Redlining in New York City: impacts on particulate matter exposure during pregnancy and birth outcomes

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► Additional supplemental material is published online only. To view, please visit the journal online (https://doi.org/10.1136/jech-2024-222134).

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Received 5 March 2024
Accepted 5 August 2024
Published Online First 6 September 2024

Check for updates

To cite: Herrera T, Seok E, Cowell W, *et al*. *J Epidemiol Community Health* 2025;**79**:12–18.

ABSTRACT

Background Evidence suggests historical redlining shaped the built environment and health outcomes in urban areas. Only a handful of studies have examined redlining's association with air pollution and adverse birth outcomes in New York City (NYC). Additionally, no NYC-specific studies have examined the impact of redlining on birth weight.

Methods This longitudinal cohort study analysed data from the National Institute of Health Environmental Influences on Child Health Outcomes Programme to investigate the extent to which maternal residence in a historically redlined neighbourhood is associated with fine particulate matter ($PM_{2.5}$) exposure during pregnancy using multivariable regression models. Additionally, we examined how maternal residence in a historically redlined neighbourhood during pregnancy influenced birth weight z-score, preterm birth and low birth weight.

Results Our air pollution model showed that living in a historically redlined census tract or an ungraded census tract was associated with increased $PM_{2.5}$ exposure during pregnancy. We also found living in a historically redlined census tract or an ungraded census tract was associated with a lower birth weight z-score. This finding remained significant when controlling for individual and census tract-level race, ethnicity and income. When we controlled $PM_{2.5}$ in our models assessing the relationship between redlining grade and birth outcome, our results did not change.

Discussion Our study supports the literature linking redlining to contemporary outcomes. However, our research in ungraded tracts suggests redlining alone is insufficient to fully explain inequality in birth outcomes and $PM_{2.5}$ levels today.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Historical redlining has been linked to contemporary levels of air pollution near schools and preterm birth in New York City (NYC).

WHAT THIS STUDY ADDS

⇒ This study examines redlining's indirect impact on birth weight in NYC using a comprehensive individual-level data set to improve our understanding of how redlining influences NYC in a local context. Our research in ungraded tracts suggests redlining alone is insufficient to fully explain spatial inequality in birth outcomes and particulate matter levels today. Finally, this study provides evidence of replicability of previous NYC studies.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ Our study demonstrates that redlining has influenced the distribution of air pollution and birth outcomes, offering insights that can guide the development of interventions to promote health equity in NYC.

INTRODUCTION

Exposure to fine particulate matter ($PM_{2.5}$) during pregnancy—a critical developmental window—is a risk factor for adverse outcomes like low birth weight (LBW) and preterm birth (PTB).[1] $PM_{2.5}$ exposure is shaped by a combination of climatic, policy and social factors, guiding the extent to which individuals are subjected to its risks. Identifying the underlying factors impacting $PM_{2.5}$ exposure and related birth outcomes is imperative to improving maternal–child health. This study investigates one potential underlying practice, historical redlining, to see its influence on $PM_{2.5}$ and birth outcome distribution in the New York City (NYC) metropolitan area.

Redlining originated in the 1930s following the Great Depression. To stabilise the housing market and limit foreclosures, the federal government designated the Home Owners Loan Corporation (HOLC) to delineate geographical areas where it was least risky to insure mortgages across US cities in collaboration with local real estate and financial leaders.[2 3] Maps (online supplemental figures 1–3) graded neighbourhoods as either A 'best' (designated as green), B 'still desirable' (as blue), C 'definitely declining' (as yellow) and D 'hazardous' (as red or redlined).[3 4] Racial and ethnic makeup was a central element in surveyors' classification of neighbourhood risk, with factors such as sales demand.[4] This component discriminated against marginalised groups, such as African Americans.[2 5] Redlining contributed to racial segregation and financial inequality at individual and neighbourhood levels.[5] The conceptual model guiding this study developed by Swope *et al* (online supplemental figure 4) depicts the effects of historical

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redlining on place-based risk factors and the built environment, indirectly contributing to contemporary health disparities.[4] This framework, along with emerging evidence, can help explain disparities in NYC.

