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CLEAN RIDES, HEALTHY LIVES:
THE IMPACT OF ELECTRIC VEHICLE ADOPTION ON AIR QUALITY AND INFANT HEALTH

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ABSTRACT

This paper provides the first nationwide evidence on how electric vehicle (EV) adoption has improved both air quality and child health. We assemble a rich dataset from 2010–2021 that links county-level EV registrations to measures of air pollution, birth outcomes, and emergency department visits. The endogeneity of EV adoption is addressed using two complementary strategies: Two-way fixed effects and instrumental variables (IV). The IV exploits the staggered rollout of Alternative Fuel Corridors as a source of exogenous variation in charging infrastructure that affected EV adoption. The estimates show that greater EV penetration significantly reduces nitrogen dioxide (NO2), a key pollutant linked to vehicular emissions. These improvements in air quality yield significant health benefits, including reductions in very low birth weight and very premature births, as well as fewer asthma-related emergency department visits among children ages 0 to 5. This is true even when potentially offsetting increases in pollution from the electricity generation needed to power EVs are accounted for. The benefits are higher in the high-pollution counties with Alternative Fuel Corridors, where baseline exposures are greatest. The resulting reductions in very low birth weight births alone could generate annual benefits of $1.2 to $4.0 billion. These findings underscore the dual environmental and public health benefits of EV adoption.

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1. Introduction

Since 2010, over 6.1 million plug-in hybrid and battery electric vehicles have been sold in the United States, including approximately 1.56 million in 2024, accounting for nearly 10 percent of all new light-duty vehicle sales (Isenstadt and Slowik, 2025). Public discussions and scholarly research have focused on the electric vehicles' potential for addressing climate change through reduced tailpipe emissions. In contrast, relatively little attention has been given to the health improvements that may result from cleaner air. These local benefits may represent some of the most immediate and tangible benefits of EVs, with potential implications for healthcare costs, quality of life, and public support for clean energy initiatives.

This paper aims to fill this gap by providing a comprehensive analysis of the effects of EV adoption on air pollution and infant health. We focus on infants given previous evidence that they are particularly susceptible to the harmful effects of air pollution. Maternal exposure to elevated air pollution levels during pregnancy has been strongly linked to adverse birth outcomes such as reduced birth weight, preterm birth, and impaired fetal growth (Alexander and Schwandt, 2022; Currie and Walker, 2011; Currie and Neidell, 2005; Knittel et al., 2016).[1] Similarly, early-life exposure to traffic-related air pollution has been associated with higher risks of respiratory illnesses, including asthma (Bettiol et al., 2021; Simeonova et al., 2021; Zanobetti et al., 2024). Yet, despite this growing evidence on the harms of pollution, little empirical research has asked whether EV adoption has in fact delivered measurable health benefits.

We address this question by assembling data for 2010 to 2021 on county-level vehicle registrations by fuel type as well as year-end county snapshots of the vehicle fleet from S&P Global; locations and opening dates for all EV charging stations from the U.S. Department of Energy (U.S. DOE, n.d.); daily air pollution levels for NO_2 and $PM_{2.5}$ from EPA air quality monitors as well as satellite-based pollution estimates from van Donkelaar et al. (2021); restricted-access geocoded U.S. Vital Statistics Natality records with detailed birth outcomes and maternal characteristics at the county level; and restricted-access outpatient visit and diagnosis data from nine states provided by the Healthcare Cost and Utilization Project (HCUP).

Causal inference about the effects of EV adoption is complicated by the fact that adoption is unlikely to be random. Wealthier households are more likely to be able to afford EVs and tend to reside in areas with better air quality and health outcomes. In addition, policy incentives, such as tax rebates and investments in charging infrastructure, often target specific areas or demographics that may already have preferences for cleaner technologies or healthier

[1] The biological mechanisms linking prenatal exposure to air pollution and adverse infant health are well-documented in the medical literature. Pollutants can disrupt placental transfer of oxygen and essential nutrients vital for healthy fetal development. See Bekkar et al. (2020) and Stieb et al. (2012) for detailed discussions and systematic reviews of related literatures.

environments. It is also possible that areas with severe air pollution are more likely to enact policies encouraging EV adoption.

Potential bias caused by the endogeneity of EV adoption is addressed in two ways. First, we estimate two-way fixed effects models controlling for county and month-by-year fixed effects, state-by-year fixed effects, and a rich set of county-level controls. This approach leverages within-county changes in EV adoption over time, but its validity depends on the parallel trends assumption that without changes in EV adoption, counties on different adoption paths would have experienced similar trends in pollution and infant health outcomes. Event study analyses provide empirical support for this assumption. Second, we estimate Instrumental Variable (IV) models, leveraging the strategic placement of charging stations along federally designated Alternative Fuel Corridors (AFCs). These new charging stations are strongly predictive of EV adoption. Their placement was determined primarily by connectivity goals, spacing requirements, and the location of existing interstate routes rather than local demographic, economic, or environmental conditions. Hence, it is plausible to assume that charging stations affected pollution and health outcomes only through their effects on EV take-up, rather than reflecting local concerns about air quality or health outcomes that might themselves drive EV adoption. These two approaches are complementary; TWFE providing estimates for the full sample assuming parallel trends, while IV identifies causal effects in areas influenced by the quasi-random placement of AFC stations, assuming the location of new stations was exogenous.

Both methods indicate that increased EV adoption is significantly associated with reductions in NO_2 concentrations. TWFE models suggest that a one standard deviation increase in EVs (about 11.98 per 1,000 vehicles) reduced the NO_2 Air Quality Index (AQI) by 1.62 percent. IV estimates are larger, implying that the same increase would reduce NO_2 AQI by 4.0 percent. These larger IV estimates are consistent with the new AFC charging stations being located in areas that have worse baseline air quality because they are located near highways.

Turning to health outcomes, a one standard deviation increase in EVs is estimated to reduce the incidence of very low birth weight (VLBW) by between 0.8 percent (TWFE) and 2.6 percent (IV) with similar estimated reductions in the incidence of very premature births. We also find that a one standard deviation change in EVs is associated with an 11.3 percent reduction in asthma visits in children under five in TWFE models. The estimates are consistent when we use alternative specifications, different EV exposure measures (e.g., EVs per population vs. EVs as a share of the fleet), and the exclusion of the COVID-19 lockdown period. The estimated effects are even larger when attention is restricted to battery electric vehicles, which represent roughly 80 percent of the market, rather than also including hybrid vehicles.

This study makes several contributions to the literature on the effects of motor vehicles on pollution and health (e.g. Currie and Walker, 2011, Garcia et al., 2023; Knittel et al., 2016; and Alexander and Schwandt, 2022). First, we show that increased EV adoption leads to significant reductions in key air pollutant, namely NO_2, which is directly linked to vehicle emissions. This is true even after accounting for pollution created by the increased electricity generation needed to fuel the EVs.

Second, we provide a comprehensive nationwide analysis of the impact of EV adoption on air pollution and infant health. Health at birth is an important measure that has been shown to have long-term consequences such as impaired cognitive development, lower educational attainment, and lower socioeconomic later in life (Currie, 2011; Black, Devereux, and Salvanes, 2007; Elder et al., 2020; Figlio et al., 2014; Isen, Rossin-Slater, and Walker, 2017; Bütikofer, Løken, and Salvanes, 2019).

Third, in addition to examining infant health we examine the impact of EV adoption on emergency department (ED) visits for respiratory conditions in young children. This extension shows that the health benefits of cleaner transportation extend to young children, who are at an age when vulnerability to environmental exposures remains high.

Greater understanding of the health risks associated with exhaust from gasoline-powered cars, and the health benefits associated with electrification of the vehicle fleet could influence consumer behavior and lead to better informed policy decisions.[2] Our back-of-the-envelope estimates suggest that reductions in the incidence of VLBW births alone could generate annual benefits of \$1.2 to \$4.0 billion. These results show that the health gains from EV adoption have substantial economic value.

The rest of the paper is organized as follows. Section 2 provides background information about EV penetration, and the AFC rollout and provides a brief overview of the relevant literature. Section 3 describes the data sources used in the analysis, including information on vehicle registrations, air pollution measures, and infant and child health outcomes. Section 4 discusses the empirical strategies. Results are presented in Section 5. Section 6 concludes, summarizing the key findings and discussing their broader policy implications.

2. Background

2.1 Previous research on health effects of motor vehicle emissions and the effects of EVs

Our study is closely related to the broader literature on the relationship between air pollution from traffic emissions and infant health. Within that literature, only a small number of studies focus on specific policy or technological interventions. Currie and Walker (2011) examine the health

[2] Users of traditional vehicles are partially exposed to their own emissions (Alexander and Schwandt, 2022; Campagnolo et al., 2023; Harik et al., 2017), so better understanding of the health effects may influence consumer behavior even when individuals are unconcerned about the externalities they impose on others.

effects of reduced traffic congestion using the introduction of EZ Pass electronic toll stations as a natural experiment that reduced pollution due to vehicle idling near toll plazas. They find significant improvements in infant health, with reductions in prematurity and low birth weight among mothers living near toll plazas. Knittel et al. (2016), focus on traffic-related air pollution in California, and construct instrumental variables based on the interaction of traffic and weather conditions. They find substantial impacts on weekly infant mortality, particularly among vulnerable subpopulations such as low birth weight or premature infants. Simeonova et al. (2021) examine the introduction of congestion pricing in Stockholm and find that it reduced asthma admissions in young children.

Most recently, Alexander and Schwandt (2022) leverage the Volkswagen emissions-cheating scandal as a natural experiment to evaluate the health impacts of diesel pollution. As they point out, the cheating diesel vehicles emitted pollutants at a rate up to 150 times greater than gas-fueled vehicles, and did so in relatively clean areas. They find that increased air pollution from cheating diesel vehicles led to worse birth outcomes, higher infant mortality, and a rise in asthma-related emergency visits among young children.

EV adoption can be viewed as the reverse experiment, replacing dirty gasoline-powered cars with cleaner vehicles. In what follows, we focus on documenting the relationship between EV adoption and nitrogen oxides (NO_x) because they are the pollutant most closely linked to cars. Motor vehicles are the largest contributors to U.S. nitrogen oxides (NO_x) emissions with transportation sources contributing approximately 50 to 60 percent of total emissions between 2010 and 2024 (U.S. EPA, 2025). Power plants are the other major source of NO_x emissions, but we are able to control directly for annual county-level emissions from power plants. In comparison, motor vehicles accounted for only 3 to 9 percent of total primary fine particulate matter ($PM_{2.5}$), which comes from many other sources including industrial activity, residential heating, agriculture, and, increasingly, wildfires.

Although battery electric vehicles produce zero tailpipe emissions, they are not entirely "clean." Emissions of $PM_{2.5}$ are significantly influenced by non-exhaust sources such as tire wear, brake wear, and road surface abrasion, which are not eliminated by switching to EVs. In fact, because EVs tend to be significantly heavier than gasoline-powered cars, they may generate more non-exhaust particulates.[3] Hence, the added weight of EVs may partially offset the gains from reduced tailpipe pollution by contributing to higher levels of non-exhaust $PM_{2.5}$ (Timmers and Achten, 2016). For these reasons, NO_x arguably provides a more direct and policy-relevant

[3] For example, the Ford F-150 Lightning, the electric version of the F-150 pickup, weighs 6500-7000 pounds compared to 4700-5200 pounds for the gas-powered model. Non-exhaust emissions now account for the majority of $PM_{2.5}$ from road traffic (Harrison et al., 2021; Grigoratos and Martini, 2014). Accordingly, while EV adoption significantly reduces nitrogen oxides and other tailpipe pollutants, its impact on $PM_{2.5}$ is less clear.

measure of the environmental impact of EV adoption than $PM_{2.5}$. While we also estimate models for $PM_{2.5}$, it is less clear that EV adoption will significantly affect this outcome.

Electricity for charging EVs may rely on coal, natural gas, or cleaner renewable sources, and may be generated at great distance from places with high EV adoption. Hence, the net emissions impact varies substantially by region, depending on the nature of the electricity grid (Holland et al., 2016; Holland et al., 2021). We therefore explore the spatial distribution of upstream pollution from electricity generation. Both the electricity grid and the gasoline fleet have become cleaner over time, while EVs have become more energy efficient. We argue that on net, EVs reduce exposure to NO_x and show that estimates of the effects of EVs on infant health outcomes are robust to controlling for pollution from the increased electricity generation that EVs require. Clearly, however, the benefits of EVs can only be fully realized when supported by clean sources of electric power.

Despite the potential for EV adoption to deliver significant health benefits through reductions in air pollution, most previous studies rely on model-based projections rather than empirical measurement, making it uncertain whether the anticipated gains are actually realized in real-world settings.[4] Assumptions underlying these projections, such as uniform EV adoption rates and pollutant dispersion patterns, may be critical to their estimates. Garcia et al. (2023) use actual zip-code level observational data from California for 2013-2019 (rather than projections) and relate within-zip code changes in EV counts to NO_2 and asthma related ED visits using random-effects models.[5] They find that a within-zip code increase of 20 EVs per 1,000 population is associated with a 0.41 ppb decrease in NO_2 levels and a 3.2 percent reduction in age-adjusted overall asthma ED visits. This paper builds on these past investigations by providing the first multi-state analysis linking observed EV adoption to actual changes in pollution levels and infant and child health outcomes.

2.2 The Alternative Fuel Corridors program and the spread of charging stations

[4] Examples include Peters et al. (2020), Choma et al. (2021), and Schmitt et al. (2024). Peters et al. (2020) assess the public health and climate impacts of U.S. EV adoption under six scenarios with varying levels of EV penetration (25 percent or 75 percent) and energy sources (combustion-based, current grid, and emission-free). They report significant climate benefits with avoided damages ranging from \$16.8 to \$70 billion annually and the highest health co-benefits when clean energy is used. Similarly, Choma et al. (2021) evaluates the health and climate benefits of reductions in on-road transportation emissions in the U.S. from 2008 to 2017, estimating \$270 billion in $PM_{2.5}$-related benefits in 2017 by comparing four counterfactual emission scenarios from earlier years to 2017 data. Schmitt et al. (2024) examine the projected air quality and health impacts of light-duty vehicle electrification in the U.S. from 2022 to 2050, finding that electrification could result in \$84–\$188 billion in air quality-related health benefits with continued grid decarbonization but could lead to \$32–\$71 billion in additional health costs if the 2022 grid is maintained. There are also a large number of model-based studies projecting health benefits of EV adoption within narrower geographic contexts, including Turin, Italy (Rizza et al., 2021), Paris, France (Maesano et al., 2020), Rotterdam, Netherlands (Tobollik et al., 2016), the Toronto/Hamilton area in Canada (Gai et al., 2020), Houston, Texas (Pan et al., 2019), and Seattle, Washington (Filigrana et al., 2022).

[5] Technically, they look at zero-emission vehicles (ZEVs) which includes fuel cell electric vehicles as well as EVs, but relatively few vehicles run on fuel cells.

Currently, the United States has nearly 70,000 EV charging stations with more than 206,000 charging ports (Caporal, 2025; Federal Highway Administration (FHA), 2025). As a result, 39 percent of Americans now live within one mile of a public charging station, and 64 percent have a charging station within two miles of their homes (Bestvater and Shah, 2024).

Some of this growth in charging infrastructure was incentivized by the strategic placement of EV charging stations along federally designated Alternative Fuel Corridors (AFCs). The AFC program, established under the Fixing America's Surface Transportation (FAST) Act of 2015, aimed to create a nationwide network of alternative fuel infrastructures to promote cleaner transportation technologies.[6] Administered by the Federal Highway Administration (FHWA), the program designated highway routes to support infrastructure development for EV charging stations, hydrogen fueling, and compressed natural gas. A key goal of the AFC initiative was to address range anxiety—a significant barrier to EV adoption—by ensuring that drivers had reliable access to charging facilities along critical transportation corridors (Federal Highway Administration, 2023).

States nominated routes for AFC status and received federal funds to create the corridors and construct charging stations to fill in gaps along the routes. To qualify as an AFC, designated routes had to meet specific requirements. Charging stations had to be spaced no more than 50 miles apart and located within one mile of the highway. These criteria aimed to ensure consistent, accessible charging options, enabling uninterrupted long-distance EV travel. Initially, the program focused on interstate highways, which form the backbone of the U.S. transportation network. Subsequent expansions included state and regional routes to encourage broader EV adoption (Federal Highway Administration, 2016).

Figure 1 presents maps of AFC charging stations, non-AFC charging stations, and alternative fuel corridors. The top panel shows stations for the whole country, while the bottom panel focuses on the greater Chicago area. These figures indicate that the AFC program was national in scope, with charging stations being added across the country. AFC stations represent 48 percent of all charging stations established during this period, underscoring the program's significant role in expanding EV infrastructure. We argue that the program created differential access to EV charging stations across counties in a manner unrelated to local air pollution or health

[6] According to the Federal Highway Administration (2023), the program's environmental objectives were central to its mission, because EV adoption was regarded as a critical strategy for reducing greenhouse gas emissions and improving air quality, aligning with national and global climate change goals. The AFC program was identified as a cornerstone effort in decarbonizing transportation and enhancing environmental and public health outcomes.

conditions, providing a credible source of exogenous variation in EV adoption that we exploit in IV estimation.

