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Observational evidence of the impact of electric vehicles on local air quality in the United States

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Replacement of internal combustion engine vehicles with battery electric vehicles (EVs) is expected to impact air quality. Previous projections, often relying on emissions inventories of precursors with high uncertainties, have yielded results that vary by model parameters and assumptions. There remains little empirical investigation of the real-world effects, particularly for the low yet growing levels of electrification in the United States. Here county-level vehicle registrations and measurements from ground-level air monitors from 2018 through 2023 were used to investigate the impacts of EV penetration on annual and seasonal concentrations of criteria air pollutants in the United States. Fixed effects regression analysis revealed that rising EV penetration was associated with reductions in mean annual concentrations of nitrogen oxides (NO_x as the sum of NO_2 and NO), carbon monoxide (CO), and fine particulate matter ($PM_{2.5}$) and in mean summer season concentrations of ozone (O_3). By contrast, there was a potential increase in sulfur dioxide (SO_2). The findings demonstrate empirical improvements in air quality associated with EV adoption yet highlight the risk of a continued reliance on fossil fuels. Strategic policies that support enhanced EV adoption must support commensurate expansion of renewable energy access in order to maximize the air quality benefits of the technology.

Environmental significance

Air quality has a substantial impact on human health, with exposure to poor outdoor air linked to millions of deaths annually. Vehicle traffic is responsible for a large fraction of emissions. Previous studies have used chemical transport models to simulate a transition from internal combustion engine vehicles to electric vehicles (EVs), but the projected impacts on air quality have yielded results that vary by model parameters and assumptions. Here, we present observational evidence of the real-world impact of EV adoption on local air quality in the United States. The findings demonstrate air quality improvements associated with EV adoption, yet they indicate that renewable energy access is essential for realization of the full air quality benefits of vehicle electrification.

1 Introduction

Poor air quality contributes to 4.2 million annual deaths globally,[1] and an estimated 100 000 U.S. annual deaths are attributed to domestic anthropogenic emissions.[2] Vehicle traffic represents a large fraction of pollutant emissions that impact outdoor air quality, with on-road sources contributing 27% of nitrogen oxides (NO_x), 22% of carbon monoxide (CO), 1.4% of primary particulate matter with a diameter less than 2.5 μm ($PM_{2.5}$), 1.1% of primary PM_{10}, and 0.5% of sulfur dioxide (SO_2) total emissions in the U.S.[3] Additionally, NO_x and SO_2 are critical species that contribute to secondary PM and ozone (O_3) formation.[4,5] Consequently, the transportation sector is a major determinant of ambient air quality in the U.S.

Previous studies have modeled varying electrification scenarios to predict the potential impacts on air quality of replacing internal combustion engine (ICE) vehicles with battery electric vehicles (EVs).[6–14] Most models predict strong declines in concentrations of NO_x and CO, which are directly emitted from vehicle tailpipes, and a rise or no change in SO_2, attributed to increased electricity production from fossil energy sources (and coal in particular) at electric power plants to charge EVs.[15] Projected impacts on PM and O_3 yield varying results,[15] reflecting uncertainties in precursor emissions and nonlinearities in reaction pathways.[4,16] Furthermore, model simulations and chemical transport models rely on emissions inventories that, while considered robust for NO_x, have greater uncertainty in the accuracy and completeness of emissions of precursors for secondary aerosols such as ammonia (NH_3) and volatile organic compounds (VOCs).[17–19] Consequently, these models may fail to capture effects stemming from emissions not reflected in current inventories and, for secondary aerosols, reaction pathways that have evolved or that lack thorough chemical description.

The real-world impacts of EVs on air quality using empirical data remain understudied. While most models have simulated EV penetration of at least 20%, EV adoption in the U.S. remains

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far below those levels. In 2023, EV registrations in California were highest in San Mateo County at 7.5% of total registrations,[20] while EVs represented only 1.2% of national light-duty vehicle registrations.[21] Few studies have investigated whether these levels of electrification have measurably affected air quality. In China, cumulative sales of EVs since 2014 [22] and the implementation of a policy subsidizing purchases of non-ICE vehicles[23] were correlated with declines in $PM_{2.5}$; a study analyzing increasing EV usage found declines in $PM_{2.5}$, PM_{10}, CO, SO_2, and O_3 but an increase in NO_2 in three Chinese cities between January 2019 and October 2020 (a period coinciding with the COVID-19 pandemic).[24] In California, there was a reduction in asthma-related hospital visits but no significant effect on mean annual NO_2 with rising EVs and plug-in hybrid vehicles (PHEVs) per capita (2013–2019).[25] In light of these sparse investigations, there remains a knowledge gap of the observed impacts of EVs on criteria air pollutants across much of the U.S.

Here, we empirically investigated the effects of EVs on air quality by examining EV registrations and observations from ground-level air monitors spanning 20 of 48 contiguous states. County-level EV registrations were obtained *via* public records requests to state departments and from open databases and paired with air quality data from the network of monitor stations that report to the U.S. Environmental Protection Agency (EPA). We examined annual and seasonal concentrations of NO_x, NO_2, NO, CO, O_3, SO_2, $PM_{2.5}$, and PM_{10} from 2018 through 2023 (Table S1) and used two-way fixed effects regression analysis to determine the relationship between EV penetration in the vehicle fleet and ambient concentrations of each pollutant. The magnitudes of the NO_x and CO results were compared with the expected concentration declines based on the associated reductions in emissions. This work aids understanding of how vehicle electrification has impacted air quality across the U.S. and informs critical policy interventions to maximize the public health benefits of EV adoption.

2 Methods

2.1 Regression model

Two-way fixed effects regression, a technique for causal inference on longitudinal data,[26] was used to evaluate the impact of EV penetration on pollution levels. The unit fixed effect controls for site-specific variables that may influence pollution levels and the time fixed effect controls for nationwide changes in pollution with time. Mathematically, the unit mean and time mean are subtracted from each observation prior to regressing the dependent variable on the independent variable.

$$y_{it} = \beta_{\mathrm{EV}}\mathrm{EVs}_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (1)$$

In eqn (1), y_{it} is the pollution level at monitoring site i in year t, β_{EV} is the change in y_{it} for a 1-unit change in EVs_{it}, EVs_{it} (%) is the fraction of the total vehicle population that is battery electric in the county of monitoring site i in year t, γ_i is the unit fixed effect (air monitor site), δ_t is the time fixed effect (year), and ε_{it} is the error term (Table S3). Potential intra-county correlation of the regression residuals due to the nesting of monitor sites i within counties (*i.e.*, multiple monitor sites in a single county) was accounted for in the calculation of the standard errors (see final paragraph of Methods).

