Zero-emissions vehicle adoption and satellite-measured NO_2 air pollution in California, USA, from 2019 to 2023: a longitudinal observational study

Sandrah P Eckel, Futu Chen, Sam J Silva, Daniel L Goldberg, Jill Johnston, Lawrence A Palinkas, Alberto Campos, Wilma Franco, Erika Garcia

Summary

Background Electrifying the transportation sector is a key climate-change mitigation strategy. Reductions in exhaust emissions have anticipated air quality co-benefits; yet, evidence is primarily based on projections. Using observed data in California, USA, we aimed to investigate whether reductions in exhaust emissions from the transition to zero-emissions vehicles (ZEVs: battery electric, plug-in hybrid, and hydrogen fuel cell) were detectable using Tropospheric Monitoring Instrument (TROPOMI) satellite measurements of nitrogen dioxide (NO_2) air pollution.

Methods In this longitudinal observational study, we combined data from 2019 to 2023 on annual light-duty ZEV registrations in 1692 California ZIP code tabulation areas (ZCTAs; cross-walked from ZIP codes) with annual mean TROPOMI-measured NO_2. We used longitudinal linear mixed-effects models to assess the association between within-ZCTA ZEV changes and within-ZCTA NO_2 changes, adjusting for temporal trends and time-varying potential confounding, or excluding 2020. In positive control analyses, we related internal combustion engine vehicle registrations to NO_2. In ground-truth analyses, we related ZEVs to NO_2 concentrations using 123 Environmental Protection Agency monitors from 2012 to 2023.

Findings The median within-ZCTA increase in ZEVs from 2019 to 2023 was 272 (IQR 18 to 839). A within-ZCTA increase of 200 ZEVs was associated with a 1·10% (95% CI –1·19 to –1·00) decrease in annual average NO_2. The main findings were supported by sensitivity analyses (–1·32% [–1·43 to –1·21] when excluding the year 2020), ground-truth analysis (–0·87% [–1·76 to 0·03] using NO_2 from ground-level monitors), and positive control analysis (0·80% [0·63 to 0·97] increase in annual average NO_2 per 800 increase in number of internal combustion engine vehicles).

Interpretation Using a natural experiment, we found that within-ZCTA increases in ZEV registrations were associated with reductions in NO_2 air pollution measured by satellite and replicated with ground-level monitors. This work in California serves as a proof-of-principle for future work using satellite-measured NO_2 to quantify effects of climate-change mitigation efforts on combustion-related air pollution within the USA and internationally.

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Introduction

Transitioning to electric vehicles is an important long-term mitigation strategy to reduce greenhouse gas emissions and slow climate change. In the short term, the transition is anticipated to reduce combustion-related air pollutants, such as nitrogen dioxide (NO_2), since fully electric vehicles have no exhaust emissions,[1] the largest source of NO_2 in most urban regions.[2] A full transition to electric vehicles is projected to reduce ambient NO_2 concentrations by 61% in the USA[3] and 30–80% in China.[4]

These anticipated reductions have important public health implications because traffic-related air pollution exposures, including NO_2, negatively affect cardiopulmonary health and contribute to premature death.[2,5] In the USA, transitioning to 100% zero emissions vehicle sales for passenger vehicles by 2035 and medium-duty and heavy-duty vehicles (gross vehicle weight rating [GVWR] >10 000 lbs [approximately 4536 kg]—eg, delivery trucks, buses, and big rigs) by 2040 is projected to have more than US$1·2 trillion in cumulative health benefits between 2020 and 2050.[3]

Real-world data on air quality co-benefits of the electric vehicle transition are important since most research to date consists of projections,[1,3] which necessarily rely on hypothetical scenarios and simplifying assumptions. Projection studies do not incorporate actual rates of the transition, the full range of vehicle types and operating characteristics, or all air pollution sources. To date, real-world evidence is scarce, with a few studies in specific cities on the association between observed changes in measured pollution and

Research in context

Evidence before this study

On Feb 26, 2025, we searched Google Scholar and PubMed for studies investigating the association between electric vehicle adoption and air pollution changes using the keywords: ("NO_2" OR "nitrogen dioxide" OR "NOx" OR "nitrogen oxides" OR "air pollution" OR "air pollutants") AND ("electric vehicle" OR "zero-emissions vehicle" OR "ZEV" OR "EV"). Several studies have projected air quality co-benefits of electrifying the transportation sector in simulation studies or models of hypothetical scenarios. A few studies have related changes in measured air pollutants within limited metropolitan areas to either modelled trends in emissions sources, observed transitions to cleaner fuel buses, or passenger train electrification. No studies have used real-world air pollution measurements to show significant reductions in nitrogen dioxide (NO_2) or nitrogen oxides associated with increasing observed numbers of light-duty electric vehicles, especially across a large geographical region. One study linked zero emissions vehicles (ZEVs) to lower NO_2, but results were not statistically significant because of limited air-monitoring sites.

Added value of this study

This is the first real-world study showing statistically significant reductions in observed NO_2 air pollution associated with the ongoing transition to light-duty electric vehicles over time. Our study leveraged the natural experiment of the early-to-mid-phase transition to ZEVs in California, USA, by comparing within-location changes in the annual number of registered light-duty ZEVs with within-location changes in annual average NO_2 air pollution, using satellite measures of NO_2 for full spatial coverage, from 2019 to 2023. Secondary analyses confirmed primary findings, including a positive control analysis showing the association between the number of registered light–duty internal combustion engine vehicles and satellite-measured NO_2 and a ground-truth analysis studying the association between ZEVs and ground-level regulatory monitors at 123 sites across California, from 2012 to 2023.

