition to electric vehicles is widely viewed as a cornerstone of transportation decarbonization, we have identified an overlooked but underexplored tension: BEV adoption may exacerbate peak-hour congestion and degrade the urban mobility system even as it reduces transportation GHG emissions. Our analysis demonstrates that doubling the BEV fleet leads to a statistically significant 1.17% reduction in weekday peak-hour traffic speeds. This effect persists across midweek periods and remains robust to multiple specifications, including two-way fixed effects and county-by-year fixed effects models that control time-varying confounders. Spatial spillover analysis confirms the stability of this negative relationship across various geographic scales, while placebo tests using midnight traffic data and lagged regression rule out broader unobserved artifacts and potential reverse causalities. Although the speed reduction is modest at current adoption levels, its aggregate impact is non-trivial. Specifically, such a reduction in speed is estimated to cost California drivers at least 615 million U.S. dollars annually in lost productivity[*]. We thus challenge the consensus that electric vehicle transition predominantly brings about environmental benefits[1,13]; rather, our findings highlight a significant negative externality induced by the fundamental behavioral shifts that accompany BEV adoption.

The investigation into the underlying behavioral mechanisms of this congestion effect elucidates how BEV adoption reshapes urban mobility. By examining associated changes in vehicle ownership, demand as measured by hourly traffic flows, and public transit ridership, Figure 4 presents a qualitative perspective on the causal pathways. First, we find that a doubling in BEV adoption correlates with a 1.42% to 1.86% increase in

[*]We estimate the statewide economic impact of a 1.17% speed reduction by applying value-of-travel-time parameters[41] to California's 15 million daily commuters. Assuming an average 60-minute round-trip commute and a VOTT of $14/hour (50% of the median state wage), this reduction translates to 2.93 hours of annual delay per driver, totaling approximately $615 million in aggregate annual productivity losses.

total vehicle registrations. This suggests that BEVs are not fully replacing ICE vehicles but are expanding the overall fleet. This expansion likely stems from households acquiring BEVs as secondary vehicles or from attracting new owners who were previously deterred by the environmental impact of conventional cars[30,31]. Second, BEV adoption is positively correlated with travel demand as measured by traffic flow, confirming that owners do not merely possess these vehicles but drive them more intensively. This phenomenon aligns with a "rebound effect" triggered by the lower per-mile operating costs of BEVs, alongside new travel demand induced by increased household access to multiple vehicles[27,42,43]. Third, and critically, the growth in BEVs appears to come at the expense of decreasing public transit ridership; at the UA level, we observe a significant negative relationship between BEV counts and transit ridership. This indicates that the environmental gains of the electric transition might be partially offset by the loss of users from other sustainable modes. Collectively, these mechanisms reveal the role of the BEV as a catalyst for unintended car dependency, where financial incentives, lower operating costs, and pro-environmental identity induce new ownership and a modal shift away from transit. These findings provide a clear explanation for the observed peak-hour slowdowns.

Heterogeneity analysis reveals that the congestion impacts of BEV adoption are not uniform but vary systematically across socioeconomic and physical contexts. By interacting BEV counts with quintiles of key ZIP code characteristics, we find consistently negative impacts on peak-hour speeds, but with significantly amplified magnitudes in certain subgroups. The impact is most acute in socioeconomically disadvantaged, lower-density communities characterized by limited transit access and longer average commutes. Furthermore, a lack of public charging infrastructure significantly exacerbates the slowdown, suggesting that restricted charger access may concentrate BEV-related travel during peak periods. Ultimately, these findings indicate that BEV-induced congestion is most severe where households lack viable alternatives to private vehicle use and where infrastructure lags behind growing demand. This adds a critical spatial dimension to equity concerns in the transition to electric vehicles[44,45].