To control for potential time-varying confounders, the following covariates at the county and year level were added to the model specification: residential heating electrification rate, total vehicle population, median income, telecommuting fraction of workers, mean air temperature, and total precipitation.

$$y_{it} = \beta_{\mathrm{EV}}\mathrm{EVs}_{it} + \beta_{\mathrm{Elec}}\mathrm{Elec}_{it} + \beta_{\mathrm{Veh}}\mathrm{Veh}_{it} + \beta_{\mathrm{Inc}}\mathrm{Inc}_{it} + \beta_{\mathrm{Tele}}\mathrm{Tele}_{it} + \beta_{\mathrm{Temp}}\mathrm{Temp}_{it} + \beta_{\mathrm{Prcp}}\mathrm{Prcp}_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (2)$$

In eqn (2), Elec_{it}, Veh_{it}, Inc_{it}, Tele_{it}, Temp_{it}, and Prcp_{it} are the fraction of occupied households using electricity as home heating fuel (%), total vehicle population, median income (dollars, adjusted for inflation), fraction of workers who worked from home (%), mean air temperature (mean of monthly means, °F), and total precipitation (inches) in the county of monitoring site i in year t, respectively, and β_{Elec}, β_{Veh}, β_{Inc}, β_{Tele}, β_{Temp}, and β_{Prcp} are the corresponding regression coefficients. For the seasonal analyses, Temp_{it} and Prcp_{it} were the mean and total, respectively, of each respective season (summer and winter). The specification with all covariates (eqn (2)) is the primary model cited in the main text (Tables S4 and S6). The results using a model specification including only the covariates that had a marked change on the regression coefficient on EV share of the vehicle fleet (β_{EV}) when added individually to eqn (1) (mean air temperature and total precipitation, Table S7) are presented in Tables S8 and S9. The results using a model specification with the meterological covariates excluded are presented in Tables S10 and S11.

Confidence intervals and *P*-values were computed using critical values from a *t*-distribution with $G - 1$ degrees of freedom, with G the number of years of the panel data (*i.e.*, 6), to account for potential correlation of the regression residuals within clusters. This is an approach proposed by Cameron & Miller[27] for data for which the use of multi-way clustered standard errors (by year and county) is not possible due to the small number of clusters (*i.e.*, 6 years) in one or both of the ways. This approach uses standard errors that assume independent and identically distributed residuals yet employs critical values from the *t*-distribution with $T(G-1)$ degrees of freedom, with G the number of clusters, in place of the *z*-distribution (*i.e.*, $T(\infty)$), thereby demanding a greater magnitude of the *t*-statistic for rejection of the null hypothesis. We additionally present the results with standard errors clustered by county (Tables S14 and S15). The standard errors clustered by county were smaller than those computed with the aforementioned approach for all pollutants except PM_{10} (due to a high number of nested sites), *i.e.*, the approach used in this work was more conservative for nearly all pollutants. Analysis was performed in R (4.4.2) using the plm package (2.6-4) specifying year and air monitor site as the fixed effects. Clustered standard errors in Tables S14 and S15 were computed using the sandwich package (3.1-1). A significance level, α, of 0.05 (two-tailed test) was used to

evaluate the regression coefficients against the null hypothesis (H_0: $\beta_{EV} = 0$).

2.2 Datasets

2.2.1 Air quality. Air quality data were obtained as pre-generated data files from EPA Air Data.[28] Annual summary files and daily summary files were downloaded for each pollutant. The annual files were used for the full-year regression and the daily files were used for computing seasonal means for analysis of seasonal subsets. The annual and daily files were filtered to exclude sites with observation percentages lower than 80% and to exclude observations noted as containing an event (*e.g.*, fireworks or wildfires). Several sites had multiple measurements for the same parameter using different instruments; readings for the same parameter at sites with identical latitude and longitude coordinates were averaged. One CO site with anomalous measurements in 2022 and 2023 (recordings of −103.132 ppb in both years) was excluded. The metric used for each pollutant of the annual data was selected to correspond with the measurement collected for compliance with the most recent National Ambient Air Quality Standard (NAAQS):[29] daily maximum 1 hour average for NO_2 and SO_2, daily mean of 24 1 hour averages for NO_x and NO (no NAAQS), daily mean of 8 hour running averages reported hourly for CO, daily maximum 8 hour average for O_3, and daily mean of 24 hour sampling or daily 24 hour block average for $PM_{2.5}$ and PM_{10} (Table S1). (Note that the most recent CO NAAQS used both 8 hour and 1 hour averaging periods; the 8 hour metric was used in this work due to presumed greater stability of measurements using the longer averaging period. Results using the 1 hour period are presented in Table S13). For computing seasonal means from the daily data, summer season was defined as the period between May 01 to October 31 and winter season between November 01 to December 31 and January 01 to April 30. Only sites with measurements for 80% or greater of the days in each of both seasonal periods (184 in summer and 181 in winter) were included. The metric used to compute seasonal means from the daily data for each pollutant was chosen to correspond with the metric of the annual data (*e.g.*, the maximum 1 hour average of each day was used for NO_2 whereas the mean 1 hour average of each day was used for NO_x and NO). Near-road NO_2 monitoring sites were identified by downloading the list of active near-road sites of the EPA Interactive Map of Air Quality Monitors.

2.2.2 Electric vehicle registrations. Time series data of EV registrations by county were obtained from online databases and *via* public records requests to state motor vehicle and environmental departments. All contiguous states for which EV registrations were not available online were contacted. Time series data dating to 2018 were available for 20 states. ZIP codes were converted to county FIPS code using the USPS ZIP Code Crosswalk Files for datasets with registrations provided by ZIP code. Out-of-state vehicles (registered in one state but with a mailing ZIP code in another) were counted in the county of the ZIP code of the other state, provided the other state was included in the analysis (had EV data available). Maine 2019 registration data were imputed as the average of the 2018 and 2020 counts by ZIP code due to missing data in that year. Full details on acquisition of data for individual states are provided in Table S20.

