

EPIDEMIOLOGY

A population-based cohort study of traffic congestion and infant growth using connected vehicle data

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More than 11 million Americans reside within 150 meters of a highway, an area of high air pollution exposure. Traffic congestion further contributes to environmental pollution (e.g., air and noise), but its unique importance for population health is unclear. We hypothesized that degraded environmental quality specifically from traffic congestion has harmful impacts on fetal growth. Using a population-based cohort of births in Texas (2015–2016), we leveraged connected vehicle data to calculate traffic congestion metrics around each maternal address at delivery. Among 579,122 births, we found consistent adverse associations between traffic congestion and reduced term birth weight (8.9 grams), even after accounting for sociodemographic characteristics, typical traffic volume, and diverse environmental coexposures. We estimated that up to 1.2 million pregnancies annually may be exposed to traffic congestion (27% of births in the United States), with ~256,000 in the highest congestion zones. Therefore, improvements to traffic congestion may yield positive cobenefits for infant health.

INTRODUCTION

More than 11 million people in the United States live within 150 m of a major highway and are exposed to elevated levels of traffic-generated air pollution (1). Traffic congestion, defined as roads operating at lower than free-flow speeds because of an excess of vehicles (2), further contributes to this problem. Congestion is a modern lifestyle inconvenience of great interest to policy-makers, researchers, and the public alike for various health and nonhealth reasons (3). Traffic congestion has increased consistently from 1982 to 2019 and is costing up to \$190 billion per year in delay time and wasted fuel (4).

Traffic congestion leads to increased motor vehicle emissions, resulting in higher levels of traffic-related air pollutants. Traffic-related air pollution is a heterogeneous mixture (5), and the concentrations and exact composition of air pollution will vary on the basis of a range of parameters, including the number of vehicles, driving conditions and vehicle speed, fuel combustion, and vehicle fleet characteristics (i.e., age of cars, proportions of cars versus trucks, etc.) (2, 6). In general, higher numbers of vehicles on the road increases traffic-related air pollution concentrations, with an exponential decrease in concentrations away from roadways but remaining elevated above background levels up to 500 m (5). Congestion can markedly increase vehicle emissions and local air pollutant concentrations (7, 8); for instance, emissions measured in passenger vehicles increased by 200% when comparing rush hour driving to free-flow driving conditions (9).

There is a large body of epidemiological literature addressing the influence of traffic-related air pollution on reproductive and infant

health outcomes (10, 11). However, limited work to date has specifically examined the potential additional influence of traffic congestion (Fig. 1), largely due to the challenges of measuring congestion accurately for large geographic areas (12). Across a wide variety of countries and settings, living near a major road during pregnancy, as well as exposure to specific traffic air pollutants, has consistently been associated with decreased birth weight and increased risk of preterm birth (5, 10, 11, 13–16). Most of the exposure assessments used in these studies were based on proximity to major roads or models of specific traffic pollutants (e.g., NO₂), with very little of this evidence incorporating traffic congestion in their exposure measures (17). No studies have specifically examined the added impact of congestion, in addition to traffic volume and “normal” background traffic air pollution levels, on adverse birth outcomes. This has important policy implications because congestion can be modified through policy and infrastructure changes that may be independent from those targeting vehicle volumes or tailpipe emissions (e.g., electronic tolling and congestion pricing).

Here, we leverage congestion measurement data derived from vehicle movement information, in the form of connected vehicles and device data on driving volumes and speeds, linked to a population-based retrospective cohort of births in Texas. Using this database, we examine associations between metrics of congestion and term birth weight. By systematically examining exposure to both vehicle volume and congestion and controlling for background air pollution levels, transportation noise, and other

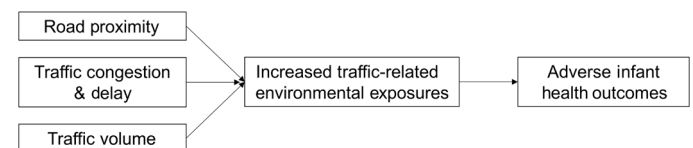


Fig. 1. Conceptual diagram of the different components contributing to increased traffic-related environmental pollution exposures. Most studies to date quantify only road proximity and traffic volume.

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environmental coexposures, this study provides important, policy-relevant insights into the extent that traffic congestion may contribute to adverse reproductive health outcomes and whether health impacts should be included in evaluations of the benefits of policies aiming to reduce congestion.

RESULTS

Descriptive statistics

We presented the metrics from the Texas' Most Congested Roadways database (18) for Houston in 2016 (Fig. 2). We reported the means and interquartile ranges for each exposure metric related to traffic (Table 1) and the correlations among congestion exposure metrics (table S1). Briefly, vehicle miles traveled (VMT) represents the annual traffic count of vehicles multiplied by the length of each road segment in the buffer distances around maternal residences, while traffic delay was the total person-hours of delay multiplied by the length of each road segment in the buffer distances around maternal residences. Congestion emissions were calculated using traffic delay to determine the total pounds of carbon dioxide emitted from all vehicles during congestion multiplied by the length of each road segment in the buffer distances around maternal residences. While traffic volume and total delay were highly correlated (0.81 for 500-m buffers around mother's home addresses), as well as traffic volume- and congestion-related emissions [correlation coefficient (r) = 0.75 for 500-m buffers], there are unique geographic patterns when comparing volume and congestion (Fig. 2); in addition, we showed that congestion-related emissions on specific road segments can exceed 50% of total emissions. The correlation between total delay and background levels of particulate matter 2.5 (PM_{2.5}), NO₂, and ultrafine particle air pollution was 0.18, 0.42, and 0.48 for the 500-m buffer area, respectively. This geographic variation provided an opportunity to isolate the unique contributions of congestion in addition to vehicle volume and background air pollution levels, on infant health.

In total, there were 579,122 term births included in our analysis (Table 2 and Fig. 3.) While mean gestational ages were similar

across quintiles of exposures for traffic delay within 500 m of their maternal residence at delivery, birth weights were, on average, 29 g lower in the highest quintile of exposure compared to the lowest quintile of exposure, and trends corresponded to the low-birth weight percentages. When comparing the lowest to the highest quintile of traffic delay, we observed that mothers were more likely to be non-White race, Hispanic ethnicity, use Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), and have normal weight in the prepregnancy period. These mothers were also less likely to be highly educated and report smoking during pregnancy. In the group experiencing the highest quintile of traffic delay, mothers were less likely to live in a single-family home and more likely to live in a structure built before 1978, although we noted that this housing-related data were not available for all mother-infant dyads. Increasing levels of all environmental coexposures corresponded to higher tertiles of traffic delay.

Traffic congestion and birth weight

In restricted cubic splines, we observed a nonlinear association between congestion metrics and term birth weight (Fig. 3). On the basis of a visual examination of where the spline knots fell, we determined that our exposure metrics should be divided into quintiles for the linear regression models.