3. Data

This section reviews the main sources of data on vehicles, air pollution, infant and child health, and county characteristics, including weather patterns and factors such as power plant emissions, and state-level vehicle miles driven.

3.1. Data on the motor vehicle fleet and electric vehicle shares

Data on the motor vehicle fleet for 2010 to 2021 comes from S&P Global, a commercial provider that makes cleaned and standardized vehicle registration records available to researchers and industry (S&P Global Mobility, 2010-2021). These records are obtained from state Departments of Motor Vehicles (DMVs). EV adoption is measured using year-end county-level snapshots of vehicle registrations. Monthly data is created by interpolating vehicle counts between annual snapshots following the approach of Alexander and Schwandt (2022). We also repeat the analyses using annual data, which abstracts from seasonal vehicle sales or administrative registration cycles. EVs are defined to include both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), as both vehicle types contribute to reductions in tailpipe emissions relative to internal combustion engine vehicles.[7] The EV share is defined as the ratio of all electric vehicles to the total number of registered vehicles in a given county and month. This metric reflects the evolving composition of the vehicle fleet and serves as the main indicator of local EV adoption.

Figures 2 and 3 illustrate the rapid growth and spatial evolution of EV adoption across the United States. Figure 2 shows the overall growth in EVs from 2010 to 2021 in both levels (in thousands) and as a share of all registered vehicles. Both metrics trend steeply upwards reflecting the rapid adoption of EVs nationwide, particularly after 2015.

Figure 3 complements this time series by mapping the county-level distribution of EV adoption at three points in time: 2010, 2016, and 2021. The 2010 map shows minimal EV presence across most U.S. counties. By 2016, adoption begins to cluster in urban and coastal regions, particularly in California and the Northeast. The 2021 map reveals broader nationwide diffusion, though EV penetration remains highly uneven across counties ranging from around a quarter of new vehicle sales in California to a negligible amount in Mississippi (Bui and Slowik, 2024). This spatial and temporal variation helps to identify the impact of EVs on pollution and health outcomes.

Data on an important control variable, the monthly number of vehicle miles travelled in each state, comes from the Federal Highway Administration (U.S. Department of Transportation, Office of Highway Policy Information, 2010-2021).

[7] As we show below, our findings are robust to using an alternative definition based solely on BEVs.

3.2. Data on air pollution

The Environmental Protection Agency (EPA) provides daily measures of air pollution from hundreds of monitoring stations through its Air Quality System (U.S. EPA, AQS, 2010-2021).[8] These stations provide data averaged to the monthly level as well as an Air Quality Index (AQI).[9] To create consistent county-level data, we use a single monitoring station per county, selecting the station with the largest coverage over the analysis period.[10]

The primary focus is on nitrogen dioxide (NO_2), a harmful air pollutant strongly linked to vehicle emissions and widely used as an indicator of traffic-related air pollution. NO_2 is part of the broader category of nitrogen oxides (NO_x), a group of reactive gases generated during combustion. As both a direct emission and a secondary byproduct of NO_x, NO_2 plays a central role in the formation of ground-level ozone and smog. Exposure to NO_2 has been associated with a range of adverse respiratory and cardiovascular outcomes, particularly for vulnerable populations (Huang et al., 2021; Stieb et al., 2020). Aggregate plant-level annual NO_x emissions at the county level come from the U.S. EPA's Clean Air Markets Program Data (U.S. EPA, CAMPD, 2010-2021).

One limitation of the AQS data is that the availability of monitoring stations varies across pollutants and regions, with stations frequently added or discontinued over time. Moreover, many county-months are lacking monitor data, and cannot be included in the pollution analysis.[11] For $PM_{2.5}$, the AQS monitor data is therefore supplemented with satellite-based pollution estimates obtained from van Donkelaar et al. (2021) which are available for all U.S. counties.[12]

Supplementary analyses also draw on annual electricity generation and emissions data from the U.S. EPA's eGRID program (U.S. EPA, eGRID, 2010–2021). The eGRID database identifies the regional electricity grid associated with each county.

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[8] Each daily observation includes pollutant concentrations measured in micrograms per cubic meter (µg/m³) or parts per billion (ppb), along with information on the monitoring station's location and characteristics.

[9] The AQI is a scaled measure from 0 to 500 which converts pollutant concentrations (in parts per billion) into a scaled value based on predefined breakpoints corresponding to health impact categories (e.g., Good, Moderate, Unhealthy).

[10] We exclude county-month observations above the 95th percentile of county-specific distributions of monthly mean NO_2 concentrations to reduce the influence of extreme pollution events. This restriction helps ensure that the estimates reflect typical variation in local air quality that might be affected by EVs rather than being driven by outliers associated with extreme events, such as wildfires or industrial accidents that are not related to routine traffic emissions. The results are robust to relaxing this criterion.

[11] Specifically, the analysis begins with 252 daily pollution monitors across 166 counties reporting data between 2010 and 2021. Following Alexander and Schwandt (2022), we retain, for each county, the monitor with the largest number of observations, resulting in a final sample of 166 monitors.

[12] These estimates combine satellite observations of aerosol optical depth, chemical transport model simulations, and information from EPA ground monitors and use AI models to predict $PM_{2.5}$ for all U.S. counties, including those lacking ground-based monitors. These measures may include prediction errors, particularly for areas with very high pollution levels (Fowlie, Rubin, and Walker, 2019).

3.3. Infant health data

Data on infant health outcomes come from restricted-use Vital Statistics Natality files with county identifiers provided by the National Center for Health Statistics (NCHS, 2010-2021). This dataset includes all live births in the United States from 2010 to 2021 with detailed information on birth outcomes and maternal demographic and health characteristics. County identifiers in the data allow each birth to be linked to local measures of air pollution and the share of EVs.

The main birth outcomes considered include VLBW (birth weight less than 1,500 grams) and very premature birth (gestation under 32 weeks) both measured as a rate per 1,000 live births. These outcomes are widely recognized to be critical indicators of infant health that are predictive of long-term developmental, educational, and economic consequences. Several secondary outcomes are also analyzed, including admission to a neonatal intensive care unit (NICU), assisted ventilation, surfactant administration, and stillbirth. These variables provide complementary indicators of infant morbidity and acute health needs at birth though we have less power to detect effects on these rarer outcomes.

These data also include maternal characteristics such as maternal age, race, education level, marital status, parity (birth order), and smoking during pregnancy. Observations with a gestational length of less than 23 weeks are excluded, since these may reflect data entry errors. The sample is also restricted to single births to avoid confounding due to the unique health risks associated with multiple births (Almond et al., 2005; Dursun et al., 2024; Koppensteiner and Menezes, 2024).

3.4. Data on emergency department visits for children 0-5

Data on ED visits come from State Emergency Department Databases (SEDD) available from the Agency for Healthcare Research and Quality's Healthcare Cost and Utilization Project (HCUP, 2010-2021).[13] State governments collect data on all hospital ED visits which are then shared with the federal government. A subset of states allows these data to be shared with qualified researchers through the HCUP.

The analysis draws on SEDD data from nine states, including Arizona, Florida, Kentucky, Maryland, Minnesota, New Jersey, New York, North Carolina, and Wisconsin, that have information about county and quarter of discharge. These data are available for varying periods of across states: 2010–2021 for Arizona and Kentucky; 2010–2020 for Florida, Maryland, North Carolina, and New Jersey; 2010–2019 for Minnesota and New York; and 2012–2021 for Wisconsin.[14] These data include diagnosis and patient characteristics including age, gender, race, and insurance status.

[13] See https://hcup-us.ahrq.gov/seddoverview.jsp for details.

[14] The SEDD databases are available for purchase from the AHRQ. We obtained the data from the National Bureau of Economic Research which has a reuse agreement with HCUP. These are the nine states NBER has access to that

County-by-quarter rates of ED visits are constructed for children aged 0 to 5. years.[15] The primary outcome is the rate of asthma-related visits per 1,000 children in this age group, since asthma has been previously linked to air pollution and is a major cause of ED visits among young children. However, since it can be difficult to diagnose asthma in young children, we also examine the broader category of acute respiratory diagnoses, though that includes many more conditions including some that may be less sensitive to air pollution.

3.5. County characteristics and weather data

Several additional variables are included as controls in our models. Annual county population estimates come from the US Census Bureau's Population Estimates program (U.S. Census Bureau, County Population Totals, 2010-2021). Overall poverty rates and child poverty rates come from the Small Area Income and Poverty Estimates program (U.S. Census Bureau, SAIPE, 2010-2021). County-level monthly weather data, including average temperature and precipitation, comes from the PRISM Climate Group at Oregon State (Vose et al. 2014). Monthly wind speed and wind direction information come from the National Oceanic and Atmospheric Administration's daily weather station data (NOAA, 2010-2021).

3.6. Descriptive Statistics

Table 1 presents summary statistics for key variables, reported separately for counties in the bottom quartile, middle 50 percent, and top quartile of the EV adoption distribution, where quartiles are defined using the average EV share over the analysis period. On average, counties in the top quartile have 26.4 electric vehicles per 1,000 registered vehicles, compared with only 5.7 in the bottom quartile. There are significant differences between counties in the bottom and top quartiles of EV adoption in terms of sociodemographic characteristics, environmental exposure, and health outcomes.

Panel A reports air pollution measures from both ground monitors and satellite sources. Ground-monitored NO_2 levels average 8.13 ppb in top-quartile EV share counties, more than double the 3.73 ppb observed in the bottom quartile of counties by EV share. The corresponding AQI values show a similar pattern, with an average of 16.4 in the top quartile versus 8.1 in the bottom. In contrast, $PM_{2.5}$ concentrations are similar across the EV share distribution. These patterns suggest that higher EV adoption is associated with greater NO_2 exposure, possibly reflecting urbanization or traffic patterns, while $PM_{2.5}$ concentrations are relatively stable across counties with varying levels of EV uptake. The lack of an apparent relationship between EV adoption and $PM_{2.5}$, is consistent with the idea that non-exhaust sources of $PM_{2.5}$, such as tire and brake wear, limit the extent to which EVs reduce $PM_{2.5}$ concentrations.

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provide on county of residence and discharge quarter for our period. Seven states provide discharge month, but we use quarterly data in order to retain the largest possible number of states.

[15] We also report results for individuals aged 65 to 79 in Appendix Table A9.

Panel B shows that infant health outcomes are somewhat worse in counties with higher EV shares: Rates of VLBW and very premature births are 15.0 and 17.3 per 1,000 births, respectively in the top quartile compared to 13.6 and 15.6 in the bottom quartile. NICU admission is also more common in the top quartile, while assisted ventilation, surfactant use, and stillbirth rates are similar across the two groups.

Panel C presents maternal and birth characteristics and shows clear socioeconomic differences across the EV share distribution. Mothers in counties with higher EV adoption tend to be older on average, have higher levels of education, and are less likely to smoke during pregnancy. The racial and ethnic composition also differs, with a greater share of White and Hispanic mothers and a smaller share of Black mothers in top-quartile counties. In addition, mothers in high-EV share counties are more likely to be married.

Panel D shows statistics on ED visits for children, from the HCUP data. Overall, respiratory-related visits are more common in counties with lower EV adoption. Asthma-related ED visits average 2.3 per 1,000 children ages 0–5 in bottom-quartile counties, compared with 1.7 per 1,000 in the top quartile. A similar gradient appears for acute respiratory disease visits, which are highest in the bottom quartile (36.6 per 1,000) and lowest in the top quartile (26.9 per 1,000). Injury-related ED visits, which serve as a placebo outcome, also follow this pattern, with higher rates in the bottom quartile than in the top quartile.

Finally, Panel E highlights large differences in county characteristics. High-adoption counties are far more urban, with an average population of nearly 258,000 residents and 98,500 registered vehicles, compared to about 22,000 residents and 7,800 vehicles in the bottom quartile. They also report more vehicle travel and greater access to alternative fuel charging stations. Poverty and child poverty rates are lower in high-EV counties than in the bottom quartile.

Together, the patterns across panels highlight that counties with greater EV adoption tend to be larger, more economically advantaged, and more educated, but also more urban. These counties face higher ambient NO_2 levels and experience higher rates of VLBW and very premature births. In contrast, ED visits due to respiratory conditions are lower in high-EV counties, which may reflect differences in access to alternative sources of health care. These differences underscore the importance of accounting for underlying geographic and demographic factors in assessing the impacts of EV penetration.

Overall, Table 1 indicates that counties with higher levels of EV adoption differ systematically from those with lower adoption across a broad set of observable characteristics. These differences underscore the importance of addressing potentially endogenous EV adoption as discussed in the next section.

4. Empirical Methodology

We implement two complementary empirical strategies to address the potential endogeneity of EV adoption. The first is to estimate two-way fixed effects (TWFE) models that exploit within-county variation in EV shares over time while controlling for county, month-by-year, and state-by-year fixed effects, as well as observable county-level covariates. This approach accounts for time-invariant county characteristics and common temporal shocks. The second strategy is to use the rollout of Alternative Fuel Corridors as an instrument for EV adoption.

The two approaches are complementary. TWFE uses variation across the full sample to compute treatment effects but requires relatively strong assumptions to return causal average treatment effects. This framework is essentially a difference-in-differences design, relying on the assumption of parallel trends between treatment and control counties and homogeneous treatment effects. For example, it might be the case that increasing the EV share has different effects depending on baseline EV shares. We investigate the plausibility of these assumptions below.

The IV strategy addresses time-varying confounders by exploiting plausibly exogenous variation in EV adoption driven by the federally coordinated rollout of AFC charging infrastructure. A limitation of the IV strategy, however, is that it reflects the impact of the treatment on the treated, that is, EV adoption in counties affected by the rollout. By construction, these must be counties with eligible road segments, i.e. interstate highways where AFC charging stations could be constructed within one mile of the road, and at the right intervals along the highways. Hence, these estimates should be interpreted as the effect of the treatment on the treated counties and are not necessarily representative of what would have happened in non-treated counties. These estimates also depend on the assumption that the AFC stations affected pollution and health outcomes only through their effects on EV adoption.

4.1. Two-Way Fixed Effects estimation

We first ask how changes in EV adoption affected air pollution levels at the county level. If there is no "first-stage" effect on air pollution levels, then there should be no downstream effect on infant health. The estimation equation is:

$$(1)\quad NO2_{cmy} = \alpha_0 + \alpha_1 EV_{cmy} + \boldsymbol{X}'_{cy}\boldsymbol{\alpha}_2 + \boldsymbol{W}'_{cmy}\boldsymbol{\alpha}_3 + \alpha_4 M_{smy} + \boldsymbol{\lambda}_c + \boldsymbol{\lambda}_{my} + \boldsymbol{\lambda}_{sy} + \varepsilon_{cmy},$$

where $NO2_{cmy}$ measures air pollution in county c, in month m, in year y. EV_{cmy} is the share of electric vehicles among all registered vehicles. The vector $\boldsymbol{X}'_{cy}$ includes log population, total poverty and child poverty rates, total number of registered vehicles, and NO_x emissions from power plants, all measured annually. The vector $\boldsymbol{W}'_{cmy}$ includes county-by-month weather conditions, including average temperature and precipitation and these variables squared, average wind speed, and eight indicators for average wind direction. M_{smy} is state total miles driven by month in each year.

The term $\boldsymbol{\lambda}_c$ denotes county fixed effects, which control for unobserved, time-invariant differences across counties. The term $\boldsymbol{\lambda}_{my}$ represents month-by-year fixed effects, which account for shocks that are common across all counties. States with more rapid EV adoption may simultaneously experience other changes correlated with air pollution, such as the implementation of environmental regulations. Additionally, urbanization or environmental awareness could also differ across states and over time. State-by-year fixed effects ($\boldsymbol{\lambda}_{sy}$) are included in Equation (1) to account for such influences.[16] Finally, ε_{cmy} is an idiosyncratic error which is clustered at the county level to allow for correlations between observations due to shared county-level factors.

Turning to the effects of EV adoption on infant health, we estimate the following model:[17]

$$(2)\quad IH_{cmy} = \beta_0 + \beta_1 EV\_Gest_{cmy} + \boldsymbol{X}'_{cy}\boldsymbol{\beta}_2 + \boldsymbol{\Gamma}'_{cmy}\boldsymbol{\beta}_3 + \beta_4 M_{smy} + \boldsymbol{\lambda}_c + \boldsymbol{\lambda}_{my} + \boldsymbol{\lambda}_{sy} + \epsilon_{cmy},$$

where IH_{cmy} represents one of the infant health indicators in county c, during month m, and year y. Conception month is calculated using the birth date and gestational age. EV_Gest_{cmy} denotes the average EV share that infants were exposed to during their 9-month period *in utero*. This measure is calculated as the 9-month average of EV shares in county c, starting from conception month m in year y.