2.2.3 Total vehicle count, residential heating electrification, median income, and telecommuting patterns. American Community Survey (ACS) data[30,31] were used to estimate the total vehicle count, home heating electrification rate, median income, and telecommuting fraction of workers by county and year. ACS 1 year estimates were available for 2018, 2019, 2021, 2022, and 2023 for counties with populations of 65 000 or greater. The 1 year estimates for 2020 were not available (presumably due to limited sampling during COVID-19). The 2020 1 year estimate was consequently imputed as the average of the 2019 and 2021 1 year estimates. For counties for which 1 year estimates were not available for one or more years (beyond 2020) for a given variable (vehicle count, home heating electrification, median income, or telecommuting), the 5 year estimates (representing the average of the preceding 5 years; *e.g.*, 2014–2018 for 2018) were used. Total vehicle count was estimated as:

$$\text{Vehicles} = 1 \times \text{Veh}_1 + 2 \times \text{Veh}_2 + 3 \times \text{Veh}_{3+} \quad (3)$$

where Veh_1, Veh_2, and Veh_{3+} were the estimated numbers of occupied housing units with 1, 2, or 3 or more vehicles available, respectively. Total vehicle registration counts by ZIP code and year were available for the state of California, therefore the ACS estimates computed using eqn (3) were compared against the state-recorded county totals. The comparison demonstrated reasonable accuracy of the ACS estimates, with mean and median percent errors of −12.0% and −21.6%, respectively, and mean and median absolute percent errors of 34.1% and 23.1% across all years and counties. Percent errors were largely consistent across years by county (*i.e.*, under or overestimated by similar percentages in each year 2018 through 2023), with the mean standard deviation of the percent errors among 2018 to 2023 for the California counties being 3.1 (%). This demonstrates that relative growth in EV percentage of the vehicle fleet should be well-approximated even if there is error in the ACS-estimated total vehicle count as compared to the true total vehicle count. Home heating electrification rate was the percentage of occupied households for which the category "Electricity" was indicated as the home heating fuel (as opposed to "Utility gas"; "Bottled, tank, or LP gas"; "Fuel oil, kerosene, *etc.*"; "Coal or coke"; "Wood"; "Solar energy"; "Other fuel"; "No fuel used"). Telecommuting rate was the percentage of workers aged 16 and older who indicated "Worked from home" as means of commuting. Median income was household income in the previous 12 months. Median income was adjusted for inflation in each year j to 2023 dollars using year-average consumer price indices:[32,33]

$$Y_{j,\text{adj}} = \frac{\text{CPI}_{2023}}{\text{CPI}_j} Y_j \quad (4)$$

In eqn (4), CPI_{2023} and CPI_j were the all-item consumer price indices in 2023 and year j, respectively. For the ACS 5 year

estimates, CPI_j was the consumer price index in the last year of each time period.

2.2.4 Temperature and precipitation. Temperature and precipitation data by year and county were obtained from the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI).[34]

2.3 Predicted concentration change calculations

An estimation of the expected NO_x and CO concentration changes for vehicle electrification was calculated based on the change in emissions, assuming linearity between concentration and emissions. The concentration decline (ppb) was computed as:

