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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**

The transition to electric vehicles (EVs) marks a pivotal shift in global efforts to reduce greenhouse gas emissions and combat climate change. While the environmental benefits of EVs are often discussed, their impact on air quality and public health, particularly for vulnerable populations such as infants, remains understudied. This study presents the first comprehensive nationwide analysis of the impact of EV adoption on air pollution and infant health outcomes in the United States. Using detailed county-level data on vehicle registrations, air pollution, and infant health between 2009 and 2021, we find that increased EV adoption significantly reduces concentrations of nitrogen dioxide ($NO_2$) and nitrogen oxides ($NO_x$), key pollutants linked to vehicle emissions. Our analysis further demonstrates that these improvements in air quality yield significant health benefits, including reductions in adverse birth outcomes such as very low birthweight and very preterm births, as well as fewer respiratory-related emergency department visits among children aged 0–4 years. Furthermore, EV adoption leads to substantial reductions in various neonatal health complications, including admissions to neonatal intensive care units (NICUs), the use of assisted ventilation and surfactant therapy, and overall infant mortality. To address potential endogeneity in EV adoption, we employ an instrumental variable approach based on the strategic placement of EV charging stations along federally designated Alternative Fuel Corridors. Our findings underscore the dual environmental and public health benefits of EV adoption, highlighting the importance of continued investment in EV infrastructure and complementary policies to accelerate the transition to cleaner transportation.

## 1. Introduction

The transition to electric vehicles (EVs) has gained significant momentum in the last decade, representing a critical shift in the global effort to reduce greenhouse gas emissions and combat climate change. Since 2010, over 6.1 million plug-in hybrid and battery electric vehicles have been sold in the United States, with California leading the way as zero-emission vehicles accounted for 25 percent of all new vehicle sales in 2023 (Argonne National Laboratory, 2024; California Energy Commission, 2025).[1] To further accelerate the transition to zero traffic emissions, President Biden signed an Executive Order in 2021 setting a goal for 50 percent of all vehicles sold in the country to be net-zero greenhouse gas emitters and the deployment of 500,000 EV chargers by 2030.[2] 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 fueling infrastructure (FHA, 2025). Although public discussions and scientific discourse about EVs often emphasize their role in combating climate change, their environmental and health benefits, especially regarding air quality improvements, remain understudied and less well understood. This paper seeks to fill this gap by providing a comprehensive analysis of the effects of the EV revolution on air pollution and infant health. Infants, as one of the most vulnerable populations, are especially susceptible to the adverse effects of air pollution, making this analysis crucial for understanding the broader public health implications of EV adoption.

Motor vehicles are the largest contributors to nitrogen oxides (NOx) emissions in the United States, responsible for 43 percent of total emissions and as much as 10 percent of fine

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

[2] Zero-emission vehicles (ZEVs) refer to a category of vehicles that includes battery electric vehicles, plug-in hybrid vehicles, and fuel cell electric vehicles, all of which do not produce direct exhaust emissions or release other pollutants during operation.

particulate matter (PM2.5), and they are a major driver of poor air quality and has well-documented adverse effects on human health (Currie and Walker, 2011; EPA, 2014). These pollutants are especially harmful to vulnerable populations, including pregnant women and young children, as maternal exposure during pregnancy has been strongly associated with adverse birth outcomes such as reduced birthweight, preterm birth, and impaired fetal growth (Alexander and Schwandt, 2022; Currie and Walker, 2001; Currie and Neidell, 2005; Knittel et al., 2016).[3] Similarly, early-life exposure to traffic-related air pollution has been associated with higher risks of respiratory illnesses, including asthma, as well as long-term developmental challenges (Bettitol et al., 2021; Zanotbetti et al., 2024). These impacts underscore the need to examine whether the displacement of internal combustion engine vehicles (ICEVs) by EVs can translate into measurable improvements in local air quality and early-life health outcomes.

Despite the potential for EV adoption to deliver significant health benefits through reductions in air pollution, most studies present engineering estimates of possible gains rather than empirical examination of the actual effects. These projections generally predict decreases in NOx, PM2.5, and carbon monoxide levels, and corresponding health benefits. Recent 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), reporting 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

[3] The etiology of the relationship between prenatal exposure to air pollution and infant health is well-documented in the medical literature. Pollutants can disrupt the placental transfer of oxygen and essential nutrients vital for healthy fetal development. Additionally, certain chemicals cross the placenta and bind to fetal hemoglobin, reducing its oxygen-carrying capacity. These biological mechanisms increase the risk of adverse birth outcomes, such as low birth weight, prematurity, and intrauterine growth restriction, with significant long-term effects on infant health and development. See Bekkar et al. (2020) and Stieb et al. (2012) for detailed discussions and systematic reviews of related literatures.

benefits of reductions in on-road transportation emissions in the U.S. from 2008 to 2017, estimating $270 billion in PM2.5-related benefits in 2017 by comparing four counterfactual emission scenarios from earlier years to 2017 data. Schmitt et al. (2024) examine the 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 disbenefits if the 2022 grid were maintained.[4] While these studies provide useful insights, they often lack empirical validation. The assumptions underlying these models, such as uniform adoption rates and pollutant dispersion patterns, may not reflect the heterogeneity in real-world impacts. Another complication is that the net impacts of EV adoption are likely to depend on the characteristics of the electrical power generation used to power the EVs.

More critically, these projections may not accurately reflect the true impact of EV adoption, as they fail to account for the likely endogeneity of EV adoption. This omission represents a significant limitation, given the multiple reasons why EV adoption is likely to be endogenous. First, wealthier households, which are more likely to afford EVs, tend to reside in areas with better air quality and health outcomes, creating a correlation between EV adoption and pre-existing conditions. Second, policy incentives, such as tax rebates and charging infrastructure investments, often target specific regions or demographics that may already exhibit a preference for cleaner technologies or healthier environments. Moreover, environmental preferences may also play a role, as areas with stronger environmental values may simultaneously adopt EVs and implement other pollution-reducing measures. Finally,

[4] Aside from these studies, there is also a large number studies documenting the health co-benefits of EV adoption within more narrow 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). Similar to the national studies, the identification strategy in these analyses is based on comparisons between model-based projections and EV adoption levels under hypothetical scenarios.

reverse causality may arise if areas with severe air pollution enact policies encouraging EV adoption, further complicating the causal effect from EV adoption to health.

The one study that stands out for its use of real-world observational data rather than modelled projections and attempts to address confounding factors is Garcia et al. (2023). They examine the relationship between zero emission vehicle adoption, air quality, and asthma in California. Specifically, they relate the within-zip code number of ZEVs to annual NO2 concentrations and asthma related emergency department visits between 2013 and 2019, while adjusting for zip code level educational attainment and zip code random effects. They find that a within-zip code increase of 20 ZEVs per 1,000 population is associated with a 0.41 ppb decrease in $NO_2$ levels and a 3.2 percent reduction in asthma-related emergency department visits. While these findings highlight the potential health co-benefits of EVs, they are limited in scope and generalizability. California's advanced EV market and stringent air quality regulations may not reflect conditions in other states.[5] Additionally, controlling for education and inclusion of random effects for zip codes may not account for all possible confounding factors. A third issue is that purchase of EVs will not lead to cleaner air unless miles driven in EVs substitute for miles driven in conventional vehicles. Hence, it is important to look at EV share rather than EV levels.

Our study seeks to address these gaps and extend the literature by providing the first comprehensive and credible nationwide evidence about the impact of EV adoption on air pollution and early-life health outcomes. To achieve this goal, we compiled an extensive dataset spanning the period from 2009 to 2021. This dataset includes county-level vehicle registrations by fuel type from S&P Global and year-end county snapshots of the vehicle fleet obtained from IHS Markit; geographic locations and opening dates for all charging stations

[5] Moreover, as noted by the authors, the ecological analyses in Garcia et al. (2023) are conducted at the zip code level, which is a suboptimal geographic unit for population health studies. Zip codes were originally designed for postal delivery, leading to variations in geographic and population sizes, potential overlaps across city, county, or census boundaries, and changes over time.

from the U.S. Department of Energy; daily air pollutant levels for PM2.5, NO2, and NOx from EPA air quality monitors as well as satellite-based pollution estimates from TEMIS and 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 U.S. states provided by the Healthcare Cost and Utilization Project (HCUP). This comprehensive, integrated dataset allows us to evaluate whether increases in EV shares lead to significant improvements in local air quality and reductions in adverse health outcomes, with a particular focus on vulnerable populations such as pregnant women and young children.

To guard against potential bias caused by the endogeneity of EV adoption, we use two approaches. First, we estimate two-way fixed effects models controlling for county fixed effects and month-by-year fixed effects in addition to a rich set of controls, including county level monthly averages on child's birth order and gender, maternal age, race, education, marital status, maternal smoking, poverty rates for total population and children, and state level monthly total miles driven. Second, we estimate Instrumental Variable (IV) models, leveraging the strategic placement of charging stations along federally designated Alternative Fuel Corridors (AFCs). The identification assumption is that the AFC program incentivized the EV adoption, but affected air quality and infant health only through its impact on EV adoption.

Our study makes several key contributions to the literature on EV adoption, air quality, and infant health. First, it provides the first comprehensive nationwide analysis of the impact of EV adoption on air pollution and infant health outcomes, including birthweight and prematurity. These outcomes are particularly critical because poor health at birth is strongly linked to long-term consequences such as impaired cognitive development, lower educational attainment, and reduced socioeconomic outcomes later in life (Currie and Moretti, 2007; Currie, 2011; Black, Devereux, and Salvanes, 2007; Isen, Rossin-Slater, and Walker, 2017;

Bütikofer, A., Løken, K. V., and Salvanes, 2019). Additionally, our analysis extends beyond birthweight and prematurity to incorporate a broader range of health indicators observed during delivery. Moreover, we explore health outcomes beyond birth by examining the impact of EV adoption on emergency department visits for respiratory conditions among young children in their early years. Second, we place a strong emphasis on addressing the potential endogeneity of EV adoption, a critical issue that, if not addressed, could bias estimates. Among existing studies, only Garcia et al. (2023) acknowledges this concern, providing estimates based on an analysis that accounts for zip code-level variations and adjusts for educational attainment. In our study, we go further by identifying and validating an instrumental variable for EV adoption. This approach not only strengthens the credibility of our findings but also provides a valuable tool for the research community, offering a framework for future studies investigating the expansion and impacts of EV adoption.

In addition to advancing scientific understanding of the relationship between EV adoption, air pollution, and health outcomes, our analysis has important policy implications. Quantifying the health impacts is EVs is crucial for assessing the costs and benefits of EV adoption and shaping effective regulatory strategies. Furthermore, since users of traditional vehicles are partially exposed to their own emissions (Alexander and Schwandt, 2022; Campagnolo et al., 2023; Harik et al., 2017), raising awareness about the health risks associated with car exhaust could play a pivotal role in influencing consumer behavior and informing policy decisions. By examining the role of EV adoption in enhancing air quality and its downstream effects on infant health, this study offers valuable insights into how transportation electrification can reduce the harmful health consequences of vehicle pollution and guide future policy initiatives.

Aside from these specific contributions, our study is closely related to the broader literature on the relationship between air pollution from traffic emissions and infant health. A

growing body of research in this literature has established the broader relationship between air pollution and adverse health outcomes among children and infant health. However, these studies often rely on generalized air pollution exposure measures and do not isolate the effects of specific policy or technological interventions, such as the adoption of EVs, on these outcomes. A few notable and relatively recent exceptions include Currie and Walker (2011), Knittel et al. (2016), and Alexander and Schwandt (2022). Currie and Walker (2011) examine the health effects of reduced traffic congestion using the introduction of E-ZPass toll systems as a natural experiment. They find significant improvements in infant health, with reductions in prematurity and low birth weight among mothers living near toll plazas. Another important study is Knittel et al. (2016), which extends this literature analysis by focusing on traffic-related air pollution in California, constructing instrumental variables based on the interaction of traffic and weather conditions to demonstrate that particulate matter and carbon monoxide have substantial impacts on weekly infant mortality, particularly among vulnerable subpopulations such as low birth weight or premature infants. Most recently, Alexander and Schwandt (2022) leverage the Volkswagen emissions-cheating scandal as a natural experiment to evaluate the health impacts of car pollution. Their findings reveal that increased air pollution from cheating diesel vehicles led to worsened birth outcomes, higher infant mortality rates, and a rise in asthma-related emergency visits among infants and children. The study is an excellent example that underscores the significant health consequences of vehicle emissions and highlights the critical role of regulatory enforcement.

Our study provides the first comprehensive nationwide analysis of the impact of electric EV adoption on air pollution and infant health. Using detailed county-level data from 2009 to 2021, we find that higher EV shares are significantly associated with reductions in nitrogen dioxide ($NO_2$) and nitrogen oxides ($NO_x$) concentrations, confirming the role of EVs in improving air quality. We further establish a causal link between increased EV adoption and

improved birth outcomes, including reductions in very low birthweight and preterm births. Our analysis also reveals declines in emergency department visits for respiratory conditions among young children, underscoring the broader health benefits of EV adoption. These results remain robust across various sensitivity checks, reinforcing the conclusion that EV adoption mitigates vehicular pollution and contributes to meaningful improvements in early-life health outcomes.