Implications of all the available evidence

The projected public health benefits of improved air quality from reduced exhaust emissions with the ZEV transition are already being realised, with observed reductions in NO_2 air pollution associated with the early-to-mid-phase transition to light-duty ZEVs in California and other reductions observed in several case studies. Satellite-measured NO_2 could be used across the globe to assess changes in NO_2 from ongoing climate mitigation efforts to reduce fossil-fuel combustion, with these data informing policy decisions to protect public health today and in the future.

modelled changes in emissions sources,[6] an early-phase transition to cleaner-fuel buses,[7] or electrification of a passenger train.[8] Our earlier longitudinal study analysed the association between the early-phase (2013–19) transition and light-duty (GVWR $\leq$10 000 lbs) zero-emissions vehicles (ZEVs) in California, USA, to within-location decreases in NO_2 at a network of regulatory monitors, although results were not statistically significant because of insufficient statistical power from the small number of monitoring sites (n=107) and the low numbers of ZEVs during the early-phase transition.[9]

In this Article, we investigated the air quality co-benefit of the early-to-mid-phase light-duty ZEV transition in California using publicly available longitudinal data. We overcame the limited spatial coverage of our previous work[9] by leveraging newly available satellite measurements of NO_2 to relate annual average atmospheric NO_2 across all of California from 2019 to 2023 to annual ZEV registrations over the same period. We complement our primary analysis with a positive control analysis using internal combustion engine vehicles (ICEVs) and with a ground-truth analysis of extended longitudinal data from ground-level NO_2 at regulatory monitors.

Methods

Study design

We leveraged the natural experiment[10] of the ongoing transition to electric vehicles in California by conducting a longitudinal study, at the spatial resolution of ZIP code tabulation areas (ZCTAs), relating within-location changes in light-duty ZEV registrations counts to within-location changes in NO_2 air pollution while adjusting for important covariates.

ZEV data

The California Energy Commission and California Department of Motor Vehicles publish annual counts of light-duty vehicles, registered by California ZIP code, with counts separated by fuel type.[11] We defined ZEVs in the same way as the California Energy Commission, with ZEVs including battery electric vehicles, plug-in hybrid electric vehicles, and hydrogen fuel cell electric vehicles. We defined ICEVs as all non-ZEVs. For each fuel type, we summed the vehicle registration counts by ZIP code and year, from 2012 until 2023. We linked ZIP code counts of light-duty vehicle types to ZCTA using longitudinal crosswalk linkages.[12]

NO_2 air pollution data

Atmospheric NO_2 air pollution

The Tropospheric Monitoring Instrument (TROPOMI) on the Sentinel-5 satellite measures tropospheric vertical NO_2 column contents (in molecules per cm^2) from low Earth orbit (approximately 824 km) once a day at approximately 13:30 h local time. The National Aeronautics and Space Administration (NASA) Health and Air Quality Applied Science Team publish freely available TROPOMI NO_2 data processed into annual averages at 0·01°×0·01°

(approximately 1 km^2) resolution, available for 2019–23.[13,14] We imported these data and projected them into the NAD83 spatial coordinate reference system using the rast() and project() functions in the R package terra.[15] Then, we spatially averaged to ZCTA boundaries in California using the extract() function and 2010 US Census ZCTA geography shapefile (in NAD83) from the tigris package in R.[16] The resultant dataset had 8845 ZCTA-year average tropospheric NO_2 values for 1769 ZCTAs in California with all ZCTAs having data for all 5 study years.

Ground-level ambient NO_2 air pollution

The US Environmental Protection Agency (EPA) publishes pre-generated datasets of annual summaries of pollutant measurements from their monitoring network.[17] We downloaded annual summary files dated Nov 19, 2024, for the years 2012–23. We restricted the data from air monitoring sites in California and annual average NO_2 (in parts per billion) calculated according to the NO_2 annual 1971 pollutant standard from monitors collecting 1-h samples, resulting in 1265 site-year records, which were reduced to 1179 after exclusions for annual averages that were calculated with 50% or less complete data (n=55), negative (n=3), or duplicative records at the same site-year (n=28; appendix p 2).

Covariate data

Using directed acyclic graph theory,[18] we encoded hypothesised causal within-location (ie, within ZCTA) associations between time-varying light-duty vehicle fleets and time-varying annual average NO_2. Our directed acyclic graph (appendix p 3) identified the following minimal adjustment set of time-varying covariates to control for confounding: year, population size, socioeconomic status, telecommuting patterns, and fuel prices. For population characteristics, we collected longitudinal ZCTA-level American Community Survey (ACS) 5-year estimates (from 2012 to 2023, with the end year of the 5-year series as the target year) from the IPUMS National Historical Geographical Information System,[19] including total population size; educational attainment, defined as percentage of the population older than 25 years with at least a bachelor's degree; median household income; and percentage of the working population older than 16 years working from home. Educational attainment and household income were used as proxies for socioeconomic status, representing possible structural and systemic biases contributing to differences in both ZEV adoption and NO_2. We subset the national ACS dataset to the 1815 unique California ZCTAs from the previously described ZEV dataset. For retail fuel prices, California state-level annual average prices from 2000–23 were obtained from the US Energy Information Administration[20] and used as proxy for local prices since finer spatial resolution data were not available with full coverage of California.

Data processing

ZEV data were combined with ACS population characteristics and fuel price datasets, henceforth called ZEV/ACS data. Then, two longitudinal datasets were created by separately merging ZEV/ACS data with: (1) ZCTA-year average TROPOMI NO_2 data from 2019 to 2023 and (2) site-year average EPA NO_2 data from 2012 to 2023. We excluded 50 (0·6%) of 8845 observations because the observation was not available in ZEV/ACS data, 345 (3·9%) of 8795 because of a ZCTA with missing or zero values at any study year for population size, and 15 (0·2%) of 8450 because of a ZCTA with unexplained extremely large changes in the total number of light-duty vehicles (>30 000) between 2019 and 2023 (appendix pp 2, 4).

Statistical analysis

In descriptive analyses, we summarised variable distributions using means (SDs) and medians (IQRs), and compared variables using correlation statistics.