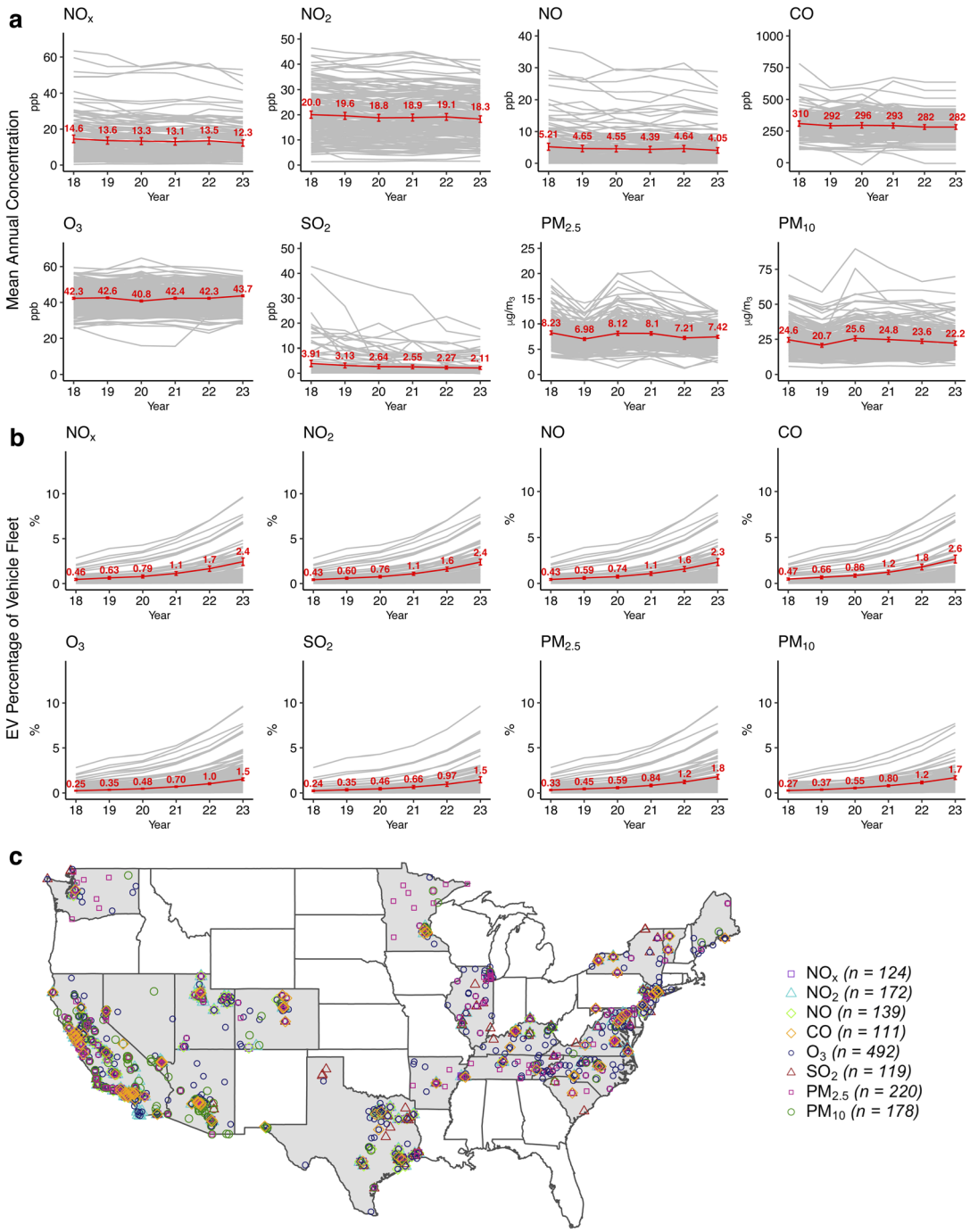

Fig. 1 Trends in pollution and EV adoption, 2018–2023. (a) Mean annual pollutant concentration and (b) electric percentage of vehicles in the counties with air quality monitors for each pollutant. Individual county data (gray lines) are illustrated with annotated mean values (red line and text ± 2 SE). For NO_2, the values are reported as daily 1 hour maxima, whereas NO_x values are reported as daily 24 hour averages (Table S1), resulting in higher NO_2 than NO_x concentrations. (c) Geographic locations of the air quality monitors (where *n* indicates the total number of sites; see Table S2 for regional counts of monitors).

$$\Delta C = C_{\text{avg}} \times f_{\text{net}} \times f_{\text{on-road}} \quad (5)$$

where C_{avg} is the average annual concentration across all sites from 2018 to 2023, f_{net} is the net fractional reduction compared with ICE vehicles on a per kilometer basis, and $f_{\text{on-road}}$ is the fraction of emissions from on-road sources. For NO_x, f_{net} was assumed to be 0.50, representing the difference between the 0.15 g km^{-1} emitted from ICE vehicles in 2021 [35] and the 0.075 g km^{-1} from the electricity required for EV charging, assuming an electricity economy of 0.17 kWh km^{-1} (the average EV electricity efficiency in 2019, weighted by model sales)[36] and using the mean national average marginal emissions factor for NO_x between 2018 and 2023.[37] $f_{\text{on-road}}$ was assumed to be to 0.27 or 1, representing monitors for which 27% or 100% of the recorded concentration is attributable to on-road sources (*i.e.*, near-road monitors for the latter). For CO, f_{net} was assumed to be 1.0 (due to the minimal CO emissions from electricity generation), and $f_{\text{on-road}}$ was assumed to be 0.22 or 1, representing monitors for which 22% or 100% of recorded concentration is attributable to on-road sources.

2.4 Future SO_2 concentration projections

Projections of the light-duty vehicle stock by technology type and net electricity generation by fuel type were obtained from the projection tables of the U.S. EIA Annual Energy Outlook 2023.[38,39] Note that the 2025 Outlook did not forecast impacts associated with the 2022 Inflation Reduction Act. EV share was computed as the sum of electric vehicles divided by the total stock of cars and light trucks in each year. Coal share of the electricity portfolio was computed as the net electricity generation from coal divided by the total net electricity generation in each year. SO_2 concentration in each year i (SO_{2_i}) following year j was computed as:

$$SO_{2_i} = SO_{2_j} + (EV_i - EV_j) \times \left(\frac{\text{coal}_i}{\text{coal}_{2023}}\right) \times 0.53 \quad (6)$$

where coal_i is the coal fraction of the energy mix in year i and $EV_{i,j}$ is the electric share of the vehicle stock in year i or j, respectively. $SO_{2_{2023}}$ was the mean 2023 concentration of all SO_2 sites of 2.1 ppb.

3 Results and discussion

3.1 Trends in annual concentrations and EV penetration

Between 2018 and 2023, there were declines for all pollutants except O_3, for which there was an increase of 3.2% (Fig. 1). The largest declines were observed for SO_2 (46%), NO (22%), and NO_x (16%), and smaller declines were observed for $PM_{2.5}$ (9.9%), PM_{10} (9.8%), NO_2 (8.9%), and CO (8.8%). The trends are similar to those reported by the EPA for its entire national monitoring network,[40] adding confidence that the subset of sites located in states with EV registration data available and used in this work is representative of the complete network. The declines in NO_x and SO_2 reflect the implementation of regulatory standards governing power plant and vehicle emissions.[41] While declines in NO_x and SO_2 reduce PM, other PM sources, including agriculture and wildfires, emit precursors such as NH_3 and VOCs that remain largely unabated.[4,42–44] These nationwide trends in pollution over time were accounted for in the model specification through the inclusion of a year fixed effect, which subtracted the year mean from each observation. In other words, the overall nationwide declines in pollution from all causes were controlled for when analyzing the impact of local changes in EV adoption on pollution levels. EV penetration levels were similar among the counties of monitors for each pollutant and increased from 0.25% (2018) to 1.5% (2023).

3.2 Impact of EV penetration on pollution

Two-way fixed effects regression was used to examine the impacts of EV penetration on local air pollution (Fig. 2). Briefly, the model specification included fixed effects to control for monitor site variables that do not change with time (*e.g.*, local topography of the monitor site) and for nationwide changes over time (*e.g.*, reduced industrial activity during COVID-19). Therefore, any unobserved systematic differences between sites and any universal time shocks across sites were controlled for in the regression. The following covariates were added to control for potential time-varying confounders: total precipitation, average air temperature, home heating electrification rate, total vehicle population, median income, and telecommuting patterns. Therefore, county-specific changes in these factors over time were additionally controlled for in the model. The change in concentration of each pollutant for each percentage point increase in EV penetration (*i.e.*, the regression coefficient of EV share of the vehicle fleet) was evaluated against the null hypothesis assuming no impact of EV penetration on ambient pollution.