Our findings reveal several important insights. First, we show that increased EV adoption leads to significant reductions in key air pollutants, including $NO_2$ and $NO_x$, which are directly linked to vehicle emissions. This improvement in air quality translates into meaningful health benefits, particularly for infants and young children. Specifically, we find that higher EV adoption is associated with lower rates of adverse birth outcomes, such as low birthweight and prematurity, both of which have critical long-term implications for cognitive development and socioeconomic outcomes. Moreover, our analysis extends beyond health at birth to demonstrate reductions in respiratory-related emergency department visits among children aged 0–4 years, highlighting the broader public health impacts of EVs. Our results remain robust across numerous sensitivity checks, reinforcing the conclusion that EV adoption mitigates vehicular pollution and contributes to meaningful improvements in early-life health outcomes. Together, these findings underscore the environmental and health co-benefits of transitioning to electric vehicles, offering valuable evidence for policymakers aiming to mitigate air pollution and enhance public health.

The rest of the paper is organized as follows. Section 2 describes the data sources used in the analysis, including information on vehicle registrations, air pollution measures, and infant and child health outcomes. Section 3 discusses the empirical methodology. Section 4 presents the results, highlighting the impact of EV adoption on air quality, birth outcomes, and neonatal health, alongside numerous robustness checks. Lastly, Section 5 concludes the paper by summarizing the key findings and discussing their broader policy implications.

## 2. Data

### 2.1. Data on Electric Vehicle Shares

We obtained our data on electric vehicles (EVs) from vehicle registration records purchased from IHS Markit. The IHS Markit offers comprehensive and accurate vehicle registration records. The dataset spans from 2009 to 2021, capturing the rapid growth in EV across United States adoption over this period. To measure EV adoption, we use year-end county-level snapshots of vehicle registrations. These data include detailed counts of all vehicles under registration, categorized by fuel type, allowing us to calculate EV shares within each county over time.

EV shares are defined as the proportion of battery electric vehicles relative to the total number of registered vehicles in a given county at a specific point in time. Since vehicle registration renewals occur year-round and monthly data are not directly available, we interpolate monthly counts between annual snapshots to create a consistent, temporal series. This approach minimizes potential distortions from seasonal or administrative registration cycles.

Figure 1 depicts the growth in the total number of battery EVs registered (in thousands) alongside their share as a proportion of all registered vehicles from 2009 to 2021. Both metrics exhibit a steep upward trend starting around 2015, reflecting the rapid adoption of EVs in recent years. While the past fifteen years have witnessed a significant increase in the share of EVs, this growth displays substantial variation across the United States. Figure 2 captures the evolution of EV penetration at the county level across three time points: 2009, 2016, and 2021. Each map depicts the share of EVs as a proportion of total registered vehicles in counties. The first panel shows relatively low adoption rates in 2009, with most counties exhibiting minimal EV penetration. By 2016, the second panel reveals noticeable growth in EV shares, particularly

concentrated in urban areas and coastal regions. The third panel highlights further expansion by 2021, with widespread increases in EV adoption across counties, reflecting a broader national trend toward electrification. This progression demonstrates the growing diffusion of EV technology over time.

**2.2. Air Pollution Data**

The air pollution data used in our analysis are obtained from the Environmental Protection Agency (EPA) through its Air Quality System (AQS), a comprehensive database that provides daily measures of key air pollutants. [6] The Clean Air Act mandates that states maintain a network of air monitoring stations to track daily readings of various pollutants, including $NO_2$, $NO_x$, and PM2.5.[7] To comply with this mandate, the AQS compiles data from hundreds of monitoring stations across urban, suburban, and rural regions in the United States, ensuring broad geographic coverage. These stations provide data on the average concentration of each pollutant over all daily observations within a month, as well as the Air Quality Index (AQI), a scaled measure from 0 to 500 based on EPA methodologies that contextualizes pollutant concentrations in terms of health risks.[8] To maintain consistency, we use a single monitoring station per county, selecting the station with consistent coverage over the analysis period, and construct a county-month level panel of pollution measures, following Alexander and Schwandt (2022).

Our primary focus is on pollutants most directly linked to vehicle emissions—nitrogen dioxide ($NO_2$) and nitrogen oxides ($NO_x$).[9] Additionally, we provide results for fine particulate

[6] Each daily observation includes pollutant concentrations measured in micrograms per cubic meter ($\mu g/m^3$) or parts per billion (ppb), along with information on the monitoring station's location and characteristics.
[7] $NO_2$ is a primary pollutant generated from combustion processes, particularly those involving motor vehicles; $NO_x$ is a broader category that encompasses $NO_2$ and other nitrogen compounds, and play a key role in the formation of ground-level ozone and smog; and PM2.5 consists of tiny airborne particles that pose serious health risks, particularly for vulnerable populations such as pregnant women and young children.
[8] The AQI converts pollutant concentration (in ppb) into a scaled value based on predefined breakpoints corresponding to health impact categories (e.g., Good, Moderate, Unhealthy).
[9] $NO_x$ refers to a group of nitrogen oxides, primarily nitric oxide (NO) and nitrogen dioxide ($NO_2$) that are produced during combustion processes, especially in vehicle engines. While NO is initially emitted in larger quantities, it rapidly reacts with oxygen in the atmosphere to form $NO_2$ , which is more harmful to human health.

matter (PM2.5 and PM10), although the role of EV adoption in reducing PM and carbon monoxide (CO) is less clear.[10]

While the AQS datasets provide valuable pollution measures, it is not without limitations. The availability of monitoring stations varies across pollutants and regions, with stations frequently added or discontinued over time. Additionally, monitoring stations are not randomly distributed within counties and may avoid pollution hotspots to comply with federal standards. This placement often biases measurements toward urban areas, potentially underestimating pollution levels in rural regions.

Therefore, we supplement our analysis with satellite-based pollution estimates obtained from Boersma et al. (2011) and van Donkelaar et al. (2021). These estimates combine satellite observations of aerosol optical depth, chemical transport model simulations, and information from EPA monitors. Satellite-based estimates provide a comprehensive database by offering $NO_2$ and PM2.5 levels for all U.S. counties, including those lacking ground-based monitoring stations. However, these estimates are indirect and may include prediction errors, particularly underestimations at high pollutant concentrations, as noted in previous studies (Fowlie, Rubin, and Walker, 2019).

### 2.3. Vital Statistics Natality Data

The data on infant health outcomes are obtained the restricted-access Vital Statistics Natality files, provided by the National Center for Health Statistics. This dataset includes all

$NO_2$ is a key component of NOx and is directly linked to adverse respiratory and cardiovascular effects. (Blaszczak, 1999)

[10] This is because PM2.5 emissions are also influenced by non-exhaust sources, such as tire wear, brake wear, and road surface abrasion, which are not directly reduced by transitioning to EVs. In fact, the increased weight of EVs, due to their batteries, may exacerbate these non-exhaust emissions, offsetting some of the benefits from eliminating tailpipe emissions (Timmers and Achten, 2016). Studies have shown that non-exhaust emissions now account for the majority of PM2.5 from road traffic, highlighting their growing dominance as exhaust emissions decline (Harrison et al., 2021; Grigoratos and Martini, 2014). Accordingly, while EV adoption significantly reduces nitrogen oxides and other tailpipe pollutants, its impact on PM2.5 is less straightforward and reflects the persistence of these non-exhaust sources. Similarly, the impact of EVs on carbon monoxide (CO) emissions is less clear because, while EVs produce zero tailpipe emissions, upstream CO emissions depend on the energy mix used for electricity generation (Peters et al., 2020).

live births in the United States from 2009 to 2021 and provides detailed information on birth outcomes, maternal characteristics, and geographic identifiers. It is one of the most comprehensive sources for studying infant health, as it captures a near-complete record of live births during the study period.

The main birth outcomes considered in our analysis include very low birth weight (birthweight less than 1,500 grams) and very premature births (gestation under 34 weeks), which are widely recognized as critical indicators of infant health. These outcomes are associated with long-term developmental, educational, and economic consequences, making them essential for evaluating the potential health benefits of reduced air pollution due to EV adoption. In addition to birth outcomes, the data provide a rich set of maternal characteristics such as age, race, education level, marital status, parity, and smoking status during pregnancy. We exclude observations with implausible or missing values for birthweight or gestational age. Furthermore, we restrict the sample to singleton births to avoid confounding due to the unique health risks associated with multiple births (Almond et al., 2011; Dursun et al., 2024; Koppensteiner and Menezes, 2024). The geographic identifiers in the dataset, including county and state of residence, allow us to link births to local air pollution levels and the share of EVs in each area.

### 2.4. Healthcare Cost and Utilization Project (HCUP) Data

In a supplementary analysis, we examine the impact of EV adoption on healthcare utilization among young children using the State Emergency Department Databases (SEDD) from the Agency for Healthcare Research and Quality's Healthcare Cost and Utilization Project (HCUP). [11] The SEDD captures emergency department (ED) visits at hospital-owned facilities that do not result in hospitalization. These databases are developed through the data collection

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

efforts of statewide organizations that partner with AHRQ to maintain comprehensive healthcare datasets.

Our analysis utilizes SEDD data from nine states—Arizona, Florida, Kentucky, Maryland, Minnesota, New Jersey, New York, North Carolina, and Wisconsin—covering the years 2009 to 2021, with varying periods of availability across states.[12] The data include detailed information on patient characteristics such as age, gender, race, primary diagnosis, insurance status, county of residence, and discharge quarter.

For this study, we focus on quarterly county-level ED visit data for children aged 0–4 years with respiratory diagnoses, asthma and bronchitis. These conditions are widely recognized as being sensitive to air quality changes, particularly vehicle emissions, making them critical indicators of child health outcomes (Alexander and Schwandt, 2022). We calculate rates of ED visits for respiratory diagnoses per 1,000 children in this age group to provide a measure of acute health impacts that may be associated with local air pollution and changes in EV adoption rates.

**2.5. Descriptive Statistics**

The summary statistics presented in Table 1 provide an overview of key variables used in the analysis. The table begins with the monthly average share of battery electric vehicles at the county level, which is reported as 0.048 percent, with a standard deviation of 0.153.

Panel A presents summary statistics for air pollution measures, encompassing both ground-based and satellite-derived pollutants, provide a snapshot of baseline air pollution levels and their distribution across the sample. The mean $NO_2$ concentration is 7.619 ppb, with an AQI averaging 15.571, while $NO_x$ levels average 7.145 ppb. Particulate matter concentrations, including PM2.5 and PM10, reflect similar trends with moderate variability

[12] The SEDD databases are available for purchase from the AHRQ. However, the NBER has a current data use agreement with HCUP, which allows NBER affiliated faculty to have access these data for a subset of states. These are the nine states that provide on county of residence and discharge quarter for the period considered in our study.

across counties. Satellite-based estimates indicate that tropospheric $NO_2$ averages 7.264 ($\times 10^{15}$ molecules per $cm^2$).

Panel B illustrates the prevalence of adverse birth outcomes in the sample and provide a benchmark for assessing potential health improvements linked to EV adoption. The average birthweight is approximately 3,290 grams and the incidence of very low birthweight (less than 1,500 grams) is 1.3 percent, while low birthweight (less than 2,500 grams) occurs in 7.1 percent of births. Prematurity rates also show variation, with 9.2 percent of births occurring before 37 weeks of gestation, and 2.5 percent being classified as very premature (before 34 weeks). The rate of neonatal intensive care unit (NICU) admissions is 7.3 percent, while the need for assisted ventilation and surfactant treatment is 1.6 percent and 0.6 percent, respectively. The stillbirth rate is 0.2 percent, and the infant mortality rate is 0.543 per 1,000 live births.

Panel C reports key birth characteristics available in the Vital Statistics data. Approximately 30.7 percent of births are first births, and 48.8 percent of infants are male. The average maternal age is 27 years. In terms of educational attainment, 13.7 percent of mothers have less than a high school education, 28.2 percent have completed high school, and 52.3 percent have education beyond high school. The racial composition indicates that 10.6 percent of mothers are Black, 84.8 percent are White, and 12 percent are Hispanic. Additionally, 58.4 percent of mothers are married, and 8.1 percent report smoking during pregnancy.

Panel D of the summary statistics table focuses on health outcomes derived from the HCUP data, specifically emergency department (ED) visits for children aged 0–4. The average total ED visits per 1,000 children in this age group is 68 visits, with respiratory disease-related ED visits averaging 18 per 1,000 children. Among specific respiratory conditions, asthma-related visits occur at a rate of 1 per 1,000 children, while bronchitis-related visits are lower, averaging 0.2 per 1,000 children. Combined asthma and bronchitis visits amount to 0.3 per 1,000 children.

Finally, Panel E summarizes county-level control variables used in the analysis. During the analysis period. the overall poverty rate is 16 percent, while the child poverty rate is higher at 22 percent. The number of registered vehicles in a county averages 39,529, and the total monthly miles driven at the state level averages 7.122 million miles.

## 3. Empirical Methodology

We aim to evaluate the causal impact of EV adoption on air pollution and infant health outcomes. Our hypothesis is that greater adoption of EVs leads to improved birth outcomes by reducing air pollution. Specifically, as EV penetration increases within a county, vehicular emissions are expected to decrease, resulting in better air quality and, consequently, positive effects on infant health. To capture this causal pathway, we specify a series of regression equations that allow us to empirically examine the relationship between EV adoption, air pollution, and infant health outcomes. The first step in this framework involves estimating the impact of EV adoption on air pollution levels, leveraging within-county variation in EV adoption over time. This relationship can be expressed by following regression equation:

$$Pollution_{cmy} = \alpha + \beta\, EV_{cmy} + X_{cy}\gamma + \mu M_{cmy} + \lambda_c + \lambda_{my} + my.\theta_s + \epsilon_{cmy}, \qquad (1)$$

where $Pollution_{cmy}$ represents a measure of air pollution, such as $NO_2$, $NO_x$, or PM2.5 concentrations, or the air quality index in county c in month m in year y. The variable $EV_{cmy}$ is the share of electric vehicles among all registered vehicles. $X_{cy}$ represents a vector of control variables including annual county estimates for total population, total and child poverty rates, logarithm of total number of registered vehicles. In equation (1), we also account for the state level total miles driven by month in each year. The term $\lambda_c$ denotes county fixed effects, which control for unobserved, time-invariant differences across counties. The $\lambda_{my}$ represents month-by-year fixed effects, which account for shocks that are common across all counties.