A 2022 study examining temporal trends of $PM_{2.5}$ around NYC schools found schools in historically redlined neighbourhoods saw a smaller reduction in $PM_{2.5}$ exposure over time compared with other neighbourhoods.[6] This study was limited to census tracts containing schools, limiting the ability to generalise findings to the wider area. In a national study assessing the impact of redlining on air pollution across 202 US cities, redlining was associated with substantial intraurban disparities for $PM_{2.5}$.[7] Low-income and communities of colour face disproportionate exposure to sources of $PM_{2.5}$ like heavy-duty diesel truck traffic, bus depots and waste transfer stations in NYC. Yet, some affluent communities can also experience high environmental $PM_{2.5}$, from sources like truck traffic, but they suffer fewer pollution-related health outcomes due to access to mitigating factors.[8] This highlights the need to understand how historical disinvestment has influenced environmental exposures and health outcomes, especially as NYC's population dynamics have changed.

Studies examining the role of redlining and birth outcomes rarely explore birth outcomes alongside environmental exposures. An NYC study analysing redlining scores based on maternal residence found increased odds of PTB in census tracts historically graded D compared with A (OR 1.2, 95% CI 1.05 to 1.32), with similar findings for B-graded and C-graded zones adjusting for maternal characteristics.[9] This paper did not explore birth weight. Similar findings have been replicated in other regions. A California study found the prevalence of PTB, small-for-gestational age and perinatal mortality to be significantly higher in C-graded and D-graded areas while the prevalence of LBW varied across grades.[10] These studies had limitations, such as using the address at delivery. Prospective cohorts with repeated assessments during pregnancy provide more precision and allow examining concurrent $PM_{2.5}$ exposure with redlining.

To address these gaps in the NYC literature, we aimed to (1) determine if living in a redlined census tract during pregnancy contributed to increased exposure to $PM_{2.5}$ a known risk factor for adverse birth outcomes and (2) if residence in a redlined census tract influenced adverse birth outcomes in this longitudinal cohort study. We hypothesised maternal residence in a D-graded census tract would be linked to higher exposure to air pollution, increased birth weight z-score (BWZ) and higher odds of PTB and LBW.

METHODS

Study population

We leveraged data from the National Institutes of Health Environmental Influences on Child Health Outcomes (ECHO) Programme.[11] ECHO is composed of 69 pregnancy cohorts across the USA and collects data on health outcomes, environmental and social exposures throughout the life course. We included only mother–singleton infant pairs enrolled during pregnancy in one of eight ECHO cohorts recruited at three NYC sites (online supplemental table 1), with a geocoded address indicating residence in the NYC tri-state area (94% from NYC counties) during pregnancy. Participants without census tract information were excluded (online supplemental figure 5). We included pregnant mothers from 2005 to 2022 who had available air pollution estimates.[11]

Exposure: historical redlining

Historical redlining data sourced from the Inter-University Consortium for Political and Social Research overlaid the HOLC mortgage security risk maps from the 1930s with 2010 census tracts assigned numerical values to HOLC grades and then determined the proportion of grades contained within a tract.[12] Historic redlining scores were calculated from the summed proportion of HOLC grades multiplied by a weighting factor based on land area within each census tract.[12] They created four equal interval divisions of redlining (A, B, C, D) to link to existing data sources by census tract.[12] Tracts with less than 20% graded land area were deemed ungraded.[12]

We then assigned a HOLC grade to the census tract participants resided in during pregnancy (online supplemental table 2). Out of NYC's 2168 graded census tracts, 1.9% were A-graded, 15.8% as B, 41.2% as C and 31.0% as D. Due to the small number of participants living in A-graded tracts, we combined A-graded, B-graded and C-graded tracts into one group labelled as 'not redlined' and D-graded tracts as 'redlined'.[6] If a participant moved during pregnancy, we assigned them based on their exposure to the lowest HOLC grade. We included participants who lived in 'ungraded' tracts.