Our primary analysis aimed to relate within-ZCTA changes in annual ZEV registrations to within-ZCTA changes in annual mean NO_2. We visualised unadjusted associations by plotting predicted 5-year change in NO_2 versus predicted 5-year change in ZEVs. To estimate adjusted associations, we used longitudinal linear mixed effects models of the following form relating TROPOMI NO_2 (y_{ij}) to ZEV registration counts (x_{ij}) for ZCTA i at year j:

See Online for appendix

$$\log y_{ij} = \beta_0 + \beta_1(x_{ij} - \overline{x}_{i\cdot}) + \ldots + u_i + \varepsilon_{ij}$$

where u_i represents ZCTA-level random intercepts. Because NO_2 was right-skewed, we natural log transformed the annual average NO_2 data before modelling and reported the transformed regression coefficient ((exp(β_1)-1)*100), interpreted as the percentage difference in NO_2 per unit change in x_{ij}. To ensure this quantity targeted only the within-ZCTA association as intended, we group-mean centred[21] the time-varying annual number of ZEVs by subtracting the ZCTA-level mean ZEV ($\overline{x}_{i\cdot}$) since ZEV numbers varied considerably across ZCTAs during the study period. We scaled to a 200 ZEV change, approximately the median ZEV increase across ZCTAs from 2019 to 2023. We fit a series of models with additional adjustment terms (denoted "…" in the equation). The unadjusted model (model 1) included only ZEVs and the random intercept; model 2 adjusted for a non-linear effect of calendar year using a quadratic polynomial of year and year squared, with year centred at 2019; model 3 was additionally adjusted for time-varying population size, socioeconomic status, fuel price, and telecommuting patterns; and model 4 further adjusted for time-varying number of ICEVs. In sensitivity analyses, we fit model 3 (1) to the subset of data excluding 2020 (ie, the set of 6748 observations from 1687 ZCTAs over 4 years), since 2020 was the year with the largest anticipated COVID-19 pandemic effects on air pollution concentrations, and (2) to the subset of 1473 ZCTAs (7365 observations) with total population size at least 500 in all study years to provide a comparison for studies using alternative ZEV metrics (eg, number of ZEVs per 1000 population) that require exclusion of smaller ZCTAs.[9] To investigate associations of ZEV subtypes, we did similar analyses for battery electric vehicles (scaled to a 200 vehicle change) and for plug-in hybrid electric vehicles (scaled to a 50 vehicle change), but not for hydrogen fuel cell electric vehicles because of their small numbers.

We did two secondary analyses. First, as a positive control, we did similar unadjusted and adjusted longitudinal analyses relating annual average TROPOMI NO_2 to annual ICEV registrations (scaled to a change of 800 vehicles), since ICEVs have exhaust emissions that produce NO_2. Second, we did a ground-truth analysis relating ZEVs to surface-level NO_2 from EPA monitors from 2012 to 2023. Again, we fit similar unadjusted and adjusted longitudinal models, but now with random intercepts for both ZCTA (n=111) and monitoring sites within ZCTAs (n=123). Because of the longer 12-year study period, we also considered adjustment for more complicated non-linear functions of calendar year, including linear, quadratic, and up to cubic polynomial terms for calendar year centred at 2019.

Analyses were done in R (version 4.4.1).

Role of the funding source

The funders of the study had no role in study design, data collection, data analysis, data interpretation, or writing of the report.

Results

The final TROPOMI-linked dataset included 1687 ZCTAs, each with all 5 years of data from 2019 to 2023 (ie, 8435 ZCTA-year observations). These ZCTAs varied in geographical size (median 42·6 km^2 [IQR 13·7–183·9]) and represented 95·4% (1687 of 1769) of California ZCTAs and contained 99·6% (39 028 858 of 39 183 443) of California's population. From 2019 to 2023, within-ZCTA population size was fairly stable, educational attainment increased slightly, and work-from-home activity increased (table). Annual average NO_2 declined as assessed by both TROPOMI and EPA monitors (figure 1). Correlation of TROPOMI and EPA NO_2 was high (Spearman's r=0·825; appendix p 6). TROPOMI NO_2 data were available for the entire state whereas EPA NO_2 monitors had less coverage (appendix p 7) and non-representative siting. Compared with ZCTAs without EPA NO_2 monitors, ZCTAs with EPA monitors had higher TROPOMI NO_2 concentrations ($p<0·0001$ for each year 2019–23), larger populations ($p<0·0001$ for each year 2019–23), and more ZEVs (p=0·0003 in 2019, p=0·0001 in 2020, p=0·0001 in 2021, p=0·0001 in 2022, and p=0·0001 in 2023) as well as lower percentages of residents who work from home (p=0·0003 in 2019, p=0·0001 in 2020, p=0·0001 in 2021, p=0·0001 in 2022, and p=0·0001 in 2023; appendix p 5).

From 2019 to 2023, ZEVs increased from 2·0% (559 943 of 28 237 734) to 5·1% (1 460 818 of 28 498 496) of total registered light-duty vehicles. We found considerable spatial heterogeneity in ZEV registrations across California (appendix p 7) and battery electric vehicles were the most common type of ZEV (appendix p 8). Within-ZCTA ZEV registrations generally increased from 2019 to 2023 (median 272 [IQR 18–839]) and ICEV registrations remained stable (table; figure 2). Within-ZCTA correlation of ZEV and ICEV registrations was moderate and negative (Spearman's r=–0·40). The 2012–23 study years for EPA NO_2 analyses included the dramatic increase in ZEVs, from essentially zero (appendix p 8). Finally, compared with alternative metrics (eg, percentage of total vehicles or ZEVs per 1000 population), trends in ZEV registration counts were more monotonic over time for ZCTAs of all sizes (appendix p 9). Analyses with alternative metrics would have required excluding smaller ZCTAs.

In longitudinal analyses, ZEV registrations were negatively associated with TROPOMI NO_2 in both unadjusted and adjusted models (Figures 3, 4A). A within-ZCTA increase of 200 ZEVs was associated with a 1·10% (95% CI –1·19 to –1·00) decline in annual average TROPOMI NO_2, after adjusting for time trends, and time-varying population size, educational attainment, telecommuting, and fuel prices. Results were quantitatively similar with different adjustments and qualitatively similar in sensitivity analyses excluding the year 2020 (–1·32% [–1·43 to –1·21]) or excluding ZCTAs with a population below 500 (–0·82% [–0·93 to –0·72]). Analyses with battery electric vehicles instead of ZEVs showed similar associations (appendix p 10).

Positive control analyses relating ICEV registrations to annual average TROPOMI NO_2 were consistently positive (figure 4B), although were more sensitive to model specification compared with the primary analyses of ZEV registrations. Estimated within-ZCTA increases in annual average NO_2 per 800 ICEV registration increase ranged from 0·80% (95% CI 0·63–0·97) in a model adjusted for time trends and time-varying covariates to 1·75% (1·58–1·92) in the unadjusted model.

Ground-truth analyses in the subset of ZCTAs with EPA data showed a negative association (figure 4B), consistent with the primary satellite data analysis, although were not statistically significant. A within-ZCTA increase of 200 ZEVs was associated with a 0·87% (95% CI –1·76 to 0·03) decline in annual average EPA NO_2, after adjusting for time trends with a cubic polynomial, and the time-varying covariates. The unadjusted EPA association (–4·69% [–5·20 to –4·18) was larger than the adjusted associations and adjusted results were less sensitive to the type of adjustment for year or covariates.