We found consistent associations between congestion metrics and term birth weight in base (model 1), individual variable (birth certificate)-adjusted (model 2), and environmental coexposure-adjusted models (model 3) (Table 3). In base models, we observed reduced term birth weight with increasing traffic delay, relative to mothers with no congestion exposure: -7.57 [95% confidence interval (CI): -11.62 , -3.53], -21.86 (95% CI: -25.93 , -17.8), -24.2 (95% CI: -28.31 , -20.08), -24.55 (95% CI: -28.77 , -20.33), and -31.88 (95% CI: -36.92 , -26.83). In models adjusted for individual variables from the birth certificate (model 2), associations were attenuated across the quintiles of exposure: -3.15 (95% CI: -6.95 , 0.64), -8.66 (95% CI: -12.42 , -4.91), -9.35 (95% CI: -13.18 , -5.52), -10.33 (95% CI: -14.28 , -6.37), and -15.21 (95% CI: -20 , -10.42). In models

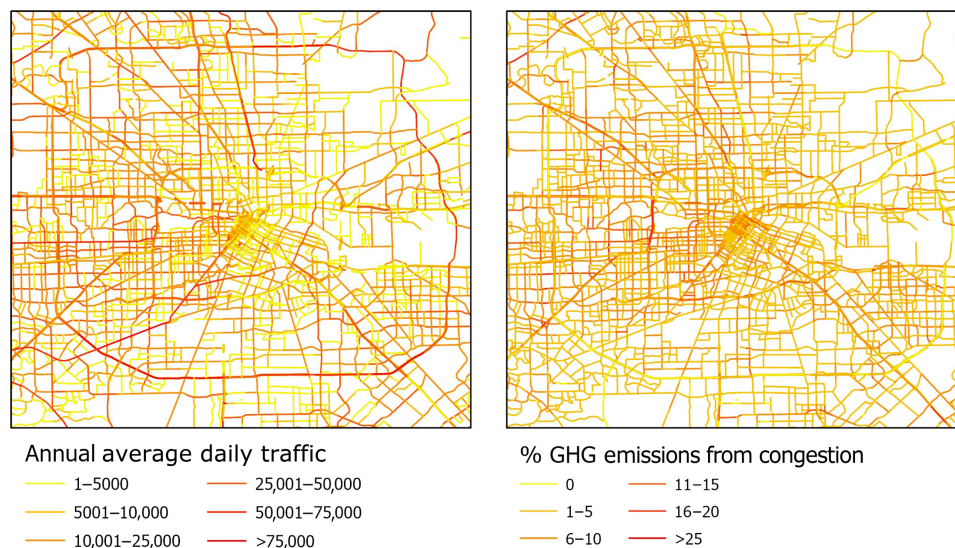


Fig. 2. A comparison of traffic characteristics in Houston, Texas, 2016. Displayed data show road segments by traffic volume and percent of total greenhouse gas (GHG) emissions due to congestion.

Table 1. Summary of data used to estimate traffic congestion.

Adapted from the Texas A&M Transportation Institute reports on the Top 100 Most Congested Roadways program (18, 41). Study population is maternal-infant dyads for births in Texas between 2015 and 2016, where the maternal residence is within 500 m of a road segment in the Top 100 Most Congested Roadways program. IQR, interquartile range; N/A, not applicable.

Specific metric	Data contributed to analysis	All traffic median (IQR)	Truck-only median (IQR)
VMT	Annual traffic count of vehicles multiplied by the length of each road segment in the buffer distances around maternal residences	7901 (2032, 17,627)	340 (87, 798)
Delay	Total person-hours of delay multiplied by the length of each road segment in the buffer distances around maternal residences	14,587 (2512, 38,164)	457 (71, 1540)
Congestion emissions	Total pounds of CO ₂ emitted from all vehicles during congestion multiplied by the length of each road segment in the buffer distances around maternal residences	69 (11, 186)	N/A

further adjusted for environmental coexposures, associations were further attenuated: -3.43 (95% CI: $-7.24, 0.38$), -6.55 (95% CI: $-10.35, -2.75$), -5.79 (95% CI: $-9.72, -1.86$), -5.48 (95% CI: $-9.63, -1.32$), and -8.93 (95% CI: $-14.08, -3.79$). Similar associations were found for truck delay and congestion emissions. When we examined mothers living within 100 and 300 m of major roadways (Table 3 and tables S2 and S3), we observed slightly larger associations. For example, in model 2 comparing the highest quintile of all traffic delay to no exposure, we observed -13.73 g (95% CI: $-21.20, -6.26$) of reduced term birth weight for the 100-m exposure buffer distance and -10.90 g (95% CI: $-16.30, -5.50$) for the 300-m exposure buffer. We also saw strong associations among an interquartile range increase in PM_{2.5}, NO₂, and ultrafine particle concentrations and reduced term birth weight in adjusted models (table S4).

Sensitivity analyses

We found similar magnitude results as described for our main adjusted regression model when we conducted extensive sensitivity analyses (Fig. 4 and tables S5 to S12). Traffic exposure misclassification due to a mother moving in pregnancy is a common concern in birth cohort studies that rely on home addresses at time of delivery. We used property data linkage to identify movers and then restricted analyses to mothers who lived at an address that did not have a housing transaction during pregnancy (and therefore were less likely to have moved during pregnancy); this restriction did not change the overall interpretation of our results (table S5). Similarly, among mothers who reported being a homemaker or unemployed (and therefore likely to spend more time at the home location used for exposure assignment), we observed a larger estimated effect size

than the ones presented as our main adjusted results above, but for mothers who reported being employed, associations are largely similar, although with wider CIs (tables S6 and S7). Among mothers whose addresses correspond to a single-family home, we find similar results as for the adjusted main model (table S8). However, we find no association among mothers who lived in multifamily homes or apartments (table S9). For mothers born in the United States (table S10) and births not induced (table S11), the results are largely similar to those from our adjusted main model. For sociodemographic characteristics such as payment mechanism for delivery (tables S12 and S13), WIC usage (tables S14 and S15), education level (tables S16 and S17), and maternal race and ethnicity (tables S18 and S19), the results are also similar to the main adjusted model.

Population burden estimate

Our results show that 84.9% of the term births in our sample reside in a congested exposure zone (within 500 m of a road segment with traffic congestion), and we observe an inverse association between traffic delay and term birth weight in all quintiles of exposure. We also find that 17.0% of term births are located in the highest exposure zones, where we observe the largest magnitude of association with traffic delay. On the basis of the number of term births in the United States per year (3,362,371) and the proportion of the national population that resides near major roads (30 to 45%), we estimate that between 856,276 and 1,284,414 term births per year may be exposed to traffic delay, of which we estimate that between 171,252 and 256,879 term births per year are in the highest exposure zones.

DISCUSSION

Our analysis of term births suggests that traffic congestion, as measured by delay per mile and greenhouse gas emissions from congestion, may adversely affect term birth weight, beyond the impacts of traffic volume, background air pollution, and noise on nearby roads. Specifically, traffic delay within 500 m of a maternal residence at delivery was associated with an estimated mean decrease of 9 g when comparing the highest to the lowest quintile of exposure after adjusting for individual covariates and environmental coexposures. Mothers who lived closer to these roadways (i.e., 100 and 300 m) experienced slightly larger impacts. Although congestion and total traffic volumes are highly coupled, these results suggest that there are additional health impacts from congestion-related air pollution emissions separate from traffic volume. We estimate that up to 1.3 million term births per year in the United States are exposed to traffic delay at levels that may restrict infant growth, indicating that this exposure may have wide-reaching population health implications. Furthermore, we estimate that up to 260,000 term births are in the highest exposure zones where we observe the largest magnitude of association. This has important policy implications: First, congestion can be reduced through specific infrastructure and policy changes that may be independent from those targeting vehicle volumes and tailpipe emissions, and second, health impacts should be included in evaluations of the benefits of policies aiming to reduce congestion.

Our present results do not suggest that redesigning highways and expressways with more lanes and higher throughput is the solution to improving population health outcomes associated with traffic-related air pollution. Rather, we argue that vehicle congestion is an understudied and quantified component of traffic-related air pollution that can be easily intervened upon at a local level. Reducing

Table 2. Study characteristics of included mother-infant dyads, born between 37 and 42 weeks gestation, Texas, USA, 2015–2016. HS, high school; NDVI, normalized different vegetation index.