3.2.1 Nitrogen oxides and carbon monoxide. Rising EV penetration was associated with reduced annual concentrations of the nitrogen oxides, measured as combined NO_x or separately as NO_2 or NO. A 0.44 ppb decline in mean annual NO_2 concentration (95% confidence interval (CI) −0.64 to −0.25; $P = 0.0020$) was estimated for a one percentage point increase in EV penetration in a county, using the model specification controlling for temperature, precipitation, home heating electrification, vehicle population size, income, and telecommuting. For seasonal analysis, summer and winter means were computed from the daily data. For NO_2, EV coefficient estimates in summer and winter were not significantly different ($n = 136$; summer $P = 0.0040$, winter $P = 0.0019$), implying that the impact of EV penetration on NO_2 levels was largely seasonally invariant. There were small seasonal sample sizes of NO_x and NO ($n = 21$ and $n = 23$), yet the overlapping CIs suggested a similarly constant effect size by season (Table S6). For CO, there was a 6.3 ppb decline (CI: −12, −0.17; $P = 0.046$) in mean annual concentration associated with each percentage point increase in EV penetration, using the model with the aforementioned control variables. As with NO_2, the magnitude of the effect was seasonally invariant. Separate analysis of the subset of sites in the EPA near-road monitoring network was performed but did not suggest differing effect sizes at near-road *versus* non-near-road sites (Fig. S3). Comparing these findings

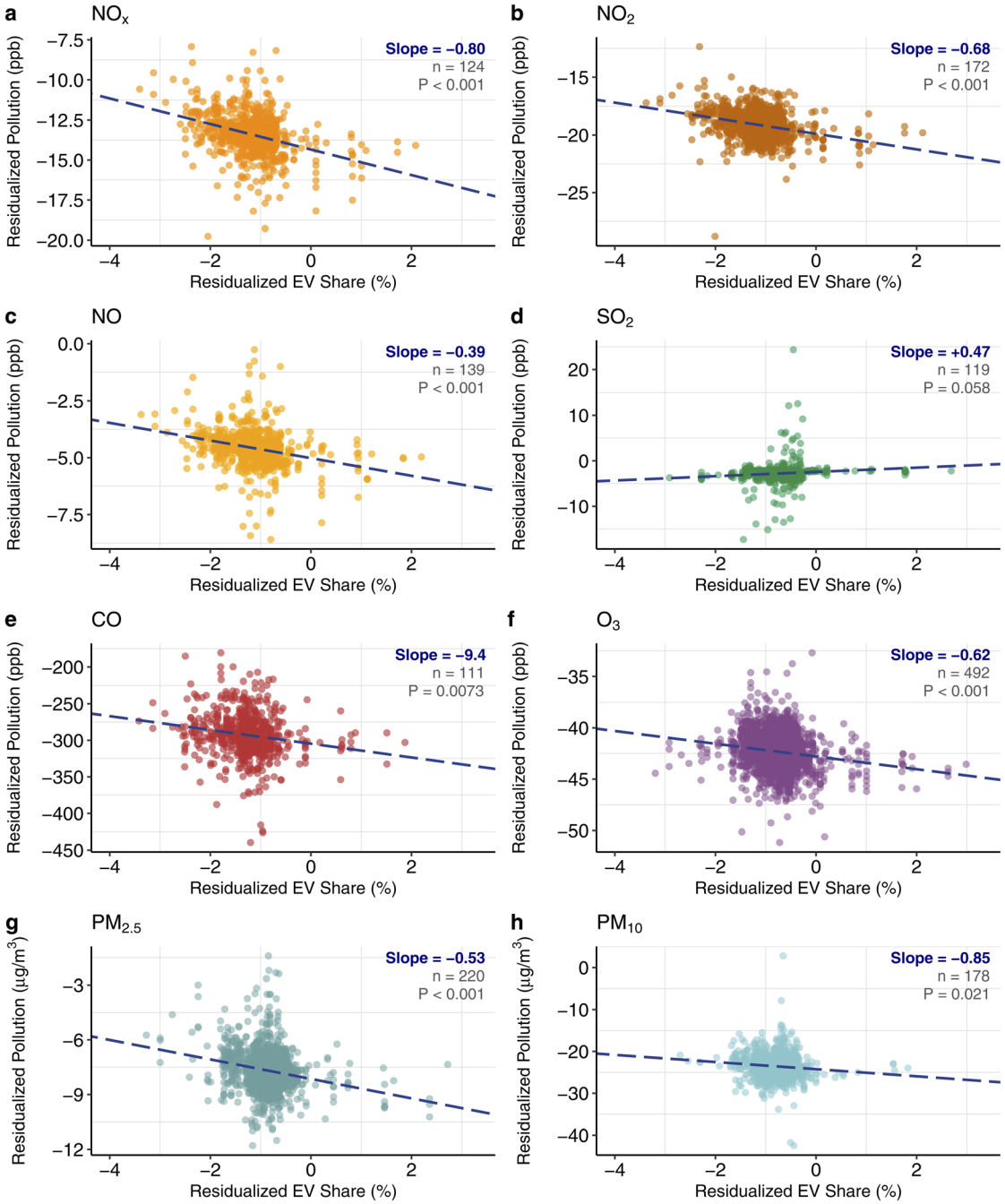

Fig. 2 Impact of increasing EV penetration on ambient pollution. (a–h) Subplots show the results of two-way fixed effects regression of pollution level against EV percentage of the vehicle fleet. Each data point represents one air monitor site in a given year between 2018 and 2023, for a total of 6 × *n* points per subplot, where 6 is the number of years and *n* is the number of air monitor sites. The residualized value of each observation is shown (*i.e.*, each point represents the observation corrected for site and year means). The expected change in pollution level for each percentage point increase in EV penetration (slope in inset text) was calculated using linear regression (dashed line) of those residualized data (eqn (1) and Table S3). Plots visualize the baseline regression model without additional covariates (eqn (1)).

with previous work, a majority of previous modeling studies have predicted declines in NO_x and CO with vehicle electrification,[13,15,45] and a non-significant decrease in NO_2 was observed with increasing EV and PHEV adoption in California.[25]

However, a concurrent increase in NO_x from point sources may be expected due to the greater demand on electric power plants for vehicle charging.[6] A calculation of the expected net effect on NO_x in the U.S. is in favor of a decline: converting NO_x emissions from above-baseload electricity generation using the average U.S. marginal emissions factor from 2018 to 2023,[37] assuming an EV electricity efficiency of 0.17 kWh km^{-1},[36] yields 0.075 g NO_x per km. This value is 50% of the estimated 0.15 g NO_x per km emitted from the tailpipes of gasoline-powered light-duty vehicles in 2021.[35] Therefore replacing ICE vehicles

with EVs is expected to result in a net decrease in total NO_x emissions, even under the current U.S. electricity generation portfolio in which 60% of electricity is generated from fossil fuels.[46] This is in agreement with the decline empirically observed in this work. Put another way, electricity generation from renewable sources could double the NO_x reduction effects described here. Regarding CO, emissions from point sources represent a small fraction of total CO emissions (3.1%),[3] because stationary fuel combustion processes are usually designed with sufficient aeration for complete rather than incomplete combustion (with the latter being the process that produces CO).[47] The increase in CO emissions from electricity generation for EV charging is therefore expected to be minimal.