We also control for state-specific linear time trends ($my.\theta_s$).[13] Finally, $\epsilon_{cmy}$ is an idiosyncratic error. The standard errors in Equation (1) are clustered at the county level.

The next step in our empirical strategy is to examine the downstream effects of EV adoption on infant health. If the coefficient $\beta$ from Equation (1) is negative, it logically follows to hypothesize a positive causal relationship between EV adoption and infant health. This inference is grounded in the well-documented scientific consensus on the adverse effects of air pollution on infant health, as discussed earlier (e.g., Currie and Neidell, 2005; Currie et al., 2009; Currie, 2013).[14] The regression equation capturing this relationship can be formulated similarly to Equation (1) as follows:

$$Infant_Health_{cmy} = \alpha + \rho\, EV_Gestation_{\,cmy} + X_{cmy}\gamma + \lambda_c + \lambda_{my} + my.\theta_s + \epsilon_{cmy}, \quad (2)$$

where $Infant_Health_{cmy}$ represents one of the infant health outcomes (e.g., indicators of very low birthweight and very preterm) measured as the incidence rate per 1,000 births for infants conceived in county c, during month m, and year y. Conception month is calculated using the birth date and gestational age. $EV_Gestation_{\,cmy}$ denotes the average EV share that infants were exposed to during their in utero period. This measure is calculated as the 9-month average of EV share in county c, starting from the conception month m in year y. The vector $X_{cmy}$ 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 other variables in Equation (2) are defined in the same manner as those Equation (1). The

[13] States with more rapid EV adoption may simultaneously experience other changes correlated with air pollution, such as the implementation of environmental regulations. Additionally, variations in factors like urbanization or environmental awareness across states could contribute to these trends. To account for such influences, we include state-specific time trends in Equation (1). However, we also present results from models that exclude these trends to assess their role.

[14] Because our data include measures of both air pollution and infant health, we can demonstrate the negative relationship between these two variables within a unified framework. However, to conserve space, we do not present or discuss these results here. They are available from the authors upon request.

regression is weighted by the number of births. Note that the data used for estimating Equation (2) are collapsed at the county-month level.[15]

The key parameter in Equation (2), ρ, represents the effect of prenatal exposure to EVs on infant health outcomes. The causal interpretation of this parameter relies on the assumption that increases in EV shares are not correlated or driven by simultaneous socioeconomic changes that increase EV adoption and improve infant health. A direct approach to assess whether the exclusion restriction is violated involves performing a series of balancing exercises in which we regress each of our child and maternal characteristic on the EV shares (Currie and Walker, 2011; Alexander and Schwandt, 2022). Furthermore, we implement an additional identification strategy using an instrumental variables approach, as described later in the section. As shown in Table A1, the results from the balancing exercise demonstrate that 9-month average of EV shares are largely orthogonal to demographic as well as maternal and child characteristics, once county and time fixed effects are incorporated into the analysis. This finding supports the validity of our empirical approach, suggesting that the variation in EV adoption used in the analysis is exogenous to maternal and child characteristic

### 3.1. Instrumental Variable Strategy

An empirical challenge in credibly estimating the causal impact of EV adoption on infant health is addressing the potential endogeneity of EV adoption. Failing to account for this issue may result in biased estimate. Furthermore, the direction of bias from endogeneity is uncertain a priori. One could overestimate the true impact if wealthier households, who are more likely to adopt EVs, reside in areas with better pre-existing air quality, healthcare access, or health outcomes, thereby inflating the observed relationship. Similarly, counties or states with strong environmental preferences or policies promoting EV adoption may have already

[15] We also perform our analysis using micro-level data. This analysis produced results that closely align with those presented in this paper. These additional findings are available upon request.

implemented other pollution-reducing measures, further exaggerating the effect. On the other hand, one could underestimate the true effect if EV adoption is more concentrated in urban areas with higher baseline pollution levels, where the health benefits of reduced pollution are partially offset by other environmental stressors. Additionally, externalities such as increased traffic from EV adoption could negatively impact health, further diminishing the measured benefits.

To the extent that these confounding factors are captured by the control variables and the fixed effects alongside the state-specific trends, the estimates from Equations (2) and (3) would have a causal interpretation. Despite the results from the balancing tests in support of this assumption, one may argue that there are additional remaining factors that are not properly accounted for. Therefore, we turn to another identification strategy that is based on an instrumental variable approach.

Our instrument leverages 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, aims to create a nationwide network of alternative fuel infrastructure to promote cleaner transportation technologies. Administered by the Federal Highway Administration (FHWA), the program designates highway routes to support infrastructure development for EV charging stations, hydrogen fueling, and compressed natural gas. A key goal of the AFC initiative is to address range anxiety—a significant barrier to EV adoption—by ensuring drivers have reliable access to charging facilities along critical transportation corridors (Federal Highway Administration, 2023).

To qualify as an AFC, designated routes must meet specific requirements. For EVs, charging stations must be spaced no more than 50 miles apart and located within one mile of the highway. These criteria aim 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).

The program's environmental objectives are central to its mission, as EV adoption is a critical strategy for reducing greenhouse gas emissions and improving air quality, aligning with national and global climate change goals. The AFC initiative has significantly accelerated EV adoption by closing infrastructure gaps and increasing public confidence in EV technology. Its federally coordinated approach ensures efficient and equitable deployment of charging stations, making EV travel more feasible across diverse regions. By aligning infrastructure development with broader climate and transportation goals, the AFC program is a cornerstone effort in decarbonizing transportation and enhancing environmental and public health outcomes (Federal Highway Administration, 2023).

To construct the instrumental variable, we compiled data on charging stations opened between 2015 and 2021 that are located within one mile of designated AFCs. Stations opened before 2015 were excluded to align with the timeline of the AFC program rollout under the FAST Act. The AFC stations represent 56 percent of all charging stations established during this period, underscoring the program's significant role in expanding EV infrastructure. Using these data, we calculated the stock of AFC charging stations per 10,000 population in each county for a given month, which serves as our instrument.

The validity of our instrumental variable strategy hinges on the assumption that any rise in EV shares along the AFC corridor experienced after 2015 above and beyond the existing national trend are the result of the AFC program and no other development. To assess this assumption, we perform an event-study analysis that examines trends in EV shares for counties that eventually became part of the AFC program. As shown in Figure A1, he coefficients on

AFC county status interacted with year dummies show no evidence of pre-existing trends in EV shares prior to the designation of AFCs in 2015. The estimated coefficients are close to zero and statistically insignificant in the years leading up to 2015, indicating that counties treated by AFCs were not experiencing differential growth in EV adoption before the program's implementation. Following the establishment of AFCs in 2015, the coefficients become positive and statistically significant, reflecting a marked increase in EV shares in treated counties. These findings confirm that the expansion of AFCs is associated with a post-2015 surge in EV adoption, supporting the validity of the research design by demonstrating the absence of pre-trends that could confound the estimated impact of AFCs on EV adoption.

To further evaluate the validity of the IV strategy, we assess whether the instrumental variable is correlated with maternal and child characteristics at the county level in a balancing exercise. The lack of systematic correlation would suggest that AFC charging stations are not established in areas specifically targeting or avoiding populations with distinct demographic profiles. This strengthens the argument that any observed effects of EV shares on infant health are plausibly causal rather than driven by underlying population characteristics correlated with AFC station placement.

The results from this analysis are presented in Table A2. The table shows that population characteristics, such as percentage male, percentage Black, percentage White, maternal age, percentage Hispanic, percentage married, and percentage of first births, are not related to the placement of AFC stations. Among the nine characteristics examined, the only variable correlated with the number of AFC charging stations is the percentage of low-educated mothers. However, this characteristic is accounted for in our models. Overall, these findings suggest that the placement of AFC charging stations is not systematically associated with these demographic characteristics after controlling for fixed effects.

Figure 3 shows the spatial distribution of AFCs along with electric vehicle charging stations, highlighting their role in connecting urban centers while extending into less densely populated rural areas. The figure also emphasizes their prominence along major interstate routes. We argue that the rollout of AFCs is a candidate for a plausible instrument for addressing the potential endogeneity of EV adoption. First, charging infrastructure is a key driver of EV adoption, as it reduces range anxiety and enhances the convenience of EV use, satisfying the relevance condition for an instrument (Sierzchula et al., 2014; Shen et al., 2019). The AFC program, mandated at the federal level, determined the placement of charging stations based on connectivity and spacing requirements, rather than local conditions such as air quality or health outcomes, ensuring exogeneity (Federal Highway Administration, 2023). Furthermore, the exclusion restriction is supported by the assumption that AFC charging stations impact air quality and infant health only through their influence on EV adoption. This assumption stems from the federally mandated nature of the AFC program, where the placement of charging stations was primarily driven by national connectivity goals and compliance with specific spacing requirements, rather than local factors such as environmental conditions or health outcomes. The program's strategic emphasis on establishing infrastructure along major transportation corridors can be seen in Figure 4, which compares the placement of AFC and Non-AFC charging stations in the Greater Chicago area. The figure highlights how the AFC program complemented existing infrastructure to enhance EV accessibility while facilitating connectivity across major routes. This planning underscores the plausibility of the exclusion restriction, as the primary purpose of the AFC placements was to facilitate EV adoption rather than respond to localized environmental or health-related factors.

In summary, we argue that the program's federally coordinated rollout creates spatial and temporal variation in charging station availability, providing exogenous variation in EV

adoption rates across counties and over time. These characteristics make the AFC-based instrument a valid tool for isolating the causal impact of EV adoption on infant health.

Exploiting this plausibly exogenous instrument, we estimate the IV specification using two-stage least squares (TSLS). In the first stage, we regress EV adoption on the instrument and other control variables, capturing the variation in EV adoption attributable to the AFC charging station rollout. The regression equation representing the first stage can be specified as follows:

$$EV_{cmy} = \alpha + \gamma \cdot AFC_{cmy} + X_{cy}\Gamma + \lambda_c + \lambda_{my} + \epsilon_{cmy}, \quad (3)$$

where $EV_{cmy}$ represents the share of electric vehicles among registered vehicles. The variable $AFC_{cmy}$ denotes the stock of AFC charging stations per 10,000 population in county c in month m in year y, which serves as the instrument for EV adoption. $X_{cy}$ is a vector of control variables as described above. Equation (3) also includes county fixed effects and month-by-year fixed effects.

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.

$$Y_{cmy} = \alpha + \beta \cdot \widehat{EV_Gestation}_{cmy} + X_{cmy}\gamma + \lambda_c + \lambda_{my} + my.\theta_s + \epsilon_{cmy}, \quad (4)$$

where $Y_{cmy}$ is one of the outcome measures representing the domains of air pollution or infant health. The variable $EV_{Gestation_{cmy}}$represents the 9-month average EV share that infants were exposed to during their in utero period, as predicted from the first-stage regression.

## 4. Results

### 4.1. Effect of Electric Vehicles on Air Pollution

Table 2 presents the results of estimating equation (1), which captures the impact of air pollution on electric vehicle shares. The first four columns report estimates for $NO_2$ and the

AQI, while columns (5) and (6) display the results for $NO_x$. Each model incorporates county fixed effects, month-by-year fixed effects, and county-level control variables, including annual estimates for total population, total and child poverty rates, and the logarithm of the total number of registered vehicles. For each outcome, estimates are provided both with and without state-specific linear trends, ensuring robustness.

The estimates in Table 2 consistently show that an increase in the share of battery electric vehicles leads to significant improvements in air quality, as indicated by reductions in $NO_2$ and $NO_x$. These effects remain robust across various specifications, including those with and without state-specific linear trends. For $NO_2$, the results with trends indicate that a one standard-deviation increase in EV share reduces monthly mean $NO_2$ levels by 3.3 percent. Similarly, the AQI for NO2 improves by 1.7 percent with a one standard-deviation increase in EV shares. For $NO_x$ , the corresponding reduction is 7.1 percent, further underscoring the major impact of EV adoption in reducing vehicular emissions, which are the primary contributors to $NO_2$ and $NO_x$ pollution.

In Table 3, we turn to the effects of EV shares on other pollutants, including fine particulate matter (PM2.5), larger particulate matter (PM10), and carbon monoxide (CO). The results indicate that higher EV shares are associated with significant declines in PM2.5 concentrations, ranging from 1.9 percent to 2.3 percent per standard deviation increase in EV share, depending on the measure. However, reductions in PM10 are smaller and less precisely estimates, as expected due to the limited influence of vehicle emissions on larger particulates. For CO, no significant relationship is obtained, with coefficients close to zero, reflecting the unclear role of EV adoption in reducing this type of pollutant, as described earlier. These findings suggest that while EV adoption has a notable effect on fine particulate pollution, the effect size is smaller, and the impact on CO is negligible, likely due to contributions from non-tailpipe sources or variations in energy generation and consumption patterns.