Characteristic	Full study population	500–1000 m (comparison group)	Total delay within 500 m of the residence				
			Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Total births	579,122	87,528	98,319	98,319	98,319	98,319	98,318
Infant characteristics							
Birth weight (mean in grams)	3350	3370	3362	3348	3344	3343	3333
Gestational age (mean in weeks)	38.9	38.9	38.9	38.9	38.9	38.9	38.9
Low birth weight (%)	2.6	2.3	2.4	2.5	2.7	2.7	2.8
Female infant (%)	49.1	49.3	49.1	49.2	49.2	49.1	48.9
Maternal characteristics							
Age at delivery (mean in years)	27.8	28.2	27.4	27.7	27.7	27.7	28.0
Maternal race (%)							
White	73.0	76.3	79.0	74.2	72.5	70.9	65.0
Black	12.8	10.0	9.5	12.9	13.7	13.7	16.7
American Indian or Alaskan Native	0.3	0.3	0.4	0.3	0.2	0.2	0.2
Asian	5.7	5.2	3.5	4.8	5.3	6.9	8.7
Pacific Islander	0.1	0.2	0.1	0.2	0.2	0.2	0.1
Other race	8.1	8.1	7.6	7.7	8.1	8.1	9.2
Hispanic/Latina ethnicity (%)	48.7	44.8	42.9	49.1	51.8	52.2	51.0
Educational attainment (%)							
Eighth grade or less	4.0	3.3	3.3	3.5	3.7	4.4	5.6
Ninth grade, no diploma	15.2	12.1	13.9	14.8	15.5	16.5	17.7
HS grad or GED	26.8	23.6	28.1	27.8	27.9	27.2	25.5
Some college credit but no degree	22.0	22.8	23.8	22.8	22.2	21.2	18.9
Associate's	5.9	6.8	6.7	6.1	5.8	5.4	4.9
Bachelor's	17.8	21.6	17.2	17.2	16.9	16.9	17.4
Master's	6.5	7.7	5.6	6.1	6.3	6.3	7.3
Doctorate	1.9	2.0	1.4	1.7	1.7	2.0	2.7
Cigarette user (%)	4.8	4.8	7.6	5.4	4.3	3.8	2.7
Payment mechanism for delivery (%)							
Medicaid	46.6	40.2	46.8	47.7	48.2	48.4	47.6
Private insurance	39.2	47.3	41.7	39.3	37.6	36.0	34.3
Self-pay	7.9	6.5	6.4	7.6	8.4	9.0	9.6
Other	6.2	6.0	5.2	5.4	5.8	6.5	8.5
WIC usage (%)	45.1	38.1	43.3	45.9	46.7	47.6	48.2
No prenatal care (%)	4.5	3.6	3.3	4.3	4.8	5.2	5.7
Prepregnancy body mass index (%)							
Underweight	3.6	3.6	3.4	3.5	3.5	3.6	3.8
Normal weight	45.3	45.3	42.9	44.1	44.8	46.7	48.4
Overweight	26.1	26.5	26.6	26.1	26.1	25.6	25.9
Obese	25.0	24.6	27.1	26.3	25.6	24.2	21.9
Mother born outside the United States (%)	29.4	25.0	20.9	25.9	28.9	33.5	41.9
Mother employed (%)	48.0	45.4	48.6	47.6	47.6	48.5	50.0

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Characteristic	Full study population	500–1000 m (comparison group)	Total delay within 500 m of the residence				
			Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Housing characteristics							
Dwelling type (%)*							
Single-family home	72.3	78.4	82.0	80.8	76.5	66.7	47.2
Mobile home	5.4	7.6	10.8	5.2	3.5	2.9	2.3
Multifamily dwelling/apartment	22.3	10.4	10.8	14.1	20.0	30.4	50.5
Structure built before 1978 (%)†	38.5	24.1	33.3	38.3	44.2	46.9	45.3
Housing transaction during pregnancy (%)	9.0	10.1	8.4	9.1	8.9	8.8	9.1
Neighborhood characteristics							
Area deprivation index (state rank, mean)‡	5.5	4.9	5.7	5.7	5.7	5.4	5.1
PM _{2.5} (µg/m ³ , mean) [§]	9.2	8.9	8.6	9.1	9.3	9.4	9.6
NO ₂ (µg/m ³ , mean) [§]	6.5	5.4	4.6	6.0	6.8	7.5	8.7
Ultrafine particles (count, mean) [§]	7,102	5,512	4,919	6,458	7,397	8,286	9,870
Transportation noise (decibels, mean)	9.9	2.8	6.8	6.7	8.6	13.1	20.5
NDVI within 500 m (mean)	0.56	0.60	0.62	0.58	0.55	0.53	0.48

*A total of 509,794 records for this characteristic due to only a subset of linked tax records containing these data from CoreLogic. †A total of 474,148 records for this characteristic due to only a subset of linked tax records containing these data from CoreLogic. ‡Derived from the 2015 Area Deprivation Index (43, 44). §Derived from the Center for Air, Climate, and Energy Solutions land use regression model (46, 48). ||Derived from the Center for Air, Climate, and Energy Solutions land use regression model (47). ¶Derived from the National Transportation Noise Map (45).

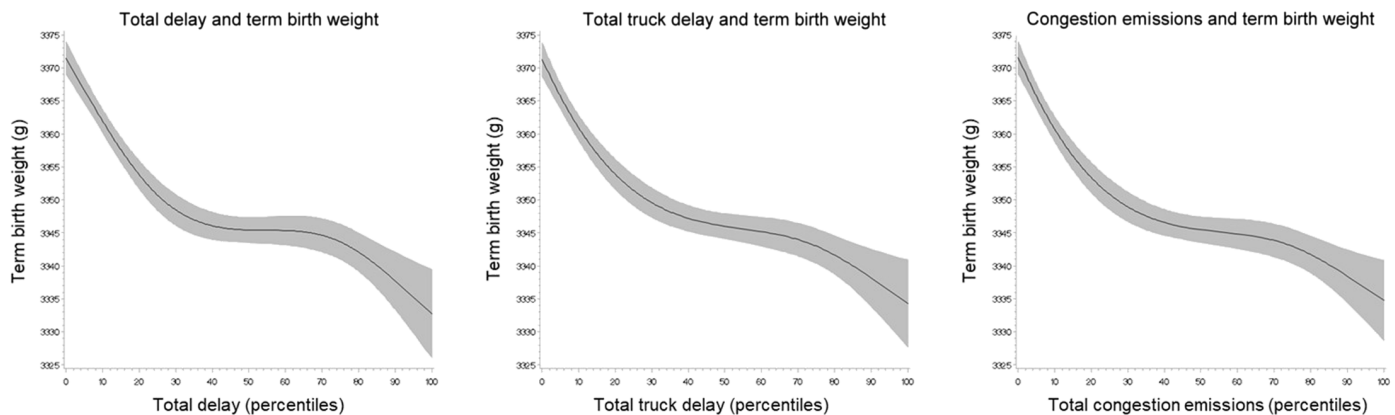


Fig. 3. Restricted cubic splines of the association between metrics of traffic delay and term birth weight. The solid line is the prediction for mean term birth weight, and the shaded area is the 95% CI band. Models contain a covariate for total VMT within the respective buffer of the residence. On the basis of the data distribution, splines were fit with six knot points at the following percentiles: 0, 5, 25, 50, 75, and 95.

transportation sector are designed and implemented, such as highway reclamation projects, increases to active transportation and public transportation, and a transition to battery electric vehicles. It is predicted that the prevalence of internal combustion vehicles on the road may markedly decrease over the next few decades (19, 20). This change in the vehicle fleet mix will reduce the toxicity of tailpipe emissions because battery electric vehicles do not produce incomplete combustion by-products from the burning of gasoline or diesel. However, a fully electric vehicle fleet would not entirely remove the hazards related to traffic congestion and resulting air pollution. Tailpipe emissions represent only one component of

the complex mixture of traffic-related air pollution that could be exacerbated by traffic congestion. For instance, electric vehicles are, on average, between 197 and 362 kg heavier than their internal combustion counterparts, largely because of the battery size (21, 22). The extra battery weight produces additional wear on the vehicle’s brakes and tires, which, in turn, produces air pollution at higher concentrations (e.g., PM_{2.5}) (22, 23). Therefore, unless substantial investment is made in reducing traffic volume and delay, the impending transition away from internal combustion vehicles would likely attenuate, but not remove, the adverse associations between traffic congestion and infant growth presented in our analysis.