Discussion

This longitudinal study used real-world data from a natural experiment to document air quality co-benefits of the

	2019	2023	Within-ZCTA change (2019–23)*
Registered light-duty vehicles			
ZEVs	140·0 (11·0 to 470·5)	425·0 (29·0 to 1332·0)	272·0 (17·5 to 839·0)
BEVs	61·0 (4·0 to 236·0)	273·0 (17·0 to 965·5)	207·0 (12·0 to 698·5)
PHEVs	74·0 (6·0 to 229·0)	135·0 (11·0 to 358·5)	49·0 (5·0 to 118·0)
FCEVs	0·0 (0·0 to 4·0)	1·0 (0·0 to 11·0)	0·0 (0·0 to 6·0)
ICEVs	13 018·0 (1795·0 to 26 532·0)	12 638·0 (1776·5 to 26 010·0)	–100·0 (–965·5 to 20·0)
Total	13 324·0 (1834·5 to 27 221·5)	13 433·0 (1815·0 to 27 243·0)	–24·0 (–273·5 to 269·5)
Total population size	18 269·0 (2116·5 to 37 846·0)	18 300·0 (2136·5 to 37 563·0)	–17·0 (–648·5 to 562·5)
Bachelor's degree	27·7% (16·2 to 45·7)	30·8% (17·6 to 48·9)	2·5% (0·3 to 4·9)
Work from home	6·0% (3·7 to 9·7)	13·9% (8·1 to 22·1)	7·0% (2·4 to 13·3)
Annual average tropospheric NO_2, molecules cm^{-2}	$2·57 \times 10^{15}$ ($1·46 \times 10^{15}$ to $4·62 \times 10^{15}$)	$2·51 \times 10^{15}$ ($1·53 \times 10^{15}$ to $4·14 \times 10^{15}$)	$–7·02 \times 10^{13}$ ($–6·52 \times 10^{14}$ to $5·02 \times 10^{13}$)

Data are median (IQR). *ZEV registrations generally increased from 2019 to 2023, but ICEV registrations were stable or fluctuated less predictably. To complement the median within-ZCTA change for study endpoints (2023–2019), we calculated the median of the within-ZCTA range (max–min) of vehicle registration by type from 2019 to 2023: 273 for ZEVs, 209 for BEVs, 54 for PHEVs, 1 for FCEVs, 867 for ICEVs. BEV=battery electric vehicle. FCEV=hydrogen fuel cell electric vehicle. ICEV=internal combustion engine vehicle. PHEV=plug-in hybrid electric vehicle. ZCTA=ZIP code tabulation area. ZEV=zero-emissions vehicle.

Table: **Characteristics of 1687 ZCTAs in California, 2019–23**

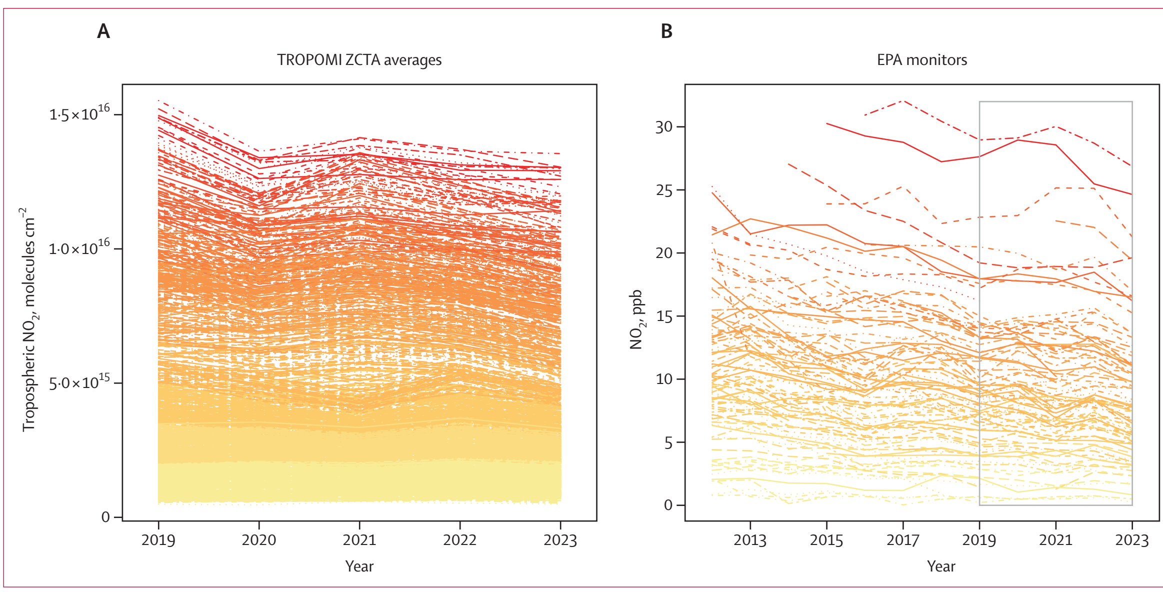

Figure 1: **Longitudinal trends in annual average NO_2**

Figure shows annual NO_2 as measured in the atmosphere by TROPOMI and averaged by ZCTA, 2019–23 (A) and at ground-level by US EPA monitors, 2012–23, with the overlapping 5-year period indicated by the grey box (B). To visualise trends over time, the gradient colour scheme is based on categorised values at 2019 (closest available year for EPA data). EPA=Environmental Protection Agency. ppb=parts per billion. NO_2=nitrogen dioxide. TROPOMI=Tropospheric Monitoring Instrument. ZCTA=ZIP code tabulation area.

2019–23 transition to electric vehicles in California. Within-ZCTA increases in the number of registered light-duty ZEVs were associated with within-ZCTA reductions in annual average NO_2 air pollution, as measured by satellite and replicated with ground-level EPA monitors. Associations were robust to adjustment for potential confounding, including adjustments for covariates related to the COVID-19 pandemic, as well as to exclusion of the year 2020. A positive control analysis further validated the approach, showing positive associations between ICEV registrations and NO_2. Taken together, these results document observed, real-world air quality co-benefits of the early-to-mid-phase ZEV transition in California. Results also support use of publicly available satellite measurements to measure changes in NO_2 associated with ZEV adoption.