Overall, these results in Tables 2 and 3 provide strong evidence that increasing EV shares leads to tangible benefits for air quality, particularly through reductions in $NO_2$ and $NO_x$, with more modest effects on particulate matter and limited impacts on CO emissions.

We further evaluate the robustness of our findings by incorporating satellite-based estimates of $NO_2$ and PM2.5 to complement the primary analysis described above. As shown in Table 4, the results indicate that higher EV shares are associated with significant reductions in both pollutants. Specifically, a one standard-deviation increase in EV share corresponds to a 2.1 percent reduction in tropospheric $NO_2$ and a 0.8 percent reduction in PM2.5. These findings align closely with those reported in Tables 2 and 3, reinforcing the environmental benefits of EV adoption. The results underscore EVs' substantial impact on reducing $NO_2$, again a pollutant closely linked to vehicle emissions, and highlight the modest yet meaningful improvements in PM2.5, which can also stem from non-tailpipe sources.

#### 4.1.2. Robustness Analyses Assessing the Effect of EV Adoption on Air Pollution

Before turning the discussion to our primary focus on the impact of EV adoption on infant health, we subject the analysis of the relationship between EV shares and air pollution to a comprehensive set of robustness checks. These analyses aim to reinforce the conclusion that EV adoption plays a significant role in reducing harmful air pollutants. The robustness checks examine various dimensions of the relationship between EV shares and key air pollutants under different specifications and sample restrictions.

In the main analysis, we restrict our attention to only one monitor for each county, the one with the most extensive temporal coverage to avoid compositional changes in air pollution measurements that might arise from the presence of additional monitors. Table A3 expands this analysis by including all available monitoring stations. The estimates from this expanded analysis are consistent with those in the main results, confirming that higher EV shares significantly reduce concentrations of $NO_2$ and $NO_x$, as well as the AQI for $NO_2$.

Table A4 extends the analysis to the commuting zone level, capturing broader pollution markets that span beyond county boundaries.[16] The results show even larger reductions in air pollutants, with a one standard-deviation increase in EV shares leading to a 4.6 percent decline in mean $NO_2$, a 3.6 percent decrease in the $NO_2$ AQI, and a 10.6 percent reduction in $NO_x$. These findings suggest that the benefits of EV adoption are not confined to localized areas but extend across larger geographic regions, emphasizing the wide-reaching impact of electrification.

Table A5 presents results using annual EV shares, without interpolation, to demonstrate that our findings remain consistent even when relying solely on the available annual snapshots of the data. The results remain very similar to those presented in Table 2, with significant reductions in mean $NO_2$, the $NO_2$ AQI, and mean $NO_x$. These findings underscore the robustness of the relationship across different temporal aggregations.

Table A6 excludes data from the COVID-19 lockdown period (March to June 2020) to account for potential disruptions in economic activity and pollution patterns. The results are consistent with the main findings, demonstrating significant reductions in air pollutants. Specifically, a one standard-deviation increase in EV shares reduces mean $NO_2$ by 2.9 percent, the $NO_2$ AQI by 1.5 percent, and mean $NO_x$ by 6.4 percent. This analysis confirms that the observed effects are not driven by temporary pandemic-related anomalies. This finding is perhaps not surprising, as vehicle usage declined sharply at the start of the pandemic in March 2020 but largely returned to near pre-pandemic levels by July 2020, as illustrated by the daily average vehicle miles traveled shown in Figure A2.

Finally, Table A7 incorporates controls for non-road emissions, such as industrial and agricultural pollution, to isolate the impact of EV adoption on air quality. The inclusion of these

[16] Commuting zones are geographic units that represents local labor markets that are more comprehensive than counties. These zones are constructed based on patterns of commuting and economic interdependence, allowing for the analysis of broader labor and pollution markets that extend beyond individual county borders. For more details, see https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas._

controls does not alter our finding. A one standard-deviation increase in EV shares reduces mean $NO_2$ by 2.9 percent, the $NO_2$ AQI by 1.1 percent, and mean $NO_x$ by 7.3 percent. These results affirm that the air quality improvements are primarily attributable to reductions in vehicular emissions, independent of other pollution sources.

Overall, these robustness checks demonstrate the consistency and reliability of the findings, highlighting the significant role of EV adoption in reducing harmful air pollutants across diverse contexts and specifications.

**4.2. Effect of Electric Vehicles on Infant Health**

After establishing the positive role of EV adoption in improving air quality, we shift our focus to its impact on infant health outcomes. Table 5 presents the results of this analysis, examining the effects of the 9-month average of EV share on the proportion of infants born with very low birthweight (i.e., birthweight <1,500 grams) births and very premature (i.e., gestation length <34 weeks) births. Additionally, the analysis includes a Severe Birth Outcomes Index, a composite measure incorporating multiple adverse outcomes, including very low birthweight, very prematurity, NICU admissions, use of assisted ventilation, surfactant therapy, and stillbirths. Each component of this index is standardized to have a mean of zero and a standard deviation of one, with higher values indicating more adverse outcomes. This index provides a comprehensive assessment of severe health risks at birth.

The results reveal that higher EV shares are significantly associated with reductions in both individual and composite measures of adverse birth outcomes. Specifically, a one standard-deviation increase in the 9-month average EV share reduces the incidence of very low birthweight births by 0.38 percent and very premature births by 0.32 percent. Likewise, the Severe Birth Outcomes Index shows a significant decline, reflecting broader improvements in neonatal health. These findings emphasize the role of reduced air pollution, driven by EV adoption, in promoting maternal and fetal health. The standardized nature of the index also

highlights the consistency of this positive impact across a range of severe health measures, underscoring the importance of electrifying transportation as a strategy to protect the health of newborns and mitigate risks associated with adverse birth outcomes.

Table 6 examines the relationship between EV shares and a broad spectrum of adverse birth outcomes, providing deeper insights into the health benefits of vehicle electrification. These outcomes include admission to the NICU, use of assisted ventilation, surfactant use, stillbirth, birthweight, low birthweight (i.e., birthweight <2,500 grams), two alternative prematurity measures based on gestation lengths of 32 and 37 weeks, a Broad Birth Outcomes Index, and infant mortality.[17] The Broad Birth Outcomes Index encompasses all outcomes presented in columns (1) through (8) as well as the measures of very low birthweight (i.e., birthweight < 1,500 grams) and very premature (i.e., gestation length < 34 weeks) births from Table 6, and is constructed similarly to the Severe Birth Outcomes Index in Table 5. The analysis uses the 9-month average of EV shares, controlling for county fixed effects, conception month-year fixed effects, maternal and child characteristics, county-level controls, and state-specific linear trends.

The findings reveal that an increase in the 9-month average EV share is associated with consistent and significant improvements across several adverse birth outcomes. For instance, a one standard-deviation increase in EV shares leads to a 0.96 percent reduction in NICU admissions, a 0.87 percent decrease in the use of assisted ventilation, and a 1.30 percent decline in surfactant use. Regarding low birthweight, a one standard-deviation increase in the 9-month average of EV shares reduces its prevalence by 0.14 percent. The effect on continuous birthweight is negative but very close to zero, indicating that the impact of EV shares is primarily concentrated at the lower tail of the birthweight distribution. Similarly, while both

[17] In vital statistics data, infant mortality is defined as the death of an infant younger than one year of age. It is calculated by linking death certificate information to the corresponding birth certificate for each infant who died during the calendar year.

measures of prematurity show negative effects, only the estimate for prematurity based on gestation lengths of fewer than 32 weeks is statistically significant, again suggesting that the effect of EV adoption is more pronounced at the lower tail of the distribution. Additionally, the Broad Birth Outcomes Index shows a significant decline, reflecting overall improvements in neonatal health. Importantly, infant mortality is reduced by a small but statistically significant margin, with a 0.004 percent decline per standard deviation increase in the 9-month average of EV shares.

Overall, these findings underscore the extensive health benefits for infants resulting from EV adoption beyond the scope of air quality improvements. By reducing exposure to vehicular emissions, which are linked to poor birth outcomes, EVs contribute to significant improvements in both individual and aggregate measures of neonatal health.

#### 4.2.1. Results from Analysis with HCUP Data

The results discussed above indicate sizeable benefits associated with EV adoption on infant health as measured at birth. Now, we turn to health measured in the first four years of childhood, extending the focus beyond the point of delivery to examine respiratory-related ED visits. These results are based on an analysis of data from nine states, covering the period from 2009 to 2021, with consistent information on county of residence and quarter of discharge obtained from HCUP.

Before discussing the results of EV shares on healthcare utilization outcomes, we first confirm that the negative impact of EV adoption on air pollution observed in the national data also holds for the HCUP sample, which includes data from nine states. Table 7 presents findings from this analysis, demonstrating that despite significant reductions in sample size, the estimates remain statistically significant and indicate sizeable air quality improvements. Specifically, a one standard-deviation increase in EV share leads to a 3.1 percent reduction in $NO_2$ levels and a 5.2 percent decrease in $NO_x$ concentrations. Additionally, the results show

modest improvements in PM2.5, with a 1.7 percent decline in concentrations. These findings underscore the robustness of the air quality benefits associated with EV adoption, even within this more limited sample.

We next examine whether the air quality improvements driven by increased EV adoption translate into measurable health benefits for young children. As shown in Table 8, the results reveal a consistent pattern of reduced ED visits for this age group as EV shares increase. Specifically, a one standard-deviation increase in EV share is associated with a 1.7 percent decline in overall ED visits and a 1.9 percent reduction in visits for respiratory conditions. Among specific diagnoses, asthma-related visits decrease by 10.8 percent, while bronchitis-related visits show a decline of 2.4 percent, though the estimate is not statistically significant. When combining asthma and bronchitis cases however, the results indicate a statistically significant 5.2 percent reduction. These findings suggest that the air quality improvements associated with greater EV adoption translate into measurable reductions in respiratory illnesses among young children. The stronger effects for asthma-related visits underscore the acute sensitivity of this condition to air pollution levels, a finding consistent with prior literature that links vehicular emissions to respiratory health risks.

#### 4.2.2. Robustness Analyses Assessing the Effect of EV Adoption on Infant Health

In this section, we subject our analysis to a broad set of robustness exercises to assess the reliability of the main findings. Table 9 presents results for our main outcomes from several alternative specifications, including models with additional controls, variations in the sample period, and adjustments to the sample selection criteria.

Panel A of Table 9 presents estimates from a specification that includes non-road emissions as a control, accounting for pollution sources unrelated to vehicles.[18] The results

[18] Data on non-road emissions are available from the national emissions inventory of the U.S. Environmental Protection Agency. See https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei.

remain consistent, with significant reductions in very low birthweight, very premature births, and the Severe Birth Outcomes Index. This suggests that the effects of EV adoption on birth outcomes are specifically attributable to reductions in vehicular emissions rather than being confounded by changes in air quality from non-road pollution sources, such as industrial facilities, construction equipment, and agricultural operations.

Panel B of Table 9 excludes observations from the period after June 2019 to account for potential confounding effects from the COVID-19 pandemic.[19] The pandemic caused significant disruptions in air pollution and economic activity, with reduced industrial activity and vehicle usage temporarily lowering pollution levels. To evaluate whether these changes artificially amplify the observed relationship between EV adoption and improved birth outcomes, we repeat our analysis, excluding data from the pandemic period. The results remain consistent, with significant improvements in birth outcomes persisting even after this exclusion. This provides strong evidence that the findings are not driven by temporary shifts in pollution or economic activity during the pandemic.

Panels C and D examine the robustness of the results by modifying the sample criteria to account for specific subgroups. Panel C removes births to mothers under 18 years of age, a demographic that may differ significantly in health and socioeconomic characteristics. The results remain robust, indicating that the inclusion of this subgroup does not bias the findings. Panel D includes births with gestation lengths below 23 weeks, which were excluded from the main analysis to minimize potential noise from measurement error or extreme values. The inclusion of these cases does not alter the overall pattern of results, reaffirming the consistency of the findings across the full range of gestation lengths. Together, these analyses demonstrate

[19] 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.

that the main results are not driven by outlier subgroups or extreme cases, further validating the robustness of the findings.

Panel F excludes counties without $NO_2$ monitoring stations, ensuring that the analysis only includes counties with a measurement of $NO_2$ - the most directly emitted pollutant from vehicles – is available. Despite the substantial reduction in sample size by approximately 20-fold, the results remain significant, further validating the main findings and highlighting the robustness of the relationship between EV shares, air quality, and improved health outcomes.

Finally, Panel G aggregates the analysis to the commuting zone level, capturing broader labor and pollution markets that span beyond individual county boundaries.[20] While the effects remain significant for very low birthweight and very premature births, the results for the Severe Birth Outcomes Index are slightly attenuated and lose statistical significance. This suggests some heterogeneity in the strength of the relationship at a larger spatial scale.

Overall, the robustness exercises discussed above provide strong evidence that the observed improvements in birth outcomes associated with higher EV shares are not sensitive to specific modeling choices, data periods, or sample restrictions. These findings reinforce the conclusion that increased EV adoption contributes to meaningful reductions in adverse birth outcomes, likely through its impact on air quality.