Table 3. Associations between metrics of traffic congestion within 500 m of a maternal residence and term birth weight, Texas, USA, 2015–2016. Models are linear regressions with robust SEs by quintile (Q) of the exposure, based on the distribution in the sample. Model 1 contained a covariate for VMT within the respective buffer of the residence. Model 2 contained the following covariates: county of maternal residence at delivery (indicator for each county), birth year, birth month, maternal age, infant sex, maternal race, maternal ethnicity, maternal educational attainment, method of payment for delivery, maternal cigarette usage, month of prenatal care initiation, prepregnancy body mass index, infant gestational age, and total VMT within the respective buffer of the residence. Model 3 contained the covariates from Model 2 with the addition of the following: area deprivation index (state ranking for Texas), transportation noise, previous year concentration of PM_{2.5}, previous year concentration of NO₂, previous year concentration of ultrafine particles, and green space within 500 m of the residence (measured by NDVI).

Exposure metric	Effect estimates (95% CI)					
	<i>n</i>	Model 1: Base model	<i>n</i>	Model 2: Birth certificate characteristics	<i>n</i>	Model 3: Environmental coexposures
All traffic delay						
No congestion exposure	87,528	Reference	87,528	Reference	87,528	Reference
Q1	98,319	−7.57 (−11.62, −3.53)	98,319	−3.15 (−6.95, 0.64)	98,319	−3.43 (−7.24, 0.38)
Q2	98,319	−21.86 (−25.93, −17.8)	98,319	−8.66 (−12.42, −4.91)	98,319	−6.55 (−10.35, −2.75)
Q3	98,319	−24.2 (−28.31, −20.08)	98,319	−9.35 (−13.18, −5.52)	98,319	−5.79 (−9.72, −1.86)
Q4	98,319	−24.55 (−28.77, −20.33)	98,319	−10.33 (−14.28, −6.37)	98,319	−5.48 (−9.63, −1.32)
Q5	98,318	−31.88 (−36.92, −26.83)	98,318	−15.21 (−20.00, −10.42)	98,318	−8.93 (−14.08, −3.79)
Truck delay						
No congestion exposure	87,661	Reference	87,661	Reference	87,661	Reference
Q1	98,294	−8.72 (−12.77, −4.68)	98,294	−3.71 (−7.51, 0.09)	98,294	−3.72 (−7.52, 0.09)
Q2	98,291	−20.47 (−24.53, −16.41)	98,291	−8.31 (−12.07, −4.54)	98,291	−6.34 (−10.14, −2.54)
Q3	98,294	−24.13 (−28.25, −20.02)	98,294	−8.63 (−12.43, −4.82)	98,294	−5.13 (−9.02, −1.24)
Q4	98,291	−25.67 (−29.88, −21.45)	98,291	−10 (−13.91, −6.1)	98,291	−5.5 (−9.56, −1.44)
Q5	98,291	−31.06 (−36.14, −25.97)	98,291	−13.43 (−18.14, −8.73)	98,291	−8.42 (−13.3, −3.53)
Congestion emissions						
No congestion exposure	95,478	Reference	95,478	Reference	95,478	Reference
Q1	96,729	−9.59 (−13.56, −5.62)	96,729	−3.62 (−7.31, 0.07)	96,729	−3.62 (−7.32, 0.07)
Q2	96,729	−22.35 (−26.33, −18.36)	96,729	−8.76 (−12.46, −5.06)	96,729	−6.64 (−10.39, −2.9)
Q3	96,733	−24.76 (−28.81, −20.72)	96,733	−8.82 (−12.59, −5.05)	96,733	−5.21 (−9.09, −1.32)
Q4	96,726	−26.96 (−31.1, −22.82)	96,726	−11.01 (−14.89, −7.12)	96,726	−6.15 (−10.25, −2.05)
Q5	96,727	−32.52 (−37.35, −27.69)	96,727	−15.53 (−20.08, −10.97)	96,727	−9.49 (−14.42, −4.56)

This study is among the first epidemiologic studies to leverage detailed traffic congestion metrics at a large geographic scale, and our results align with previous health impact assessments of traffic congestion, environmental pollution, and human health outcomes (10, 11). Thanks to substantial investments in the Texas' Most Congested Roads database (18), we were able to quantify congestion metrics and exposures for a large population-based cohort of mother-infant dyads across the entire state for singleton births. The use of connected vehicle and device data to quantify vehicle travel patterns, types, volumes, and speeds is becoming more accessible to exposure scientists, and this type of data should be further incorporated into air pollution exposure models and other epidemiological studies to confirm our findings. Current approaches to estimate traffic-related air pollution exposures using road proximity or density, VMT, and land use regression models do not capture all air pollution exposure contributions from congestion, and regional air pollution monitoring data do not address more localized exposure hot spots including those from traffic sources. Given the

long-term improvements that helped reduce vehicle exhaust over the past few decades (24) and previous work that shows that air pollution reductions paralleled improvements in infant birth weight (14), focusing on improving traffic congestion may be highly beneficial to population health and help reduce local exposure inequalities (25, 26).

Our results align with a robust literature that demonstrated that traffic-related air pollution and close proximity to major roads is associated with adverse reproductive and infant health outcomes, including reduced birth weight (10, 11). For example, a meta-analysis found a −28.1-g reduction in birth weight (95% CI: −11.5, −44.8) per 20-parts per billion (ppb) increase in NO₂, showing that there is a substantial association between markers of traffic-related air pollution and infant health (11). In comparison, in our current analysis, we observed a −25-g reduction in term birth weight for a 20-ppb increase in NO₂. In addition, we found an association for the additional influence of traffic congestion, and this association remains after adjusting for vehicle volume and NO₂, PM_{2.5}, and