Outcome: $PM_{2.5}$

We examined $PM_{2.5}$ exposure estimates at the individual level throughout the pregnancy. Estimates were predicted using an extreme gradient boosting modelling approach combining satellite data, $PM_{2.5}$ monitoring data and a series of spatiotemporal predictors to predict air pollution exposure at the residential address level.[13] $PM_{2.5}$ values were validated using data collected by the Environmental Protection Agency.[14] Arithmetic averages of daily $PM_{2.5}$ concentrations were calculated to derive overall pregnancy-specific values, which served as our air pollution metric. Further details on the creation of these models are referenced elsewhere.[14] We chose this model because of its specific consideration for urban areas, high spatial resolution and estimation at the residential address level.[14]

Outcome: birth outcomes

All birth outcome data were harmonised according to the ECHO-wide protocol.[11] The three outcomes evaluated in this study included birth weight-for-gestational age and sex z-scores (a continuous variable), LBW (dichotomous) and PTB (dichotomous).[15] Health outcomes were selected because of established disparities in NYC and relevance for translation of findings. LBW was defined as birth weight of less than 2500 g.[16] PTB was defined as gestational age at birth less than 37 weeks.[17]

Covariates

We considered both individual-level and neighbourhood-level variables in our analysis. Data on maternal characteristics were collected and/or harmonised as part of the ECHO-wide protocol. Maternal age (in years), parity (counts of live births), marital status (married/not married) and child sex (male/female) were considered in models for precision. We considered maternal race and ethnicity (American Indian Non-Hispanic (NH), Asian/Pacific Islander NH, black or African American NH, mixed NH, other/do not know NH, white NH and Hispanic/Latinx) and annual household income (<US\$30 000, US\$30 000–US\$49 999, US\$50 000–US\$74 999, US\$75 000–US\$99 999 and >US\$100 000) for the analysis. We define race as a socially constructed variable dividing people into distinct groups based on factors such as skin colour, for which there is no biological basis.[18] The