### 4.3. Results from the Instrumental Variables Analysis

Table 10 presents the first-stage results, which establish the relationship between the instrumental variable—the number of charging stations within one mile of designated AFCs per 10,000 population—and the share of EVs. Due to differences in the number of observations available for $NO_2$, $NO_x$, and the birth outcome variables, the first-stage results are presented separately to match the samples for each outcome. The coefficient on the instrument is both

[20] Commuting zones are geographic units that represents local labor markets that are more comprehensive than counties. These zones are constructed based on patterns of commuting and economic interdependence, allowing for the analysis of broader labor and pollution markets that extend beyond individual county borders. For more details, see https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas._

statistically significant and economically meaningful across all three estimations, showing that an increase of one AFC station per 10,000 population leads to a 0.005 percentage point increase in the share of EVs in a county. The validity of the instrument is further supported by high F-statistics from the Kleibergen-Paap F-test, indicating the instrument's strength and its relevance for explaining variation in EV shares. This significant relationship underscores the importance of infrastructure availability in reducing range anxiety and increasing the feasibility of EV ownership.

The IV estimates for impact of EV shares on air pollution are presented in Table 11. The results indicate significant improvements in air quality linked to increased EV adoption, as identified through our instrumental variables approach. The estimates show that a one percentage point increase in EV share leads to reductions of 0.955 ppb in arithmetic mean NO2, 1.306 units in NO2 AQI, and 1.381 ppb in arithmetic mean NOX, respectively. To gauge the magnitude of these effects through our instrument, we find that a one standard deviation increase in AFC stations per 10,000 population reduces arithmetic mean NO2 by 2.4%, NO2 AQI by 1.6%, and arithmetic mean NOX by 3.7% through its impact on EV adoption. The strength of our identification strategy is supported by Kleibergen-Paap F-statistics ranging from 30.13 to 33.05, well above conventional weak instrument thresholds. These effects are larger than those from the reduced form models presented in Table 2, and underscore the essential role of EV adoption in mitigating vehicle emissions, particularly $NO_2$ and $NO_x$, which are directly emitted by internal combustion engine vehicle.

Table 12 shifts the focus to infant health outcomes, revealing significant benefits for infant health associated with increased EV adoption. Specifically, when quantified through our instrument, a one standard deviation increase in AFC stations leads to reductions of 0.63% in very low birthweight incidence and 0.35% in very premature births. These results align with

existing literature that identifies air pollution as a critical risk factor for adverse neonatal outcomes.

Table 13 presents the IV estimates of the effect of EV adoption on emergency department (ED) visits among children aged 0–4, using the number of EV charging stations near AFCs as an instrument for EV adoption. The instrumental variable estimates remain precisely estimated despite the reduced sample size, which is limited to data availability from nine states and the quarterly nature of the HCUP dataset.[21] The results indicate a significant reduction in total ED visits, particularly for respiratory conditions. Specifically, a one standard deviation increase in AFC stations leads to reductions of 5.5% in all ED visits, 5.7% in respiratory visits, 23% in asthma visits, 3.3% in bronchitis visits, and 9.1% in combined asthma and bronchitis visits. These results suggest that increased EV adoption contributes to significant improvements in pediatric health outcomes, particularly by reducing air pollution exposure.

Taken together, these results provide compelling evidence for the broader benefits of EV adoption, with clear impacts on both environmental and infant health outcomes. The reductions in pollutants such as $NO_2$ and $NO_x$ emphasize the environmental gains associated with electrification, while the concurrent improvements in neonatal health outcomes illustrate its public health implications.

## 5. Conclusions

This study provides comprehensive nationwide evidence on the environmental and health benefits of EV adoption. Our findings highlight that increased EV penetration significantly reduces key air pollutants, including $NO_2$ and $NO_x$, which are major contributors to poor air quality caused by vehicle emissions. These reductions in air pollution translate into

[21] The Kleibergen-Paap F-statistic, while lower than in the main analysis, remains above the conventional threshold of 10, confirming that the instrument is sufficiently strong to address potential endogeneity concerns.

meaningful health improvements for infants and young children. Specifically, we observe significant declines in adverse birth outcomes, including very low birthweight and very preterm births, as well as reductions in respiratory-related emergency department visits among children aged 0–4 years. In addition, EV adoption is associated with substantial reductions in various neonatal health complications, including lower rates of admissions to neonatal intensive care units (NICUs), reduced use of assisted ventilation and surfactant therapy, and declines in overall infant mortality. These results emphasize the dual benefits of EV adoption for both environmental quality and public health.

In addressing potential endogeneity of EV adoption, we make a significant methodological contribution by employing an instrumental variable approach based on the strategic placement of charging stations along federally designated Alternative Fuel Corridors. This strategy not only strengthens the causal interpretation of our findings but also serves as a valuable framework for future research into the impacts of transportation electrification.

Our findings carry important policy implications. First, they underscore the importance of continued investment in EV infrastructure, such as charging stations, to reduce barriers to EV adoption and accelerate the transition away from internal combustion engine vehicles. Policymakers should prioritize the equitable distribution of such infrastructure to ensure that the health and environmental benefits of EVs are accessible to all communities, including those in underserved and rural areas. Second, the results highlight the value of complementary policies that incentivize EV adoption, such as tax rebates, subsidies, and public awareness campaigns. These measures can amplify the environmental and health benefits identified in this study.

Moreover, our analysis provides evidence to support integrating public health considerations into transportation and environmental policymaking. The documented reductions in adverse birth outcomes and respiratory illnesses underscore the need for

policymakers to consider the long-term societal benefits of EV adoption, including potential reductions in healthcare costs and improvements in human capital. By framing transportation electrification as a public health intervention in addition to an environmental strategy, policymakers can build stronger, more comprehensive cases for investment in clean transportation.

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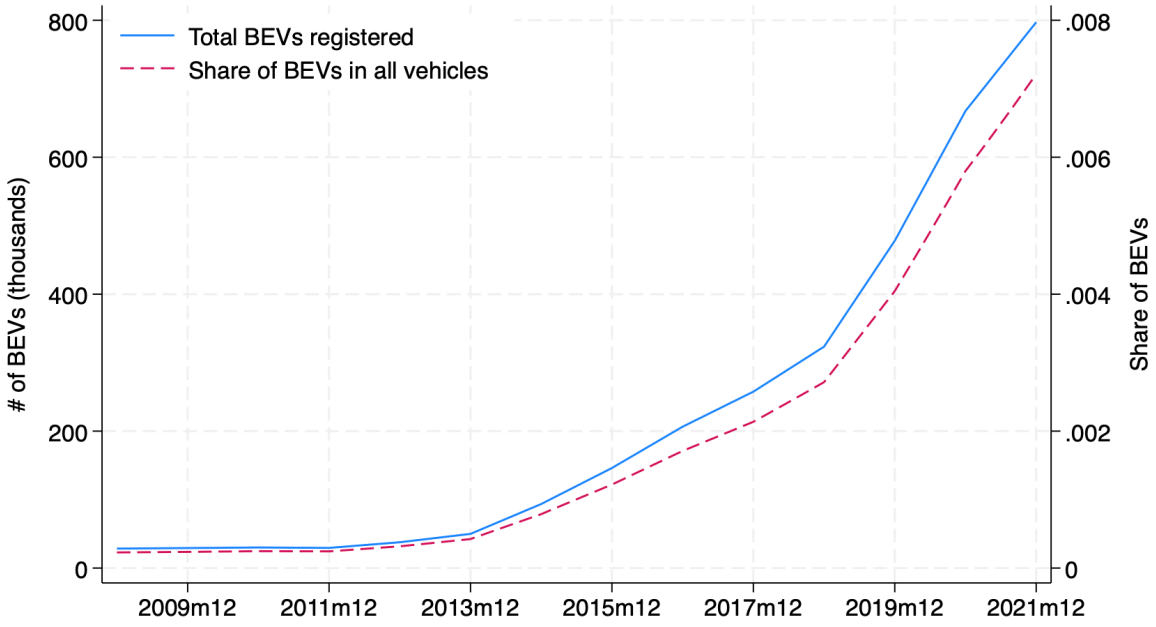
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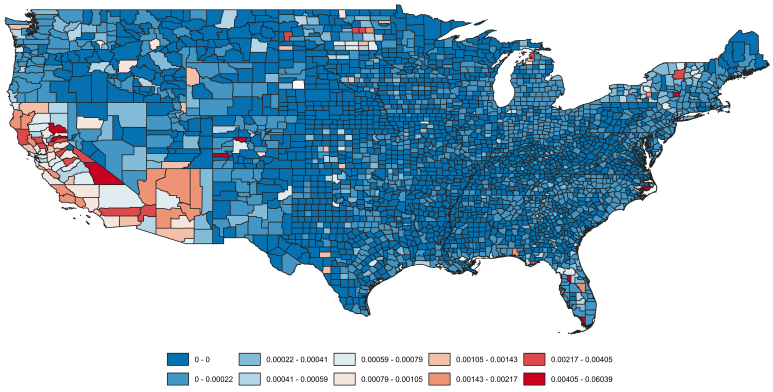
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Figure 1: US BEV adoption over time

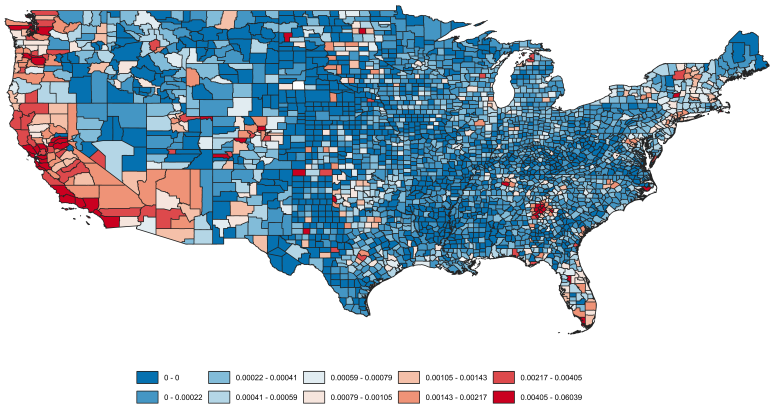



Notes: The figure displays total number of BEVs (Battery electric vehicle) in thousands (blue line on the left axis) and share of registered BEVs among all registered vehicles (red dashed line on the right axis) for the entire U.S. in a given month. Vehicle registration data come from IHS Markit.

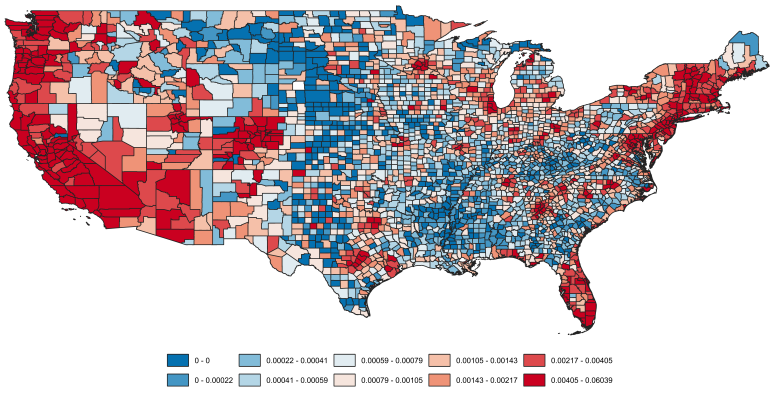
Figure 2: County Level Evolution in the Share of Electric Vehicles