By documenting and exploring the congestion effects of BEVs, we provide a clear framework for policymakers to deal with the societal cost of electrification. Rather than viewing BEVs solely as an innovation for transportation decarbonization, policymakers must be aware that they can mitigate GHG emissions and induce new travel demand at the same time[46,47]. Failure to account for these effects may lead to a scenario where the benefits of emission reductions are significantly eroded by the costs of induced demand and fuel-tax revenue loss. To internalize these spatial and economic costs without undermining the environmental advantages of the electric vehicle transition, we propose possible policy interventions. To curb the induced demand of lower operating costs, it is reasonable for state and local authorities to implement road-pricing mechanisms—such as congestion fees or mileage-based user fees—that apply equitably to all vehicles, including BEVs. Although such fees have been widely discussed recently in the context of transportation finance[48,49], our findings suggest that they are also essential to internalize the true cost of private road occupancy. Also, existing and new purchase incentives for electric vehicles should be restructured to require or at least encourage the retirement of an existing ICE vehicle to prevent the expansion of multi-car household fleets. Additionally, to ensure the electric vehicle transition does not exacerbate transportation inequities, public investment must prioritize the deployment of infrastructure in underserved neighborhoods. By shifting the policy focus from individual vehicle acquisition to total system efficiency, we can ensure the electric transition delivers an urban mobility future that is sustainable, efficient, and equitable.

This study has several limitations that offer valuable directions for future research. First, we assume a static supply-side condition and do not account for long-term equilibrium effects, such as how urban planning and infrastructure development might evolve in response to the electric vehicle transition. Second, while we identify a significant negative externality, we do not conduct a full-scale welfare analysis; a comprehensive quantitative policy design would require weighing these congestion costs against the localized air quality and global GHG benefits. Third, our analysis does not incorporate the potential impact of other emerging transportation technologies, such as transportation network companies and autonomous vehicles, which may fundamentally reshape the urban mobility systems. Fourth, our traffic data is derived from the PeMS freeway sensor network, which covers highways but not arterial roads; the congestion effects on local streets, where much urban driving occurs, remain unmeasured.

## Display items

Table 1: Effects of BEV adoption on traffic congestion

| | Log speed (weekday peak) | | Log speed (midweek peak) | | Log speed (midnight) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log BEV count | -0.0117* | -0.0118** | -0.0116* | -0.0129** | 0.0007 | 0.0025** |
| | (0.0050) | (0.0040) | (0.0051) | (0.0042) | (0.0011) | (0.0008) |
| Year fixed effects | Yes | No | Yes | No | Yes | No |
| ZIP fixed effects | Yes | No | Yes | No | Yes | No |
| County-year fixed effects | No | Yes | No | Yes | No | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 7506 | 7484 | 7505 | 7482 | 7506 | 7484 |
| Unit clusters | 816 | 837 | 816 | 837 | 816 | 837 |
| Adj. $R^2$ | 0.747 | 0.381 | 0.751 | 0.392 | 0.559 | 0.244 |

Note: * $p < 0.05$, ** $p < 0.01$. Standard errors are in parentheses and clustered at the ZIP-code level.

Table 2: Effects of BEV adoption on vehicle ownership, traffic flow, and transit ridership

| | Δ Log vehicle ownership | | Log hourly flow | | Log transit ridership |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Δ Log BEV count | 0.0142** | 0.0186** | | | |
| | (0.0037) | (0.0038) | | | |
| Log BEV count | | | 0.0116 | 0.1754** | -0.2366* |
| | | | (0.0166) | (0.0293) | (0.1041) |
| Year fixed effects | Yes | No | Yes | No | Yes |
| ZIP fixed effects | Yes | No | Yes | No | No |
| UA fixed effects | No | No | No | No | Yes |
| County-Year fixed effects | No | Yes | No | Yes | No |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 12400 | 12412 | 7613 | 7598 | 315 |
| Unit clusters | 1512 | 1547 | 826 | 845 | 35 |
| Adj. $R^2$ | 0.626 | 0.623 | 0.905 | 0.606 | 0.993 |

Note: $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$. Standard errors in parentheses.

Columns (1)-(4) clustered at ZIP level, column (5) clustered at UA level.

UA = Urbanized Area.