The vector $\boldsymbol{X}'_{cy}$ includes the same variables as Equation (1). The vector $\boldsymbol{\Gamma}'_{cmy}$ in Equation (2) includes county-level averages of various measures derived from the Vital Statistics data. These measures, aggregated at the monthly level, include the child's birth order, gender, maternal age, race, maternal education, marital status, and maternal smoking status. The weather variables included in $\boldsymbol{\Gamma}'_{cmy}$ are 9-month averages of the monthly weather variables that were included in Equation (1). M_{smy} is also calculated as a 9-month average over the period of gestation. The data used for estimating Equation (2) are collapsed at the county-conception-month-year level and the regression is weighted by the number of births in each conception month-year-county cell.

The key identifying assumption underlying equations (1) and (2) is that counties on different paths of EV adoption would have followed similar trends in the absence of adoption. Any systematic differences in pre-adoption dynamics correlated with the timing or intensity of EV take-up could otherwise bias the estimates. To address this potential contamination, we specify modified versions of equations (1) and (2) adding leads and lags of treatment following the event-study framework of de Chaisemartin and D'Haultfoeuille (2024).[18]

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[16] The results are similar when we control for state-specific linear time trends instead.

[17] Because these data include measures of both air pollution and infant health, we can investigate the relationship between these two variables in a unified framework. However, to conserve space, and given a large previous literature doing so (see for example, Currie and Neidell, 2005; Currie et al., 2009; Currie, 2013) we do not present or discuss these results here. They are available from the authors upon request.

[18] These estimates use the did_multiplegt_dyn command from de Chaisemartin and D'Haultfoeuille (2024), which addresses the limitations of TWFE estimators in staggered adoption settings. In particular, the estimator avoids inappropriate comparisons and negative weightings.

In our implementation, monthly county EV shares are discretized into bins (i.e., quintiles), and "treatment" is defined as crossing a bin boundary. The treatment measure is categorical, defined by the quintile distribution of county-level EV shares. Leads and lags of this switching indicator are included to estimate dynamic effects. Specifically, we estimate:

$$(3)\quad Y_{cmy} = \gamma_0 + \sum_{l=-3}^{l=5} \gamma_1^{(l)}\ EV_{cmy}^{(l)} + \boldsymbol{X'_{cy}\gamma_2} + \mathbf{W'_{cmy}}\boldsymbol{\gamma_3} + \gamma_4 M_{smy} + \boldsymbol{\Gamma'_{cmy}\gamma_3} + \boldsymbol{\lambda_c} + \boldsymbol{\lambda_{my}} + v_{cmy},$$

where Y_{cmy} denotes either air pollution or an infant health outcome. The variable $EV_{cmy}^{(l)}$ indicates that county c in month-year my is l months relative to the month when it transitions into a higher EV adoption bin. The set of controls is consistent with the corresponding baseline models: $\boldsymbol{X'_{cy}}$, $\boldsymbol{W'_{cmy}}$, and M_{smy} are defined as in equation (1), and in the infant health specifications, $\boldsymbol{\Gamma'_{cmy}}$ is defined as in equation (2). All specifications include county fixed effects $\boldsymbol{\lambda_c}$ and month-by-year fixed effects $\boldsymbol{\lambda_{my}}$. Standard errors are clustered at the county level, and the infant-health regressions are weighted by births. The coefficients $\gamma_1^{(l)}$ thus provide a test of the parallel trends and no-anticipation assumptions and trace out the dynamic effects of EV adoption after treatment.

4.2. Instrumental Variable Strategy

The instrumental variable is constructed using data on charging stations that opened between 2016 and 2021 and were located within one mile of designated AFCs. Stations that opened before 2016 preceded the AFC rollout under the FAST Act and were therefore not affected by the AFC program. Forty-eight percent of all new charging stations established during this period were along AFC corridors, underscoring the program's significant role in expanding EV infrastructure. The instrument is the stock of AFC charging stations per 10,000 population in each county and month.[19]

The first identifying assumption underlying the IV estimates is that the AFC charging stations incentivized EV ownership. Previous work suggests that charging infrastructure is a key driver of EV adoption, as it reduces range anxiety and enhances the convenience of EV use (Sierzchula et al., 2014; Shen et al., 2019). We will show that the availability of new AFC charging stations is strongly predictive of increases in EV shares at the county level.

A second identifying assumption is that AFC charging stations only affected outcomes through their effects on EV shares. In turn, this assumption implies that in the absence of the new AFC charging stations, counties that received these stations would have continued on the same trends as other counties. To assess this assumption, we perform an event-study analysis that

[19] Results are robust to scaling the instrument by the number of registered vehicles rather than population. We prefer population scaling here because it provides a more stable denominator, and avoids potential endogeneity concerns that may arise if the total number of vehicles responds to changes in charging infrastructure.

examines trends in EV shares in counties that eventually became part of the AFC program. The event study is based on an equation of the following form:

$$(4)\quad EV_{cy} = \delta_0 + AFC_c * \boldsymbol{I}_y \boldsymbol{\delta}_1 + \boldsymbol{X}^{'}_{cy}\boldsymbol{\delta}_2 + \delta_3 M_{sy} + \boldsymbol{\lambda}_c + \boldsymbol{\lambda}_y + \boldsymbol{\lambda}_{sy} + z_{cy},$$

where AFC_c is a flag indicating that the county was eventually treated by acquiring new AFC charging stations. This flag is fully interacted with a vector of year indicators, $\boldsymbol{I}_y$, so that it is possible to see if trends in EV_{cy} began to diverge in recipient counties relative to other counties prior to the rollout of the AFC program.

The regression equation representing the first stage is specified as follows for the pollution outcomes:

$$(5)\ EV_{cmy} = \theta_0 + \theta_1 AFC_{cmy} + \boldsymbol{X}^{'}_{cy}\boldsymbol{\theta}_2 + \boldsymbol{W}^{'}_{cmy}\boldsymbol{\theta}_3 + \theta_4 M_{smy} + \boldsymbol{\lambda}_c + \boldsymbol{\lambda}_{my} + \boldsymbol{\lambda}_{sy} + u_{cmy},$$

where AFC_{cmy} denotes the stock of AFC charging stations per 10,000 population in county c in month m in year y, and the other variables are as defined above. In IV models with infant health outcomes, all variables are measured using the 9-month average from the month of conception.

The second stage uses the predicted values of EV shares from the first stage to estimate the causal effect of EV adoption on air pollution and infant health outcomes. That is, we estimate versions of Equations (1) and (2) in which EV_{cmy} and EV_Gest_{cmy} are replaced by their predicted values from the first stage.

5. Estimates

5.1 Event studies testing parallel trends

Figure 4 presents the event-study estimates for nitrogen dioxide (NO_2), while Figures 5a and 5b report the corresponding estimates for very low birth weight (VLBW) and very premature (VP) births. The coefficients $\gamma_1^{(l)}$ measure changes in outcomes from three months before to five months after a county transition into a higher EV adoption bin, relative to the month just before the transition. The control group at each event time consists of counties that have not yet crossed into a higher bin, ensuring that the estimates compare switchers to counties that remain in lower adoption categories.[20]

Across all outcomes, the pre-treatment coefficients are close to zero and statistically insignificant, supporting the validity of the parallel trends and no-anticipation assumptions necessary for valid TWFE estimation. In the post-treatment period, Panel (a) of Figure 4 shows that NO_2 concentrations fall sharply once counties transition into higher EV adoption bins. The

[20] A simple DiD would pool early and late adopters and implicitly assume homogeneous effects of crossing into a higher EV adoption bin. In contrast, the estimator developed by de Chaisemartin and D'Haultfoeuille (2024) allows treatment effects to vary across cohorts and over time by comparing switchers to never treated and not-yet-treated units and aggregating these cohort-specific effects into dynamic estimates. All event-study estimates are based on the monitor counties sample used in the air pollution analysis in order to overcome computational constraints associated with implementing the did_multiplegt_dyn estimator on the full set of counties.

reduction is apparent within the first few months after the transition and persists throughout the post-period. Panels (a) and (b) of Figure 5 show that infant health outcomes follow a similar dynamic pattern. Counties that cross into higher EV adoption bins experience sustained declines in both VLBW and VP births. The point estimates indicate reductions in adverse birth outcomes of several cases per 1,000 births, which represent meaningful improvements relative to baseline rates.[21] Together, these findings suggest that improvements in local air quality associated with EV adoption translate into tangible health benefits for newborns.

Appendix Figure A1 replicates the infant health event-study analysis using deciles of county EV shares rather than quintiles. Using deciles increases the number of potential crossings, but also implies stronger linearity assumptions, that is, that transitions between low deciles are similar to transitions among higher deciles. The dynamic patterns are very similar, with small pre-treatment coefficients consistent with flat pre-trends, followed by persistent post-treatment declines in VLBW and very premature births. This robustness check confirms that the event study results are not driven by the choice of binning scheme and that the health benefits of EV adoption emerge consistently across alternative specifications.

Figure 6 plots the estimated $\boldsymbol{\delta}_1$ coefficients from equation (4), which asks whether, in counties that eventually received an AFC charging station, EV shares had begun to change prior to the rollout of the AFC program. The figure shows that there was no differential growth in EV adoption prior to 2015, while after the program began in 2015, the coefficients become positive and statistically significant, reflecting a marked increase in EV shares in treated counties.

5.2 Balancing tests

To further investigate the assumptions underlying the TWFE estimates, we perform a series of balancing exercises in which each of the child and maternal characteristic is regressed on the EV share (Currie and Walker, 2011; Alexander and Schwandt, 2022). As shown in Appendix Table A1, the results show that 9-month averages of EV shares during pregnancy are largely orthogonal to demographic as well as maternal and child characteristics once the other variables included in Equations (1) and (2) are included.[22] These findings suggest that the variation in EV adoption is largely exogenous to maternal and child characteristics.

To evaluate the exogeneity of the instrument, we perform an additional balancing exercise asking whether the adoption of AFC charging station was correlated with county maternal and

[21] For example, in Figure 5a, the third post-treatment coefficient for VLBW is –0.77 (s.e. = 0.33), indicating that three months after a county crosses into a higher EV adoption quintile, the incidence of VLBW falls by about 0.8 cases per 1,000 births relative to the pre-transition baseline. This effect is statistically significant at the 5 percent level and corresponds to a 5.7 percent decline relative to the sample mean incidence of 13.57 per 1,000 births.
[22] The sole exception is that there is a negative relationship between the share of mothers who are Hispanic and EV shares within counties. Given that Hispanic mothers tend to have better birth outcomes than other mothers after conditioning on other characteristics (e.g., Giuntella, 2016; Shaw and Pickett, 2013), this correlation may bias the estimated effects of EV adoption on infant health towards zero.

child characteristics. The results are shown in Appendix Table A2. The percent Hispanic shows a statistically significant but very small association with the instrument, and the other estimated coefficients are all statistically insignificant. Appendix Table A3 shows the results of a second exercise, which asks whether places that higher pollution levels in the previous six months or in the previous year were more likely to get AFC charging stations. There is no evidence that this is the case.

5.3 Effects of electric vehicles on air pollution and infant health

Table 2 presents estimates of Equation (1), which captures the impact of EVs on NO_2. Columns (1) and (2) show estimates from the TWFE model, while columns (3) and (4) present IV estimates. Estimates are reported for the AQI for NO_2 and the arithmetic mean of daily NO_2 concentrations.

The TWFE estimates suggest that a one-unit increase in EVs per 1,000 vehicles is associated with a significant 0.020-point reduction in the NO_2 AQI (Column 1) and a 0.019 ppb decline in the arithmetic mean of NO_2 concentrations (Column 2). These estimates correspond to reductions of approximately 0.14 percent and 0.27 percent, respectively, relative to the sample means. Scaling the estimates by a one-standard deviation increase in EV share (11.98 vehicles per 1,000) implies declines of 1.62 percent in AQI and 3.19 percent in mean NO_2 levels.

The IV estimates in Columns (3) and (4) are larger, with a one-unit increase in EVs per 1,000 vehicles associated with a 0.050-point reduction in AQI and a 0.043 ppb drop in the arithmetic mean. These effects translate to declines of 0.34 percent and 0.60 percent, respectively. When scaled by a one-standard deviation increase in the instrumental variable, i.e., the number of EV charging stations along the AFC corridor per 10,000 people, the estimates imply reductions of 0.8 percent in AQI and 1.4 percent in mean NO_2 concentrations.

The first stage estimates shown in Appendix Table A4 indicate that AFC charging stations are strongly predictive of EV take up, with each additional charging station per 10,000 population being associated with an increase in EV shares of 10 per 1,000 vehicles. The Kleibergen-Paap F-statistic is 17.9. The reduced form estimates reported in Appendix Table A4 indicate that the presence of AFC stations is associated with significant reductions in NO_2 concentrations, as measured by both the AQI and the arithmetic mean. Taken together, these results imply that the expansion of charging infrastructure not only promotes EV adoption but also leads to improvements in local air quality.

A supplementary analysis of effects on $PM_{2.5}$ is shown in Appendix Table A5. EV adoption does not have a statistically significant effect on this outcome, although the point estimates are consistently negative. These findings suggest that while EV adoption may yield modest reductions in $PM_{2.5}$, its effectiveness is far more pronounced for pollutants like NO_2 that are directly tied to combustion. As discussed above, EVs may generate significant amounts of $PM_{2.5}$ from non-combustion sources like tire wear and tear.

Table 3 presents estimates of the impact of EV adoption on VLBW and very premature births, Columns (1) and (2) show estimates from the TWFE models, where a one-unit increase in EVs per 1,000 vehicles (measured as the 9-month average during gestational period) is associated with statistically significant declines in both very low birth weight and very premature births—by 0.009 and 0.0109 per 1,000 births, respectively. These estimates translate into percent reductions of approximately 0.1 percent at the sample means. When scaled by a one-standard deviation increase in EV share, the implied declines are around 0.8 percent for both outcomes.

Columns (3) and (4) report IV estimates. The estimated effects are larger implying that a one-unit increase in EVs per 1,000 vehicles leads to a 0.03 decline in VLBW and a 0.04 decline in very premature births per 1,000 births. These estimates correspond to percentage reductions of about 0.2 percent relative to their respective means and imply that a one-standard deviation increase in AFC station availability translates into roughly 0.5 percent declines in both outcomes. The first stage estimates shown in Appendix Table A6 indicate that each additional AFC station per 10,000 population increases EV adoption by about 9.1 vehicles per 1,000. The reduced-form estimates show that a one-unit increase in AFC station availability per 10,000 population is associated with declines of 0.27 and 0.35 cases of VLBW and very premature births per 1000 births respectively. The reduced form estimates are shown in Appendix Table A6 and are in line with the IV estimates.

The IV estimates reported in Tables 2 and 3 are notably larger than the TWFE estimates, suggesting that IV identifies a local average treatment effect specific to AFC settings. Because AFC stations are typically located near highways, average AQI and NO_2 levels are 26 to 30 percent higher within one mile of an AFC, and 11 to 14 percent higher within five miles. Similarly, areas near an AFC also experience worse infant health, with the incidence of VLBW about 54 percent higher and the incidence very premature births about 57 percent higher within five miles along an AFC compared to the full sample. Hence the comparison between TWFE and IV suggests that the effects of EV adoption are greater in high pollution settings.

Table 4 focuses on counties with pollution monitors that are within five miles of an AFC to assess whether the larger IV estimates indeed reflect the higher baseline pollution and health risks in communities located near AFC infrastructure. The first four columns report estimates for air quality measured by AQI and mean NO_2, while Columns 5 through 8 report estimates for infant health outcomes measured by VLBW and very premature births. Columns (1) and (2) show TWFE estimates which suggest that EV adoption is associated with substantially larger improvements in air quality than in the full sample, with coefficients roughly 50 percent larger in magnitude than those reported in Table 2. In contrast, the IV estimates in Columns (3) and (4) are close to those reported previously. These results support the idea that the IV is capturing larger effects of EV adoption in high-pollution areas.

The infant health results in Columns (5) through (8) show a similar pattern. Both the TWFE and IV estimates are larger in the restricted sample than in the full sample, consistent with the higher baseline incidence of adverse birth outcomes in these counties. The TWFE estimates point to stronger improvements in VLBW and very premature births, and the IV estimates likewise yield somewhat larger coefficients in the restricted sample than in the full sample. Taken together, the results support the interpretation that EV adoption generates particularly large health benefits in communities located near AFC infrastructure, where both pollution levels and infant health risks are greatest.

A supplementary analysis of a broader range of birth outcomes is shown in Appendix Table A7: Neonatal intensive care (NICU) admissions, assisted ventilation, surfactant therapy, and stillbirth, and an index that includes these variables along with VLBW and very premature.[23] The effects of EVs on these adverse outcomes are consistently negative, but mostly imprecisely estimated. The TWFE models indicate that a one-unit increase in EVs per 1,000 vehicles is associated with a statistically significant 0.0352 decrease in surfactant therapy per 1,000 births ($p<0.01$), and with a significant effect on the index. The IV estimates suggest that there is a significant negative effect on stillbirths.