Air quality co-benefits of transportation electrification have largely been based on projections, although the following studies have investigated real-world effects on measured pollutants: a dense network of sensors in the San Francisco Bay area of California detected a 1·8% per year reduction in carbon dioxide emissions from 2018 to 2022, attributed to the electrification of light-duty vehicles reducing on-road emissions through spatiotemporal models of

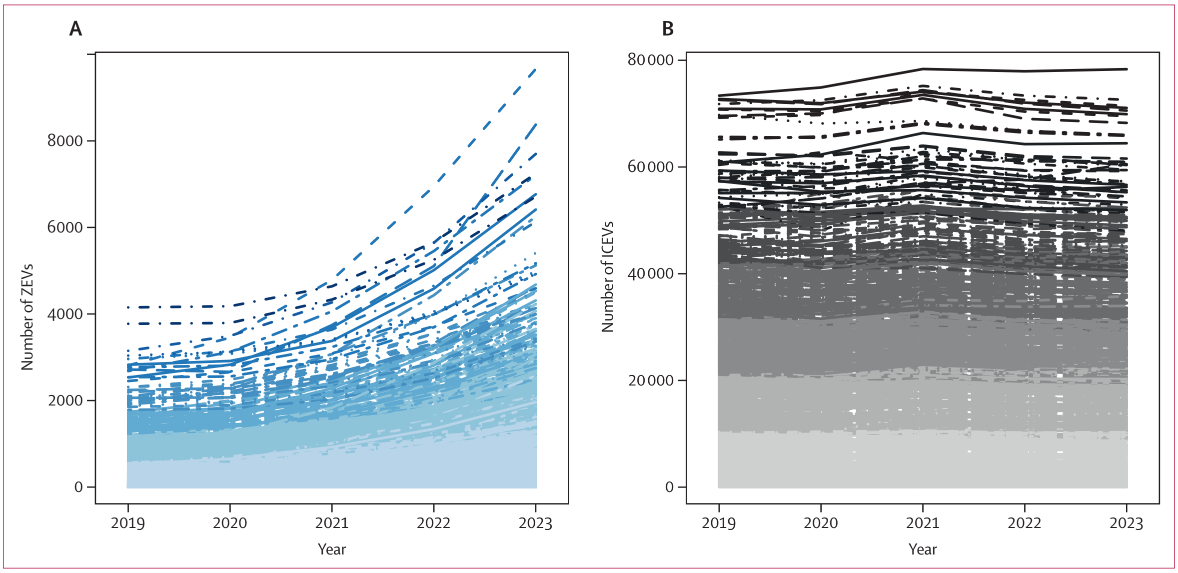

Figure 2: **Longitudinal trends, 2019–23, in the ZCTA-level counts of registered light-duty vehicles**
Figure shows vehicles classified as ZEVs (A) or ICEVs (B). Gradient colour scheme is based on categorised values at 2019. ICEV=internal combustion engine vehicle. ZEV=zero-emissions vehicle. ZCTA=ZIP code tabulation area.

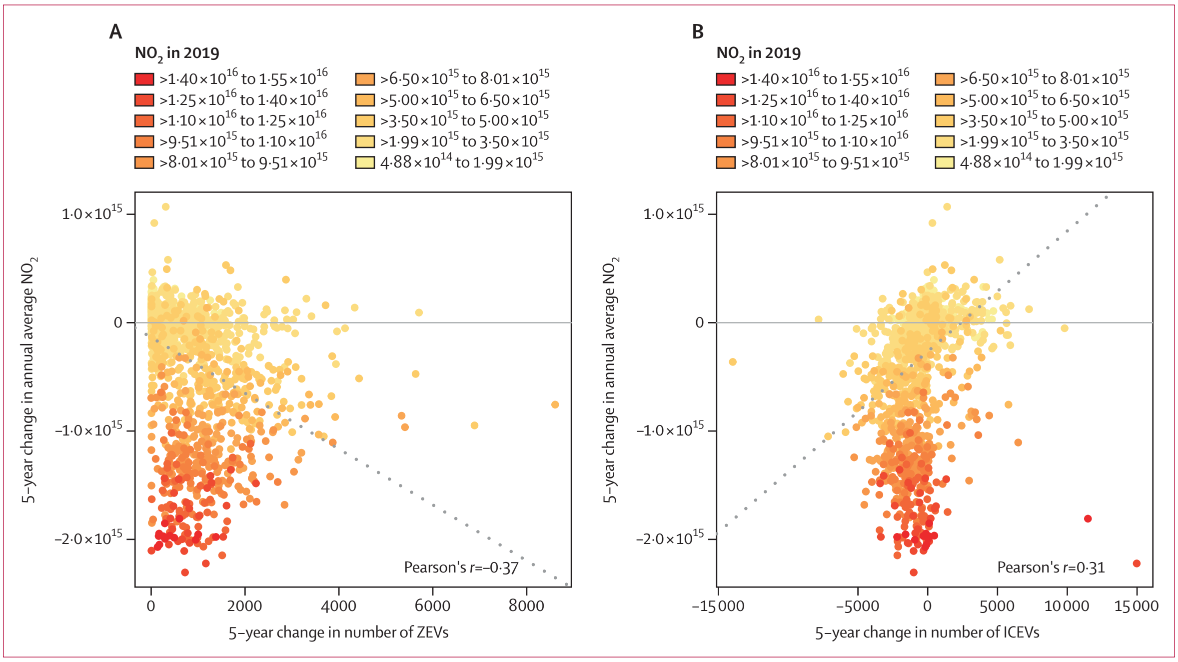

Figure 3: **Unadjusted associations of change in number of light-duty vehicle by type with change in TROPOMI annual average NO_2**
Figure shows unadjusted associations of change in light-duty ZEVs (A) and change in ICEVs (B) with change in TROPOMI-measured annual average NO_2 (molecules per cm^2), 2019–23. To smooth observed data, we used predicted 5-year change obtained by fitting a simple linear regression model of observed ZEV registrations (or NO_2) versus calendar year for each ZCTA and calculating $\widehat{Y}_{2023} - \widehat{Y}_{2019}$. ICEV=internal combustion engine vehicle. NO_2=nitrogen dioxide. TROPOMI=Tropospheric Monitoring Instrument. ZEV=zero-emissions vehicle.