Table 1 Maternal characteristics

	Total study population	A	B	C	D	Ungraded	
	(N=3160)	(N=32)	(N=463)	(N=930)	(N=1444)	(N=291)	P value
Age							
Mean (SD)	31.5 (5.8)	32.7 (6.2)	31.9 (5.8)	31.2 (5.8)	31.3 (5.9)	33.0 (5.3)	0.1
Race (non-Latino)							
American Indian	25 (0.79%)	0 (0.00%)	< 5 (<1.08%)	10 (1.08%)	10 (0.69%)	< 5 (<1.72%)	<0.001
Asian/Pacific Islander	298 (9.43%)	0 (0.00%)	56 (12.10%)	99 (10.65%)	106 (7.34%)	37 (12.71%)	
Black	536 (16.96)	<5 (<15.62%)	52 (11.23%)	96 (10.32%)	335 (23.20%)	<55 (<18.9%)	
Multiple/other race	926 (29.30%)	5 (15.62%)	145 (31.32%)	371 (39.89%)	361 (25%)	44 (15.12%)	
White	1111 (35.16%)	21 (65.62%)	173 (37.37%)	274 (29.46%)	508 (35.18%)	135 (46.39%)	
Missing	264 (8.4%)	<5 (<15.62%)	<5 (<1.08%)	80 (8.6%)	124 (8.6%)	24 (8.2%)	
Ethnicity (Latino)							
Non-Latino	1481 (46.87%)	23 (71.88%)	210 (45.36%)	308 (33.12%)	747 (51.73%)	193 (66.32%)	<0.001
Latino	1581 (50.03%)	6 (18.75%)	239 (51.62%)	604 (64.95%)	650 (45.01%)	82 (28.18%)	
Missing	98 (3.1%)	3 (9.4%)	14 (3.0%)	18 (1.9%)	47 (3.3%)	16 (5.5%)	
Education level							
Less than high school	368 (11.65%)	0 (0.00%)	48 (10.37%)	163 (17.53%)	144 (9.97%)	13 (4.47%)	<0.001
High school degree, GED	>567 (>17.94%)	<5 (<15.62%)	87 (18.79%)	222 (23.87%)	244 (16.90%)	18 (6.19%)	
Some college +	>1758 (>55.63%)	>21 (>65.63%)	266 (57.45%)	434 (46.67%)	831 (57.55%)	206 (70.79%)	
Missing	457 (14.5%)	5 (15.6%)	62 (13.4%)	111 (11.9%)	225 (15.6%)	54 (18.6%)	
Annual household income							
<US$30 000	>785 (>24.84%)	<5 (<15.62%)	103 (22.25%)	251 (26.99%)	391 (27.08%)	42 (14.43%)	0.002
US$30 000–US$49 999	>212 (>6.71%)	<5 (<15.62%)	27 (5.83%)	63 (6.77%)	115 (7.96%)	10 (3.44%)	
US$50 000–US$74 999	>166 (>5.25%)	<5 (<15.62%)	29 (6.26%)	52 (5.59%)	72 (4.99%)	16 (5.50%)	
US$75 000–US$99 999	>111 (>3.51%)	<5 (<15.62%)	16 (3.46%)	40 (4.30%)	49 (3.39%)	10 (3.44%)	
US$100 000	879 (27.82%)	19 (59.38%)	123 (26.57%)	182 (19.57%)	422 (29.22%)	133 (45.70%)	
Missing	987 (31.2%)	5 (15.6%)	165 (35.6%)	342 (36.8%)	395 (27.4%)	80 (27.5%)	
Marriage status							
Married	2059 (65.16%)	23 (71.88%)	311 (67.17%)	592 (63.66%)	926 (64.13%)	207 (71.13%)	0.035
Not married	668 (21.14%)	5 (15.62%)	102 (22.03%)	243 (26.13%)	283 (19.60%)	35 (12.03%)	
Missing	433 (13.7%)	4 (12.5%)	50 (10.8%)	95 (10.2%)	235 (16.3%)	49 (16.8%)	
Parity							
Nulliparous	1061 (33.58%)	12 (37.50%)	180 (38.88%)	275 (29.57%)	466 (32.27%)	128 (43.99%)	<0.001
Missing	888 (28.1%)	11 (34.4%)	98 (21.2%)	221 (23.8%)	485 (33.6%)	73 (25.1%)	
Gestational diabetes							
No	>2360 (>74.68%)	>20 (>62.50%)	331 (71.49%)	673 (72.37%)	1100 (76.18%)	236 (81.10%)	<0.001
Yes	>499 (>15.79%)	< 5 (<15.62%)	93 (20.09%)	193 (20.75%)	189 (13.09%)	26 (8.93%)	
Missing	291 (9.2%)	4 (12.5%)	39 (8.4%)	64 (6.9%)	155 (10.7%)	29 (10.0%)	
Hypertensive disorders							
No	>2550 (>80.70%)	>22 (>68.75%)	369 (79.70%)	772 (83.01%)	1148 (79.50%)	239 (82.13%)	0.289
Yes	>507 (>16.04%)	<5 (<15.62%)	77 (16.63%)	139 (14.95%)	251 (17.38%)	43 (14.78%)	
Missing	93 (2.9%)	3 (9.4%)	17 (3.7%)	19 (2.0%)	45 (3.1%)	9 (3.1%)	
Alcohol use							
No	>1904 (>60.25%)	>9 (>28.13%)	282 (60.91%)	604 (64.95%)	845 (58.52%)	164 (56.36%)	0.002
Yes	>195 (>6.17%)	<5 (<15.62%)	15 (3.24%)	52 (5.59%)	114 (7.89%)	16 (5.50%)	
Missing	1051 (33.3%)	15 (46.9%)	166 (35.9%)	274 (29.5%)	485 (33.6%)	111 (38.1%)	
Tobacco use							
No	2354 (74.49%)	24 (75.00%)	345 (74.51%)	652 (70.11%)	1120 (77.56%)	213 (73.20%)	0.289
Yes	91 (2.88%)	0 (0.00%)	9 (1.94%)	19 (2.04%)	51 (3.53%)	12 (4.12%)	
Missing	715 (22.6%)	8 (25.0%)	109 (23.5%)	259 (27.8%)	273 (18.9%)	66 (22.7%)	

Per NIH ECHO policy, cells with participants <5 people are hidden in order to protect participant identity.
ECHO, Environmental Influences on Child Health Outcomes; NIH, National Institute of Health.

2019 American Community Survey provided median household income at the census tract level and the proportion of residents in a census tract by racial and ethnic group.