5.4 Robustness

Table 5 presents a series of robustness checks to evaluate the consistency of the main findings. Panel A shows that using annual EV shares rather than monthly shares produces very similar estimates, mitigating concerns about using interpolated monthly data.

Panel B excludes data from the COVID-19 lockdown period (March to June 2020) to account for potential disruptions in economic activity, pollution, and driving patterns.[24] The results are consistent with the main findings, demonstrating significant reductions in NO_2 concentrations. This analysis confirms that the observed effects are not driven by temporary pandemic-related anomalies.

[23] According to the CDC, a stillbirth refers to the loss of a baby at 20 weeks of pregnancy or later, occurring either before or during delivery. The composite index follows Currie et al. (2022). It combines VLBW and very premature birth with NICU admissions, assisted ventilation, surfactant therapy, and stillbirths, all measured per 1,000 births. Each component is oriented so that higher values reflect worse outcomes, standardized using the mean and standard deviation of the control group, and then summed to create the index.

[24] The rationale for selecting June 2019 is that the lockdown began in March 2020, and the analysis uses a 9-month average of EV shares to measure exposure during the *in utero* period. Vehicle usage declined sharply at the start of the pandemic in March 2020 but had largely returned to near pre-pandemic levels by July 2020, as illustrated by the daily average vehicle miles travelled shown in Appendix Figure A2.

In Panel C, the treatment is redefined using EVs per 1,000 population rather than per 1,000 registered vehicles. While the units are different, both TWFE and 2SLS models yield negative and statistically significant coefficients, suggesting that the main results are not sensitive to how EV penetration is scaled.

Panel D focuses exclusively on battery electric vehicles (BEVs), which account for about 80 percent of electric vehicles and generate zero tailpipe emissions. Since plug-in hybrid EVs may still emit pollutants through gasoline usage, the estimated effects are expected to be larger when we focus on BEV-only, a prediction that is confirmed by the data.

Panel E shows estimates controlling for non-AFC charging stations in the analyses. Again, the estimates are very similar to the baseline shown in Table 2, suggesting that the observed improvements in air quality in the IV are specifically driven by EV adoption spurred by the exogenous location of AFC charging stations rather than by broader trends captured by the expansion of charging networks outside the AFC program.

Finally, Panel F restricts the analysis to counties with populations of at least 250,000 since EV adoption and monitoring infrastructure may differ in rural and urban settings. The estimates are similar to the baseline, suggesting that the improvements in air quality are concentrated in larger, more urban settings where both EV penetration and pollution concerns are greatest.

Table 6 presents a range of largely similar robustness checks examining the relationship between EV adoption and infant health outcomes. Panel A shows estimates based on annual rather than monthly data. Panel B excludes births conceived during the COVID-19 lockdown period. Panel C excludes births to mothers younger than 18 years old, who may face elevated risks for adverse birth outcomes for reasons unrelated to pollution exposure. Panel D includes births with gestational ages below 23 weeks, which had been excluded due to concerns about measurement error or data quality. Panel E excludes county-month-year cells with fewer than five conceptions to ensure that the results are not driven by small-sample noise. Across these specifications, the estimates are similar to those reported in Table 3.

Panel F redefines EV penetration using EVs per 1,000 population rather than per 1,000 registered vehicles. Although the units differ, the results are consistent with the baseline, with both TWFE and 2SLS estimates indicating statistically significant improvements in infant health outcomes. Panel G focuses exclusively on battery electric vehicles, which produce zero tailpipe emissions, and finds somewhat larger effects, consistent with expectations.

Panel H restricts the analytic sample to counties with NO_2 monitoring data. While the point estimates for VLBW are somewhat larger in the TWFE models, the overall pattern is consistent with the full sample of counties, and IV estimates are not statistically different. Panel I includes controls for non-AFC charging stations, showing that the main results are not affected by the inclusion of these controls. Finally, Panel J restricts the sample to counties with populations of at least 250,000. The estimates are negative and statistically significant in most specifications.

Overall, these robustness checks demonstrate the consistency of the main findings, highlighting the significant role of EV adoption in reducing harmful air pollutants and improving infant health.

5.5 Effects of electric vehicles on Emergency Department visits

The estimates discussed above indicate sizeable effects of EV adoption on infant health at birth. This section extends the analysis of health outcomes to children under five in the nine states where we have quarterly HCUP data. Given limitations of the HCUP data described below which result in smaller sample sizes, we report only TWFE estimates. Nonetheless, the IV results were qualitatively similar and yield statistically significant effects for asthma-related ED visits.

Before turning to healthcare utilization, we first confirm that the negative relationship between EVs and air pollution holds in these states. The TWFE estimates in Appendix Table A8 show that an additional EV per 1,000 vehicles reduces the NO_2 AQI by 0.100 points relative to a mean of 17.6 (a decline of about 0.6 percent) and lowers average NO_2 concentrations by 0.081 ppb relative to a mean of 8.7 (a decline of roughly 0.9 percent). These estimates are consistent with the nationwide analysis.

Next, Table 7 presents the main estimates for ED visits for children 0–5.[25] TWFE estimates show that an additional EV per 1,000 vehicles is associated with a statistically significant decline of 0.022 asthma-related ED visits per 1,000 children, which corresponds to roughly 1.1 percent of the mean rate. For acute respiratory visits, the coefficient is also negative (–0.016 relative to a mean of 31.3), though the estimate is not statistically significant for this broader measure. The final column in Table 7 reports the estimate for injury-related ED visits, which serves as a placebo outcome. The coefficient is small and statistically insignificant.

Overall, these estimates support the main findings, showing that improvements in air quality from greater EV adoption translate into reductions in healthcare utilization, underscoring that young children are particularly sensitive to vehicular pollution and that EV adoption can be effective in mitigating asthma risks.

To provide additional context, we also estimated models for older adults (ages 65–79) as shown in Appendix Table A9. Elderly people are also especially sensitive to air pollution (Walker and Schlenker, 2016; Deryugina et al. 2019). Although we find little evidence of an effect on asthma-related ED visits, there is a statistically significant decline in acute respiratory visits: an additional EV per 1,000 vehicles is associated with a reduction of 0.018 visits per 1,000 older adults, equivalent to about 0.5 percent of the mean rate. The final column reports estimates for injury-related visits, which serve as a placebo outcome. The coefficient is close to zero and statistically insignificant. Overall, these results suggest that while asthma appears less responsive in this age group, EV adoption still contributes to measurable improvements in respiratory health among older adults, particularly for acute respiratory conditions.

Although the HCUP ED data are highly detailed, they have limitations. First, the ED discharge records only include patients who were discharged directly from the emergency department and therefore exclude patients who were subsequently admitted to hospital. This restriction may lead to an undercounting of the most serious respiratory cases. Second, the HCUP data are only available for a subset of states, which reduces the variation available for analysis and may limit generalizability. The number of counties that can be included in the analysis of pollution is further limited because not all counties in these 9 states have monitor data. In total, we observe usable pollution measures for 26 counties. Finally, we analyse HCUP data at the quarterly rather than monthly level which also limits the number of observations.

5.6 EVs and their evolving environmental footprint

While electric vehicles reduce local tailpipe emissions, charging them requires electricity that may be generated from fossil fuels. Upstream pollution from power plants may reduce or offset some of the air quality gains from EVs. Moreover, the places that benefit from EVs may not be the same as those that suffer from the increased electricity generation, leading to environmental inequities.

Understanding these trade-offs requires information about trends in several quantities which are shown in Appendix Table A10. The first is how much pollution is created by the electricity generation needed to power EVs. Given the on-going decarbonization of the electricity grid and improvements in the efficiency of EVs, emissions from EV charging have declined substantially, falling from 4.33 pounds of nitrogen oxides per vehicle per year in 2010 to just 1.51 pounds in 2021.[26] Appendix Figure A3 complements this analysis for California, which is one of the largest EV markets, by showing how the mix of California's electricity imports has evolved over time.[27] The figure highlights a clear shift toward cleaner sources for energy imported, with declining reliance on coal and growing shares of hydroelectric and other renewable sources. These changes suggest that spillover emissions, those generated elsewhere by EV energy demands, also fall over time.

The second quantity is how much pollution is averted when EVs replace gasoline powered cars. This quantity has also been falling over time as the gasoline fleet has become cleaner and

[26] Estimates combine average NO_x emissions per megawatt-hour of electricity generation from EPA's eGRID (2010–2021) with annual electricity demand per EV from EV-Database.org and sales-weighted model averages. For comparison, we also obtain gasoline-vehicle emission estimates based on EPA's MOVES model (U.S. Bureau of Transportation Statistics, 2025). See Appendix Table A10.

[27] To our knowledge, California is the only state that consistently reports fuel sources for electricity generated within California and outside of the state (California Energy Commission, 2009-2023).

more efficient. Exhaust emissions from conventional gasoline vehicles fell from 29.33 pounds per vehicle in 2010 to 5.50 pounds in 2021. However, Appendix Table A10 shows that the reduction in pollution from substitution of EVs for gasoline cars is still substantial.

A third factor that is important to understand is how the burden of pollution from electricity generation is distributed, and how much of it falls in the same places that benefit from local reductions in pollution following EV adoption. Appendix Table A11 gets at this question for California. Column 1 shows the huge growth in the number of EVs. Column 2 shows trends in the amount of tailpipe NO_x averted by these EVs (based on the calculations in Appendix Table A10). Column 3 shows the growth in in-state NO_x emissions required to power these vehicles. Column 4 indicates that EV adoption led to net pollution reductions within California, even when power plant emissions are accounted for. In 2021, EVs displaced more than 4200 tons of nitrogen oxides from tailpipes while generating approximately 850 tons from electricity use. This implies a net reduction of roughly 3400 tons.

However, some of California's electricity is generated out-of-state. The last column shows the burden that California EV adoption imposes on other states in the same electricity grid. This amount is relatively small but does represent a negative externality of California EV adoption.

Finally, we re-evaluate the pollution-reducing impact of electric vehicle (EV) adoption accounting for NO_x emissions produced by the power plants supplying electricity to EVs within the same energy grid nationally. First, we calculate the total number of registered EVs within each grid using county-level vehicle registration data and the total annual electricity demand from EVs in each grid. This demand is then allocated across power plants based on each plant's share of total annual generation within its grid, allowing us to estimate the emissions attributable to EV charging for each power plant. Finally, these EV-related emissions are aggregated to the county level based on the geographic location of each plant. Appendix Tables A12 and A13 report estimates of the effects of EVs on pollution and health controlling for the spillover effects of EV adoption to all counties within the same grid.

The findings are consistent with recent studies that use dynamic modelling to assess the environmental and welfare implications of EV adoption. For example, Holland et al. (2020) document a sharp decline in pollution from electricity generation between 2010 and 2017. They attribute this shift primarily to changes in the generation mix and improvements in plant-level emissions performance. Building on this work, Holland et al. (2021) show that these reductions in power sector emissions have significantly improved the environmental footprint of EVs in recent years.

These results suggest that EV adoption has delivered meaningful air quality benefits even after accounting for emissions from electricity generation as electricity generation continued to decarbonize over time.

6. Conclusions

This study provides a first nationwide look at the environmental and health benefits of EV adoption within the same framework. To address the potential endogeneity of EV adoption, we employ two empirical strategies, two-way fixed effects and an instrumental variables approach that exploits the staggered rollout of Alternative Fuel Corridors. We find that greater EV penetration leads to significant reductions in NO_2, a primary pollutant associated with vehicle emissions and adverse health outcomes. These improvements in air quality translate into meaningful health benefits for infants and young children (as well as the elderly, though they are not our main focus). Specifically, we document significant declines in adverse birth outcomes, including VLBW and very premature births, as well as reductions in asthma-related emergency department visits among children aged 0-5. These results highlight the dual role of EV adoption in improving environmental quality and protecting public health.

IV estimates suggest that the largest benefits are concentrated in high-pollution communities located near AFCs, where both baseline NO_2 levels and the incidence of adverse infant health outcomes are substantially higher. This result highlights the disproportionate burden of vehicle pollution borne by some communities and suggests that strategic EV adoption could play an important role in reducing health inequities.

To assess the economic implications of these health benefits, we provide back-of-the-envelope estimates of potential benefits. On average during the study period, there were about 3.7 million singleton births per year in the United States, with approximately 1.36 percent, or 50,215 births, classified as VLBW. Based on our estimates, a one standard deviation increase in EV adoption (equivalent to 11.98 EVs per 1,000 vehicles) reduces the incidence of VLBW births by about 0.79 percent in the TWFE specification and 2.63 percent in the IV specification. These estimates correspond to preventing approximately 398 to 1,318 VLBW births annually. Given that the average lifetime cost associated with one VLBW birth is estimated at 3.06 million in 2024 dollars, the resulting savings range from 1.22 billion to 4.03 billion dollars per year.[28] These savings likely represent only a fraction of the broader societal benefits, which also include reductions in respiratory illnesses in other age groups and may have other as yet undocumented health benefits.

[28] See Appendix Table A14 for details on lifetime cost calculations for VLBW births and the estimated savings from electric vehicle adoption. Burlig et al. (2021) point out that EVs may not fully replace gas-powered vehicles as consumers tend to drive them less, but this could be due in part to incomplete charging networks.

The IV findings underscore the important role of investment in EV infrastructure in supporting EV adoption. The estimates suggest that targeting areas with high pollution and high rates of adverse birth outcomes for EV infrastructure investments was an effective way to improve health in these areas. Alternative policies such as tax rebates, subsidies, and public awareness campaigns promote EV adoption, but have been shown to do so relatively inefficiently, suggesting that building out EV charging infrastructure might be one of the more effective policies tools available.[29]

To further accelerate the transition to zero traffic emissions, President Biden signed an Executive Order in 2021 setting a goal of deploying 500,000 EV charging stations by 2030 with the ultimate aim of having 50 percent of all U.S. vehicles sold be net-zero greenhouse gas emitters by that date. In January 2025, the U.S. Department of Transportation's Federal Highway Administration (FHWA) announced $635 million in grants to continue building out EV charging and alternative fuelling infrastructure (FHA, 2025), funding subsequently cancelled by the new administration. Unfortunately, in the United States, EV adoption has become a highly partisan issue (Davis et al., 2025). Elsewhere, the European Union has set ambitious targets for EV infrastructure, aiming to install one million public charging points by 2025, and three million by 2030 to support its growing electric vehicle fleet.[30]

The reductions in adverse birth outcomes and respiratory illnesses that we document underscore the need to look beyond politics and consider the long-term societal benefits of EV adoption, including potential reductions in healthcare costs and improvements in human capital in addition to effects on climate. Framing transport electrification as a public health intervention in addition to an environmental strategy, might help to build a stronger, more comprehensive case for infrastructure investments supporting clean transportation.

[29] Xing et al. (2024) find that many EV subsidies go to people who would have purchased EVs in any case, and that subsidies targeted to people who would otherwise be driving, older, dirty, gasoline vehicles would be more effective. Allcott et al. (2024) argue that subsidies calibrated to the size of the externalities generated by EVs would also be more effective. Beyond access, the quality of the infrastructure may also matter, as higher charging speeds generate substantial benefits for EV users in the form of reductions in the time costs of recharging (Dorsey et al., 2025).

[30] These goals are part of *Fit for 55*. This is a comprehensive package of laws intended to reduce greenhouse gas emissions in the EU by at least 55 percent by 2030, and to place the region on a path toward climate neutrality by 2050 (European Council, n.d.).