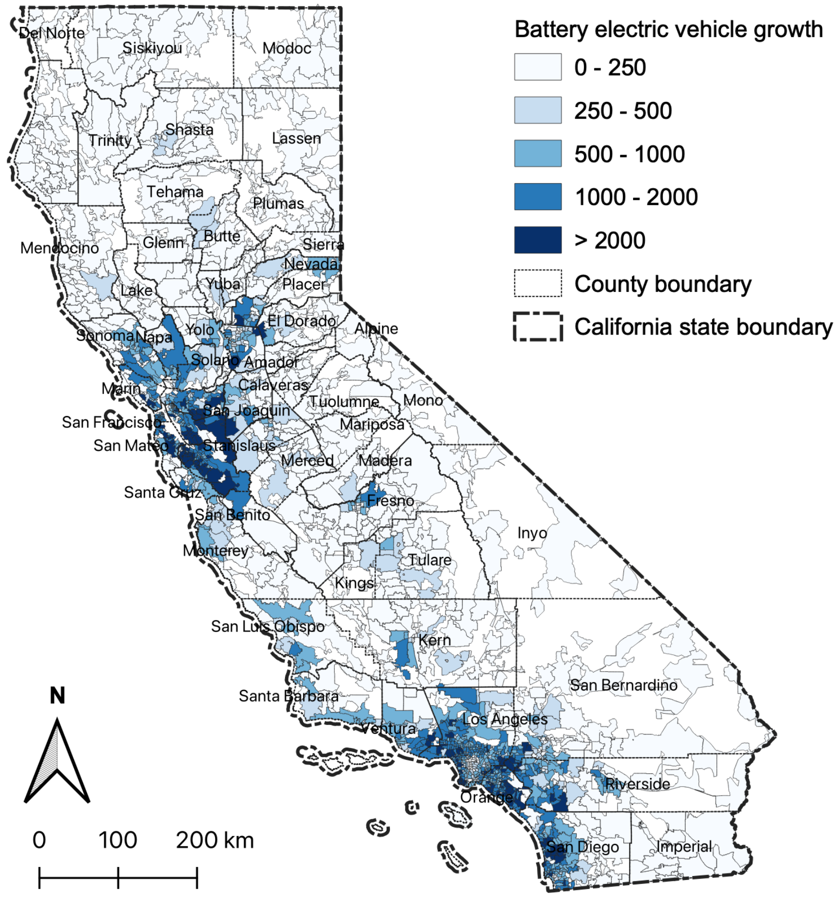


Figure 1: Growth of BEVs across California ZIP codes (2014-2023)