Statistical analysis

In descriptive analyses, we summarised maternal and outcome characteristics by redlining grades. We reported means and SD of

Table 2 Outcome characteristics

	Total	A	B	C	D	Ungraded	
	(N=3160)	(N=32)	(N=463)	(N=930)	(N=1444)	(N=291)	P value
Birth weight (g)							
Mean (SD)	3197.6 (614.5)	3364.6 (700.1)	3218.7 (621.1)	3259.2 (569.6)	3157.8 (621.7)	3146.4 (676.3)	0.001
Birth weight z-score							
Mean (SD)	−0.1 (1.0)	0.2 (1.3)	−0.1 (1.0)	−0.0 (1.1)	−0.2 (1.0)	−0.2 (1.0)	0.002
Preterm birth							
No	>2823 (>89.34%)	>26 (>81.25%)	416 (89.85%)	844 (90.75%)	1281 (88.71%)	256 (87.97%)	0.353
Yes	>327 (>10.35%)	<5 (<15.63%)	47 (10.15%)	86 (9.25%)	163 (11.29%)	35 (12.03%)	
Low birth weight							
No	>3076 (>97.34%)	>26 (>81.25%)	449 (96.98%)	919 (98.82%)	1405 (97.30%)	277 (95.19%)	0.114
Yes	>74 (>2.34%)	<5 (<15.63%)	14 (3.02%)	11 (1.18%)	39 (2.70%)	14 (4.81%)	
Average $PM_{2.5\ \mu g/m^3}$ exposure during pregnancy							
Mean (SD)	7.0 (1.2)	7.2 (0.9)	6.8 (1.1)	6.7 (1.2)	7.2 (1.1)	7.4 (1.1)	<0.001

PM, particulate matter.

continuous variables and counts and percentages of categorical variables. We used analysis of variance tests and χ^2 for analysis.

For our primary analysis, we conducted a series of regression models to assess the association of redlining with $PM_{2.5}$ and birth outcomes, separately. For all models, a combined group of A, B and C-graded census tracts served as our reference group and was compared with D-graded and ungraded tracts. Due to the temporal gap between redlining grade assignments and our outcomes, the confounding assumptions of mediation analysis were not met.[19] We did not pursue causal mediation analysis. To assess the relationship between redlining and average $PM_{2.5}$ exposure during pregnancy, we used linear regression and included year of pregnancy and birth season as covariates for precision.

Next, we conducted a series of multivariable linear and logistic regression models to explore the impact of redlining on our three birth-related outcomes, BWZ, LBW and PTB. In primary models for BWZ, LBW and PTB, we adjusted for parity, marital status and maternal age conceptualised as precision variables. Additionally, for LBW and PTB models, we included sex in the model as an additional precision variable. We acknowledge race and ethnicity at the individual level act as effect modifiers. Due to insufficient power for race stratification, we opted not to pursue it, but with a sufficient sample size for ethnicity, we conducted a stratified analysis on BWZ. At the tract level, we conceptualise racial and ethnic composition (via segregation) as mediators and precision variables. Considering demographic shifts since redlining, we included these variables in secondary models as covariates to try to account for processes like gentrification and to explore how identity influences birth outcomes through pathways distinct from redlining (medical racism). To aid in the interpretation of the data, we considered whether adding $PM_{2.5}$ to the model as a covariate impacted results. We assumed covariate missingness occurred at random and imputed missing data using multiple imputations using the MICE package V.3.16.0. All analyses were conducted in RStudio using R V.4.2.2.

Table 3 Regression results redlining and air pollution

Historical redlining group	Beta estimates	95% CI
Not redlined (A, B, C)	Ref	Ref
Redlined (D)	0.43	0.36 to 0.51
Ungraded	0.59	0.45 to 0.72

The unit of $PM_{2.5}$ exposure is μg/m^3. The model included year of birth and seasonality as a covariate.
PM, particulate matter.

RESULTS

Descriptive

The study sample consisted of 3160 mother–singleton pairs enrolled in 6 NYC birth cohorts. In table 1, we describe participant characteristics by redlining grade. The majority of participants who identified as either black or white lived in D-graded census tracts. Additionally, the majority of participants who identified as Hispanic lived in C-graded and -graded census tracts. Across all grades, most participants were college educated. The average birth weight of infants in the study was 3198 g; notably, average birth weight decreased across HOLC grades. Just over 89% of infants were carried to term and 97% had normal birth weight with little difference across grades (table 2). The average residential $PM_{2.5.}$ exposure during pregnancy was 7.0 μg/m^3 and the ungraded census tracts had the highest average exposure (table 2).