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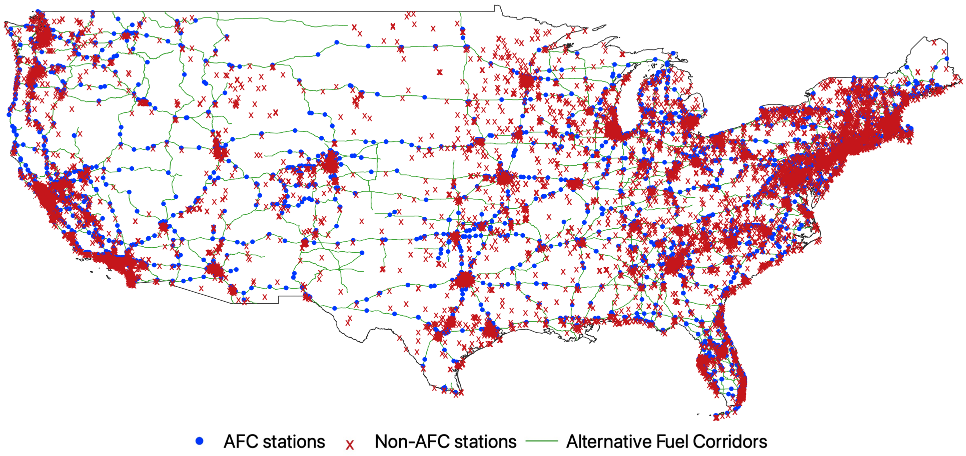
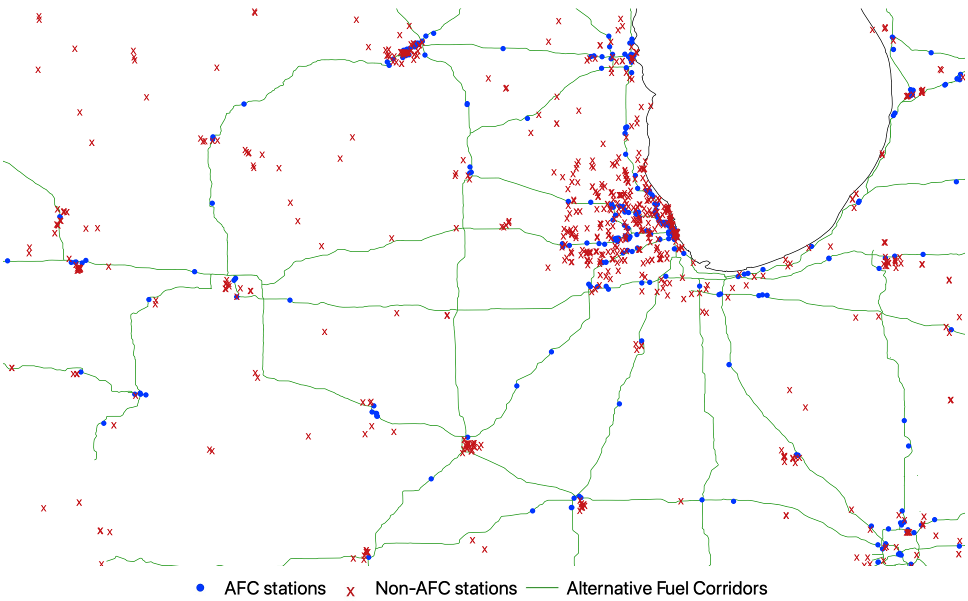
Figure 1: Alternative Fuel Corridors and Electric Vehicle Charging Stations

(a) Contiguous United States

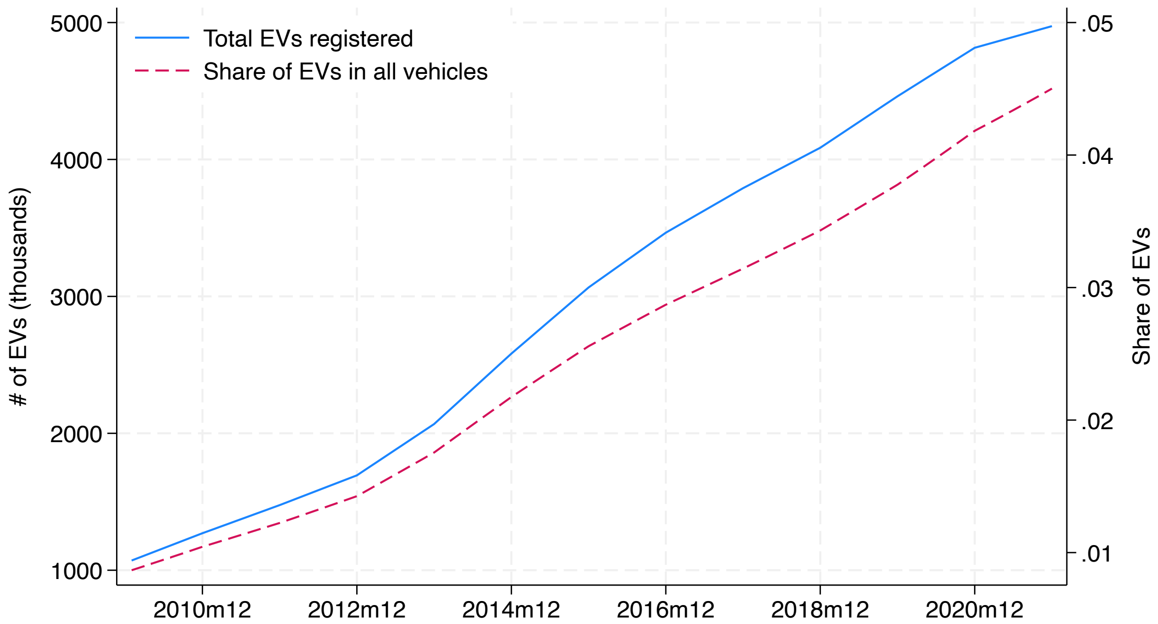


(b) Greater Chicago Area



Notes: The figure displays the locations of Alternative Fuel Corridors (AFC) shown in green and electric vehicle (EV) charging stations in contiguous United States and greater Chicago area based on data from U.S. Department of Energy and Federal Highway Administration. Blue dots represent stations opened after 2015 within one mile of a corridor. Red dots represent all other stations, including those located farther from corridors or established before the initial AFC announcement.

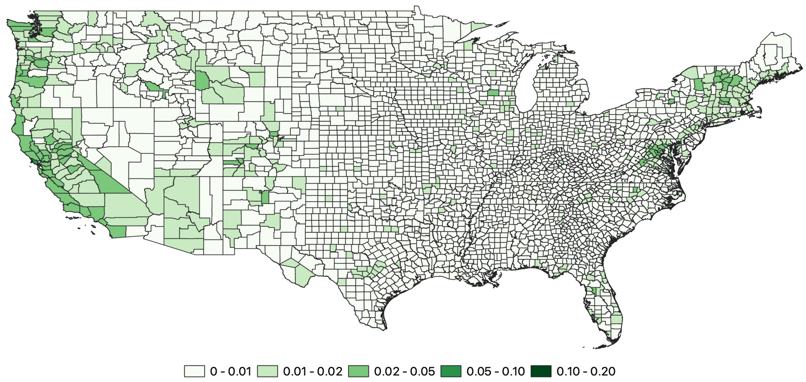
Figure 2: Adoption of Electric Vehicles in the U.S. Over Time



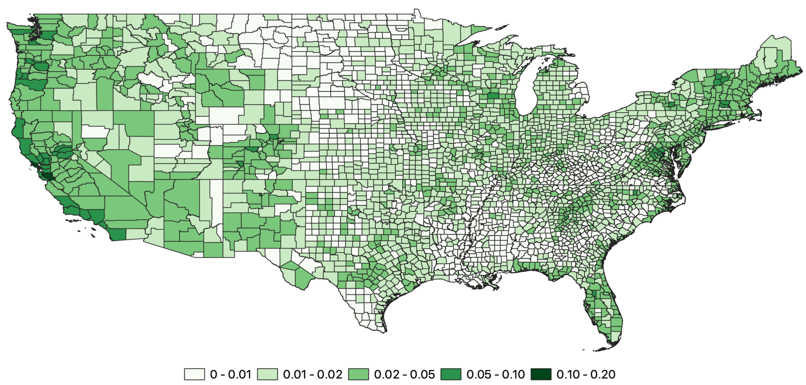
Notes: The figure displays total number of EVs (electric vehicle) in thousands (blue line on the left axis) and share of registered EVs among all registered vehicles (red dashed line on the right axis) for the entire U.S. in a given month. Vehicle registration data come from S&P Global.

Figure 3: County Level Evolution of Electric Vehicle Shares

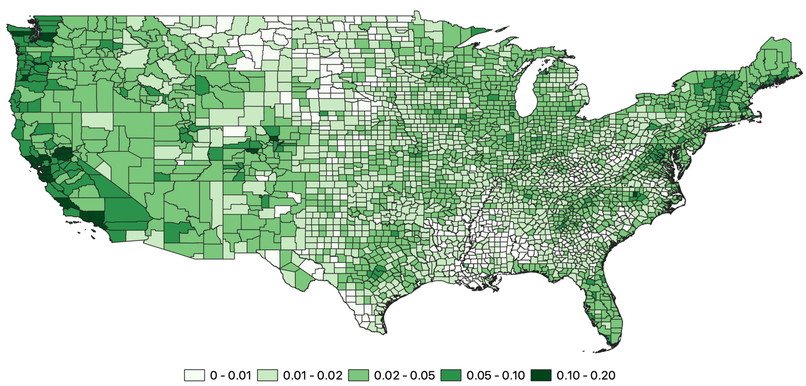
(a) Share of Electric Vehicles in 2010



(b) Share of Electric Vehicles in 2016



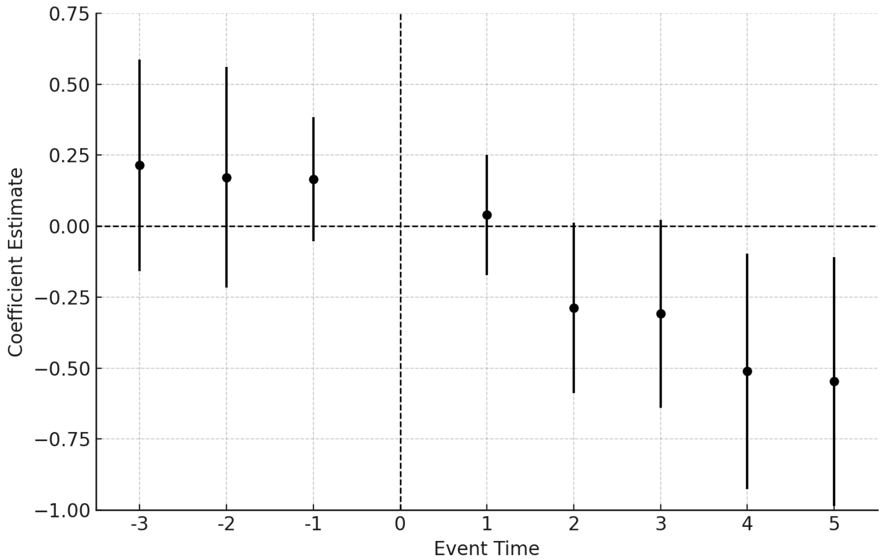
(c) Share of Electric Vehicles in 2021



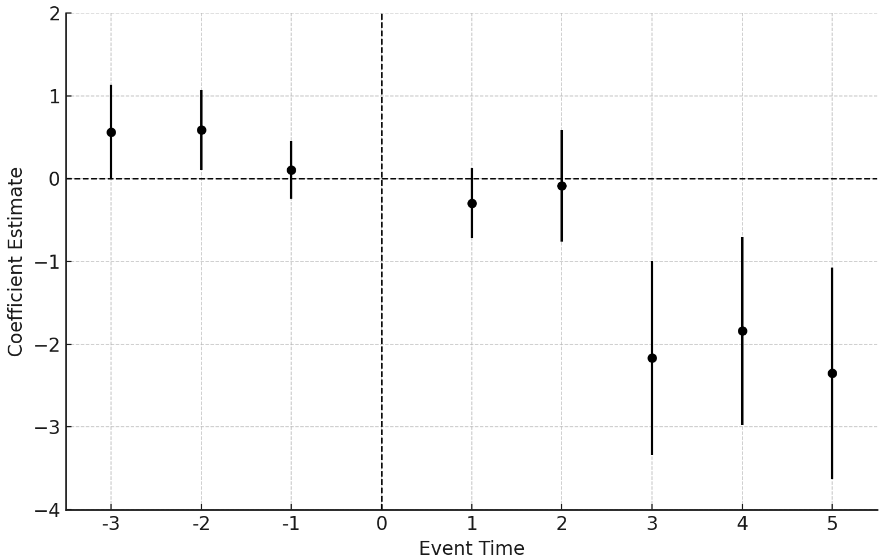
Notes: The figure displays the evolution of county shares of registered EVs (electric vehicle) among all registered vehicles. Vehicle registration data come from S&P Global.

Figure 4: Event-Study Results for Air Quality

(a) Arithmetic Mean, NO_2



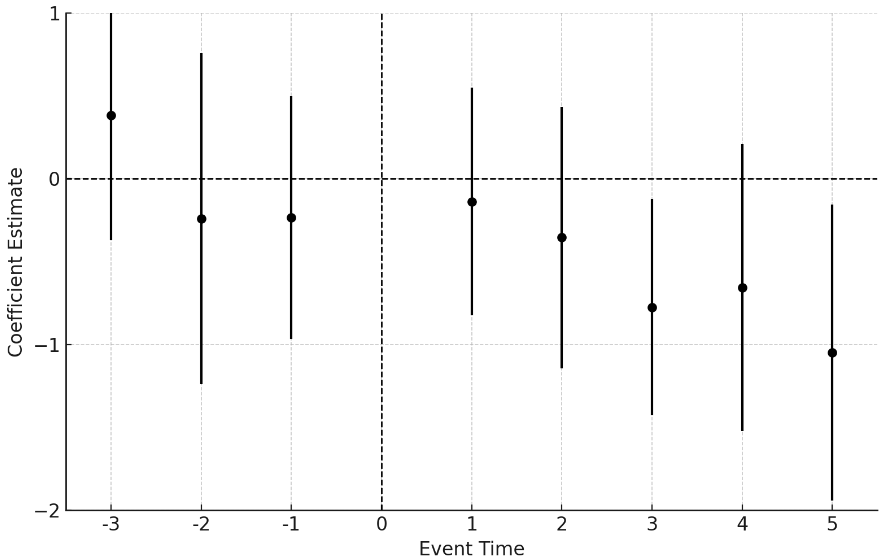
(b) Air Quality Index, NO_2



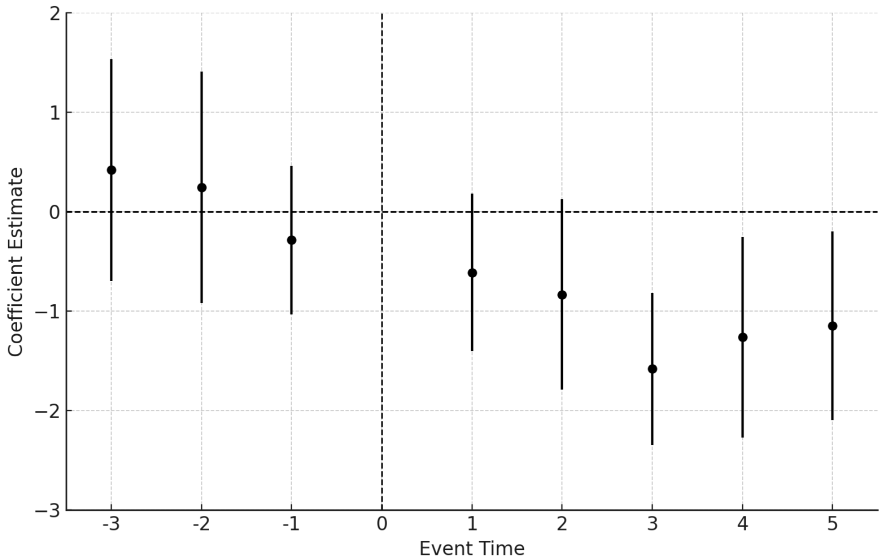
Notes: This figure plots event-study estimates of the effect of EV adoption on nitrogen dioxide NO_2 concentrations, based on equation (3). Estimates are obtained using the did_multiplegt_dyn estimator of de Chaisemartin and D'Haultfoeuille (2024), with county and month-by-year fixed effects, and controls for county demographics, weather, and state miles driven. The outcome is the monthly average NO_2 concentration in the monitor counties sample. The coefficients trace dynamic effects from three months before to five months after a county transitions into a higher EV adoption quintile, with the month prior to transition as the omitted category. 95 percent confidence intervals, based on county-clustered standard errors, are shown.

Figure 5: Event-Study Results for Adverse Birth Outcomes

(a) Very Low Birth Weight per 1,000 births

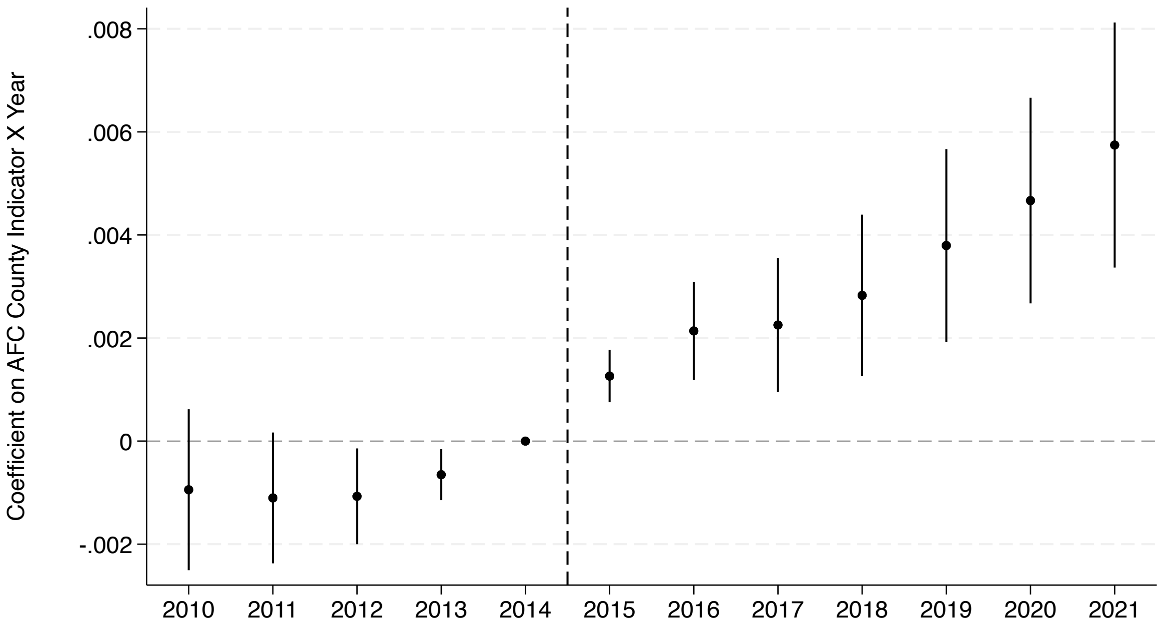


(b) Very Premature per 1,000 births



Notes: This table reports event-study estimates of the effect of EV adoption on infant health outcomes, based on equation (3). The outcomes are the incidence of very low birth weight (VLBW,<1500g) and very preterm (VP, <32 weeks) births per 1,000 live births, measured at the county–conception month level. Estimates are obtained using the did_multiplegt_dyn estimator of de Chaisemartin and D'Haultfoeuille (2024), with county and month-by-year fixed effects, and controls for county demographics, maternal characteristics from Vital Statistics, weather, and state miles driven. The treatment is defined as crossing into a higher quintile of EV adoption; three pre-treatment leads and five post-treatment lags are included, with the month prior to transition omitted. Standard errors are clustered at the county level, and regressions are weighted by births. 95 percent confidence intervals, based on county-clustered standard errors, are shown.