3.2.2 Ozone. There was a 0.21 ppb decline in mean annual O_3 concentration (CI: −0.40, −0.016; $P = 0.039$) associated with each percentage point increase in EV penetration, using the model specification with all covariates, but analysis of the summer and winter means computed from the daily data revealed a strong seasonal effect. There was a decline of 0.71 ppb (CI: −1.0, −0.43; $P = 0.0013$) per percentage point increase in EV share of the vehicle fleet in summer, and there was no effect in winter. This seasonal impact of EV penetration on O_3 is consistent with the effect of local photochemical production in NO_x-limited regimes, for which a decrease in NO_x results in a decrease in O_3.[41] Winter O_3 trends are more defined by long-range sources and transport due to the comparatively limited local *in situ* production.[41]

For greater insight into NO_x and VOC-limited regimes, separate regression analyses were performed on the sites in the upper and lower quartiles of the data by NO_x : VOC ratio. The ratio of total NO_x : VOC emissions for each site was computed from the county-wide emissions estimates of the 2020 National Emissions Inventory (NEI).[3] A greater impact of EV penetration on O_3 was expected in the comparatively NO_x-limited subset, yet there were no significant differences in the EV coefficient estimates of the lower and upper quartiles by NO_x : VOC ratio on either annual or seasonal O_3 (Table S12). This potentially suggests that the annual and summer O_3 sites were all largely NO_x-limited regimes, and it may additionally reflect the high uncertainties in emissions inventories of VOC precursors.[17–19] Broadly, reducing NO_x emissions is expected to result in O_3 declines in much of the U.S.,[48] and continued declines in NO_x are causing more regions to transition from VOC- to NO_x-limited.[49] Furthermore, strong reductions in NO_x have been identified as the most feasible avenue for O_3 control in both NO_x and VOC-limited regimes, given that the majority of VOC emissions, even in dense urban areas, have been attributed to sources that are difficult to regulate.[19,50,51] The results observed here provide evidence that increasing EV penetration was linked to declines in summer O_3 across the sites studied.

3.2.3 Particulate matter. There was a decrease of 0.28 μg m^{-3} (CI: −0.46, −0.10; $P = 0.010$) in annual $PM_{2.5}$ associated with each percentage point increase in EV share of the vehicle fleet, controlling for all covariates. The effect was seasonally invariant. By contrast, there was no significant association between EV penetration and either annual or seasonal concentrations of PM_{10} when controlling for the covariates. The difference in the effects for $PM_{2.5}$ and PM_{10} likely reflects the composition of each species: a large fraction of PM_{10} is composed of coarse particles (*e.g.*, road and agricultural dust) that are expected to be less impacted by vehicle electrification than fine particles. A decline in $PM_{2.5}$ associated with increasing EV adoption was observed in Chinese provinces,[22] and declines in $PM_{2.5}$ have been predicted by previous model simulations of vehicle electrification.[7,9,52] Some models have projected a minimal change in PM, however, due to increased $PM_{2.5}$ precursor emissions from power plants[45] and to increased or unchanging non-exhaust $PM_{2.5}$ and PM_{10} emissions from tire and brake wear.[53,54] The empirical results observed here demonstrate a net decline in annual $PM_{2.5}$ and no change in PM_{10} in the U.S. associated with EV adoption between 2018 and 2023. The decline in $PM_{2.5}$ is likely attributable to reductions in both direct vehicle emissions (primary $PM_{2.5}$) and to reductions in NO_x that reduced formation of secondary $PM_{2.5}$; therefore, the favorability of the net decline is expected to improve with a transition from fossil fuel to renewable energy sources.

3.2.4 Sulfur dioxide. In contrast to the reductions observed in NO_x, CO, seasonal O_3, and $PM_{2.5}$, there was a potential increase, significant at the $\alpha = 0.10$ level, in mean annual SO_2 concentration of 0.53 ppb associated with each percentage point increase in EV penetration (CI: −0.011, 1.1; $P = 0.053$), using the model specification with all covariates. There was a significant increase in winter SO_2 (0.76 ppb; CI: 0.15, 1.4; $P = 0.024$) but no effect in summer ($P = 0.12$). An increase in SO_2 has been predicted by previous modeling studies of EV adoption and attributed to increased electricity production at coal-fired power plants.[13,15,45] The result may also reflect an impact of the decreases in NO_x associated with EV adoption. NO_x can oxidize SO_2 to sulfate,[55,56] therefore reduced oxidation of SO_2 by NO_x could result in an increase in ambient SO_2.

Unlike NO_x, there is no corresponding emissions decrease in the transportation sector for SO_2 with increasing EV adoption. These results suggest a potential air quality risk of increasing electrification if there is not a concurrent transition to renewable energy. SO_2 exposure is associated with respiratory ailments, and SO_2 serves as a precursor of sulfate $PM_{2.5}$, which has an elevated mortality risk compared with other $PM_{2.5}$ species.[4,57] Additionally, SO_2 emissions result in the wet deposition of sulfuric acid rain that adversely impacts water and soil quality.[58] While the implementation of evolving regulatory standards has resulted in strong nationwide decreases in SO_2 since 1970,[40] these results suggest that electrification without simultaneous reduction in coal combustion may halt or reverse the declines.