trends in emissions sources.[6] A study[7] of a programme introducing lower-emissions buses (compressed natural gas, hybrid-electric, and ultra-low-sulphur diesel) in New York (NY, USA) documented declines in local nitric oxide (NO) and NO_2 between 2009 and 2014, especially in areas with high levels of bus service, of which a larger proportion shifted to lower-emissions buses. Before and after electrification of a diesel passenger train in Israel, researchers tracked annual average air pollution at train station monitoring sites and found significantly lower NO_2 (reductions

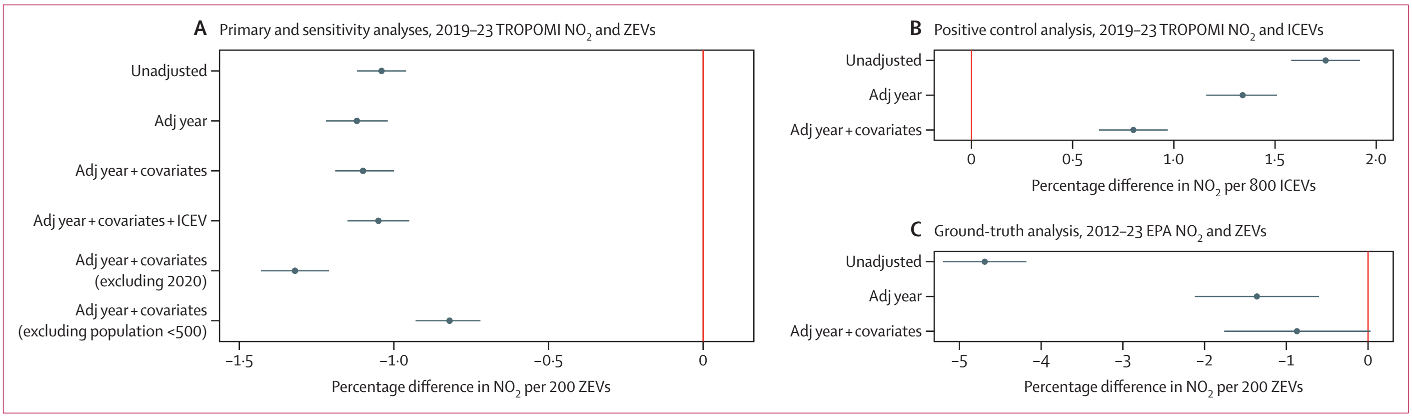

Figure 4: **Estimated adjusted associations of annual vehicle registration counts and annual average NO_2 in California from longitudinal linear mixed effects models**
Figure shows primary and sensitivity analyses that show the association between ZEVs and tropospheric NO_2 in 1687 ZCTAs, 2019–23 (A); positive control analyses that show the association between ICEVs and tropospheric NO_2 in 1687 ZCTAs, 2019–23 (B); and ground-truth analyses that show the association between ZEVs and annual average surface-level NO_2 from EPA monitors at 123 sites, 2012–23. Models with "adj year" adjust for time trends using quadratic polynomial terms for calendar year (ie, including terms for year and year^2, with year centred at 2019) for TROPOMI NO_2 analyses of 5 years of data and cubic polynomial terms for the EPA NO_2 analysis with 12 years of data. Models with "adj year + covariates" include the previously mentioned adjustment for time trend plus adjustment for the following time-varying annual ZCTA-level characteristics: total population size, educational attainment, work-from-home, as well as state-level annual average gas prices. Sensitivity analyses additionally adjusted for ICEVs, excluded the year 2020, or excluded the 214 ZCTAs with a population below 500. EPA=Environmental Protection Agency. ICEV=internal combustion engine vehicle. NO_2=nitrogen dioxide. TROPOMI=Tropospheric Monitoring Instrument. ZCTA=ZIP code tabulation area. ZEV=zero-emissions vehicle.

of 29–45% across three sites), NO (79–85%), nitrogen oxides (65–75%), and fine particulate matter ($PM_{2·5}$; reductions at two of three sites).[8] These studies along with the present work show that transportation electrification has observable effects on air quality.

A novelty of our work is NO_2 measurement by satellite. TROPOMI NO_2 has fine-scale spatiotemporal variability with lower values on weekends compared with weekdays, high correlation with annual average NO_2 from non-roadway EPA monitors (r^2=0·66 in 2019),[13] and has detected emissions from highways and urban areas;[22] power plants; mining, oil, and gas facilities;[23] as well as differential reductions in NO_2 from COVID-19-related lockdowns.[24] A major advantage of TROPOMI NO_2 is global availability, especially in locations without dense surface-level monitoring networks. However, at shorter timescales (eg, days to weeks), cloud cover can limit data availability and wind variability can complicate interpretation.[25] Note that rural areas have a smaller dynamic range of NO_2 than urban areas, so instrument noise has a larger effect for both TROPOMI and EPA monitors, and a larger fraction of the NO_2 column might not be near surface.

Strengths of our study include the longitudinal design allowing us to estimate the pooled association of within-ZCTA changes in ZEV registrations with within-ZCTA changes in NO_2, inherently controlling for confounding by time-invariant factors. The natural experiment of the ongoing ZEV transition provided considerable within-ZCTA heterogeneity in ZEV registration counts, providing a stronger design than a typical observational study.[10] We controlled for time-varying factors informed by our hypothesised causal relationships. Satellite measurement of NO_2 provided full spatial coverage, overcoming concerns about representativeness of EPA monitor locations.[26] California is the most populous US state and leads the USA in ZEV adoption. We validated our approach using both a positive control analysis relating ICEV registrations to TROPOMI NO_2 and a ground-truth analysis using NO_2 from EPA monitors. Finally, as an improvement over earlier work,[9] we cross-walked ZIP code data to ZCTAs, which are more appropriate units of analysis for longitudinal research than ZIP codes and avoid potential bias from exclusion in one-to-one linkages.[27] We also used ZEV counts and adjusted for time-varying total population size rather than using population-normalised ZEV counts,[9] because normalisation led to instability over time for ZCTAs with small populations and we aimed for minimal exclusion of ZCTAs.