Redlining and air pollution regression

In models evaluating the association between historical redlining and $PM_{2.5}$, residence in a redlined or D-graded and ungraded census tracts during pregnancy was associated with higher exposure to $PM_{2.5}$ compared with our reference group (table 3). More specifically, the change in $PM_{2.5}$ exposure from our combined group of A, B and C tracts to a redlined census tract increased by 0.43 μg/m^3 (95% CI 0.36 to 0.51). This association was strengthened comparing the reference (A, B and C-graded tracts) to ungraded census tracts, where residence in an ungraded tract was associated with an increase in $PM_{2.5}$ exposure by 0.59 μg/m^3 (95% CI 0.45 to 0.72).

Redlining and birth outcomes

For BWZ (table 4), we saw a decrease of 0.15 (95% CI −0.23 to –0.08) in those residing in a lower-grade census tract compared with a higher-grade census tract. Results were consistent controlling for present-day maternal sociodemographic 0.14 (95% CI −0.21 to –0.06) and when controlling for tract-level characteristics 0.16 (95% CI −0.25 to –0.07). Ungraded census tracts were associated with a decrease in BWZ of 0.14 (95% CI −0.27 to –0.02) for the minimally adjusted model.

Table 4 Regression results for redlining and birth outcomes

Outcome (year)	Historical redlining group	Minimally adjusted models		Models adjusted for maternal sociodemographic characteristics		Models adjusted for census tract-level characteristics	
		Effect estimate	95% CI	Effect estimates	95% CI	Effect estimates	95% CI
Birth weight Z-score	Not redlined (A,B,C)	Ref	Ref	Ref	Ref	Ref	Ref
	Redlined (D)	−0.15	−0.23 to −0.08	−0.14	−0.21 to −0.06	−0.16	−0.25 to −0.07
	Ungraded	−0.14	−0.27 to −0.02	−0.13	−0.26 to 0.00	−0.14	−0.28 to −0.00
Preterm birth	Not redlined (A,B,C)	Ref	Ref	Ref	Ref	Ref	Ref
	Redlined (D)	1.24	0.97 to 1.58	1.25	0.97 to 1.60	1.15	0.88 to 1.50
	Ungraded	1.28	0.86 to 1.91	1.29	0.86 to 1.95	1.36	0.89 to 2.09
Low birth weight	Not redlined (A,B,C)	Ref	Ref	Ref	Ref	Ref	Ref
	Redlined (D)	1.53	0.93 to 2.55	1.43	0.85 to 2.39	1.31	0.77 to 2.26
	Ungraded	2.56	1.31 to 5.03	2.11	1.05 to 4.20	2.37	1.16 to 4.87

Minimally adjusted models included terms for parity, marital status and maternal age. Models adjusted for maternal characteristics included terms for maternal income and race/ethnicity. Models adjusted for census tract-level characteristics included terms for per cent racial/ethnic make-up within a census tract (per cent Asian, Black, Indigenous, Latino and white) and median household income. Models for PTB and LBW included an additional term for child biological sex.
LBW, low birth weight; PTW, preterm birth.

This association was no longer significant when we adjusted for maternal demographics (beta, −0.13; 95% CI −0.26 to 0.00) but not tract-level characteristics (beta, −0.14; 95% CI −0.27 to −0.00). When adjusting for $PM_{2.5}$ (table 5), the estimates slightly decreased but largely remained unchanged for all models.

In our primary models for PTB, we saw increased odds of PTB in redlined census tracts compared with not redlined tracts (OR 1.24; 95% CI 0.97 to 1.58) and in ungraded tracts compared with not redlined tracts (OR 1.28; 95% CI 0.86 to 1.91), however, these results were null. This remained true when we controlled individual-level demographics as well as census tract composition. In $PM_{2.5}$ adjusted models, the odds of PTB decreased compared with models that did not control $PM_{2.5}$, however, the results again were not statistically significant.