(a) Weekday peak-hour speed

(b) Weekday midnight speed

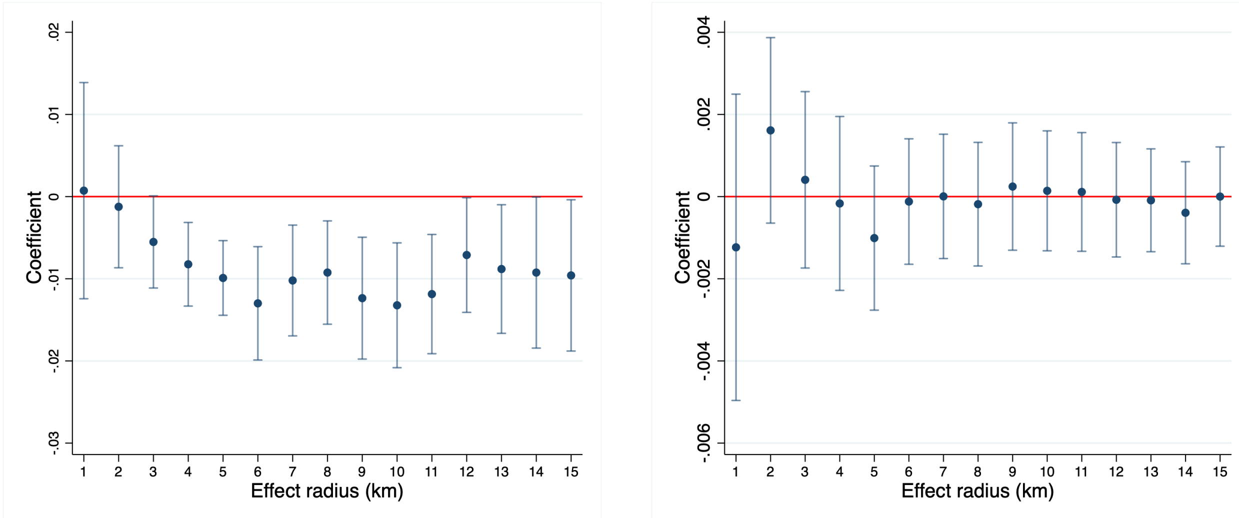


Figure 2: Spatial spillover of BEV adoption on traffic congestion

**Note:** Confidence intervals are at 95% level.

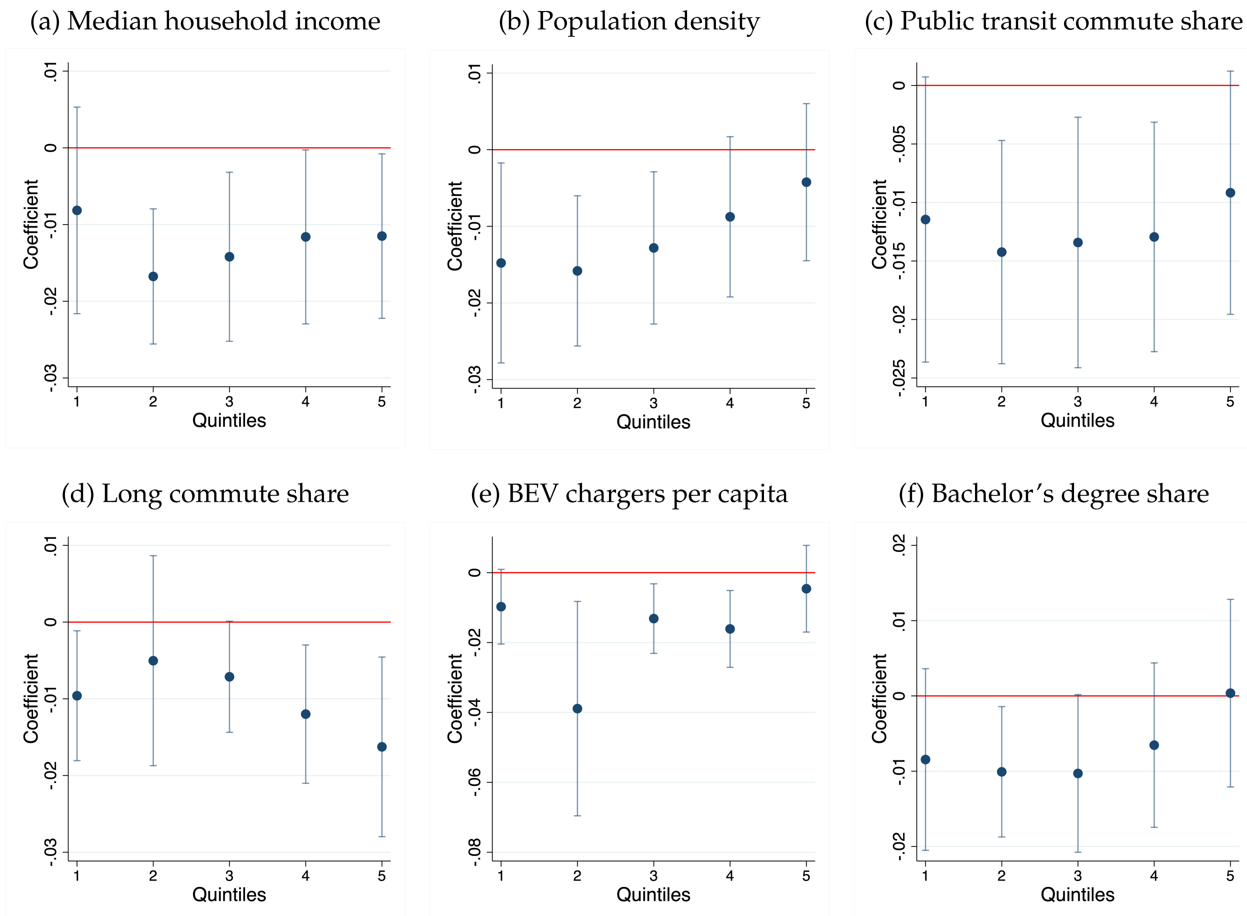


Figure 3: Heterogeneity in the effect of BEV adoption on weekday peak-hour traffic speed