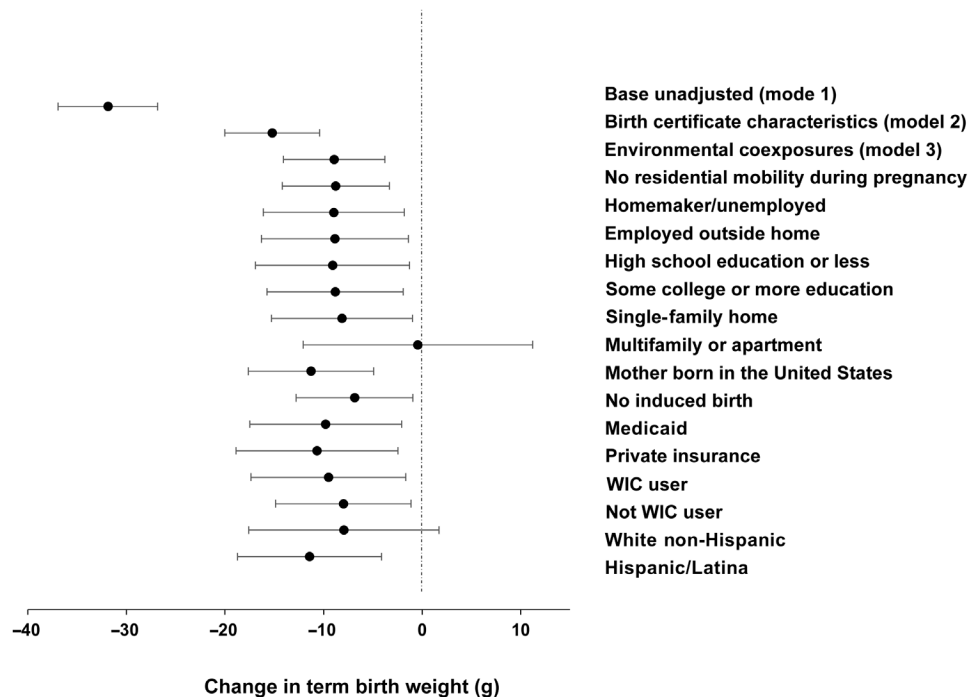


Fig. 4. Adjusted associations between the highest quartile of total delay within 500 m of mother's addresses and term birth weight for different sensitivity analyses. Model 1 contained a covariate for VMT within the respective buffer of the residence. Model 2 contained the following covariates: County of maternal residence at delivery (indicator for each county), birth year, birth month, maternal age, infant sex, maternal race, maternal ethnicity, maternal educational attainment, method of payment for delivery, maternal cigarette usage, month of prenatal care initiation, prepregnancy body mass index, infant gestational age, and total VMT within the respective buffer of the residence. Model 3 contained the covariates from model 2 with the addition of the following: Area deprivation index (state ranking for Texas), transportation noise, previous year concentration of $PM_{2.5}$, previous year concentration of NO_2 , previous year concentration of ultrafine particles, and green space within 500 m of the residence (measured by NDVI). All restricted models use the covariates from the fully adjusted model (i.e., model 3), except for the covariate related to the restriction that is removed if included in fully adjusted model specifications.

ultrafine particle background concentrations. This result suggests that local impacts near congested roadways occur, which are not typically captured in air or noise pollution models (27, 28), and that interventions to reduce congestion could provide cobenefits for infant health. A few studies have indirectly examined traffic congestion on reproductive outcomes using natural experiments (29, 30). For example, one study used the conversion from toll booths to electronic tolling to examine how reductions in traffic congestion may influence infant health, as the authors hypothesized that the switch from a stop and go toll to an overhead toll would reduce traffic congestion (29). They found a large reduction in low-birth weight infants among mothers who resided within 2 km of a toll plaza during pregnancy within 3 years before versus 3 years after this switch occurred. Our present analysis expands upon this body of work by directly measuring traffic congestion and conducting a spatially based comparison of pregnant women living closer to or farther away from congestion. Although more research is needed, these results suggest that the pregnancy period may be a particularly vulnerable time and adverse birth outcomes are a sensitive marker for the impacts of traffic congestion-related pollution.

We were able to conduct a number of sensitivity analyses that are relatively comprehensive and address the potential influence of unmeasured confounding on our results, such as using maternal occupational data that were reported on the birth certificate to examine whether a mother was likely to not be at her home for most of the working day, using property data to identify housing

characteristics and home sales data to determine whether the mother likely lived at this address throughout her pregnancy. These concerns are well documented in existing literature (31–33), but few studies have been able to quantify this source of exposure misclassification, let alone on a population-level scale as we accomplished here. We found that addressing these hypothesized sources of exposure misclassification did not change the meaning of our results; however, the magnitude of the estimated effect sizes was somewhat larger among mothers who did not report being employed at the time of delivery, which aligns with the notion that exposure misclassification is reduced among mothers who spend more time at home. We also observed large differences by housing type, with larger associations for single family homes, but less evidence of an association for multifamily or apartment buildings. Further research is needed to determine whether household characteristics are influencing the exposure to traffic-related air pollution (such as the indoor/outdoor ratios of pollutants) or are capturing unmeasured socioeconomic influences that modify or confound the associations between traffic air pollution and adverse birth outcomes.

When interpreting the results of our study, there are key limitations to keep in mind. First, our traffic congestion data are derived at an annual temporal scale and therefore represent longer-term exposure to traffic congestion. Although there are seasonal patterns to traffic (34), we assigned these annual estimates to the entire pregnancy and were unable to examine trimester-specific congestion measures. Second, vehicle fleet mixtures vary by region, including

the type of vehicles on the road (e.g., sedans, sport utility vehicles, and diesel trucks) and their age (i.e., model year). We hypothesize that there may be exposure misclassification by the type and age of the fleet mixture, which we cannot assess in this analysis. The U.S. Environmental Protection Agency (EPA) Motor Vehicle Emission Simulator 2010 (MOVES2010) model used default parameters for these characteristics to estimate the total and congestion-specific CO₂ emissions; thus, it does not consider exposure variation that may stem from the fleet mixture. However, our models did include a county fixed effect, which removes the potential exposure misclassification from fleet differences across regions of Texas but does not alleviate problems related to heterogeneity in the fleet mixture within a given county. Third, the birth certificate data do not capture any residential changes that may have occurred during pregnancy, which could introduce additional misclassification into our exposure assessment (31, 32, 35). We overcome this limitation to some degree using the housing transaction data and show that our results are largely similar when we restrict our sample to mother-infant dyads without a housing transaction at their residential address during the pregnancy period. Furthermore, maternal addresses at delivery are likely to be most accurate during the third trimester, which is the time period during pregnancy where previous studies have shown that term birth weight is likely most affected by sources of air pollution (36, 37). Fourth, given the nature of administrative data, we lacked information on some potential individual confounding factors that may influence this association, such as nutrition or lifestyle data, assuming that these are related to living near congestion. We did include detailed individual information on sociodemographic characteristics of mothers, which also may capture some major lifestyle factors. Our sensitivity analyses restricted to individual race and ethnic groups, education levels, insurance type, and WIC use were similar to our main results. Traffic congestion may also operate as an instrumental variable for personal air pollution exposures (with individuals less likely to select houses on the basis of traffic congestion compared to distance to major roads), thus reducing the potential influence of confounding from individual behavioral differences (38). Nevertheless, residual and unmeasured confounding cannot be ruled out in observational studies. Fifth, our analyses control for gestational age among term infants. This decision means that our results not only cannot be interpreted with respect to gestation length (i.e., we can only make conclusions about infant growth) but also reduces the potential for bias in our analysis (39, 40). With these limitations in mind, we note that our results are highly robust to several sensitivity analyses that we conducted.

Our study provides important previously unknown evidence that traffic congestion is associated with adverse infant health outcomes, as measured by reductions in term birth weight, in addition to total traffic volume on nearby roads and background levels of air pollution and noise. Therefore, programs and policies to reduce traffic congestion may have positive cobenefits for infant health with respect to birth weight. Future work is required to determine what programs or policies may be most effective at reducing traffic congestion to yield these potential benefits for infant health.