In models examining redlining and LBW, there were increased odds of LBW in ungraded tracts compared with non-redlined tracts. The odds of LBW in ungraded tracts were 2.56 (95% CI 1.31 to 5.03) times the odds of LBW in non-redlined tracts in the main models. These results attenuated when adjusted for individual-level demographics and group-level demographics. Finally, when controlling for $PM_{2.5}$, the odds of LBW were 2.18 (95% CI 1.10 to 4.31) times higher in ungraded tracts compared with non-redlined tracts. No statistically significant associations were found between redlined tracts and LBW.

Table 5 Regression results for redlining and birth outcomes adjusted for air pollution

Outcome (year)	Historical redlining group	Air pollution adjusted models	
		Effect estimate	95% CI
Birth weight Z-score	Not redlined (A,B,C)	Ref	Ref
	Redlined (D)	−0.14	−0.22 to −0.06
	Ungraded	−0.13	−0.26 to 0.00
Preterm birth	Not redlined (A,B,C)	Ref	Ref
	Redlined (D)	1.18	0.92 to 1.51
	Ungraded	1.20	0.80 to 1.79
Low birth weight	Not redlined (A,B,C)	Ref	Ref
	Redlined (D)	1.35	0.81 to 2.25
	Ungraded	2.18	1.10 to 4.31

These models were adjusted for parity, marital status, maternal age and air pollution. Models for PTB birth and LBW included an additional term for child biological sex.
LBW, low birth weight; PTW, preterm birth.

In stratified analyses by ethnicity (online supplemental table 3), we observed smaller BWZ in residents of redlined (−0.07, 95% CI −0.17 to 0.04) and ungraded tracts (−0.04, 95% CI −0.26 to 0.19) among Hispanic or Latino participants. Effect estimates were larger and significant for the NH group in both redlined (−0.24, 95% CI −0.35 to −0.12) and ungraded tracts (−0.22, 95% CI −0.39 to −0.06).

DISCUSSION

This study examines how historical redlining impacts $PM_{2.5}$ and three birth outcomes in NYC. In this analysis, we found those who resided in redlined census tracts experienced (1) elevated exposure to $PM_{2.5}$ and (2) lower BWZ. Additionally, we observed (3) higher levels of $PM_{2.5}$, lower BWZ and increased odds of LBW in ungraded census tracts. This paper advances NYC redlining literature by using a dataset with information on $PM_{2.5}$ exposure, exploring LBW and BWZ and including ungraded census tracts, which was not done in previous NYC-specific studies. Our study finds a correlation between residing in redlined areas and adverse birth outcomes, alongside increased exposure to $PM_{2.5}$, each posing potential risks to long-term health.

Our study findings on increased $PM_{2.5}$ levels and adverse birth outcomes in redlined census tracts are aligned with existing evidence. Our study is consistent with a previous NYC study finding smaller, $PM_{2.5}$, reductions in redlined census tracts where schools were located compared with A-graded, B-graded and C-graded tracts.[6] Less greenspace, reduced tree canopy and increased heat have been documented in redlined areas.[20–23] These could be modifying factors that explain the worsening air quality and BWZ observed in redlined tracts. In our descriptive analysis, A areas showed similar $PM_{2.5}$ levels to D areas, underscoring NYC's urban landscape complexity.[8] We saw a similar pattern for our dichotomous but not continuous birth outcome, where BWZ decreased as HOLC grades worsened. Out of NYC's 2168 census tracts with grades, 1.9% were A-graded, which may explain the larger influence B and C tracts had on our results. In addition, our results were not robust when grouping C and D neighbourhoods against A and B neighbourhoods (online supplemental table 4). After adjusting for $PM_{2.5}$ in birth outcome models, associations mostly remained, possibly because historical disinvestment affects mitigating factors to outdoor air pollution like housing quality, which we could not account for.

While our results for PTB were null, effect sizes were similar to other studies.[9 24] In our study, we observed persistent associations, even after controlling for sociodemographic variables. We believed controlling for race and ethnicity, at either the individual or tract level, would have biased our estimates towards the null. We may not have seen this because these demographic categories do not fully capture dimensions of vulnerability.