**Note:** Confidence intervals are at 95% level. Long commute refers to one-way commute that is longer than 45 minutes.

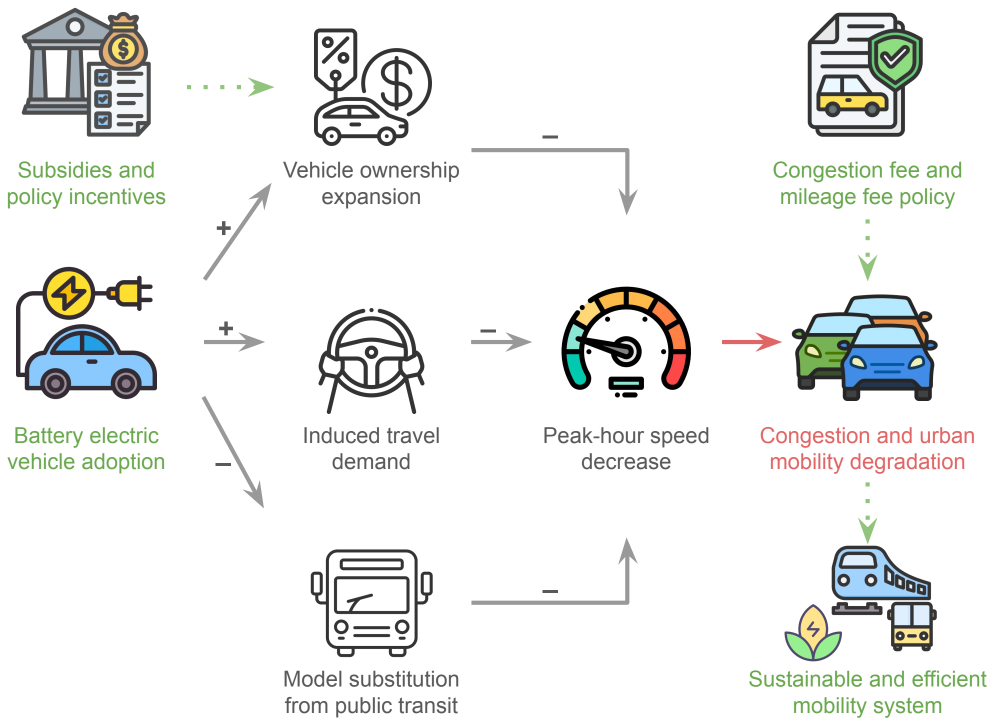


Figure 4: Conceptual framework: behavioral mechanisms and policy levers linking the electric vehicle transition to traffic congestion. Solid arrows indicate empirically documented associations in this study; dashed arrows indicate hypothesized pathways. Credit: Freepik, flaticon.com.

## Methods

### *Data*

We use the California Performance Measurement System (PeMS) database to obtain hourly, lane-specific speed data across the statewide freeway network, which has been used by several studies to measure traffic conditions[27,42]. The dataset covers a comprehensive network of freeway segments, making it invaluable for tracking congestion over time and across space. We first clean and geocoded the large-scale sensor-level speed data, which contains hourly traffic information from more than 40,000 detectors. We then aggregate the data to different spatial units—including ZIP code and circles of 1-15 kilometers radii from ZIP code centroids—and use it as our primary measure of congestion and traffic flow. Figure A.1 shows the spatial coverage of the PeMS dataset, and it shows that the dataset covers majority of populated areas in California.

We use data from the California Energy Commission to measure the adoption of BEVs over time. This dataset contains annual counts of registered light-duty vehicles by fuel type (e.g., BEVs and ICE vehicles) at the ZIP code level, aggregated from California DMV vehicle registration records. It spans from 2014 to 2023 and enables detailed tracking of BEV adoption trends.

We measure public transit ridership using data from the National Transit Database (NTD). We use the smallest available geographical unit in the NTD—the Urbanized Area (UA), as defined by the U.S. Census Bureau. We aggregate ZIP code-level BEV adoption data to the UA level using a crosswalk provided by the Department of Housing and Urban Development[50].

We include control variables in our regression models. First, we control for demographic and socioeconomic characteristics using 5-year ACS data: total population, population density, median household income, and percentage of college educated population. The variables are chosen due to the fact that the increasing consumer consciousness about carbon footprints has also led to a significant rise in BEV sales. Widely considered or advocated as an environmentally friendly product, BEVs are particularly popular among people with green-life cognition and identity. The ownership of BEVs can be significantly related to individuals' socioeconomic characteristics, including age, gender, income, and education level[31,51,52]. Second, we account for travel behavior factors, specifically the percentage of long commuters (>45 mins) and the percentage of public transit commuters, also from the 5-year ACS. Finally, we control for the number of public charging stations per capita—for both DC faster charging stations and all types of stations—using data from the U.S. Department of Energy.