Our study has limitations. First, TROPOMI NO_2 has limited historical availability, having come online in mid-2018, although this limitation is counterbalanced by continued future availability and full spatial coverage with high resolution. Note that longer-term satellite NO_2 data products have been developed for specific use cases.[28] TROPOMI is also only observed in the early afternoon, missing rush-hour traffic peaks. Future work might consider the NASA TEMPO instrument launched in 2023, which observes NO_2 during all daylight hours over North America. Second, our 2019–23 study period includes the COVID-19 pandemic, which could confound unadjusted associations because of effects on both ZEV adoption and NO_2 concentrations. To address this, we adjusted for time-varying confounders including fuel price and telecommuting patterns and did sensitivity analyses removing data from 2020. We used state-level average fuel prices because local prices were available for only select metropolitan areas (ie, Los Angeles–Long Beach–Anaheim, San Diego–Carlsbad, and San Francisco–Oakland–Hayward), and local prices closely followed state-level prices during our study period, so we expect little bias from using state-level fuel price data. Third, we examined air quality co-benefits for only one pollutant, NO_2. We focused on NO_2 since this pollutant arises from the combustion of fossil fuels, primarily from vehicle emissions,[2] and the only source of NO_2 from local vehicle operation is exhaust emissions, which fully electric vehicles do not have. Effects on other air pollutants merit further study and might be complex. For example, reduced NO_2 might increase ground-level ozone.[29] Also, $PM_{2.5}$, which cannot currently be retrieved directly by satellite,[30] has both exhaust and non-exhaust (ie, brake, tyre, and road wear) sources. Exhaust $PM_{2.5}$ is expected to decline,[31] whereas tyre and road wear emissions might increase since ZEVs tend to be heavier than ICEV equivalents because of batteries.[32] Despite the increased weight, brake wear emissions might decrease considerably because of regenerative braking technology.[33] Fourth, our work focuses on NO_2 effects of local ZEV operation and does not address the production and recycling of ZEV batteries or changes in power plant emissions due to increased electricity demands for vehicle charging. Counts of registered light-duty ZEVs are a crude measure of local ZEV operation. In neighbourhoods with primarily local traffic, local ZEV registrations are a better proxy for local ZEV operation than in neighbourhoods close to a highway or with a dense network of major roads. One approach to overcome this limitation is to combine local ZEV registrations with microscale simulations of trip routes and emissions to estimate the proportion of traffic emissions from ZEVs.[34] Indeed, researchers have suggested that locations with few ZEV registrations might still benefit from reduced emissions from nearby highway or major road traffic transitioning to ZEVs (replacing ICEVs), even though these ZEVs are registered elsewhere.[34] Future work could investigate whether ZCTA-level NO_2-ZEV registration associations vary by road density or proximity to freeways. Fifth, another limitation of vehicle registration counts by ZCTA is the spatial coarsening of approximately 1 km × 1 km TROPOMI NO_2 data to ZCTAs. Future work could improve spatial resolution using census-tract counts of ZEVs or spatiotemporal models of traffic emissions.[34] Last, our definition of ZEV aligns with California's regulatory definition and includes plug-in hybrid electric vehicles, which are not fully electric; however, our results were robust to considering only battery electric vehicles. More broadly, electrification of on-road medium-duty and heavy-duty vehicles is projected to have substantial air quality co-benefits,[3] but the transition is still in the early phase. In future work, real-world evidence on co-benefits can be studied as the transition proceeds.

Our work has broad-reaching implications and policy relevance. TROPOMI assessments are global and freely available, so our approach in California has the potential to be generalised to locations around the globe, including those without air quality monitoring networks. Furthermore, although we focused on light-duty ZEVs, our approach has the potential to be generalised to any climate-change mitigation strategy reducing combustion-related sources of NO_2. Examples include the electric motorbike transition in some low-income and middle-income countries or mode shifts to active transport, such as bicycling in Paris, France. Furthermore, given the well-documented health effects of traffic-related air pollution, future work can link air quality co-benefits of transportation electrification to improvements in health outcomes, as in our earlier work relating the ZEV transition in California to reduced asthma-related emergency department visits.[9] A scoping review of health effects of the electric vehicle transition called for such observational studies, especially for populations disproportionately exposed to traffic-related pollution.[35] These real-world data have the potential to drive effective solutions for a healthier future.

Contributors

SPE, EG, and FC conceived and designed the study. SPE and FC accessed and verified the underlying data, and FC conducted the ZCTA crosswalks. DLG processed the satellite data and provided interpretations and context, with additional input from SJS. SPE conducted the statistical analyses with the assistance of EG and FC, and wrote the first draft of the manuscript. EG, SPE, LAP, JJ, and WF contributed to funding acquisition. EG supervised the study. All authors contributed to the revision of the manuscript, interpretation of the results, and approval of the final manuscript.

Declaration of interests

EG reports stock in Tesla and Rivian Automotive, all outside the submitted work, a competing interest managed by the University of Southern California (USC) Health Science Campus Conflict of Interest Review Committee including independent review of data collection and analyses. SPE reports a spouse who works in emissions testing for a major automobile manufacturer, a competing interest managed by the USC Health Science Campus Conflict of Interest Review Committee including independent review of data collection and analyses. All other authors declare no competing interests.

Data sharing

Data used in this study are freely and openly available from California Energy Commission (http://www.energy.ca.gov/zevstats), American Community Survey Data (https://www.census.gov/programs-surveys/acs/data.html and https://www.nhgis.org/), US EPA AirData (https://aqs.epa.gov/aqsweb/airdata/download_files.html), and TROPOspheric Monitoring Instrument NO2 (https://disc.gsfc.nasa.gov/datasets).

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References

1 Peters DR, Schnell JL, Kinney PL, Naik V, Horton DE. Public health and climate benefits and tradeoffs of US Vehicle electrification. *GeoHealth* 2020; **4:** e2020GH000275.

2 US Environmental Protection Agency. Integrated science assessment for oxides of nitrogen—health criteria. Report number EPA/600/R-15/068. Office of Research and Development. National Center for Environmental Assessment, 2016.

3 American Lung Association. Zeroing in on health air. 2022. https://www.lung.org/clean-air/electric-vehicle-report (accessed March 26, 2025).

4 Wang L, Chen X, Zhang Y, et al. Switching to electric vehicles can lead to significant reductions of $PM_{2.5}$ and NO_2 across China. *One Earth* 2021; **4:** 1037–48.