3.3 Comparison of observed and predicted concentration changes

To gauge if the observed effects are plausible in magnitude, the effect sizes of increasing EV adoption on NO_x and CO concentrations were compared against calculated predictions based on the changes in emissions. Linearity between national-level emissions and concentration of NO_x was observed between 2002–2019,[59] and average CO concentrations were previously

demonstrated to be approximately linear with vehicle population in urban centers.[60] Therefore, a linear relationship between emissions and concentration of NO_x and CO was assumed for the present calculations. Predictions were not computed for the other pollutants due to the higher uncertainties regarding the relationship between emissions and concentration (*e.g.*, nonlinearity in NO_x reduction and O_3 concentration,[48] differing regional and temporal marginal emissions factors of SO_2,[61] primary emissions *vs.* formation of secondary $PM_{2.5}$ and PM_{10}). To account for uncertainty in the fraction of recorded concentration represented by on-road sources (*i.e.*, vehicle emissions may contribute a larger fraction of the emissions corresponding to recorded concentrations of near-road monitors), a range was computed by considering monitors that record largely background to fully on-road concentrations (lower and upper bounds, respectively). For NO_x, a previous calculation using a national average marginal emissions factor estimated the net NO_x emissions from EVs on a per kilometer basis as 50% of that of ICE vehicles (0.075 *vs.* 0.15 g km^{-1}). The lower bound of the expected concentration decline for replacement of 1% of vehicles with EVs was therefore estimated as 50% of 27% of 1% of the mean annual concentration, with 27% representing the fraction of total NO_x emissions from on-road sources.[3] This represents monitors measuring primarily background NO_x levels. The upper bound of the decline for replacement of 1% of vehicles with EVs was calculated as a reduction of 50% of 100% of 1% of the mean annual concentration, representing monitors for which the recorded concentration is fully dependent on on-road NO_x emissions. These estimations assume linearity in that a 1% reduction in concentration is expected for a 1% reduction in emissions. An analogous computation was performed for CO, using a range of 22% of 1% to 100% of 1% of the mean annual concentration (with 22% being the fraction of CO emissions from on-road sources[3] and there being minimal CO emissions from electricity production[47]).

The calculations predict a 0.018–0.067 ppb decline in NO_x and a 0.64–2.9 ppb decline in CO for electrification of 1% of the vehicle fleet, as compared with the effect sizes estimated from the regression on the observed data of −0.59 ppb for NO_x and −6.3 ppb for CO. The predictions are therefore smaller than the effect sizes estimated from the observed data by factors of 9 to 33 and 2 to 10, respectively. A portion of the discrepancy may be attributable to imperfect linearity between emissions and concentration, particularly on a local scale over a relatively short time period (*i.e.*, 6 years). Furthermore, these estimations did not differentiate between replacements of light-, medium-, and heavy-duty vehicles, as vehicle class breakdown was not available for all EV registration data. However, the discrepancy also suggests the possibility of an unobserved confounder. A correlation between EV adoption and replacement of older ICE vehicle models with newer lower NO_x- and CO-emitting ICE models is plausible and may account for a portion of the NO_x and CO reduction effect sizes. However, the covariate for median income included in the model specification may act as a partial control for this potential confounder. A second possibility is a correlation between vehicle electrification and electrification of building appliances and heating systems. To account for this, a covariate to control for the percentage of households using electricity as home heating fuel by county and year, *i.e.*, residential heating electrification (which may be expected to correlate more strongly with EV adoption than commercial or industrial sector electrification) was included in the model specification, thereby partially controlling for this potential confounder. In summary, the collection of observed effects suggests EV adoption as the primary causal driver, though uncertainties remain regarding the precise effect size of concentration change per percentage point electrification of the ICE vehicle fleet. Continued monitoring of effect size as EV adoption increases will provide further insight regarding the magnitudes of observed concentration changes.

3.4 Future projections

We projected the empirically observed potential relationship between EV penetration and SO_2 concentration to three case scenarios from the U.S. Energy Information Administration of potential uptake of the 2022 Inflation Reduction Act, which offers incentives to corporations and individuals to adopt renewable energy technologies[38,39] (Fig. 3). Electrification of the light-duty vehicle stock increases from 1.0% in 2023 to 11.0, 11.2, or 12.3% in 2050, and coal fraction of the electricity generation portfolio decreases from 18.8% to 7.7, 7.5, or 3.9% under the no, low-, or high-uptake scenarios, respectively. SO_2 concentration in each year was computed by scaling the estimated relationship between concentration and EVs (a 0.53 ppb concentration increase for each percentage point increase in EV penetration, eqn (2)) by the coal fraction of the electricity mix relative to its fraction in 2023. We chose to project the linear relationship estimated over the EV penetration range in this

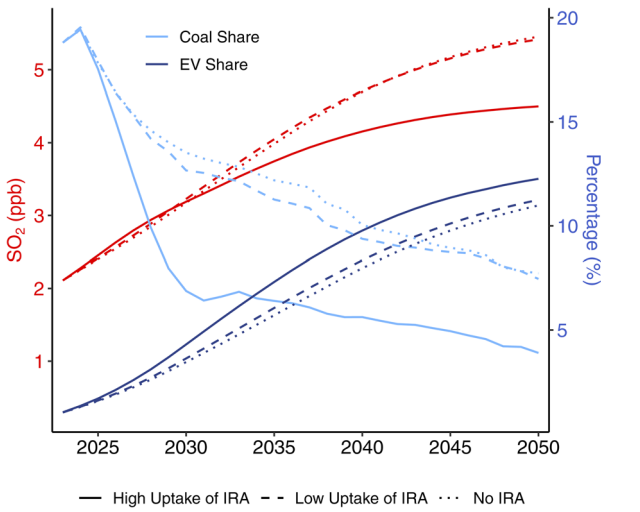

Fig. 3 Projected SO_2 concentration under scenarios of varying electrification and fossil fuel reliance. Projected ambient SO_2 concentrations (red, left axis) from the EV penetration and electricity generation portfolios (blue, right axis) predicted by the U.S. Energy Information Administration under scenarios of no, low, or high uptake of the 2022 Inflation Reduction Act (IRA).

work in order to compare different potential scenarios of EV uptake and electricity fuel mix.

The results illustrate a rise in SO_2 with greater electrification that plateaus as coal percentage of the electricity portfolio declines. The greater EV adoption rate of the high-uptake scenario results in the highest SO_2 concentrations until 2030, when the comparatively lower coal use of the scenario becomes dominant. By 2050, there is an SO_2 concentration difference of approximately 1 ppb between the high- and no- or low-uptake scenarios, and the greater electrification of the high-uptake scenario will additionally result in the lowest NO_x levels.