(a) Share of Electric Vehicles in 2009



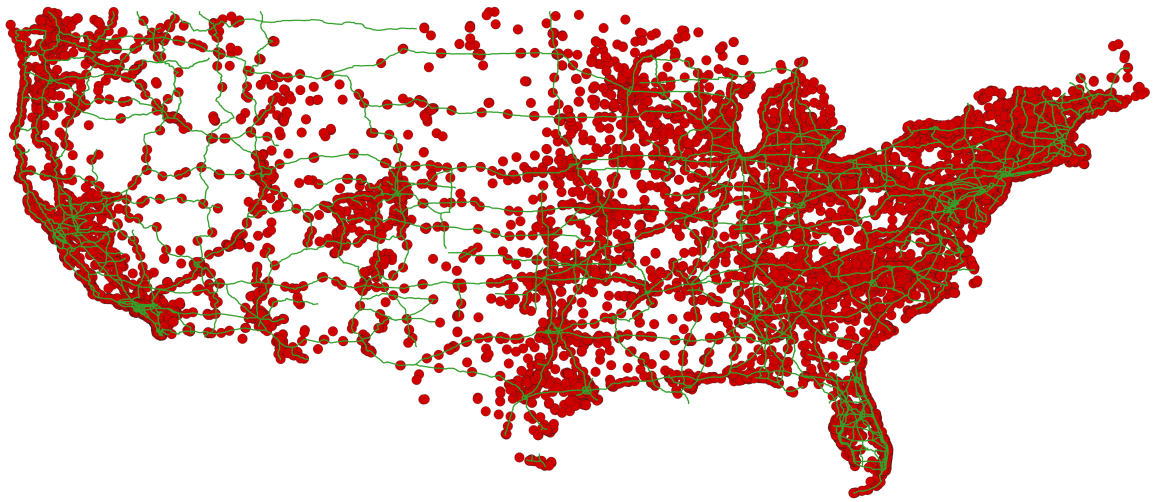

(b) Share of Electric Vehicles in 2016




(c) Share of Electric Vehicles in 2021

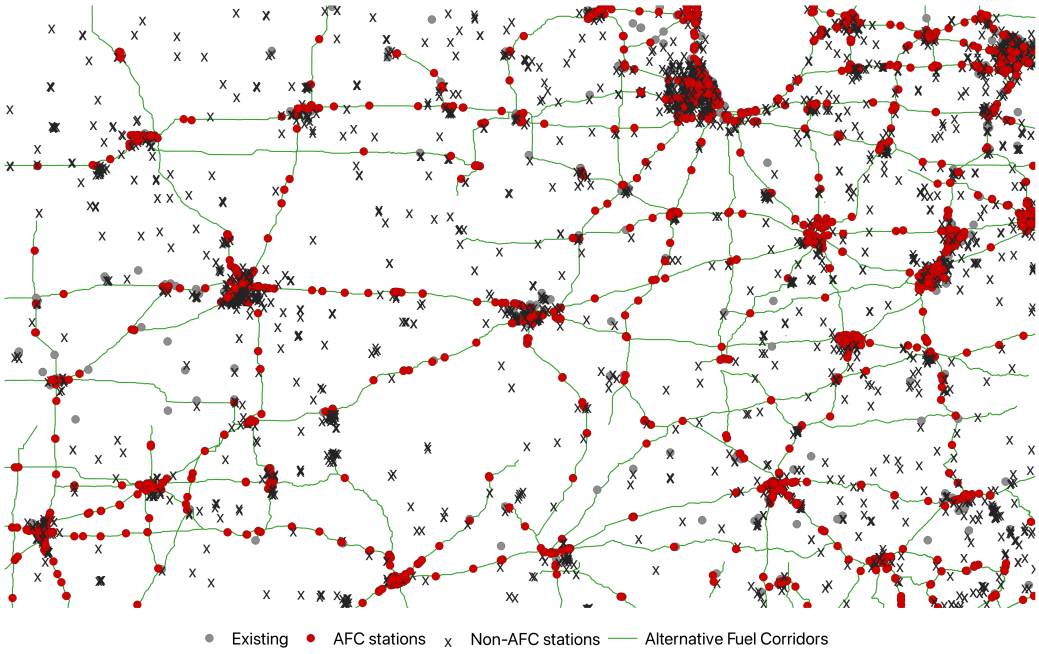
Notes: The figure displays the evolution of county shares of registered BEVs (Battery electric vehicle) among all registered vehicles. Coloring scheme is based on deciles of BEV share at the end of 2021. Vehicle registration data come from IHS Markit.

Figure 3: Alternative Fuel Corridors and Charging Stations



Notes: The figure displays the locations of Alternative Fuel Corridors and EV charging stations as of the most recent update based on data from U.S. Department of Energy and Federal Highway Administration.

Figure 4: A Snapshot of Alternative Fuel Corridors and Charging Stations, Greater Chicago Area




Notes: The figure displays the locations of Alternative Fuel Corridors (AFC) shown in green and EV charging stations in greater Chicago area as of the most recent update based on data from U.S. Department of Energy and Federal Highway Administration. Gray dots represent charging stations that already existed before the initial AFC announcement. Red dots represent stations opened after 2015 within one mile from corridors whereas gray $x$s represent stations that were not included in the corridors.

# Table 1: Descriptive Statistics

| | Observations | Mean | SD |
|---|---|---|---|
| BEV share (×100) | 444,039 | 0.048 | 0.153 |
| **Panel A: Pollution Outcomes** | | | |
| Arithmetic Mean, $NO_2$ (ppb) | 23,936 | 7.619 | 5.145 |
| AQI, $NO_2$ | 23,936 | 15.571 | 8.527 |
| Arithmetic Mean, $NO_x$ (ppb) | 22,999 | 7.145 | 7.636 |
| Arithmetic Mean, $PM_{2.5}$ ($\mu g/m^3$) | 58,736 | 8.523 | 3.855 |
| AQI, $PM_{2.5}$ | 58,733 | 33.393 | 11.480 |
| Arithmetic Mean, $PM_{10}$ ($\mu g/m^3$) | 32,423 | 19.310 | 10.760 |
| AQI, $PM_{10}$ | 32,423 | 17.568 | 8.876 |
| Arithmetic Mean, CO (ppm) | 13,679 | 0.283 | 0.159 |
| AQI, CO | 13,676 | 4.401 | 2.930 |
| Tropospheric $NO_2$ ($10^{15}$ molec $cm^{-2}$ ) | 475,830 | 7.264 | 2.575 |
| Satellite $PM_{2.5}$ ($\mu g/m^3$) | 472,402 | 1.940 | 1.281 |
| **Panel B: Infant Health Outcomes** | | | |
| Birthweight | 444,039 | 3289.807 | 248.236 |
| Very Low Birthweight | 444,039 | 0.013 | 0.064 |
| Low Birthweight | 444,039 | 0.071 | 0.106 |
| Very Premature (GL<34 Weeks) | 444,039 | 0.025 | 0.083 |
| Very Premature (GL<32 Weeks) | 444,039 | 0.015 | 0.070 |
| Premature (GL<37 Weeks) | 444,039 | 0.092 | 0.126 |
| Admission to NICU | 429,452 | 0.073 | 0.113 |
| Assisted Ventilation | 429,452 | 0.016 | 0.060 |
| Surfactant | 429,452 | 0.006 | 0.041 |
| Stillbirth | 429,532 | 0.002 | 0.022 |
| Infant mortality rate | 439,579 | 0.543 | 2.055 |
| **Panel C: Birth Characteristics** | | | |
| Percentage of first baby | 444,039 | 0.307 | 0.150 |
| Percentage of male | 444,039 | 0.488 | 0.160 |
| Mothers Age | 444,039 | 27.281 | 2.240 |
| Percentage of mothers education w/< high school | 444,039 | 0.137 | 0.131 |
| Percentage of mothers high school | 444,039 | 0.282 | 0.174 |
| Percentage of mothers education w/> high school | 444,039 | 0.523 | 0.226 |
| Percentage of black mothers | 444,039 | 0.106 | 0.179 |
| Percentage of white mothers | 444,039 | 0.848 | 0.200 |
| Percentage of hispanic mothers | 444,039 | 0.120 | 0.183 |
| Percentage of married mothers | 444,039 | 0.584 | 0.195 |
| Percentage of mothers smoked during pregnancy | 444,039 | 0.081 | 0.255 |
| **Panel D: Health Outcomes (HCUP Data)** | | | |
| Total ED visits per 1,000 children aged 0-4 | 25,803 | 0.068 | 0.058 |
| Respiratory disease ED visits per 1,000 children aged 0-4 | 25,803 | 0.018 | 0.019 |
| Asthma-related ED visits per 1,000 children aged 0-4 | 25,803 | 0.001 | 0.001 |
| Bronchitis-related ED visits per 1,000 children aged 0-4 | 25,803 | 0.002 | 0.003 |
| Asthma and bronchitis ED visits per 1,000 children aged 0-4 | 25,803 | 0.003 | 0.004 |
| **Panel E: County Characteristics** | | | |
| Total Population (1000s) | 444,039 | 103.712 | 328.062 |
| Poverty rate | 444,039 | 0.160 | 0.064 |
| Child poverty rate | 444,039 | 0.222 | 0.100 |
| Total vehicles registered (1000s) | 444,039 | 39.529 | 125.909 |
| Total miles driven by state in a month (1000s) | 444,039 | 7.122 | 6.121 |

*Notes:* BEV (Battery electric vehicle) share refers to the share of registered BEVs among all registered vehicles in a county in a given month. Vehicle registration data come from IHS Markit. Pollutant data are from the EPA daily monitor datasets. Infant health outcomes and birth characteristics are monthly county averages based on birth records from National Center for Health Statistics. Quarterly ED visits data are from HCUP. Annual county characteristics are from the Census Bureau. State-level miles driven are based on Traffic Volume Trends from Federal Highway Administration.

# Table 2: EV Shares and Air Quality

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Arithmetic Mean $NO_2$ | | Air Quality Index $NO_2$ | | Arithmetic Mean $NO_X$ | |
| BEV share | -55.29*** | -54.71*** | -64.43*** | -56.64*** | -120.23*** | -107.15*** |
| | (7.63) | (8.36) | (16.37) | (15.87) | (17.47) | (15.70) |
| % Effect of 1sd increase | -3.3 | -3.3 | -1.9 | -1.7 | -8.0 | -7.1 |
| State Specific Linear Trends | No | Yes | No | Yes | No | Yes |
| Observations | 23,640 | 23,640 | 23,640 | 23,640 | 22,855 | 22,855 |
| R-squared | 0.84 | 0.84 | 0.84 | 0.85 | 0.69 | 0.71 |

*Notes:* BEV (Battery electric vehicle) share refers to share of registered BEVs among all registered vehicles in a county in a given month. Vehicle registration data come from IHS Markit. Pollutant data are from the EPA daily monitor datasets. For both $NO_2$ (nitrogen dioxide) and $NO_X$ (nitrogen oxides), arithmetic mean refers to the monthly mean concentration reported in ppb (parts per billion). "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in BEV share. All regressions control for county and month-by-year fixed effects, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Observations at the county-by-month level span from 2009 to 2021. Standard errors are clustered at the county level. *** p<0.01,** p<0.05,* p<0.1.

Table 3: EV Shares and Air Quality: Other Pollutants

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Arithmetic Mean | | | Air Quality Index | | |
| | $PM_{2.5}$ | $PM_{10}$ | CO | $PM_{2.5}$ | $PM_{10}$ | CO |
| BEV share | -55.25*** | -69.16* | 0.24 | -179.89*** | -45.15 | 0.24 |
| | (15.12) | (40.51) | (1.23) | (46.53) | (31.80) | (16.81) |
| % Effect of 1sd increase | -2.3 | -1.4 | 0.5 | -1.9 | -1.0 | 0.0 |
| Observations | 57,154 | 31,389 | 13,427 | 57,151 | 31,389 | 13,424 |
| R-squared | 0.38 | 0.50 | 0.57 | 0.48 | 0.54 | 0.64 |

*Notes:* BEV (Battery electric vehicle) share refers to share of registered BEVs among all registered vehicles in a county in a given month. Vehicle registration data come from IHS Markit. Pollutant data are from the EPA. Arithmetic mean refers to the monthly mean concentration reported in $\mu g/m^3$ for $PM_{2.5}$ and $PM_{10}$, and in ppm (parts per million) for CO (carbon monoxide). "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in BEV share. All regressions control for county and month-by-year fixed effects, state-specific linear time trends, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Observations at the county-by-month level span from 2009 to 2021. Standard errors are clustered at the county level.*** p<0.01,** p<0.05,* p<0.1.

Table 4: EV Shares and Satellite-based Estimates

| | (1) | (2) |
|---|---|---|
| | Tropospheric $NO_2$ | Mean $PM_{2.5}$ |
| BEV share | -23.65*** | -34.47*** |
| | (3.42) | (7.72) |
| % Effect of 1sd increase | -2.1 | -0.8 |
| Observations | 472,070 | 475,191 |
| R-squared | 0.64 | 0.53 |

*Notes:* BEV (Battery electric vehicle) share refers to share of registered BEVs among all registered vehicles in a county in a given month. Vehicle registration data come from IHS Markit. Satellite-based pollutant estimates are from the Boersma et al. (2011) and van Donkelaar et al. (2021). Monthly mean tropospheric columns for $NO_2$ are reported in $10^{15}$ molec $cm^{-2}$ and monthly mean concentrations for $PM_{2.5}$ are reported in $\mu g/m^3$. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in BEV share. All regressions control for county and month-by-year fixed effects, state-specific linear time trends, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Observations at the county-by-month level span from 2009 to 2021. Standard errors are clustered at the county level.*** $p<0.01$,** $p<0.05$,* $p<0.1$.

# Table 5: EV Shares and Adverse Birth Outcomes

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Very Low Birthweight | | Very Premature (GL<34 Weeks) | | Severe Birth Outcomes Index | |
| BEV (9-month average) | -0.021*** | -0.031*** | -0.027** | -0.048*** | -1.032** | -1.261*** |
| | (0.007) | (0.008) | (0.011) | (0.014) | (0.428) | (0.430) |
| % Effect of 1sd increase | -0.27 | -0.38 | -0.18 | -0.32 | – | – |
| State Specific Linear Trends | No | Yes | No | Yes | No | Yes |
| Observations | 444,039 | 444,039 | 444,045 | 444,045 | 444,045 | 444,045 |
| R-squared | 0.45 | 0.45 | 0.48 | 0.48 | 0.31 | 0.31 |

*Notes:* BEV (Battery electric vehicle) refers to nine-month average over county share of registered BEVs among all registered vehicles starting from the month of conception. Vehicle registration data come from IHS Markit. Birth data are from National Center for Health Statistics restricted data files. Adverse birth outcomes are monthly average incidence rates in a county for all births conceived in a given month. See text for details on variable construction. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in average BEV share. All regressions control for county and month-by-year fixed effects, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Additional controls include the child's birth order, gender, maternal age, race, maternal education, marital status, and maternal smoking status. Observations at the county-by-month level span from 2009 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,* p<0.1.