Figure 6: Dynamic Effects of Alternative Fuel Corridors by Year



Notes: The figure displays the effects of Alternative Fuel Corridor (AFC) project on electric vehicle (EV) share, that is annual share of EVs among all registered vehicles for counties that began to receive EV charging stations on Alternative Fuel Corridors following the announcement in 2015. Figure plots the coefficients on the interaction between the indicator variable for AFC county inficator and year for the period between 2010 and 2021. Vehicle registration data come from S&P Global. AFC project data come from the Federal Highway Administration.

Table 1: Descriptive Statistics

	Mean	Mean	Mean	Mean	SD
	Top 25 perc. EV share	Middle 50 perc. EV share	Bottom 25 perc. EV share	Full sample	Full sample
EVs per 1000 vehicles	26.37	11.46	5.67	13.79	11.98
Panel A: Pollution Outcomes					
Monthly mean AQI NO_2	16.41	13.18	8.1	14.76	8.27
Monthly arithmetic mean NO_2	8.13	6.08	3.73	7.14	4.88
Monthly mean AQI PM2.5	31.61	33.09	33.5	32.36	10.02
Monthly arithmetic mean PM2.5	7.98	8.29	8.36	8.14	2.94
Satellite-based monthly mean concentration PM2.5	6.68	7.05	6.94	6.93	2.03
Panel B: Infant Health Outcomes					
Very Low Birth Weight per 1000 births	15.01	12.84	13.61	13.57	65.65
Very Premature per 1000 births	17.32	15.09	15.59	15.77	71.84
Admission to NICU per 1000 births	77.32	72.44	72.63	73.72	112.43
Assisted Ventilation per 1000 births	16.72	17.06	16.06	16.73	60.78
Surfactant Use per 1000 births	6	6.4	6.27	6.27	41.11
Stillbirth per 1000 births	2.03	1.84	2	1.92	22.2
Panel C: Birth and Maternal Characteristics					
Share first baby	0.32	0.3	0.3	0.31	0.15
Share male	0.49	0.49	0.49	0.49	0.16
Mother's age	28.62	27.1	26.5	27.34	2.23
Share mothers education w/< high school	0.11	0.14	0.15	0.14	0.13
Share mothers high school	0.24	0.3	0.31	0.29	0.17
Share mothers education w/> high school	0.6	0.53	0.47	0.53	0.22
Share Black mothers	0.08	0.08	0.18	0.11	0.18
Share White mothers	0.85	0.88	0.77	0.85	0.2
Share Hispanic mothers	0.16	0.12	0.09	0.12	0.18
Share married mothers	0.64	0.59	0.53	0.58	0.2
Share mothers smoking during pregnancy	0.06	0.05	0.08	0.06	0.22
Panel D: Child Health Outcomes					
Asthma-related visits per 1,000 pop. ages 0-5	1.73	1.93	2.29	1.97	1.90
Acute respiratory disease visits per 1,000 pop. ages 0-5	26.88	30.95	36.61	31.35	22.40
Injury-related visits per 1,000 pop. ages 0-5	22.86	26.87	31.15	26.94	11.19
Panel E: County Characteristics					
Total vehicles registered (1000s)	98.46	25.54	7.76	39.5	126.02
Monthly vehicle miles traveled by state (millions)	8629.66	7168.24	5537.51	7135.73	6144.34
AFC stations per 10000 population	0.09	0.03	0.01	0.04	0.24
Total Population (1000s)	257.75	67.39	21.79	104.03	329.07
Poverty rate	0.13	0.15	0.2	0.16	0.06
Child poverty rate	0.17	0.22	0.29	0.22	0.1
Annual NOx emissions from power plants (1000 tons)	0.39	0.57	0.34	0.47	2.03
Monthly mean temperature (degrees Fahrenheit)	53.98	54.86	56.78	55.11	17.86
Monthly mean precipitation (inches)	3.38	3.34	3.55	3.4	2.52
Monthly mean wind speed (m/s)	2.53	2.38	2.18	2.37	1.39
Observations	104535	209674	101978	416187	–

Notes: First three columns report summary statistics separately for counties in the bottom quartile, middle 50 percent, and top quartile of the EV adoption distribution, where quartiles are defined using the average EV share over the analysis period. Vehicle registration data come from S&P Global. Annual county characteristics are from the US Census Bureau. Vehicle miles travel are based on Traffic Volume Trends from Federal Highway Administration. Alternative Fuel Corridor (AFC) stations data are from the US Department of Energy. Power plant emissions data come from the US EPA Clean Air Markets Program. Monthly weather and wind data are from PRISM Group and NOAA. Pollutant data come from the EPA daily monitor datasets and van Donkelaar et al. (2021). Infant health outcomes and birth characteristics are monthly county averages based on birth records from National Center for Health Statistics. Quarterly emergency department (ED) visits data are from HCUP.

Table 2: EV Shares and Air Quality

	Pollutant = NO_2			
	TWFE Estimates		2SLS Estimates	
	AQI	Arithmetic mean	AQI	Arithmetic mean
	(1)	(2)	(3)	(4)
EVs per 1,000 vehicles	-0.020**	-0.019***	-0.050***	-0.043***
	(0.009)	(0.006)	(0.017)	(0.011)
Dep Var Mean	14.8	7.1	14.8	7.1
F-stat (Kleibergen-Paap)			17.9	17.9
Observations	22502	22498	22502	22498

Notes: EVs per 1,000 vehicles is county number of electric vehicles (EV) $\times$ 1,000 divided by number of all registered vehicles in a given month. Vehicle registration data come from S&P Global. Pollutant data are monthly averages calculated from the EPA daily monitor readings. For NO_2 (nitrogen dioxide), AQI stands for air quality index and arithmetic mean refers to the monthly mean concentration reported in ppb (parts per billion). All regressions control for county and month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, state monthly total miles driven, annual county NO_x emissions from power plants in tons, and monthly county weather variables including mean temperature and precipitation (plus squared), wind speed and eight wind direction dummies. Observations at the county-by-month level span from 2010 to 2021. Standard errors are clustered at the county level. *** p<0.01,** p<0.05,* p<0.1.

Table 3: EV Shares and Adverse Birth Outcomes

	TWFE Estimates		2SLS Estimates	
	VLBW per 1,000 births	Very Premature per 1,000 births	VLBW per 1,000 births	Very Premature per 1,000 births
	(1)	(2)	(3)	(4)
EVs per 1,000 vehicles (9-month average)	-0.0090**	-0.0109**	-0.0298***	-0.0385***
	(0.0040)	(0.0049)	(0.0111)	(0.0134)
Dep Var Mean	13.6	15.8	13.6	15.8
F-stat (Kleibergen-Paap)			50.0	50.0
Observations	416187	416187	416187	416187

Notes: EVs per 1,000 vehicles is county number of electric vehicles (EV) $\times$ 1,000 divided by number of all registered vehicles in a given month. We calculate and use nine-month average starting from the month of conception. Vehicle registration data come from S&P Global. Birth data are from National Center for Health Statistics restricted files. Adverse birth outcomes are county monthly average incidence rates for very low birth weight (VLBW) and very premature (VP) births per 1,000 births conceived in that month. All regressions control for county and conception-month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, and annual county NO_x emissions from power plants (tons). We also control for the nine-month average of state monthly total miles driven; county mean temperature and precipitation (and their squares); wind speed; and eight wind direction dummies. Additional controls include county incidence rates for birth and maternal characteristics. Observations at the county-by-conception-month level span from 2010 to 2021. Regressions are weighted by births in each county–month–year cell. Standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Restricting Sample to Counties with monitors within five miles of an Alternative Fuel Corridor

	Air Quality				Adverse Birth Outcomes			
	TWFE Estimates		2SLS Estimates		TWFE Estimates		2SLS Estimates	
	AQI	A. Mean	AQI	A. Mean	VLBW	VP	VLBW	VP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EVs per 1,000 vehicles	-0.030***	-0.028***	-0.051***	-0.048***				
	(0.010)	(0.006)	(0.014)	(0.011)				
EVs per 1,000 vehicles (9-month average)					-0.0140**	-0.0120*	-0.0480***	-0.0553***
					(0.0060)	(0.0071)	(0.0131)	(0.0177)
Dep Var Mean	16.5	8.1	16.5	8.1	21.4	24.3	21.4	24.3
F-stat (Kleibergen-Paap)			15.0	15.0			16.6	16.6
Observations	18028	18027	18028	18027	18336	18336	18336	18336

Notes: EVs per 1,000 vehicles is county number of electric vehicles (EV) $\times$ 1,000 divided by number of all registered vehicles in a given month. For infant health results in Columns (5)-(9), we use nine-month average starting from the month of conception. Vehicle registration data come from S&P Global. Pollutant data are monthly averages calculated from the EPA daily monitor readings. For NO_2 (nitrogen dioxide), AQI stands for air quality index and A. Mean refers to the monthly mean concentration reported in ppb (parts per billion). Birth data are from National Center for Health Statistics restricted files. Adverse birth outcomes are county monthly average incidence rates for very low birth weight (VLBW) and very premature (VP) births per 1,000 births conceived in that month. All regressions control for county and month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, state monthly total miles driven, annual county NO_x emissions from power plants in tons, and monthly county weather variables including mean temperature and precipitation (plus squared), wind speed and eight wind direction dummies. For infant health results, we calculate and use nine-month average for monthly controls starting from the month of conception and we include county incidence rates for birth and maternal characteristics. Observations at the county-by-month level span from 2010 to 2021. Infant health regressions are weighted by births in each county–month–year cell. Standard errors are clustered at the county level. *** p<0.01,** p<0.05,* p<0.1.

Table 5: Robustness Exercises for Air Quality

	Pollutant = NO_2			
	TWFE Estimates		2SLS Estimates	
	AQI	Arithmetic mean	AQI	Arithmetic mean
	(1)	(2)	(3)	(4)
Panel A: Using annual EV shares				
EVs per 1,000 vehicles	-0.023**	-0.021***	-0.051***	-0.043***
	(0.009)	(0.006)	(0.017)	(0.011)
Observations	22502	22498	22502	22498
Panel B: Excluding COVID-19 Lockdown Period				
EVs per 1,000 vehicles	-0.020**	-0.018***	-0.050***	-0.043***
	(0.009)	(0.006)	(0.016)	(0.011)
Observations	21840	21835	21840	21835
Panel C: Using per-population EV shares				
EVs per 1,000 population	-0.031*	-0.037***	-0.128***	-0.109***
	(0.019)	(0.012)	(0.048)	(0.032)
Observations	22502	22498	22502	22498
Panel D: Using only battery electric vehicles				
BEVs per 1,000 vehicles	-0.054***	-0.050***	-0.093***	-0.079***
	(0.019)	(0.010)	(0.034)	(0.022)
Observations	22502	22498	22502	22498
Panel E: Controlling for non-AFC electric vehicle charging stations				
EVs per 1,000 vehicles	-0.025***	-0.023***	-0.064***	-0.054***
	(0.009)	(0.005)	(0.017)	(0.012)
Observations	22502	22498	22502	22498
Panel F: Restricting to counties with 250,000 population or more				
EVs per 1,000 vehicles	-0.025**	-0.028***	-0.054***	-0.055***
	(0.012)	(0.007)	(0.017)	(0.014)
Observations	13304	13304	13304	13304

Notes: EVs per 1,000 vehicles is county number of electric vehicles (EV) $\times$ 1,000 divided by number of all registered vehicles in a given month, unless otherwise indicated. Vehicle registration data come from S&P Global. Pollutant data are monthly averages from EPA daily monitor readings. For NO_2, AQI denotes air quality index and arithmetic mean denotes monthly mean concentration (ppb). Panel A uses the annual share of registered EVs among all registered vehicles at year-end. Panel B excludes observations during the COVID-19 lockdown period (Mar–Jun 2020). Panel C uses EVs per 1,000 population instead of per 1,000 vehicles. Panel D uses only battery electric vehicles (BEVs) per 1,000 vehicles. Panel E controls for county number of all non-AFC electric vehicle charging stations per 10,000 population. Panel F restricts analysis sample to counties with 250,000 population or more in 2010. All regressions control for county and month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, state monthly total miles driven, annual county NO_x power-plant emissions (tons), and monthly county weather (mean temperature and precipitation and their squares), wind speed, and eight wind-direction dummies. Observations at the county-by-month level span from 2010 to 2021, unless otherwise indicated. Standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Robustness Exercises for Adverse Birth Outcomes

	TWFE Estimates		2SLS Estimates	
	VLBW per 1,000 births	Very Premature per 1,000 births	VLBW per 1,000 births	Very Premature per 1,000 births
	(1)	(2)	(3)	(4)
Panel A: Using annual EV shares				
EVs per 1,000 vehicles (9-mo average)	-0.0085**	-0.0105**	-0.0297***	-0.0380***
	(0.0039)	(0.0047)	(0.0113)	(0.0137)
Observations	416187	416187	416187	416187
Panel B: Excluding COVID-19 Lockdown Period				
EVs per 1,000 vehicles (9-mo average)	-0.0098**	-0.0107**	-0.0360***	-0.0406**
	(0.0041)	(0.0052)	(0.0119)	(0.0159)
Observations	404015	404015	404015	404015
Panel C: Excluding mothers below age 18				
EVs per 1,000 vehicles (9-mo average)	-0.0087**	-0.0109**	-0.0298***	-0.0380***
	(0.0040)	(0.0048)	(0.0112)	(0.0137)
Observations	416029	416029	416029	416029
Panel D: Including births with GL $<$ 23 wks				
EVs per 1,000 vehicles (9-mo average)	-0.0100**	-0.0119**	-0.0324***	-0.0399***
	(0.0044)	(0.0052)	(0.0118)	(0.0144)
Observations	416448	416448	416448	416448
Panel E: Excluding county-month-year cells with fewer than five conceptions				
EVs per 1,000 vehicles (9-mo average)	-0.0090**	-0.0102**	-0.0291***	-0.0385***
	(0.0040)	(0.0049)	(0.0111)	(0.0134)
Observations	370075	370075	370075	370075
Panel F: Using per-population EV shares				
EVs per 1,000 population (9-mo average)	-0.0211**	-0.0266**	-0.0708***	-0.0914***
	(0.0088)	(0.0107)	(0.0245)	(0.0298)
Observations	416187	416187	416187	416187
Panel G: Using only battery electric vehicles				
BEVs per 1,000 vehicles (9-mo average)	-0.0253***	-0.0369***	-0.0531***	-0.0685***
	(0.0088)	(0.0103)	(0.0173)	(0.0211)
Observations	416187	416187	416187	416187
Panel H: Restricting to NO_2 monitor sample				
EVs per 1,000 vehicles (9-mo average)	-0.0138**	-0.0109*	-0.0426***	-0.0481***
	(0.0053)	(0.0066)	(0.0122)	(0.0169)
Observations	22779	22779	22779	22779
Panel I: Controlling for non-AFC electric vehicle charging stations				
EVs per 1,000 vehicles (9-mo average)	-0.0090**	-0.0103**	-0.0325***	-0.0395***
	(0.0041)	(0.0050)	(0.0118)	(0.0146)
Observations	416187	416187	416187	416187
Panel J: Restricting to counties with 250,000 population or more				
EVs per 1,000 vehicles (9-mo average)	-0.0114**	-0.0083	-0.0304**	-0.0411**
	(0.0050)	(0.0060)	(0.0143)	(0.0171)
Observations	35785	35785	35785	35785