4 Conclusions

While a transition to EVs has primarily been promoted as a decarbonization strategy, there is empirical evidence that suggests the EV transition is also quantifiably improving air quality in metrics relevant to public health. This study examined observations of criteria air pollutants from the monitoring network that reports to EPA Air Data and county-level EV registrations between 2018 and 2023 to investigate the impacts of vehicle electrification on air quality. The analysis of empirical data in this work contrasted with the methodology of previous studies, which have predominantly relied upon chemical transport models to simulate potential EV adoption scenarios. Given that the results of previous models have varied due to differences in model parameters and assumptions, the approach of this work offered an evaluation of the real-world changes to U.S. air quality associated with vehicle electrification. Notably, there were significant impacts to air quality for EV penetration levels that reached a county average of 1.5% of registrations in 2023, implying that the effects are perceptible at electrification levels below those typically simulated in model projections (often 20% or greater of the vehicle fleet). Fixed effects regression analysis provided robust evidence that increasing EV adoption was linked to observed declines in annual and individual summer and winter season concentrations of NO_2, CO, and $PM_{2.5}$. There was a significant decrease in summer O_3 and no effect on winter O_3, consistent with the effect of local photochemical production. For PM_{10}, there was no significant effect of EV penetration when including all covariates. In contrast to these declines, there was a potential increase in SO_2 with rising EV penetration that suggested the adverse effect of a reliance on coal-based fossil fuels. The findings provide evidence that the effects of vehicle electrification on air quality are largely beneficial, yet using coal-based energy sources to power the electrification transition risks an increase in SO_2.

The declines in ambient concentrations of NO_x, CO, O_3, and $PM_{2.5}$ have the potential to reduce differences in air quality between heavily-trafficked and less congested corridors, which would address part of the current disparity in pollution levels between urban and suburban neighborhoods.[8,62–64] Given the health impacts of exposure to these pollutants, this has the potential to increase parity in physical and mental well-being between neighborhoods of light and heavy traffic.[65–68] However, if EVs are charged by electricity generated from fossil fuels, emissions increases from electric power plants may exacerbate disparities in air quality between those living near and far from point sources. This impact is most pressing with respect to SO_2, which is associated with the burning of coal in particular and does not have an associated decrease in the transportation sector with increasing EV penetration. Furthermore, while a decline in $PM_{2.5}$ associated with greater vehicle electrification was observed in this work, the SO_2 increases may be expected to result in localized sulfate $PM_{2.5}$ increases near power plants. Regarding NO_x, the impact of electrification on NO_x is strongly favorable in terms of a net decline (with net emissions from EVs being 50% of the emissions from ICE vehicles), yet there is the potential for localized concentration increases near point sources. Generating electricity to charge EVs from renewable sources reduces these risks, as there are no NO_x or SO_2 emissions from solar, wind, hydroelectric, or nuclear power sources. Efforts to expand EV access must simultaneously increase deployment of renewable energy for realization of the full air quality benefits of vehicle electrification.

Optimizing diurnal vehicle charging patterns can further aid in minimizing the NO_x and SO_2 emissions of additional electricity generation. Daytime charging allows a greater fraction of supplied electricity to be sourced from renewable energy and results in lower emissions than evening or night charging in most locations, with the 2018–19 average difference in carbon emissions (which likely correlate to a degree with NO_x and SO_2 emissions) between midday and nighttime charging in the U.S. being 40%.[61] Infrastructure to expand access to charging facilities during hours of non-peak demand (*e.g.*, workplace charging) can therefore serve to reduce both the carbon emissions and air quality risks of increasing vehicle electrification. Future research can further investigate methods such as charging timers and time-of-use pricing to promote vehicle charging schedules that maximize the use of renewable rather than fossil energy to meet increased demand.

Continued air quality monitoring will reveal how the magnitudes of the effect sizes of vehicle electrification on pollution levels will evolve with rising EV adoption and shifting electricity sourcing. While linearity between NO_x emissions and concentrations has been observed previously,[59] a plateauing impact of electrification in regions with low pollutant concentrations approaching background levels is plausible. Additionally, the magnitudes of the effect sizes of EV adoption on air quality are expected to be dependent on the electricity generation portfolio. A grid that relies upon an increasingly larger fraction of renewable energy is expected to result in greater decreases in NO_x, O_3, and $PM_{2.5}$ per EV replacement of an ICE vehicle; conversely, a grid powered by a larger fraction of fossil energy sources is expected to result in smaller pollutant declines. The future impacts of EV adoption on air quality are expected to be determined in large part by the sources of electricity generation, such that policies aiming to improve air quality with greater EV deployment must expand renewable energy deployment in tandem.

Furthermore, expanded air quality monitoring can allow future research to investigate regional or state-level impacts and

effect sizes, as the air quality impacts of EVs are likely to vary by local climate and topography. For instance, NO_x emissions from ICE vehicles are higher in cold ambient temperatures;[69] consequently, one may expect a larger magnitude of NO_x reduction for replacement of ICE vehicles with EVs in cold climates (comparing areas with equal NO_x emissions from electricity generation). Additionally, electricity sourcing and marginal emissions factors differ by region,[37] making the magnitudes of net NO_x and $PM_{2.5}$ decreases regionally dependent. Regional analysis was not possible in this work due to the limited number of total sites with both air quality and EV registration data for 2018 through 2023 available. Expanding the network of monitoring sites that report to EPA Air Data, in addition to creating a centralized database of state EV registrations, could allow for such analysis of regional-level differences, and access to proprietary datasets of vehicle type and driving history would further refine the analysis. In conclusion, the findings of this work support efforts to expand EV access and charging across the U.S., with a concurrent transition to renewable energy, to promote improvements in air quality.

Author contributions

ACL conceptualized the study and analyzed the data. ACL, DLP, and MAZ interpreted the results and wrote the paper.

Conflicts of interest

There are no conflicts to declare.

Data availability

All data and code scripts are available at a Zenodo repository: **https://doi.org/10.5281/zenodo.12773413**.

Supplementary information: Fig. S1–S3 and Tables S1–S21 (PDF). See DOI: **https://doi.org/10.1039/d5em00559k**.

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