# Table 6: EV Shares and Adverse Birth Outcomes

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Admission to NICU | Assisted Ventilation | Surfactant | Stillbirth | Birthweight | Low Birthweight | Very Premature (GL<32 weeks) | Premature (GL<37 weeks) | Broad Birth Outcomes Index | Infant Mortality |
| BEV (9-month average) | -0.412* | -0.084** | -0.047*** | -0.011 | -189.031* | -0.060** | -0.026** | -0.114 | -0.896*** | -1.244** |
| | (0.220) | (0.041) | (0.015) | (0.007) | (111.632) | (0.025) | (0.011) | (0.073) | (0.314) | (0.514) |
| % Effect of 1sd increase | -0.96 | -0.87 | -1.30 | -0.93 | -0.01 | -0.14 | -0.28 | -0.21 | | -0.004 |
| Observations | 429,458 | 429,458 | 429,458 | 429,538 | 444,039 | 444,039 | 444,045 | 444,045 | 444,045 | 439,579 |
| R-squared | 0.27 | 0.20 | 0.10 | 0.03 | 0.62 | 0.42 | 0.49 | 0.52 | 0.48 | 0.05 |

*Notes:* BEV (Battery electric vehicle) refers to nine-month average over county share of registered BEVs among all registered vehicles starting from the month of conception. Vehicle registration data come from IHS Markit. Birth and mortality data are from National Center for Health Statistics restricted data files. Adverse birth outcomes are monthly average incidence rates in a county for all births conceived in a given month. See text for details on variable construction. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in average BEV share. All regressions control for county and month-by-year fixed effects,state specific linear time trends, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Additional controls include the child's birth order, gender, maternal age, race, maternal education, marital status, and maternal smoking status. Observations at the county-by-month level span from 2009 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,* p<0.1.

Table 7: EV Shares and Air Quality: Estimates from the HCUP States

| | (1) | (2) | (3) |
|---|---|---|---|
| | Arithmetic Mean $NO_2$ | AQI $NO_2$ | Arithmetic Mean $NO_X$ |
| BEV share | -38.085*** | -27.428* | -106.617*** |
| | (9.030) | (16.013) | (20.108) |
| % Effect of 1sd increase | -3.00 | -1.09 | -9.46 |
| Observations | 2,797 | 2,797 | 2,740 |
| R-squared | 0.89 | 0.88 | 0.78 |

*Notes:* BEV (Battery electric vehicle) share refers to share of registered BEVs among all registered vehicles in a county in a given quarter. Vehicle registration data come from IHS Markit. Pollutant data are from the EPA. For both $NO_2$ (nitrogen dioxide) and $NO_X$ (nitrogen oxides), arithmetic mean refers to the quarterly mean concentration reported in ppb (parts per billion). Regressions repeat the main analyses on air quality by restricting the sample to nine states covered in HCUP dataset: AZ, FL,KY,MD,MN,NJ, NY,NC, WI. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in BEV share. All regressions control for county and quarter-by-year fixed effects, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given quarter. Observations at the county-by-quarter level span from 2009 to 2021. Standard errors are clustered at the county level. *** p<0.01,** p<0.05,* p<0.1.

Table 8: EV Shares and ED Visits for Ages 0-4

| Diagnosis | All Visits | Respiratory | Asthma | Bronchitis | Ast. + Bronc. |
|---|---|---|---|---|---|
| BEV share | -1.18* | -0.35** | -0.11*** | -0.05 | -0.16*** |
| | (0.55) | (0.17) | (0.04) | (0.04) | (0.06) |
| % Effect of 1-sd increase | -1.7 | -1.9 | -10.8 | -2.4 | -5.2 |
| Observations | 25,803 | 25,803 | 25,803 | 25,803 | 25,803 |
| R-squared | 0.96 | 0.91 | 0.88 | 0.77 | 0.84 |

*Notes:* BEV (Battery electric vehicle) share refers to share of registered BEVs among all registered vehicles in a county in a given quarter. Vehicle registration data come from IHS Markit. 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 at ages 0-4 from Census. See text for details on variable construction. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in BEV share. All regressions control for county and quarter-by-year fixed effects, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given quarter. Observations at the county-by-quarter level span from 2009 to 2021. Regressions are weighted by the county population at ages 0-4. Standard errors are clustered at the county level.*** p<0.01,** p<0.05,* p<0.1.

# Table 9: Robustness Exercises

| | (1) | (2) | (3) |
|---|---|---|---|
| | Very Low Birthweight | Very Premature (GL<34 Weeks) | Severe Birth Outcomes Index |
| **Panel A: Controlling for Non-Road Emissions** | | | |
| BEV (9-month average) | -0.026*** | -0.043*** | -1.107** |
| | (0.007) | (0.015) | (0.434) |
| % Effect of 1sd increase | -0.32 | -0.28 | – |
| Observations | 430,457 | 430,459 | 430,459 |
| **Panel B: Excluding Post COVID-19 Lockdown Period** | | | |
| BEV (9-month average) | -0.023** | -0.036* | -1.657** |
| | (0.011) | (0.020) | (0.689) |
| % Effect of 1sd increase | -0.26 | -0.20 | – |
| Observations | 375,564 | 375,565 | 375,565 |
| **Panel C: Excluding mothers below age 18** | | | |
| BEV (9-month average) | -0.031*** | -0.049*** | -1.236*** |
| | (0.008) | (0.014) | (0.422) |
| % Effect of 1sd increase | -0.39 | -0.32 | – |
| Observations | 443868 | 443874 | 443874 |
| **Panel D: Including births with GL < 23 wks** | | | |
| BEV (9-month average) | -0.031*** | -0.049*** | -1.256*** |
| | (0.009) | (0.014) | (0.427) |
| % Effect of 1sd increase | -0.35 | -0.30 | – |
| Observations | 444,301 | 444,374 | 444,374 |
| **Panel E: Using annual BEV shares** | | | |
| BEV (9-month average) | -0.026*** | -0.044*** | -1.195*** |
| | (0.007) | (0.012) | (0.401) |
| % Effect of 1sd increase | -0.37 | -0.33 | – |
| Observations | 444,039 | 444,045 | 444,045 |
| **Panel F: NO2 Monitors Sample** | | | |
| BEV (9-month average) | -0.038*** | -0.042** | -1.024** |
| | (0.008) | (0.018) | (0.495) |
| % Effect of 1sd increase | -0.89 | -0.59 | – |
| Observations | 22,856 | 22,856 | 22,856 |
| **Panel G: Commuting Zone Analysis** | | | |
| BEV (9-month average) | -0.054*** | -0.054** | -0.843 |
| | (0.020) | (0.024) | (0.859) |
| % Effect of 1sd increase | -0.57 | -0.32 | – |
| Observations | 88,678 | 88,680 | 88,680 |

*Notes:* BEV (Battery electric vehicle) refers to nine-month average over county (or CZ) share of registered BEVs among all registered vehicles starting from the month of conception. Vehicle registration data come from IHS Markit. Birth data are from National Center for Health Statistics restricted data files. Adverse birth outcomes are monthly average incidence rates in a county for all births conceived in a given month. See text for details on variable construction. Panel A controls for non-road emissions, annual county $NO_X$ emissions excluding on-road vehicle emissions from EPA National Emissions Inventory. Panel B drops births conceived in or after March 2020, the start of COVID-19 lockdowns. Panel C excludes births to mothers who were below age 18. Panel D includes births with gestational age less than 23 weeks. Panel E uses annual share of registered BEVs among all registered vehicles in a county at the end of each reporting year. Panel F restricts the analysis sample to counties with non-missing pollutant monitor data. Panel G repeats the main analysis using commuting zone (CZ) level observations. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in average BEV share. All regressions control for county (or CZ) and month-by-year fixed effects, state-specific linear time trends, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Additional controls include the child's birth order, gender, maternal age, race, maternal education, marital status, and maternal smoking status. Observations at the county- or CZ-by-month level span from 2009 to 2021. Regressions are weighted by the number of births in each county (or CZ)-month-year cell. Standard errors are clustered at the county (or CZ) level.*** p<0.01,** p<0.05,* p<0.1.

Table 10: First stage estimates: AFC Stations and BEV shares

| | (1) | (2) | (3) |
|---|---|---|---|
| Sample: | Arithmetic Mean NO2 | Arithmetic Mean NOx | Adverse Birth Outcomes |
| AFC stations per 10,000 pop. | 0.005*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) |
| Observations | 23,640 | 22,855 | 444,039 |
| R-squared | 0.82 | 0.83 | 0.82 |

*Notes:* Dependent variable is BEV (Battery electric vehicle) share that refers to share of registered BEVs among all registered vehicles in a county in a given month. Vehicle registration data come from IHS Markit. 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. Each column refers to a first-stage regression between our instrumental variable and BEV share using a different analysis sample. All regressions control for county and month-by-year fixed effects, state specific time trends,total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Observations at the county-by-month level span from 2009 to 2021. Standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: IV Estimates: EV Shares and Air Quality

| | (1) | (2) | (3) |
|---|---|---|---|
| | Arithmetic Mean NO2 | AQI NO2 | Arithmetic Mean NOx |
| BEV share | -95.52*** | -130.62*** | -138.05*** |
| | (17.77) | (29.75) | (26.83) |
| % Effect of 1sd increase | -2.4 | -1.6 | -3.7 |
| Observations | 23,640 | 23,640 | 22,855 |
| F-stat (Kleibergen-Paap) | 33.05 | 33.05 | 30.13 |

*Notes:* BEV (Battery electric vehicle) share refers to share of registered BEVs among all registered vehicles in a county in a given month. Vehicle registration data come from IHS Markit. 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 from the EPA. For both $NO_2$ (nitrogen dioxide) and $NO_X$ (nitrogen oxides), arithmetic mean refers to the monthly mean concentration reported in ppb (parts per billion). Each column refers to an IV regression using AFC stations per population as the instrument. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in the instrument. All regressions control for county and month-by-year fixed effects, state specific linear time trends,total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Observations at the county-by-month level span from 2009 to 2021. Standard errors are clustered at the county level. *** p<0.01,** p<0.05,* p<0.1.

Table 12: IV Estimates: EV Shares and Adverse Birth Outcomes

| | (1) | (2) | (3) |
|---|---|---|---|
| | Very Low Birthweight | Very Premature (GL<34 Weeks) | Severe Birth Outcomes Index |
| BEV (9-month average) | -0.060*** | -0.064*** | -1.462* |
| | (0.014) | (0.024) | (0.823) |
| % Effect of 1sd increase | -0.63 | -0.35 | – |
| Observations | 444,039 | 444,045 | 444045 |
| F-stat (Kleibergen-Paap) | 44.00 | 44.00 | 39.40 |

*Notes:* BEV (Battery electric vehicle) refers to nine-month average over county share of registered BEVs among all registered vehicles starting from the month of conception. Vehicle registration data come from IHS Markit. 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. Birth data are from National Center for Health Statistics restricted data files. Adverse birth outcomes are monthly average incidence rates in a county for all births conceived in a given month. See text for details on variable construction. Each column refers to an IV regression using AFC stations per population as the instrument. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in the instrument. All regressions control for county and month-by-year fixed effects, state specific linear time trends,total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Additional controls include the child's birth order, gender, maternal age, race, maternal education, marital status, and maternal smoking status. Observations at the county-by-month level span from 2009 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, * p<0.1.

Table 13: IV Estimates: EV Shares and ED Visits for Ages 0-4

| Diagnosis | All Visits | Respiratory | Asthma | Bronchitis | Ast. + Bronc. |
|---|---|---|---|---|---|
| BEV share | -17.916** | -4.965*** | -1.099** | -0.376* | -1.475*** |
| | (7.012) | (1.854) | (0.555) | (0.193) | (0.552) |
| % Effect of 1-sd increase | -5.5 | -5.7 | -23 | -3.3 | -9.1 |
| Observations | 25,803 | 25,803 | 25,803 | 25,803 | 25,803 |
| F-stat (Kleibergen-Paap) | 11.32 | 11.32 | 11.32 | 11.32 | 11.32 |

*Notes:* BEV (Battery electric vehicle) share refers to share of registered BEVs among all registered vehicles in a county in a given quarter. Vehicle registration data come from IHS Markit. 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. Emergency deparment 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 at ages 0-4 from Census. See text for details on variable construction. Each column refers to an IV regression using AFC stations per population as the instrument. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in the instrument. All regressions control for county and quarter-by-year fixed effects, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given quarter. Observations at the county-by-quarter level span from 2009 to 2021. Regressions are weighted by the county population at ages 0-4. Standard errors are 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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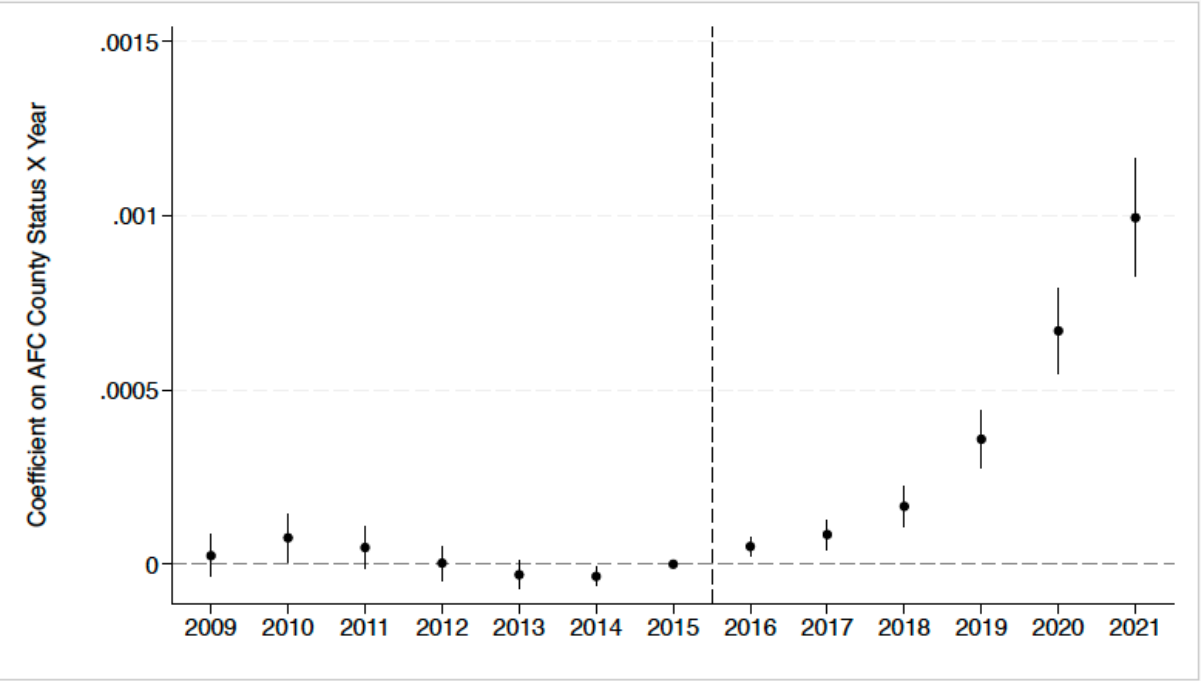
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American University