Notes: EV share is calculated as a nine-month average starting from the month of conception unless otherwise indicated. Panel A uses the annual share of registered EVs among all registered vehicles in a county at the end of each year. Panel B excludes births conceived during the COVID-19 lockdown period (Mar–Jun 2020). Panel C excludes births to mothers younger than age 18. Panel D includes births with gestational length less than 23 weeks. Panel E excludes county-month-year cells with fewer than five conceptions. Panel F uses the number of EVs per 1,000 population instead of per 1,000 vehicles. Panel G uses only battery electric vehicles (BEVs) per 1,000 vehicles. Panel H restricts the sample to counties with non-missing pollutant monitor data for NO_2. Panel I controls for county average number of all non-AFC electric vehicle charging stations per 10,000 population for nine months starting from the month of conception. Panel J restricts analysis sample to counties with 250,000 population or more in 2010. Vehicle registration data come from S&P Global. Birth data are from National Center for Health Statistics restricted files. Adverse birth outcomes are county monthly average incidence rates per 1,000 births conceived in that month. We report results for VLBW and very premature births; the composite outcomes index is omitted. All regressions control for county and conception-month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, and annual county NO_x emissions from power plants (tons). Additional controls include the nine-month average of state monthly total miles driven, county mean temperature and precipitation (and their squares), wind speed, and eight wind direction dummies, plus county incidence rates for birth and maternal characteristics. Observations at the county-by-conception-month level span from 2010 to 2021, unless otherwise indicated. Regressions are weighted by county births in each conception-month-year cell. Standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: EV Shares and Emergency Department Visits for Ages 0-5

	Asthma per 1,000 pop.	Acute Respiratory per 1,000 pop.	Injury per 1,000 pop.
	(1)	(2)	(3)
EVs per 1,000 vehicles	-0.022*	-0.016	0.013
	(0.012)	(0.054)	(0.030)
Dep Var Mean	2.0	31.3	26.9
Observations	24648	24648	24648

Notes: EVs per 1,000 vehicles is county number of electric vehicles (EV) $\times$ 1,000 divided by number of all registered vehicles in a given quarter. Vehicle registration data come from S&P Global. Emergency department visits data are from HCUP for nine states: AZ, FL, KY, MD, MN, NJ, NY, NC, WI. Dependent variable is quarterly total visits from each cause per 1,000 population ages 0-5 from Census. See text for details on variable construction. All regressions control for county and quarter-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, and annual county NO_x emissions from power plants (tons). We also control for the quarterly county share of ED visits by race (Black and White), sex (male), and insurance coverage (Medicaid, private, and self-pay); quarterly state total miles driven and county weather (mean temperature and precipitation and their squares), wind speed, and eight wind-direction dummies. Observations span 2010–2021. Regressions are weighted by county population. Standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Clean Rides, Healthy Lives: The Impact of Electric Vehicle Adoption on Air Quality and Infant Health

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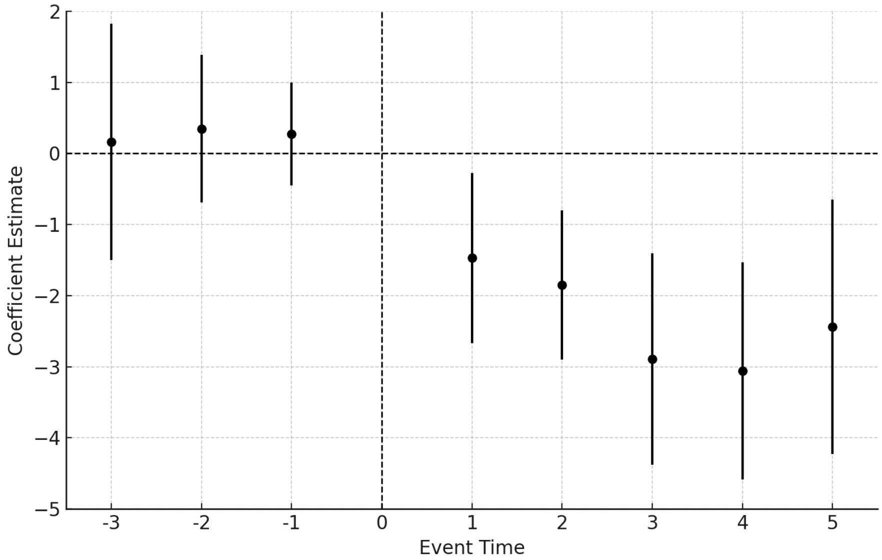
Supplementary Appendix

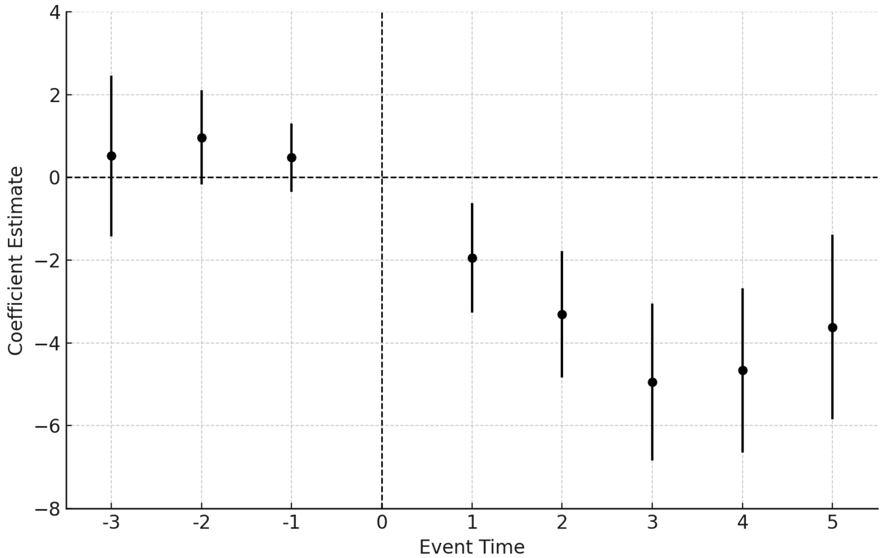
For Online Publication

Figure A.1: Event-Study Results for Adverse Birth Outcomes: Grouping EV Shares into Deciles

(a) Very Low Birth Weight per 1,000 births

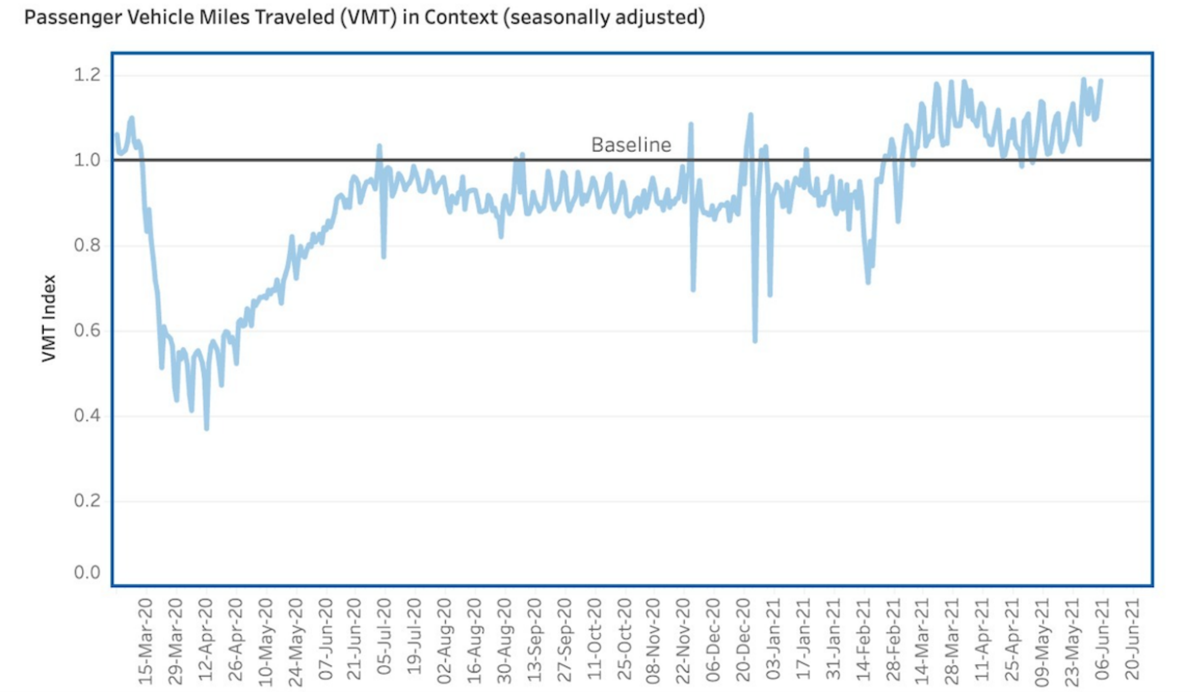


(b) Very Premature per 1,000 births



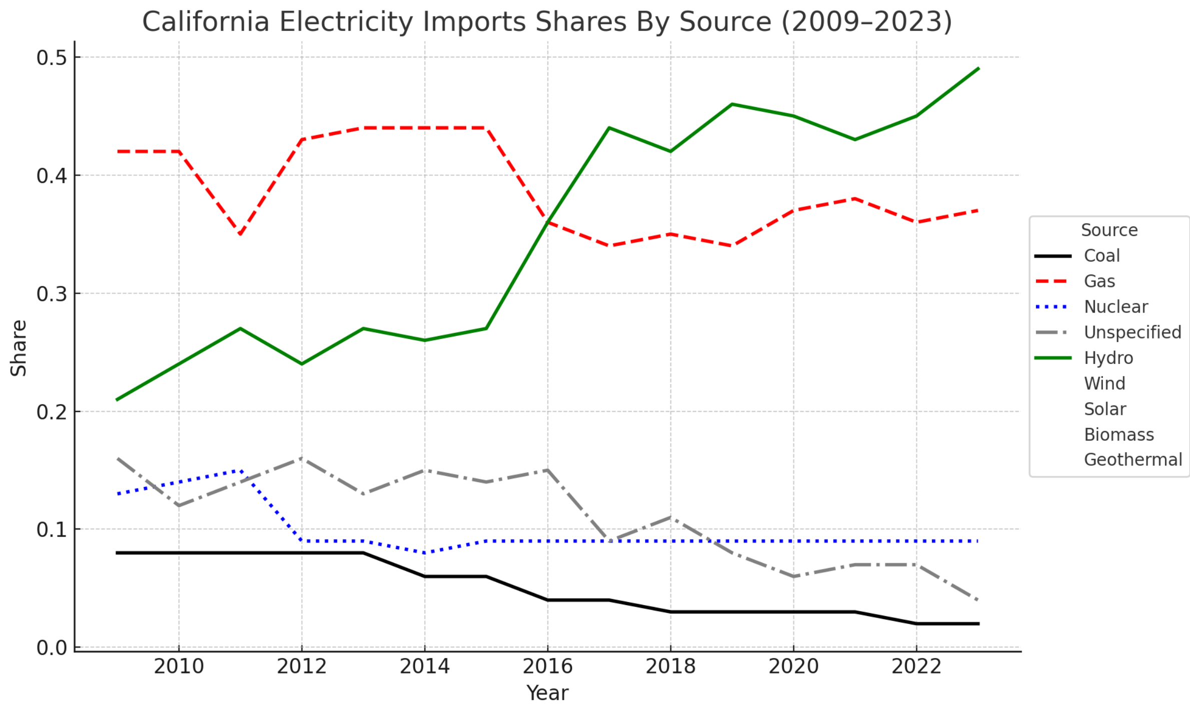
Notes: This figure replicates the infant health event-study analysis using deciles of county EV shares rather than quintiles. Estimates are based on equation (3) and obtained with the did_multiplegt_dyn estimator of de Chaisemartin and D'Haultfoeuille (2024). Outcomes are the incidence of very low birth weight (VLBW, <1500g) and very preterm (VP, <32 weeks) births per 1,000 live births at the county–conception month level. The specification includes county and month-by-year fixed effects, and controls for county demographics, maternal characteristics from Vital Statistics, weather, and state miles driven. Coefficients trace dynamic effects from three months before to five months after a county transitions into a higher EV adoption decile, with the month prior to transition as the omitted category. 95 percent confidence intervals, based on county-clustered standard errors, are shown.

Figure A.2: Daily Vehicle Travel During the COVID-19 Public Health Emergency



Notes: The figure displays the passenger vehicle miles traveled daily during the COVID-19 provided by Bureau of Transportation Statistics (https://www.bts.gov/covid-19/daily-vehicle-travel).

Figure A.3: Sources of California's Electricity Imports Over Time



Notes: Energy source information are from California's Total System Electric Generation Reports (California Energy Commission, 2009-2023).

Table A.1: Balanced Covariates

	Share Male	Share Black	Share White	Share Hispanic	Mothers Age	Share Married	Share Low Education	Share High Education
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EVs per 1,000 vehicles	0.0000	-0.0001	-0.0001	-0.0006***	-0.0007	0.0002	-0.0002	0.0003
(9-mo average)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0009)	(0.0004)	(0.0002)	(0.0002)
Dep Var Mean	0.5	0.1	0.8	0.1	27.3	0.6	0.4	0.5
Observations	416187	416187	416187	416187	416187	416187	416187	416187

Notes: EV share is calculated as nine-month average over county number of EVs times 1,000 divided by all registered vehicles starting from the month of conception. Vehicle registration data come from IHS Markit. Maternal and birth characteristics are monthly county averages based on birth records from National Center for Health Statistics. Each column regresses a separate covariate on average EV share. All regressions control for county and conception-month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, and annual county NO_x emissions from power plants in tons. We also calculate and control for nine-month average over monthly variables including state monthly total miles driven, county mean temperature and precipitation (plus squared), wind speed and eight wind direction dummies. Observations at county-by-conception-month level span from 2010 to 2021. Regressions are weighted by the number of births in each county-month-year cell. Standard errors are clustered at the county level.*** $p<0.01$,** $p<0.05$.

Table A.2: Balanced Covariates, AFC

	Share Male	Share Black	Share White	Share Hispanic	Mothers Age	Share Married	Share Low Education	Share High Education
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFC stations per 10,000 pop.	-0.000	-0.003	0.004	-0.004**	0.025	0.007	0.000	-0.001
(9-mo average)	(0.000)	(0.002)	(0.002)	(0.002)	(0.025)	(0.008)	(0.002)	(0.004)
Dep Var Mean	0.5	0.1	0.8	0.1	27.3	0.6	0.4	0.5
Observations	416187	416187	416187	416187	416187	416187	416187	416187

Notes: AFC stations per population is 9-month average of county stock of EV charging stations opened after 2015 within 1 mile from an Alternative Fuel Corridor (AFC) per 10,000 population. Station and AFC project data come from the U.S. Department of Energy and Federal Highway Administration. Maternal and birth characteristics are monthly county averages based on birth records from National Center for Health Statistics. Each column regresses a separate covariate on the instrument, AFC stations per 10,000 population. All regressions control for county and conception-month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, and annual county NO_x emissions from power plants in tons. We also calculate and control for nine-month average over monthly variables including state monthly total miles driven, county mean temperature and precipitation (plus squared), wind speed and eight wind direction dummies. Observations at county-by-conception-month level span from 2010 to 2021. Regressions are weighted by the number of births in each county-month-year cell. Standard errors are clustered at the county level.*** p<0.01,** p<0.05.

Table A.3: Lagged Air Pollution and AFC Station Openings

	Monthly AFC station openings per 10,000 population	
	(1)	(2)
Panel A: Mean NO_2 **levels during...**		
Months -1 to -6	-0.00027	
	(0.00036)	
Months -1 to -12		-0.00312
		(0.00171)
Observations	10811	9749
Panel B: Mean $PM_{2.5}$ **levels during...**		
Months -1 to -6	-0.00004	
	(0.00009)	
Months -1 to -12		0.00008
		(0.00017)
Observations	24766	21958

Notes: Outcome of interest is monthly Alternative Fuel Corridor (AFC) station openings per 10,000 population for the period between 2015 and 2021. AFC station data refer to EV charging stations opened after 2015 within 1 mile of an AFC route, based on data from the U.S. Department of Energy and Federal Highway Administration. The key independent variables are mean air quality indices (AQI) for NO_2 and $PM_{2.5}$ averaged over months -1 to -6 or months -1 to -12 prior to each observation. Pollution data are calculated from EPA daily monitor readings. All regressions include county and month-by-year fixed effects, state-by-year fixed effects, and control for log total population, total poverty and child poverty rates, total vehicles registered, state monthly total miles driven, and annual county-level NO_x emissions from power plants. Weather controls include mean temperature (plus squared), precipitation, wind speed, and eight wind direction dummies. Standard errors are clustered at the county level. *** $p<0.01$, ** $p<0.05$.