MATERIALS AND METHODS

Study population

We leveraged birth certificate data from the Texas Department of Health and Human Services to extract information on residential

birth address, demographics, risk factors, and birth outcomes (table S20). Each maternal address at time of delivery was geocoded to examine births between 1 January 2015 and 31 December 2016 ($n = 820,328$). We removed records for which the maternal address at delivery could not be precisely geocoded ($n = 43,306$, 5.3%) and any births that were missing one or more key fields: Birth weight, gestational age, maternal age, and number of fetuses in this pregnancy ($n = 1082$, <0.1%). Births were excluded on the basis of improbable birth weight (<500 or >5000 g, $n = 1989$, <0.1%), maternal age (<10 or >65 years old, $n = 0$, 0%), and any deliveries with multiple births ($n = 24,834$, 3.0%). Since our outcome is term birth weight, we removed births with gestational age <37 or >42 weeks ($n = 63,217$, 7.7%). We then removed births with maternal residences located more than 1000 m away from at least one road in the congestion database with more than 500 vehicles per day, which we used to derive exposure measures ($n = 67,788$, 8.2%). This ensures that our exposed and unexposed populations are similar with respect to geographic distribution in Texas. Note that this database contains congestion measurements on road segments that are smaller than major roadways; thus, we were able to retain the majority of the births in the cohort. In addition, we removed births in counties with fewer than 100 term births ($n = 2673$, <0.1%). Last, we removed births ($n = 36,317$, 4.4%) that are missing covariates needed in our adjusted regression models (i.e., we conducted a complete case analysis). In total, applying these criteria yielded 579,122 births for analysis. This study was approved by the Texas State Department of Health and Human Services (no. 15-063) and the Oregon State University Institutional Review Board (no. 6692).

Traffic congestion exposure assessment

We used the database for the Texas' Most Congested Roadways that was developed by researchers at the Texas A&M Transportation Institute (18, 41), relying on data that covered the 2015 and 2016 period (table S20). Each annual database contains detailed information on factors related to traffic volume (including trucks), delay, fuel type, and emissions (Table 1). Congestion metrics are derived down to the road section level on the basis of congestion performance measure calculations based on the state's roadway inventory and a proprietary data source of Global Positioning System speed reports generated from individual vehicles and cell phones (i.e., connected vehicle data). We examined several different measures of congestion. VMT is the number of vehicles that travel on a given road (i.e., a metric for overall traffic) multiplied by the length of each road segment. Annual delay per mile is a metric in person-hours of delay that occurs per mile along a given road (i.e., a metric for traffic congestion). Total person-hours of delay were calculated on the basis of traffic volumes for each 15-min time interval, calculated from average daily traffic counts using hourly volume profiles, and calculated from corresponding travel speed, measured from the vehicle movement database. Peak morning and evening commute travel speeds were then compared to free-flow (low volume) travel speeds using speeds from 10 p.m. to 6 a.m. or the speed limit for each road section as an upper limit. Delay metrics were calculated for all vehicles and for trucks only. Parsing apart congestion related to truck traffic versus cars allows for additional insights into truck-specific emissions such as diesel particulate matter and benzene, both of which are known reproductive toxicants. We also examined a metric that measured the greenhouse gas emissions (represented by CO₂) from all traffic on a road segment and from congestion-specific

traffic. The greenhouse gas emissions are calculated as pounds of CO₂ using the EPA's MOVES2010 model that incorporates vehicle volumes, vehicle emission rates, climate data, and vehicle speeds. The model was run for each 15-min period for both the measured speed and corresponding free-flow speed to calculate the amount of excess CO₂ produced during congestion. Full details of the congestion calculation methods are published elsewhere (41).

Each maternal residence was assigned congestion values based off all roads within a given buffer of their home (100, 300, and 500 m). To account for multiple roads and segments lengths, we calculated the total length of each road segment that fell into the buffer and weighted the road length by each congestion metric in separate exposure estimates. Our metrics can be interpreted as the total VMT, person-hours of delay, and greenhouse gas emissions within 100, 300, and 500 m of a home address (Table 1). We present exposure measures for the 500-m buffer here, while the influence of the 100- and 300-m buffer distances is presented in the supplementary tables.

Infant health outcome assessment

We ascertained infant health outcomes from the birth certificate. Term birth weight (primary outcome) is the weight reported at birth among infants born at 37 to 42 weeks of estimated gestation.

Covariate assessment

We used covariates from the birth certificate to ascertain additional information on the mother-infant dyad. For this analysis, we examined the following covariates: county of maternal residence at delivery, birth year, maternal age, infant sex, maternal race, maternal ethnicity, maternal educational attainment, method of payment for delivery, maternal cigarette usage, month of prenatal care initiation, prepregnancy body mass index, and infant gestational age at delivery.

In addition to the detailed data provided on the birth certificate, we integrated external data sources to estimate household characteristics and residential mobility, neighborhood context, and background (noncongestion) levels of noise and air pollution (table S20). We examined housing characteristics by linking the maternal address to housing valuation data to determine whether the mother likely lived in a single-family home, a mobile home, or multifamily home (e.g., apartments) (42). We used the housing valuation data to check whether there was a housing transaction during the pregnancy period (42). For residential locations with a transaction, the mother likely changed residences during pregnancy, and therefore, the exposure assessment for early pregnancy may be inaccurate. We accounted for the neighborhood's deprivation status via the 2015 Area Deprivation Index, which provides a metric that ranks census tracts within a state on socioeconomic characteristics (43, 44). We included residential green space using the yearly normalized different vegetation index (NDVI) from Landsat 8 images within 500 m of maternal addresses. Transportation noise level was assessed using the 2016 U.S. Department of Transportation national transportation noise map predictions, which we assigned to maternal addresses (45). We also linked annual NO₂ and PM_{2.5} in the year before the delivery and ultrafine particles in 2017 (due to data limitations) using existing hybrid land use regression model estimates (46–48). Many existing air pollution exposure models do not capture sharp changes in the exposure gradient (27, 28); thus, controlling for background exposure levels allows our regression results to parse out the additional influence of congestion.

Statistical analysis

We first calculated descriptive statistics on the cohort by levels of traffic delay exposure and examined relationships between different traffic-related exposure measures. We also built restricted cubic splines to visually examine the relation between metrics of traffic delay and term birth weight by percentile of exposure in the cohort, which informed our decisions regarding cut points in the quintile models. These models contained a covariate for the VMT within the respective buffer distance of the residence, which allowed us to disentangle the influence of traffic congestion from vehicle volume.

We implemented a set of linear regressions to estimate to what extent, if any, congestion exposures were associated with term birth weight. We ran base (unadjusted except for vehicle volume) models (model 1), models adjusted for individual covariates (model 2), and models adjusted for individual covariates and other environmental coexposures (model 3). Model 1 only contained a covariate for the VMT within the respective buffer distance of the residence, which allowed us to isolate the influence of traffic congestion from vehicle volume. Model 2 contained the following covariates: county of maternal residence at delivery (indicator for each county), birth year (indicator for each year), maternal age (continuous), infant sex (male or female), maternal race (white, black, American Indian or Alaskan Native, Asian, Pacific Islander, or other race), maternal ethnicity (Hispanic/Latina or not Hispanic/Latina), maternal educational attainment (8th grade or less, 9th to 12th grades without a diploma, high school graduate or equivalent, some college credit but no degree, associate's, bachelor's, master's, or doctorate), method of payment for delivery (Medicaid, private insurance, self-pay, or other), maternal cigarette usage (yes or no), month of prenatal care initiation (indicator for no reported care of each 1 to 9 months), prepregnancy body mass index (underweight, normal weight, overweight, or obese), and infant gestational age (indicator for each week). Model 3 contained the covariates from model 2 with the addition of the following covariates: VMT within the respective buffer distance of the residence, area deprivation index (state ranking for Texas), transportation noise, PM_{2.5}, NO₂, ultrafine particles, and green space. We included VMT within the same buffer distance as the main congestion exposure measure, such that we estimate only the effects from congestion metrics for traffic delay, truck-only traffic delay, and greenhouse gas emissions. We included annual concentrations of NO₂, PM_{2.5}, and ultrafine particle air pollution concentrations, which can be interpreted as non-congestion-related ambient concentrations because these predictive models do not include congestion as a predictor (46, 47). This model therefore isolates the impact of congestion on term birth weight in addition to vehicle volume and background air pollution and noise levels. Additional models examine the associations between an interquartile range increase in PM_{2.5}, NO₂, and ultrafine particle concentrations and term birth weight, which allow for comparison to our congestion models.