## Supplementary Appendix

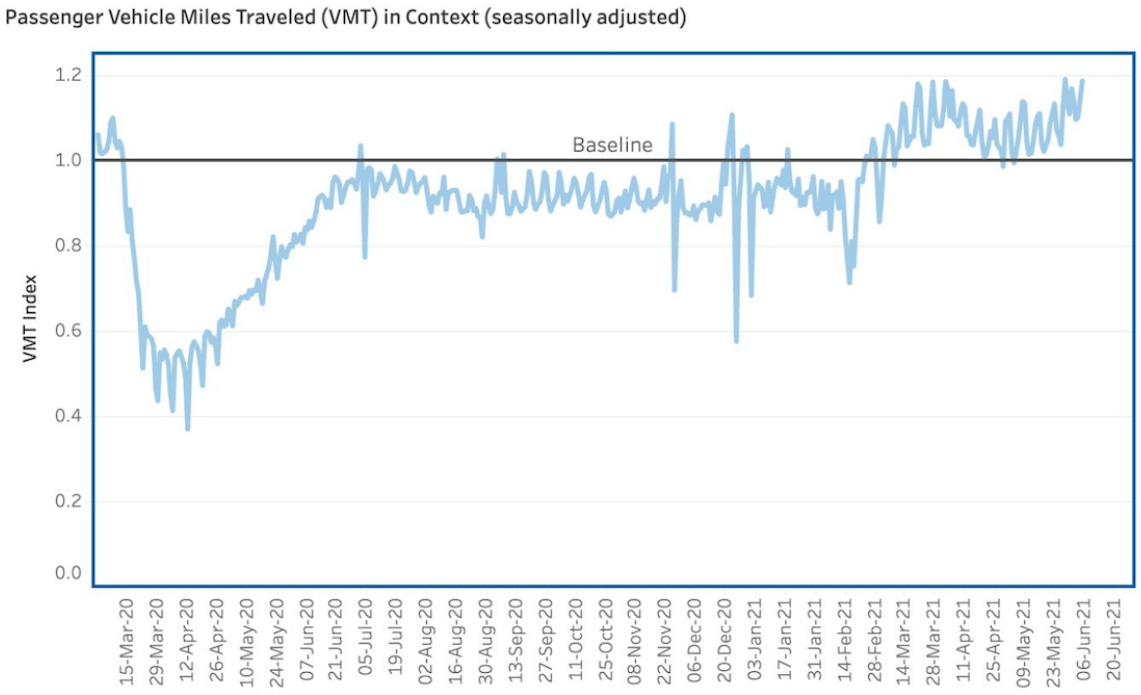
For Online Publication

Figure A.1: Dynamic Effects of Alternative Fuel Corridors by Year




Notes: The figure displays the effects of Alternative Fuel Corridor (AFC) project on BEV (Battery electric vehicle) share, that is annual share of registered BEVs 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 status and year for the period between 2009 and 2021. Vehicle registration data come from IHS Markit. AFC project data come from the Federal Highway Administration.

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).

# Table A.1: Balanced Covariates

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Percentage Male | Percentage Black | Percentage White | Mothers Age | Percentage Hispanic | Percentage Married | Percentage First Baby | Perc. Low Education | Perc. High Education |
| BEV (9-mo average) | -0.001 | 0.225 | -0.297 | -3.092* | -0.520** | 0.209 | 0.025 | 0.426 | 0.345 |
| | (0.048) | (0.139) | (0.211) | (1.581) | (0.236) | (0.794) | (0.133) | (0.383) | (0.452) |
| % Effect of 1sd increase | -0.00 | 0.35 | -0.06 | -0.02 | -0.72 | 0.06 | 0.01 | 0.17 | 0.11 |
| Observations | 444,045 | 444,045 | 444,045 | 444,045 | 444,045 | 444,045 | 444,045 | 444,045 | 444,045 |
| R-squared | 0.01 | 0.97 | 0.99 | 0.92 | 0.98 | 0.71 | 0.58 | 0.90 | 0.92 |

*Notes:* Maternal and birth characteristics are monthly county averages based on birth records from National Center for Health Statistics. BEV (Battery electric vehicle) refers to nine-month average over county share of registered BEVs among all registered vehicles starting from the month of conception. Vehicle registration data come from IHS Markit. Each column regresses a separate covariate on average BEV share. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in average BEV share. All regressions include county and month-by-year fixed effects, state-specific linear time trends, and controls for total population, poverty rate, child poverty rate, the log of total registered vehicles, and total miles driven at the state level each month. Additionally, maternal characteristics, excluding the dependent variable, include the child's birth order, gender, maternal age, race, education, marital status, and smoking status. Observations at the county-by-month level span from 2009 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, * p<0.1.

# Table A.2: Balanced Covariates, AFC

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Percentage Male | Percentage Black | Percentage White | Mothers Age | Percentage Hispanic | Percentage Married | Percentage First Baby | Perc. Low Education | Perc. High Education |
| AFC stations | 0.000 | -0.001 | 0.002 | 0.030 | 0.000 | 0.003 | 0.001 | 0.005** | -0.001 |
| per 10,000 pop. | (0.001) | (0.002) | (0.002) | (0.026) | (0.002) | (0.009) | (0.001) | (0.002) | (0.003) |
| % Effect of 1sd increase | 0.00 | -0.29 | 0.05 | 0.03 | 0.07 | 0.13 | 0.05 | 0.28 | -0.03 |
| Observations | 453,210 | 453,210 | 453,210 | 453,210 | 453,210 | 453,210 | 453,210 | 453,210 | 453,210 |
| R-squared | 0.01 | 0.97 | 0.99 | 0.92 | 0.98 | 0.72 | 0.58 | 0.91 | 0.93 |

*Notes:* Maternal and birth characteristics are monthly county averages based on birth records from National Center for Health Statistics. 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. Each column regresses a separate covariate on the instrument, AFC stations per 10,000 population. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in the instrument. All regressions include county and month-by-year fixed effects, state-specific linear time trends, and controls for total population, poverty rate, child poverty rate, the log of total registered vehicles, and total miles driven at the state level each month. Additionally, maternal characteristics, excluding the dependent variable, include the child's birth order, gender, maternal age, race, education, marital status, and smoking status. Observations at the county-by-month level span from 2009 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, * p<0.1.

Table A.3: EV Shares and Air Quality: Multiple Monitors Sample

| | (1) | (2) | (3) |
|---|---|---|---|
| | Arithmetic Mean $NO_2$ | AQI $NO_2$ | Arithmetic Mean $NO_X$ |
| BEV share | -46.27*** | -43.34*** | -103.63*** |
| | (10.19) | (14.77) | (17.28) |
| % Effect of 1sd increase | -2.7 | -1.3 | -6.6 |
| Observations | 36,079 | 36,079 | 34,118 |
| R-squared | 0.74 | 0.76 | 0.61 |

*Notes:* BEV (Battery electric vehicle) share refers to share of registered BEVs among all registered vehicles in a county in a given month. Vehicle registration data come from IHS Markit. Pollutant data are from the EPA. For both $NO_2$ (nitrogen dioxide) and $NO_X$ (nitrogen oxides), arithmetic mean refers to the monthly mean concentration at the monitor level reported in ppb (parts per billion). "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in BEV share. All regressions control for county and month-by-year fixed effects, state specific linear time trends, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Observations at the monitor-by-month level span from 2009 to 2021. Standard errors are clustered at the county level.*** p<0.01,** p<0.05,* p<0.1.

Table A.4: EV Shares and Air Quality: Commuting Zone Analysis

| | (1) | (2) | (3) |
|---|---|---|---|
| | Arithmetic Mean $NO_2$ | AQI $NO_2$ | Arithmetic Mean $NO_X$ |
| BEV share | -96.62*** | -160.21*** | -203.07*** |
| | (28.86) | (43.56) | (66.00) |
| % Effect of 1sd increase | -4.6 | -3.6 | -10.6 |
| Observations | 14,563 | 14,563 | 14,535 |
| R-squared | 0.85 | 0.86 | 0.73 |

*Notes:* BEV (Battery electric vehicle) share refers to share of registered BEVs among all registered vehicles in a commuting zone (CZ) in a given month. Vehicle registration data come from IHS Markit. Pollutant data are from the EPA. For both $NO_2$ (nitrogen dioxide) and $NO_X$ (nitrogen oxides), arithmetic mean refers to the monthly mean concentration reported in ppb (parts per billion). "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in BEV share. All regressions control for CZ and month-by-year fixed effects, CZ specific linear time trends, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Observations at the CZ-by-month level span from 2009 to 2021. Standard errors are clustered at the CZ level.*** p<0.01,** p<0.05,* p<0.1.

Table A.5: EV Shares and Air Quality: Using Annual Shares

| | (1) | (2) | (3) |
|---|---|---|---|
| | Arithmetic Mean $NO_2$ | AQI $NO_2$ | Arithmetic Mean $NO_X$ |
| BEV share | -56.98*** | -60.51*** | -108.78*** |
| | (7.92) | (15.42) | (14.99) |
| % Effect of 1sd increase | -3.8 | -2.0 | -8.0 |
| Observations | 23,640 | 23,640 | 22,855 |
| R-squared | 0.84 | 0.85 | 0.71 |

*Notes:* BEV (Battery electric vehicle) share refers to annual share of registered BEVs among all registered vehicles in a county at the end of each reporting year. Vehicle registration data come from IHS Markit. Pollutant data are from the EPA. For both $NO_2$ (nitrogen dioxide) and $NO_X$ (nitrogen oxides), arithmetic mean refers to the monthly mean concentration reported in ppb (parts per billion). "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in annual BEV share. All regressions control for county and month-by-year fixed effects, state specific linear time trends, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Observations at the county-by-month level span from 2009 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 Air Quality: Dropping COVID-19 Lockdowns

| | (1) | (2) | (3) |
|---|---|---|---|
| | Arithmetic Mean $NO_2$ | AQI $NO_2$ | Arithmetic Mean $NO_X$ |
| BEV share | -49.61*** | -51.30*** | -101.05*** |
| | (8.33) | (15.77) | (15.17) |
| % Effect of 1sd increase | -2.9 | -1.5 | -6.4 |
| Observations | 23,017 | 23,017 | 22,254 |
| R-squared | 0.84 | 0.85 | 0.71 |

*Notes:* BEV (Battery electric vehicle) share refers to share of registered BEVs among all registered vehicles in a county in a given month. Vehicle registration data come from IHS Markit. Pollutant data are from the EPA. For both $NO_2$ (nitrogen dioxide) and $NO_X$ (nitrogen oxides), arithmetic mean refers to the monthly mean concentration reported in ppb (parts per billion). "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in BEV share. All regressions control for county and month-by-year fixed effects, total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Observations at the county-by-month level span from 2009 to 2021 with the exception of COVID-19 lockdown period between March 2020 and June 2020. Standard errors are clustered at the county level.*** p<0.01,** p<0.05,* p<0.1.

Table A.7: EV Shares and Air Quality: Controlling for Non-Road Emissions

| | (1) | (2) | (3) |
|---|---|---|---|
| | Arithmetic Mean $NO_2$ | AQI $NO_2$ | Arithmetic Mean $NO_X$ |
| BEV share | -47.89*** | -38.31** | -109.46*** |
| | (8.27) | (15.04) | (17.61) |
| Non-road Emissions | 53.51*** | 77.26*** | 82.58*** |
| | (16.22) | (28.48) | (26.14) |
| % Effect of 1sd increase | -2.9 | -1.1 | -7.3 |
| Observations | 21,805 | 21,805 | 21,073 |
| R-squared | 0.84 | 0.85 | 0.71 |

*Notes:* BEV (Battery electric vehicle) share refers to share of registered BEVs among all registered vehicles in a county in a given month. Vehicle registration data come from IHS Markit. Pollutant data are from the EPA. For both $NO_2$ (nitrogen dioxide) and $NO_X$ (nitrogen oxides), arithmetic mean refers to the monthly mean concentration reported in ppb (parts per billion). Non-road emissions reported in thousand tonnes are annual county $NO_X$ emissions excluding on-road vehicle emissions from EPA National Emissions Inventory. "% Effect of 1 sd increase" refers to percentage change in dependent variable as a response to one-standard-deviation increase in BEV share. All regressions control for county and month-by-year fixed effects, state specific linear time trends,total population, poverty rate, child poverty rate, the log total vehicles registered, and total miles driven by state in a given month. Observations at the county-by-month level span from 2009 to 2020. Standard errors are clustered at the county level.*** p<0.01,** p<0.05,* p<0.1.