5 Boogaard H, Samoli E, Patton AP, et al. Long-term exposure to traffic-related air pollution and non-accidental mortality: a systematic review and meta-analysis. *Environ Int* 2023; **176:** 107916.

6 Asimow NG, Turner AJ, Cohen RC. Sustained reductions of Bay Area CO_2 emissions 2018–2022. *Environ Sci Technol* 2024; **58:** 6586–94.

7 Lovasi GS, Treat CA, Fry D, et al. Clean fleets, different streets: evaluating the effect of New York City's clean bus program on changes to estimated ambient air pollution. *J Expo Sci Environ Epidemiol* 2023; **33:** 332–38.

8 Tartakovsky D, Kordova-Biezuner L, Broday DM. $PM_{2·5}$ and NO_X concentrations decrease as a result of a railway electrification. *Environ Monit Assess* 2025; **197:** 188.

9 Garcia E, Johnston J, McConnell R, Palinkas L, Eckel SP. California's early transition to electric vehicles: observed health and air quality co-benefits. *Sci Total Environ* 2023; **867:** 161761.

10 de Vocht F, Katikireddi SV, McQuire C, Tilling K, Hickman M, Craig P. Conceptualising natural and quasi experiments in public health. *BMC Med Res Methodol* 2021; **21:** 32.

11 California Energy Commission. California Energy Commission Zero emission vehicle and infrastructure statistics. 2024. https://www.energy.ca.gov/zevstats (accessed May 1, 2024).

12 Uniform Data System. ZIP code to ZCTA crosswalk—UDS mapper. https://udsmapper.org/zip-code-to-zcta-crosswalk/ (accessed March 18, 2024).

13 Goldberg DL, Anenberg SC, Kerr GH, Mohegh A, Lu Z, Streets DG. TROPOMI NO_2 in the United States: a detailed look at the annual averages, weekly cycles, effects of temperature, and correlation with surface NO_2 concentrations. *Earth's Future* 2021; **9:** e2020EF001665.

14 Goldberg DL. HAQAST Sentinel-5P TROPOMI nitrogen dioxide (NO_2) CONUS annual level 3 0·01 × 0·01 degree gridded data V2.4. Goddard Earth Sciences Data and Information Services Center. 2024. https://doi.org/10.5067/ACADNS5UBWPQ (accessed Aug 1, 2024).

15 Hijmans RJ. terra: spatial data analysis, R package version 1.8–31. 2025. https://github.com/rspatial/terra (accessed March 24, 2025).

16 Walker K. tigris: load census TIGER/line shapefiles, R package version 2.1.2. 2024. https://github.com/walkerke/tigris (accessed March 24, 2025).

17 US Environmental Protection Agency. Air data: air quality data collected at outdoor monitors across the US, pre-generated data files annual summary data. https://aqs.epa.gov/aqsweb/airdata/download_files.html (accessed Nov 19, 2024).

18 Greenland S, Pearl J, Robins JM. Causal diagrams for epidemiologic research. *Epidemiology* 1999; **10:** 37–48.

19 Ruggles S, Flood S, Sobek M, et al. IPUMS USA: version 16.0 [dataset]. 2025. https://doi.org/10.18128/D010.V16.0 (accessed March 26, 2025).

20 US Energy Information Administration. Petroleum & other liquids data. 2025. https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=emm_epm0_pte_sca_dpg&f=a (accessed March 26, 2025).

21 Kreft IG, de Leeuw J, Aiken LS. The effect of different forms of centering in hierarchical linear models. *Multivariate Behav Res* 1995; **30:** 1–21.

22 Filonchyk M, Peterson MP. Analysis of air pollution from vehicle emissions for the contiguous United States. *J Geovis Spat Anal* 2024; **8:** 16.

23 Goldberg DL, Lu Z, Streets DG, et al. Enhanced capabilities of TROPOMI NO2: estimating NO_X from North American cities and power plants. *Environ Sci Technol* 2019; **53:** 12594–601.

24 Kerr GH, Goldberg DL, Anenberg SC. COVID-19 pandemic reveals persistent disparities in nitrogen dioxide pollution. *Proc Natl Acad Sci USA* 2021; **118:** e2022409118.

25 Goldberg DL, Anenberg SC, Griffin D, McLinden CA, Lu Z, Streets DG. Disentangling the impact of the COVID-19 lockdowns on urban NO_2 from natural variability. *Geophys Res Lett* 2020; **47:** e2020GL089269.

26 US Environmental Protection Agency. Who decides where monitors get placed? Updated Aug 16, 2024. https://www.epa.gov/outdoor-air-quality-data/who-decides-where-monitors-get-placed (accessed March 26, 2025).

27 Chen F, MacDonald B, Xu Y, et al. ZIP code and ZIP Code tabulation area linkage: implications for bias in epidemiologic research. *Epidemiology* 2025; **36:** 115–18.

28 Geddes JA, Martin RV, Boys BL, van Donkelaar A. Long-term trends worldwide in ambient NO_2 concentrations inferred from satellite observations. *Environ Health Perspect* 2016; **124:** 281–89.

29 Camilleri SF, Montgomery A, Visa MA, et al. Air quality, health and equity implications of electrifying heavy-duty vehicles. *Nat Sustain* 2023; **6:** 1643–53.

30 Shen S, Li C, van Donkelaar A, Jacobs N, Wang C, Martin RV. Enhancing global estimation of fine particulate matter concentrations by including geophysical a priori information in deep learning. *ACS ES T Air* 2024; **1:** 332–45.

31 Skipper TN, Lawal AS, Hu Y, Russell AG. Air quality impacts of electric vehicle adoption in California. *Atmos Environ* 2023; **294:** 119492.

32 Rakha HA, Farag M, Foroutan H. Electric versus gasoline vehicle particulate matter and greenhouse gas emissions: Large-scale analysis. *Transp Res Part D Transp Environ* 2025; **140:** 104622.

33 Zhang Q, Yin J, Fang T, et al. Regenerative braking system effectively reduces the formation of brake wear particles. *J Hazard Mater* 2024; **465:** 133350.

34 Yu Q, He BY, Ma J, Zhu Y. California's zero-emission vehicle adoption brings air quality benefits yet equity gaps persist. *Nat Commun* 2023; **14:** 7798.

35 Pennington AF, Cornwell CR, Sircar KD, Mirabelli MC. Electric vehicles and health: a scoping review. *Environ Res* 2024; **251:** 118697.