Table A.4: EV Shares and Air Quality: IV Analysis Results

	Pollutant = NO_2	
	AQI	Arithmetic mean
	(1)	(2)
Panel A: Two-stage least squares		
EVs per 1,000 vehicles	-0.050***	-0.043***
	(0.017)	(0.011)
Panel B: Reduced form		
AFC stations per 10,000 pop.	-0.50**	-0.43***
	(0.23)	(0.16)
Panel C: First stage		
AFC stations per 10,000 pop.	10.05***	10.06***
	(2.37)	(2.37)
F-stat (Kleibergen-Paap)	17.9	17.9
Observations	22502	22498

Notes: Vehicle registration data come from S&P Global. AFC stations per population is county stock of EV charging stations opened after 2015 within 1 mile from an Alternative Fuel Corridor (AFC) per 10,000 population. Station and AFC project data come from the U.S. Department of Energy and Federal Highway Administration. Pollutant data are monthly averages calculated from the EPA daily monitor readings. For NO_2 (nitrogen dioxide), AQI stands for air quality index and arithmetic mean refers to the monthly mean concentration reported in ppb (parts per billion). All regressions control for county and month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, state monthly total miles driven, annual county NO_x emissions from power plants in tons, and monthly county weather variables including mean temperature and precipitation (plus squared), wind speed and eight wind direction dummies. Observations at the county-by-month level span from 2010 to 2021. Standard errors are clustered at the county level. *** $p<0.01$,** $p<0.05$,* $p<0.1$.

Table A.5: EV Shares and Air Quality: $PM_{2.5}$ Results

	TWFE Estimates					2SLS Estimates				
	Satellite-based	$PM_{2.5}$ Monitors		$PM_{2.5}$ & NO_2 Monitors		Satellite-based	$PM_{2.5}$ Monitors		$PM_{2.5}$ & NO_2 Monitors	
		AQI	Arith. mean	AQI	Arith. mean		AQI	Arith. mean	AQI	Arith. mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EVs per 1,000 vehicles	-0.002*	-0.018	-0.006	-0.037	-0.013	0.002	-0.044	-0.013	-0.092	-0.027
	(0.001)	(0.022)	(0.007)	(0.041)	(0.013)	(0.010)	(0.043)	(0.013)	(0.057)	(0.018)
Dep Var Mean	6.9	32.4	8.1	32.9	8.3	6.9	32.4	8.1	32.9	8.3
Observations	425079	53846	53849	12658	12659	425079	53846	53849	12658	12659

Notes: Vehicle registration data come from S&P Global. Columns 1 and 6 usessatellite-based estimates from van Donkelaar et al. (2021). Columns 2-3 and 7-8 use the EPA daily pollutant data from $PM_{2.5}$. Columns 4-5 and 9-10 restrict attention to monitors that report data on both $PM_{2.5}$ and NO_2. AQI stands for air quality index and arithmetic mean refers to the monthly mean concentration. All $PM_{2.5}$ data is reported in $\mu g/m^3$. All regressions control for county and month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, state monthly total miles driven, annual county NO_x emissions from power plants in tons, and monthly county weather variables including mean temperature and precipitation (plus squared), wind speed and eight wind direction dummies. Observations at the county-by-month level span from 2010 to 2021. Standard errors are clustered at the county level. *** p<0.01,** p<0.05,* p<0.1.

Table A.6: EV Shares and Adverse Birth Outcomes: IV Analysis Results

	VLBW per 1,000 births	Very Premature per 1,000 births
	(1)	(2)
Panel A: Two-stage least squares		
EVs per 1,000 vehicles (9-mo average)	-0.029***	-0.038***
	(0.010)	(0.013)
Panel B: Reduced form		
AFC stations per 10,000 pop.	-0.27**	-0.35**
	(0.12)	(0.15)
Panel C: First stage		
AFC stations per 10,000 pop.	9.14***	9.14***
	(1.29)	(1.29)
F-stat (Kleibergen-Paap)	50.0	50.0
Observations	416187	416187

Notes: EV share is calculated as a nine-month average starting from the month of conception: county EVs × 1,000 divided by all registered vehicles. Vehicle registration data come from S&P Global. AFC stations per population is the county stock of EV charging stations opened after 2015 within one mile of an Alternative Fuel Corridor (AFC), per 10,000 population. Station and AFC project data come from the U.S. Department of Energy and Federal Highway Administration. Birth data are from National Center for Health Statistics restricted files. Outcomes are county monthly average incidence rates per 1,000 births conceived in that month. We report results for very low birth weight (VLBW) and very premature births only; the composite outcomes index is omitted. All regressions control for county and conception-month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, and annual county NO_x emissions from power plants (tons). We also control for the nine-month average of state monthly total miles driven; county mean temperature and precipitation (and their squares); wind speed; and eight wind direction dummies. Additional controls include county incidence rates for birth and maternal characteristics. Observations span 2010–2021. Regressions are weighted by the number of births in each county–month–year cell. Standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: EV Shares and Other Adverse Birth Outcomes

	NICU per 1,000 births	Asst. Vent. per 1,000 births	Surfactant per 1,000 births	Stillbirth per 1,000 births	Severe Birth Outcomes Index
	(1)	(2)	(3)	(4)	(5)
Panel A: TWFE Estimates					
EVs per 1,000 vehicles (9-mo average)	-0.1199	-0.0251	-0.0352***	-0.0052	-0.0005**
	(0.1022)	(0.0246)	(0.0119)	(0.0037)	(0.0002)
Panel B: 2SLS Estimates					
EVs per 1,000 vehicles (9-mo average)	0.1052	-0.0405	-0.0161	-0.0129**	-0.0003
	(0.1139)	(0.0471)	(0.0167)	(0.0053)	(0.0003)
Dep Var Mean	73.7	16.7	6.3	1.9	–
Observations	406821	406821	406821	406870	406821

Notes: EV share is calculated as a nine-month average starting from the month of conception: county EVs $\times$ 1,000 divided by all registered vehicles. Vehicle registration data come from S&P Global. Birth data are from National Center for Health Statistics restricted files. Adverse birth outcomes are county monthly average incidence rates per 1,000 births conceived in that month, calculated for admission to NICU, assisted ventilation, surfactant use, stillbirth, and the Severe Birth Outcomes Index (composite; see text). All regressions control for county and conception-month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, and annual county NO_x emissions from power plants (tons). We also control for the nine-month average of state monthly total miles driven; county mean temperature and precipitation (and their squares); wind speed; and eight wind-direction dummies. Additional controls include county incidence rates for birth and maternal characteristics. Observations span 2010–2021. Regressions are weighted by births in each county–month–year cell. Standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: EV Shares and Air Quality: Estimates from the HCUP States

	Pollutant = NO_2	
	AQI	Arithmetic mean
	(1)	(2)
EVs per 1,000 vehicles	-0.100***	-0.081***
	(0.030)	(0.026)
Dep Var Mean	17.6	8.7
Observations	3531	3530

Notes: EV share is calculated as number of all registered electric vehicles $\times$ 1,000 divided by all registered vehicles. Vehicle registration data come from S&P Global. Pollutant data are monthly averages calculated from the EPA daily monitor readings. For NO_2 (nitrogen dioxide), AQI stands for air quality index and arithmetic mean refers to the monthly mean concentration reported in ppb (parts per billion). Regressions repeat the TWFE analysis on air quality by restricting the sample to nine states covered in HCUP dataset: AZ, FL, KY, MD, MN, NJ, NY, NC, WI. All regressions control for county and month-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, state monthly total miles driven, annual county NO_x emissions from power plants in tons, and monthly county weather variables including mean temperature and precipitation (plus squared), wind speed and eight wind direction dummies. Observations at the county-by-month level span from 2010 to 2021. Standard errors are clustered at the county level. *** p<0.01,** p<0.05,* p<0.1.

Table A.9: EV Shares and Emergency Department Visits for Ages 65-79

	Asthma per 1,000 pop.	Acute Respiratory per 1,000 pop.	Injury per 1,000 pop.
	(1)	(2)	(3)
EVs per 1,000 vehicles	0.001	-0.018***	-0.002
	(0.001)	(0.006)	(0.015)
Dep Var Mean	0.3	3.3	15.7
Observations	24648	24648	24648

Notes: EV share is calculated as number of all registered electric vehicles × 1,000 divided by all registered vehicles for each county in a given quarter. Vehicle registration data come from S&P Global. Emergency department visits data are from HCUP for nine states: AZ, FL, KY, MD, MN, NJ, NY, NC, WI. Dependent variable is quarterly total visits from each cause per 1,000 population ages 65-79 from Census. See text for details on variable construction. All regressions control for county and quarter-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, and annual county NO_x emissions from power plants (tons). We also control for the quarterly county share of ED visits by race (Black and White), sex (male), and insurance coverage (Medicaid, private, and self-pay); quarterly state total miles driven and county weather (mean temperature and precipitation and their squares), wind speed, and eight wind-direction dummies. Observations span 2010–2021. Regressions are weighted by county population. Standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.10: Per-Vehicle NO_x Emission Calculations

	NO_x emissions per MWh	Energy demand per EV	NO_x emissions per EV	Exhaust NO_x emissions per gas car
	lb/MWh	MWh/yr	lb/yr	lb/yr
Year	(1)	(2)	(1) × (2) = (3)	(4)
2010	1.12	3.87	4.33	29.23
2012	0.95	4.06	3.85	20.32
2014	0.93	3.58	3.32	15.61
2016	0.72	3.29	2.37	11.43
2018	0.62	3.00	1.85	8.31
2019	0.57	2.92	1.66	7.35
2020	0.49	2.96	1.45	6.03
2021	0.51	2.94	1.51	5.50

Notes: Column (1) reports average NO_x emissions per megawatt-hour (MWh) of electricity generated in the U.S., based on data from the EPA's eGRID database (U.S. EPA, eGRID, 2010–2021). Column (2) provides estimated annual electricity demand per electric vehicle (EV), derived from model-level consumption data compiled by EV-Database.org and sales-weighted averages based on top-selling EV models in each year. Column (3) multiplies emissions per MWh by energy demand to yield the estimated annual NO_x emissions attributable to each EV. Column (4) shows annual tailpipe NO_x emissions from an average gasoline-powered passenger vehicle, based on observed emissions data that incorporate actual driving behavior, traffic patterns, and weather conditions (U.S. Bureau of Transportation Statistics, 2025)

Table A.11: NO_x Emission Calculations for California

	Number of EVs registered	Exhaust NOx averted	NOx from elec. gen. In-state	Net savings	NOx from elec. gen. Out-of-state
	000s	tons/yr	tons/yr	tons/yr	tons/yr
Year	(1)	(2)	(3)	(2)-(3)=(4)	(5)
2010	329	4,811	479	4,331	199
2012	428	4,348	494	3,854	255
2014	676	5,274	718	4,556	353
2016	987	5,640	807	4,832	376
2018	1,234	5,124	762	4,362	354
2019	1,374	5,054	851	4,203	328
2020	1,498	4,517	791	3,726	339
2021	1,546	4,253	853	3,400	368

Notes: Column (1) shows the number of electric vehicles (EVs) registered in California (in thousands), based on county vehicle registration data. Column (2) estimates the total annual NO_x emissions averted by replacing gasoline-powered vehicles with EVs, using real-world tailpipe emissions factors (U.S. Bureau of Transportation Statistics, 2025) that reflect actual driving conditions including traffic, weather, and road types. Column (3) calculates NO_x emissions from electricity generation required to power EVs, considering only in-state power plants and their annual generation and emissions data from the EPA's eGRID program. Column (4) represents the net emissions savings, computed as the difference between averted tailpipe emissions and emissions from in-state electricity generation. Column (5) separately reports the additional NO_x emissions attributable to imported electricity used to charge EVs, based on California's grid import profile and the average emission intensity of out-of-state generation sources (California Energy Commission, 2009-2023).

Table A.12: EV Shares and Air Quality: Accounting for Spillover Effects

	Pollutant = NO_2			
	TWFE Estimates		2SLS Estimates	
	AQI	Arithmetic mean	AQI	Arithmetic mean
	(1)	(2)	(3)	(4)
EVs per 1,000 vehicles	-0.022**	-0.019***	-0.046***	-0.041***
	(0.009)	(0.006)	(0.017)	(0.011)
EV-caused NO_x emissions	0.013	0.004	0.014	0.005
	(0.013)	(0.007)	(0.013)	(0.007)
Dep Var Mean	14.8	7.1	14.8	7.1
F-stat (Kleibergen-Paap)			17.6	17.6
Observations	15093	15084	15093	15084

Notes: EVs per 1,000 vehicles is county number of electric vehicles (EV) $\times$ 1,000 divided by number of all registered vehicles in a given month. Vehicle registration data come from S&P Global. Pollutant data are monthly averages calculated from the EPA daily monitor readings. For NO_2 (nitrogen dioxide), AQI stands for air quality index and arithmetic mean refers to the monthly mean concentration reported in ppb (parts per billion). EV-caused NO_x emissions are annual emissions from each county's power plants to power all electric vehicles within the electricity grid region, which come from US EPA eGRID database. All regressions control for county and month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, total vehicles registered, state monthly total miles driven, and monthly county weather variables including mean temperature and precipitation (plus squared), wind speed and eight wind direction dummies. Observations at the county-by-month level span years 2010, 2012, 2014, 2016, 2018, 2019,2020,2021, for which grid-level data is available. Standard errors are clustered at the county level. *** p<0.01,** p<0.05,* p<0.1.

Table A.13: EV Shares and Adverse Birth Outcomes: Accounting for Spillover Effects

	TWFE Estimates		2SLS Estimates	
	VLBW per 1,000 births	Very Premature per 1,000 births	VLBW per 1,000 births	Very Premature per 1,000 births
	(1)	(2)	(3)	(4)
EVs per 1,000 vehicles (9-mo average)	-0.0112**	-0.0122**	-0.0337***	-0.0425***
	(0.0045)	(0.0052)	(0.0105)	(0.0142)
EV-caused NO_x emissions	0.0077*	0.0006	0.0108***	0.0047
	(0.0043)	(0.0044)	(0.0039)	(0.0049)
Dep Var Mean	15.8	18.4	15.8	18.4
F-stat (Kleibergen-Paap)			50.4	50.4
Observations	269696	269696	269696	269696

Notes: EVs per 1,000 vehicles is county number of electric vehicles (EV) × 1,000 divided by number of all registered vehicles in a given month. We calculate and use nine-month average starting from the month of conception. Vehicle registration data come from S&P Global. EV-caused NO_x emissions are annual emissions from each county's power plants to power all electric vehicles within the electricity grid region, which come from US EPA eGRID database. Birth data are from National Center for Health Statistics restricted files. Adverse birth outcomes are county monthly average incidence rates for very low birth weight (VLBW) and very premature (VP) births per 1,000 births conceived in that month. All regressions control for county and conception-month-by-year fixed effects, state-by-year fixed effects, log total population, poverty rate, child poverty rate, and total vehicles registered. We also control for the nine-month average of state monthly total miles driven; county mean temperature and precipitation (and their squares); wind speed; and eight wind direction dummies. Additional controls include county incidence rates for birth and maternal characteristics. Observations at the county-by-month level span years 2010, 2012, 2014, 2016, 2018, 2019,2020,2021, for which grid-level data is available. Regressions are weighted by births in each county–month–year cell. Standard errors clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.14: Estimated Savings Related to Very Low Birth Weight Births

Channel	Estimate	Source
(1) Cost due to infant death =	**$1,337,113**	
Change in infant mortality per VLBW x	0.206	Matthews et al. (2015)
Cost of infant mortality	$6,490,839	Cutler and Meara (2000)
(2) Infant medical care cost =	**$260,108**	Rogowski (1998)
(3) Childhood disability cost =	**$68,740**	
Change neurosensory disability per VLBW x	0.1	Hack et al. (2002)
Cost of childhood disability (18 years)	$687,398	Stabile and Allin (2012)
(4) Cost due to reduction in adult income =	**$21,517**	
Average lifetime income x	$652,030	American Communities Survey
Percent income loss from VLBW	0.033	Bharadwaj et al. (2018)
(5) Cost of adult disability (medical care) =	**$69,822**	
Change in adult disability per VLBW x	0.1	Hack et al. (2002)
Cost of adult disability medical care (ages 19 to 67)	$698,220	Anderson et al. (2010)
(6) Cost of long-term mortality risk =	**$1,300,661**	
Average change in life expectancy x	11.6	Bharadwaj et al. (2018)
Statistical value of year of life	$112,126	Lee et al. (2009)
Estimated savings by 1-SD increase in EV share		
Δ VLBW $\times$ [(1) + (2) + (3) + (4) + (5) + (6)] = **$1,217,370,835**		

Notes: This table calculates estimated savings from eliminating very low birth weight (VLBW) births as a result of increasing EV share by one standard deviation. We use the estimated effect on number of VLBWs per 1,000 births from our two-way fixed effects model (-0.009, see Table 3). We multiply number this by standard deviation of EV share (11.98 per 1,000 vehicles, see Table 1). We then multiply the change in share of VLBW births by total number of VLBW births annually during our sample period (50,215), where $\Delta VLBW$ is estimated as 398.10. All costs per VLBW birth are reported in 2024 US dollars adjusted using the US consumer price index. For infant mortality, we conservatively assume that upon eliminating the risk of VLBW, infants face the mortality risk associated with low birth weight (LBW). For calculating average lifetime income and life expectancy, we follow the methods outlined in Currie et al. (2022).