Sensitivity analyses

We conducted a number of sensitivity analyses to better understand what sources of bias may be present in our data. First, we restricted our sample to pregnant women without a housing transaction during their pregnancy period, which removes mothers who likely moved during pregnancy and hence could introduce exposure misclassification for whole pregnancy exposures. Second, we restricted

analyses to women who did not report a labor induction because there are several medical reasons for induction that are likely not related to traffic-related air pollution (49). Third, we stratified the population by reported occupational status (homemaker or unemployed versus currently employed), as traffic congestion may negatively affect women who commute during their pregnancy relative to women who stay home. At the same time, our traffic-related air pollution exposure metrics for traffic congestion will be more accurate for mothers who spend more time at home. Fourth, we stratified the population by household type (single family versus multifamily home) to determine how housing type may be influencing our results. Housing type could operate as an effect modifier for air pollution exposures (50) or may be an additional surrogate for socioeconomic status (51). Fifth, we restrict the population by maternal birth location to only women who reported being born in the United States to reduce measurement bias that may stem from timing and access to prenatal care and difficulties related to accurate gestational age dating. Sixth, we examine the influence of socioeconomic and demographic disparities on our effect estimates by implementing models restricted by education (high school or less or some college or higher) payment mechanism for delivery (private insurance or Medicaid), WIC usage (no or yes), and maternal race and ethnicity (non-Hispanic white or Hispanic/Latina). While further disaggregation of these groups would be ideal, we were largely limited to broad categories because of sample size.

Population burden estimate

We further sought to extrapolate our results to estimate the burden of traffic delay on infant health across the United States. Given that there were 3,362,371 term births in 2019 (52) and estimates indicate that 30 to 45% of Americans reside within 500 m of a highway or 50 to 100 m of a major road (1), we calculated the national population of term births that are exposed to levels of traffic delay that are associated with reduced birth weight based on the results of our sample. In other words, we multiplied the number of term births in the United States by the proportion of the population who resides near major roads; then, we further multiplied that product by the proportion of births in our analysis that reside in high traffic congestion zones where we observe an adverse association between traffic congestion and term birth weight. We also completed this calculation where the proportion of births in our analysis was switched to the highest traffic congestion zones.

SUPPLEMENTARY MATERIALS

Supplementary material for this article is available at <https://science.org/doi/10.1126/sciadv.abp8281>

REFERENCES AND NOTES

1. T. K. Boehmer, S. L. Foster, J. R. Henry, E. L. Woghiren-Akinnifesi, F. Y. Yip; Centers for Disease Control and Prevention (CDC), Residential proximity to major highways—United States, 2010. *MMWR Suppl.* **62**, 46–50 (2013).
2. Cambridge Systematics, Texas Transportation Institute, Traffic congestion and reliability: Linking solutions to problems (Cambridge, MA, 2004); https://ops.fhwa.dot.gov/congestion_report_04/.
3. T. Litman, Transportation and public health. *Annu. Rev. Public Health* **34**, 217–233 (2013).
4. D. Schrank, L. Albert, B. Eisele, T. Lomax, 2021 Urban Mobility Report (Texas A&M Transportation Institute, College Station, TX, 2021); <https://static.tti.tamu.edu/tti.tamu.edu/documents/mobility-report-2021.pdf>.
5. Health Effects Institute, Traffic-related air pollution: A critical review of the literature on emissions, exposure, and health effects (HEI, 2010).
6. United States Environmental Protection Agency, Smog, Soot, and other air pollution from transportation (2022); www.epa.gov/transportation-air-pollution-and-climate-change/smog-soot-and-local-air-pollution.
7. K. Zhang, S. Batterman, F. Dion, Vehicle emissions in congestion: Comparison of work zone, rush hour and free-flow conditions. *Atmospheric Environ.* **45**, 1929–1939 (2011).
8. R. Smit, A. L. Brown, Y. C. Chan, Do air pollution emissions and fuel consumption models for roadways include the effects of congestion in the roadway traffic flow? *Environ. Model. Software* **23**, 1262–1270 (2008).
9. I. De Vlieger, D. De Keukeleere, J. G. Kretzschmar, Environmental effects of driving behaviour and congestion related to passenger cars. *Atmos. Environ.* **34**, 4649–4655 (2000).
10. P. Klepac, I. Locatelli, S. Korošec, N. Künzli, A. Kukec, Ambient air pollution and pregnancy outcomes: A comprehensive review and identification of environmental public health challenges. *Environ. Res.* **167**, 144–159 (2018).
11. D. M. Stieb, L. Chen, M. Eshoul, S. Judek, Ambient air pollution, birth weight and preterm birth: A systematic review and meta-analysis. *Environ. Res.* **117**, 100–111 (2012).
12. J. I. Levy, J. J. Buonocore, K. von Stackelberg, Evaluation of the public health impacts of traffic congestion: A health risk assessment. *Environ. Health* **9**, 65 (2010).
13. L. Wang, P. Guo, H. Tong, A. Wang, Y. Chang, X. Guo, J. Gong, C. Song, L. Wu, T. Wang, P. K. Hopke, X. Chen, N. Tang, H. Mao, Traffic-related metrics and adverse birth outcomes: A systematic review and meta-analysis. *Environ. Res.* **188**, 109752 (2020).
14. M. D. Willis, E. L. Hill, M. L. Kile, S. Carozza, P. Hystad, Assessing the effectiveness of vehicle emission regulations on improving perinatal health: A population-based accountability study. *Int. J. Epidemiol.* **49**, 1781–1791 (2021).
15. M. Wilhelm, B. Ritz, Residential proximity to traffic and adverse birth outcomes in Los Angeles county, California, 1994–1996. *Environ. Health Perspect.* **111**, 207–216 (2003).
16. M. Wilhelm, J. K. Ghosh, J. Su, M. Cockburn, M. Jerrett, B. Ritz, Traffic-related air toxics and preterm birth: A population-based case-control study in Los Angeles county, California. *Environ. Health* **10**, 89 (2011).
17. S. Batterman, J. Burke, V. Isakov, T. Lewis, B. Mukherjee, T. Robins, A comparison of exposure metrics for traffic-related air pollutants: Application to epidemiology studies in Detroit, Michigan. *Int. J. Environ. Res. Public Health* **11**, 9553–9577 (2014).
18. Texas A&M Transportation Institute, Texas' Most Congested Roadways, Texas' Most Congested Roadways (2021); <https://mobility.tamu.edu/texas-most-congested-roadways/>.
19. Light Duty Electric Drive Vehicles Monthly Sales Updates|Argonne National Laboratory; www.anl.gov/es/light-duty-electric-drive-vehicles-monthly-sales-updates.
20. Summary Report on EVs at Scale and the U.S. Electric Power System 2019, Energy.gov (2019); www.energy.gov/eere/vehicles/downloads/summary-report-evs-scale-and-us-electric-power-system-2019.
21. N. Hoofman, M. Messagie, F. Joint, J.-B. Segard, T. Coosemans, In-life range modularity for electric vehicles: The environmental impact of a range-extender trailer system. *Appl. Sci.* **8**, 1016 (2018).
22. Y. Liu, H. Chen, J. Gao, Y. Li, K. Dave, J. Chen, M. Federici, G. Perricone, Comparative analysis of non-exhaust airborne particles from electric and internal combustion engine vehicles. *J. Hazard. Mater.* **420**, 126626 (2021).
23. E. Adamiec, E. Jarosz-Krzemińska, R. Wieszała, Heavy metals from non-exhaust vehicle emissions in urban and motorway road dusts. *Environ. Monit. Assess.* **188**, 369 (2016).
24. United States Environmental Protection Agency, Nitrogen Dioxide Trends (2016); www.epa.gov/air-trends/nitrogen-dioxide-trends.
25. A. Jbaily, X. Zhou, J. Liu, T.-H. Lee, L. Kamareddine, S. Verguet, F. Dominici, Air pollution exposure disparities across U.S. population and income groups. *Nature* **601**, 228–233 (2022).
26. J. Liu, L. P. Clark, M. J. Bechle, A. Hajat, S.-Y. Kim, A. L. Robinson, L. Sheppard, A. A. Szpiro, J. D. Marshall, Disparities in air pollution exposure in the United States by race/ethnicity and income, 1990–2010. *Environ. Health Perspect.* **129**, 127005 (2021).
27. Y. Zhou, J. I. Levy, Factors influencing the spatial extent of mobile source air pollution impacts: A meta-analysis. *BMC Public Health* **7**, 89 (2007).
28. S. Arunachalam, A. Valencia, Y. Akita, M. L. Serre, M. Omary, V. Garcia, V. Isakov, A method for estimating urban background concentrations in support of hybrid air pollution modeling for environmental health studies. *Int. J. Environ. Res. Public Health* **11**, 10518–10536 (2014).
29. J. Currie, R. Walker, Traffic congestion and infant health: Evidence from E-ZPass. *Am. Econ. J. Appl. Econ.* **3**, 65–90 (2011).
30. C. R. Knittel, D. L. Miller, N. J. Sanders, Caution, Drivers! Children present: Traffic, pollution, and infant health. *Rev. Econ. Stat.* **98**, 350–366 (2015).
31. M. A. Canfield, T. A. Ramadhani, P. H. Langlois, D. K. Waller, Residential mobility patterns and exposure misclassification in epidemiologic studies of birth defects. *J. Expo. Sci. Environ. Epidemiol.* **16**, 538–543 (2006).
32. M. L. Bell, K. Belanger, Review of research on residential mobility during pregnancy: Consequences for assessment of prenatal environmental exposures. *J. Expo. Sci. Environ. Epidemiol.* **22**, 429–438 (2012).