***Empirical strategies***

*Two-way fixed effects models*

To estimate the impact of BEV adoption on traffic congestion and other mobility outcomes, we employ a two-way fixed effects model using panel data at the ZIP code level. This approach exploits within-ZIP variation in BEV adoption over time while controlling for unobserved heterogeneity across locations and common temporal shocks. Our baseline specification is given by:

$$Y_{it} = \beta \log(\mathrm{BEV}_{it}) + X_{it}'\gamma + \mu_i + \lambda_t + \varepsilon_{it}, \tag{1}$$

where $Y_{it}$ denotes the outcome of interest in ZIP code $i$ and year $t$, including traffic speed, vehicle ownership, traffic flow, or public transit ridership. $\log(\mathrm{BEV}_{it})$ represents the logarithm of the number of registered BEVs, and $X_{it}$ is a vector of time-varying control variables capturing demographic, socioeconomic, travel behavior, and charging infrastructure characteristics. ZIP code fixed effects $\mu_i$ absorb time-invariant local factors such as road network design and long-run land-use patterns, while year fixed effects $\lambda_t$ control for statewide shocks, including macroeconomic conditions and transportation policies.

Under the identifying assumption that, conditional on these fixed effects and time-varying controls, short-run changes in BEV adoption within a ZIP code are not systematically driven by unobserved shocks to peak-hour traffic demand, the estimated coefficient $\beta$ admits a causal interpretation. Specifically, ZIP code fixed effects absorb all time-invariant local characteristics, including baseline road capacity, urban form, and persistent travel preferences, while year fixed effects capture statewide trends such as fuel prices, macroeconomic conditions, and EV-related policies. We further include time-varying ZIP code-level socioeconomic and commuting controls, as well as county-by-year fixed effects in more stringent specifications, which absorb localized shocks such as infrastructure investment, land use changes, and regional economic cycles.

As an alternative specification, we replace the ZIP code and year fixed effects with county-by-year fixed effects. This specification absorbs all shocks that are common to ZIP codes within the same county in a given year, such as county-level transportation investments or policy changes. Relative to the baseline two-way fixed effects model, this approach is less demanding in terms of identifying variation, as it no longer requires within-ZIP changes over time and instead exploits cross-ZIP variation within the same county-year. Comparing results across the two specifications allows us to assess the robustness of our findings to alternative assumptions about the spatial and temporal structure of unobserved confounders. Standard errors are clustered at the ZIP code level to account for serial correlation and spatially correlated shocks. We also test the robustness of the model using a lagged independent variable to rule out potential reverse causalities.

*Spatial spillover effects*

Traffic congestion is inherently spatial, as travel behavior and road network performance extend beyond administrative boundaries. While the baseline specification treats congestion as a local outcome, BEV adoption in one ZIP code may influence traffic conditions in neighboring areas through commuting flows and network spillovers. To assess the robustness of our results to such spatial dependence, we conduct a spatial spillover analysis based on geographic aggregation.

Specifically, we construct alternative congestion measures by aggregating freeway segments within progressively larger buffers—ranging from 1-15 kilometers—around each ZIP code centroid. For each buffer radius, we estimate the same two-way fixed effects model using the corresponding aggregated traffic speed as the dependent variable. This procedure allows us to examine how the estimated effect of BEV adoption evolves as the spatial scale of measurement expands.

If the baseline results are driven by arbitrary ZIP code boundaries, the estimated coefficients would be expected to attenuate or change as the radius increases. Stability of the estimates across spatial scales instead indicates that the congestion effect of BEV adoption is localized yet robust. As a placebo test, we replicate the same spatial analysis using midnight traffic speeds, when congestion effect is expected to be minimal.

*Heterogeneity analyses*

To examine whether the congestion effects of BEV adoption vary across local contexts and different communities, we conduct heterogeneity analyses based on observed ZIP code characteristics. Specifically, we stratify ZIP codes into quintiles according to baseline socioeconomic, demographic, commuting, and infrastructural attributes, including median household income, population density, public transit commute share, long-commute share, BEV charger availability, and educational attainment. For each dimension, we re-estimate the baseline two-way fixed effects model separately within each quintile, focusing on weekday peak-hour traffic speed as the outcome variable. This flexible stratification approach allows the estimated effect of BEV adoption to vary across environments with differing degrees of car dependence, transit accessibility, and infrastructure capacity. All specifications maintain the same fixed effects structure and control variables, ensuring comparability across subgroups.