Our study highlights that ungraded tracts deserve attention in the redlining literature. Generalising about consistent features of ungraded tracts in our study requires deeper historical analysis. Local actors' influence on lending practices led to inconsistencies in why neighbourhoods were ungraded, often representing underdeveloped or mixed-use areas.[3] One analysis of Los Angeles revealed racial, ethnic and income segregation persisted within ungraded areas, demonstrating societal processes perpetuate spatialised inequality beyond redlining performed by HOLC.[25] An analysis in Seattle found that gentrified non-redlined tracts had high policing rates similar to non-gentrified redlined tracts. Providing further evidence for how contemporary practices reproduce racism over time in non-redlined areas.[26]

Our study has several strengths. The prospective design allowed us to consider $PM_{2.5}$ exposure throughout the pregnancy period. We were able to link multiple data sources to include multiple related outcomes. We also explored ungraded tracts. Our study does have limitations. Due to power limitations, we only performed stratified models by ethnicity, not race. Future studies should disaggregate large datasets like birth certificate data by race to explore racialised impacts.[4] Our smaller sample size was a trade-off to use a dataset with perinatal $PM_{2.5}$. Exposure misclassification is a concern using census tracts but less so in dense cities.[27] Our study might also be prone to selection bias as those who did not meet the inclusion criteria had different characteristics than the study population (online supplemental table 5). Due to the missingness of data in those excluded, we were unable to address this using techniques like inverse probability weighting. We lacked data on policies preceding or co-occurring with the creation of these maps, preventing us from isolating the role of redlining in our models. Given the debate on the use of these maps and the multifaceted nature of structural racism, future research should consider practices like racial exclusionary zoning fully understand the extent of redlining's impact and capture the range of historically marginalising policies.

A few potential approaches to address redlining include reparations, greenspace, opportunities for home ownership and roadway rerouting in historically redlined communities. In pursuing these strategies, we must consider the increased susceptibility pregnant people have to air pollution, which may be lower than current regulatory standards.[28] The intentional consideration of the most vulnerable is essential in the pursuit of equity.

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Contributors TH and AG conceptualised and designed the study. TH acted as guarantor, accepted full responsibility for all aspects of the work and controlled the decision to publish. TH analysed the data and drafted the manuscript. AG supervised the work. All other authors were involved in interpretation of the data and critical review of the manuscript.

Funding Research reported in this publication was supported by the Environmental influences on Child Health Outcomes (ECHO) Programme, Office of the Director, National Institutes of Health, under Award Numbers U2COD023375 (Coordinating Center), U24OD023382 (Data Analysis Center), U24OD023319 with cofunding from the Office of Behavioral and Social Science Research (PRO Core), UH3OD023320 (Aschner), UH3OD023328 (Duarte), UH3OD023290 (Herbstman), UH3OD023282 (Gern), UH3OD023305 (Trasande) and UH3OD023337 (Wright).

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Competing interests None declared.

Patient consent for publication Not applicable.

Ethics approval This study involves human participants and was approved by IRB number: s23-01039; Properly constituted Institutional Review Boards—either the ECHO single IRB or the ECHO cohort's local IRB—are accountable for compliance with regulatory requirements for the ECHO-wide Cohort Data Collection Protocol at participating cohort sites. Governing IRBs review ECHO protocols and all informed consent/assent forms, HIPAA authorisation forms, recruitment materials and other relevant information prior to the initiation of any ECHO-wide Cohort Data Collection Protocol-related procedures or activities. ECHO Cohort Investigators (or their designated study personnel) obtain written informed consent or parent's/guardian's permission along with child assent as appropriate, for ECHO-wide Cohort Data Collection Protocol participation and for participation in their specific cohorts. The work of the ECHO Data Analysis Centre is approved through the Johns Hopkins Bloomberg School of Public Health Institutional Review Board. Participants gave informed consent to participate in the study before taking part.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement No data are available. Select deidentified data from the ECHO Programme are available through NICHD's Data and Specimen Hub (DASH). Information on study data not available on DASH, such as some Indigenous datasets, can be found on the ECHO study DASH webpage. Additionally, it is important to note that the code associated with the study is not available for public access.

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