33. K. J. Lane, M. Kangsen Scammell, J. I. Levy, C. H. Fuller, R. Parambi, W. Zamore, M. Mwamburi, D. Brugge, Positional error and time-activity patterns in near-highway proximity studies: An exposure misclassification analysis. *Environ. Health* **12**, 75 (2013).
34. S. Batterman, R. Cook, T. Justin, Temporal variation of traffic on highways and the development of accurate temporal allocation factors for air pollution analyses. *Atmos. Environ.* **107**, 351–363 (2015).
35. P. J. Lupo, E. Szymanski, D. K. Waller, W. Chan, P. H. Langlois, M. A. Canfield, L. E. Mitchell, Maternal exposure to ambient levels of benzene and neural tube defects among offspring: Texas, 1999–2004. *Environ. Health Perspect.* **119**, 397–402 (2011).
36. N. L. Fleischer, M. Meriandi, A. van Donkelaar, F. Vadillo-Ortega, R. V. Martin, A. P. Betran, J. P. Souza, Outdoor air pollution, preterm birth, and low birth weight: Analysis of the World Health Organization global survey on maternal and perinatal health. *Environ. Health Perspect.* **122**, 425–430 (2014).
37. D. Q. Rich, K. Liu, J. Zhang, S. W. Thurston, T. P. Stevens, Y. Pan, C. Kane, B. Weinberger, P. Ohman-Strickland, T. J. Woodruff, X. Duan, M. V. Assibey, J. Zhang, Differences in birth weight associated with the 2008 Beijing Olympics air pollution reduction: Results from a natural experiment. *Environ. Health Perspect.* **123**, 880–887 (2015).
38. M. G. Weisskopf, M.-A. Kioumourtzoglou, A. L. Roberts, Air pollution and autism spectrum disorders: Causal or confounded? *Curr. Envir. Health Rpt.* **2**, 430–439 (2015).
39. A. J. Wilcox, On the importance—and the unimportance—of birthweight. *Int. J. Epidemiol.* **30**, 1233–1241 (2001).
40. A. M. Neophytou, M.-A. Kioumourtzoglou, D. E. Goin, K. C. Darwin, J. A. Casey, Educational note: Addressing special cases of bias that frequently occur in perinatal epidemiology. *Int. J. Epidemiol.* **50**, 337–345 (2021).
41. Texas A&M Transportation Institute, Technical Memorandum: Analysis Procedures and Mobility Performance Measures 100 Most Congested Texas Road Sections (Texas A&M University, College Station, TX, 2021); <https://static.tti.tamu.edu/tti.tamu.edu/documents/TTI-2021-5.pdf>.
42. CoreLogic, www.corelogic.com (2020).
43. University of Wisconsin School of Medicine and Public Health, 2015 Area Deprivation Index; www.neighborhoodatlas.medicine.wisc.edu.
44. A. J. H. Kind, W. R. Buckingham, Making neighborhood-disadvantage metrics accessible—The neighborhood atlas. *N. Engl. J. Med.* **378**, 2456–2458 (2018).
45. National Transportation Noise Map, U.S. Department of Transportation (2016); www.arcgis.com/home/item.html?id=a63bceb18109418f8af32ecbb7270f7d.
46. S.-Y. Kim, M. Bechle, S. Hankey, L. Sheppard, A. A. Szpiro, J. D. Marshall, Concentrations of criteria pollutants in the contiguous U.S., 1979–2015: Concentrations of criteria pollutants in the contiguous U.S., 1979–2015: Role of prediction model parsimony in integrated empirical geographic regression. *PLOS ONE* **15**, e0228535 (2020).
47. P. K. Saha, S. Hankey, J. D. Marshall, A. L. Robinson, A. A. Presto, High-spatial-resolution estimates of ultrafine particle concentrations across the continental United States. *Environ. Sci. Technol.* **55**, 10320–10331 (2021).
48. CACES RCM/LUR data download, CACES; www.caces.us/data.
49. Mayo Clinic, Labor induction (2020); www.mayoclinic.org/tests-procedures/labor-induction/about/pac-20385141.
50. A. R. Pickett, M. L. Bell, Assessment of indoor air pollution in homes with infants. *Int. J. Environ. Res. Public Health* **8**, 4502–4520 (2011).
51. A. Makri, N. I. Stilianakis, Vulnerability to air pollution health effects. *Int. J. Hyg. Environ. Health* **211**, 326–336 (2008).
52. B. Hamilton, J. Martin, M. Osterman, Births: Provisional Data for 2020 (National Center for Health Statistics, 2021).

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