## Data availability

All datasets used in this study are from publicly available sources. Traffic speed and flow are calculated based on hourly traffic information from 40,000+ detectors on highway segments in the California Performance Measurement System (PeMS, https://pems.dot.ca.gov, accessed on Feb 27, 2026). Vehicle ownership data is the California Energy Commission database (https://www.energy.ca.gov/zevstats, accessed on Feb

27, 2026), containing both total vehicle and BEV counts. Public transit ridership data at the urbanized area level is from the National Transit Database (https://www.transit.dot.gov/ntd, accessed on Feb 27, 2026). Control variables are mostly from American Community Survey data (https://www.census.gov/programs-surveys/acs/data.html, accessed on Feb 27, 2026). Public charging station data is from the U.S. Department of Energy (https://afdc.energy.gov/data_download, accessed on Feb 27, 2026). All datasets are harmonized at the ZIP code level except the public transit ridership. The final compiled ZIP code-level dataset and Stata code can be found on GitHub after the publication of the article.

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# Appendix

The map in Figure A.1 shows that the spatial coverage of the PeMS sensors. We use the traffic data from the sensors to calculate our primary outcome variable in the study. The map shows that the dataset covers majority of populated areas in California.

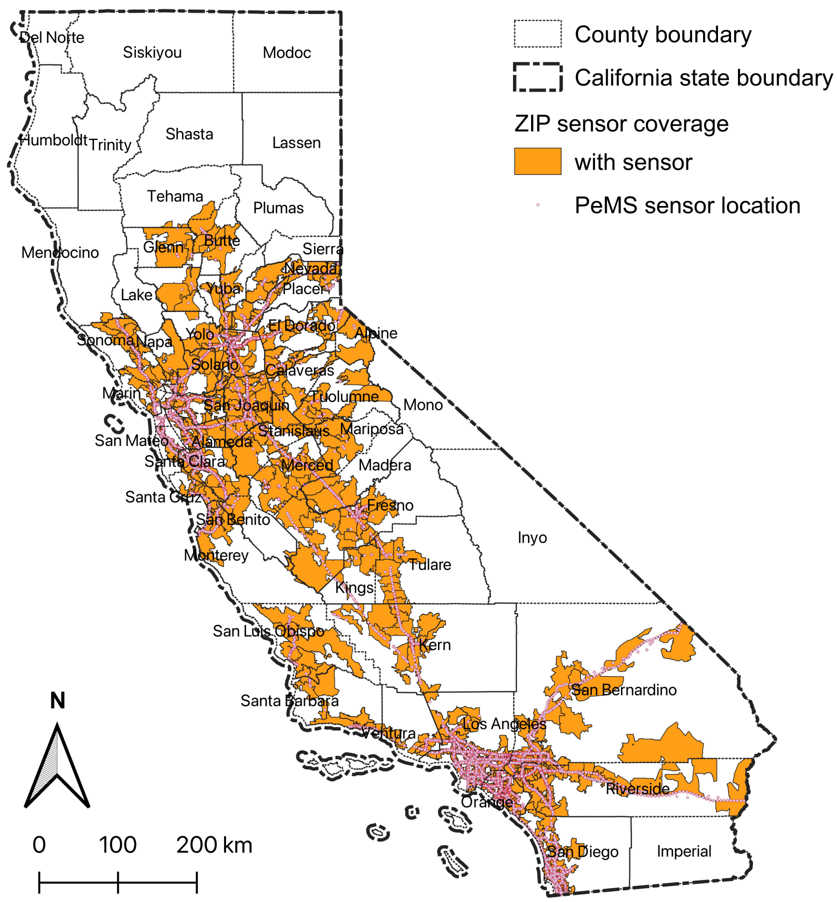


Figure A.1: Spatial coverage of PeMS sensors in California

Table A.1 shows the lagged regression results using the specifications in Table 1, which can help rule out potential reverse causality.

Table A.1: Effects of BEV adoption (3-year lag) on traffic congestion

| | Log speed (weekday peak) | | Log speed (midweek peak) | | Log speed (midnight) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log BEV count (lagged) | -0.0102* | -0.0120** | -0.0102* | -0.0132** | 0.0018 | 0.0030** |
| | (0.0042) | (0.0046) | (0.0044) | (0.0048) | (0.0013) | (0.0011) |
| Year fixed effects | Yes | No | Yes | No | Yes | No |
| ZIP fixed effects | Yes | No | Yes | No | Yes | No |
| County-year fixed effects | No | Yes | No | Yes | No | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5259 | 5254 | 5258 | 5252 | 5259 | 5254 |
| Unit clusters | 792 | 811 | 792 | 811 | 792 | 811 |
| Adj. $R^2$ | 0.842 | 0.389 | 0.840 | 0.399 | 0.644 | 0.236 |

Note: $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$. Standard errors are in parentheses and clustered at the ZIP-code level.