# ENVIRONMENTAL RESEARCH LETTERS

## **LETTER • OPEN ACCESS**

## Does racism have inertia? A study of historic redlining's impact on present-day associations between development and air pollution in US cities

To cite this article: Patrick Trent Greiner and Rachel G McKane 2022 Environ. Res. Lett. 17 104008

View the article online for updates and enhancements.

## You may also like

- <u>Which came first, people or pollution? A</u> review of theory and evidence from longitudinal environmental justice studies Paul Mohai and Robin Saha
- <u>The classification of PM<sub>10</sub> concentrations</u> in Johor Based on Seasonal Monsoons Hazrul Abdul Hamid, Muhamad Hanafi Rahmat and Siti Aisyah Sapani
- <u>Heat exposure and resilience planning in</u> <u>Atlanta, Georgia</u> Nkosi Muse, David M Iwaniec, Chris Wyczalkowski et al.

## ENVIRONMENTAL RESEARCH LETTERS



## LETTER

**OPEN ACCESS** 

**RECEIVED** 5 July 2022

REVISED

6 September 2022

8 September 2022

PUBLISHED 20 September 2022

Original content from this work may be used under the terms of the Creative Commons Attribution 4.0 licence.

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.



Does racism have inertia? A study of historic redlining's impact on present-day associations between development and air pollution in US cities

Patrick Trent Greiner<sup>1,\*</sup> and Rachel G McKane<sup>2</sup>

Department of Sociology, and Department of Public Policy Studies, Vanderbilt University, Nashville, TN 37235

<sup>2</sup> Population Studies and Training Center, and Spatial Structures in the Social Sciences, Brown University, Providence, RI 02912
 \* Author to whom any correspondence should be addressed.

E-mail: patrick.t.greiner@vanderbilt.edu

**Keywords:** redlining, inequality, development, air pollution Supplementary material for this article is available online

#### Abstract

We explore how Home Owners' Loan Corporation (HOLC) scores of the 1930s impact 2010 and 2015 inhalable particulate matter ( $PM_{10}$ ) concentrations for 15,232 census tracts, clustered in 196 cities throughout the contiguous United States. Using areal apportionment, we assign a HOLC score to housing tracts and construct hierarchical linear models to examine the relationship between the policy practice of redlining, PM pollution, and urban economic development. We find that redlining is associated with higher  $PM_{10}$  concentrations, and that higher HOLC grades also intensify the association of per capita income, median rent, median home values, and racial composition with  $PM_{10}$ . These findings suggest that historical policy programs that were grounded in racial logics—such as the HOLC practice of 'redlining'—have an inertia that results in them influencing development pathways and environmental outcomes of built environments for decades.

## 1. Introduction

In the late 1930s, the Home Owners' Loan Corporation (HOLC) generated a series of maps and accompanying social surveys to evaluate the investment worthiness of neighborhoods in over 200 cities (Jackson 1985, Hiller 2003). Although it is unclear whether these maps were directly used by the Federal Housing Authority to deny mortgages (Fishback et al 2021), they nonetheless reflect systemic bias through direct documentation of racist, classist, and xenophobic attitudes of those responsible for shaping US housing policy in a pivotal era of city development. Neighborhoods were rated on a four-point scale, with redlined areas given a score of D-for 'hazardous'. Many of these neighborhoods were, and are, home to Black and/or immigrant communities, and neighborhood area description by the HOLC surveyors frequently mention the dual presence of Black communities and common sources of environmental pollution such as extractive industries, trash incinerators, and highways. On the contrary,

descriptions of more favorably rated neighborhoods cite the presence of exclusionary policies—such racial covenants that create 'whites only' neighborhoods as a rationale for favorable conditions to mortgage lending.

Longstanding discriminatory housing practices that reinforce residential segregation not only vastly restricted the ability of Black Americans to build wealth but reinforced and exacerbated the siting of environmental toxins in historically disadvantaged neighborhoods (Rothstein 2017). Research linking redlining to modern day environmental externalities and subsequent poor health outcomes shows the pervasive nature of environmental justice struggles that operate at multiple spatial and temporal scales (Pellow 2018). Nardone et al (2021) found that neighborhood areas assigned worse HOLC grades are associated with reduced present-day greenspace. Nowak et al (2022) found that redlined areas have lower canopy cover and greater impervious cover compared to non-redlined areas. Research shows that redlined areas have higher land surface temperatures than

those that received more favorable ratings (Hoffman *et al* 2020, Wilson 2020). And subsequently, redlined areas have been linked to numerous health disparities (Nardone *et al* 2020a), including asthma (Nardone *et al* 2020b).

Recent research has also explored the association between redlining and air pollution in US urban areas at the census tract level. Although air quality has improved in the US over the last couple decades, air pollution still disproportionately impacts people of color, who consistently live in areas with higher levels of ambient fine particulate matter (PM) air pollution (PM<sub>2.5</sub>)—a sub component of inhalable PM pollution (PM<sub>10</sub>)—regardless of income levels (Tessum et al 2021). Through a cross sectional analysis using 2010 data, Lane et al (2022) find that redlined neighborhoods have worse air quality, measured both as PM<sub>2.5</sub> and nitrogen dioxide (NO<sub>2</sub>). Though not focused on the historical process of redlining, many studies have shown that sociodemographic characteristics of urban spaces are an important predictor of pollution. Recent research has shown that in the US people of color are more likely to be exposed to PM pollution from several sources, including cooking (Shah et al 2020), chromium, and diesel exhaust (Marshall 2008). Studies have also demonstrated how the relationship between health impacts, including life expectancy, and air pollution directly relates to regionality, race, and socioeconomic position including income inequality (O'Neil et al 2003, Jorgenson et al 2020, Daouda et al 2021).

This paper connects the aforementioned research on air pollution and inequality to a broader literature within environmental social sciences and development studies that investigates factors that influence the relationship between economic development, or affluence, and environmental externalities (Dietz and Rosa 1994) including racial inequality (McGee et al 2018). We explore how redlining, an indicator of systematic racial inequality, impacts the relationship between economic development and air pollution in neighborhoods across 196 US cities. We expand on previous literature in three key ways. First, we focus our attention on inhalable PM pollution, which is defined as airborne particulate pollution with an aerodynamic diameter of 10  $\mu$ m or less (henceforth PM<sub>10</sub>) and has been linked to numerous negative health outcomes (Abbey et al 1999, Hamra et al 2014)-whereas most previous research has focused almost exclusively on PM2.5. Second, while most work concerning redlining is cross-sectional and takes place at the neighborhood level, we explore the impact of redlining on tract-level longitudinal panel data-allowing us to leverage greater spatial and temporal granularity to better control for exogenous factors. Finally, whereas previous research has characterized the direct relationship HOLC grading holds with various environmental outcomes, here we explore how development processes associated

with pollution function differently in tracts with A, B, C, and D HOLC scores. The results from this study highlight the long-standing impacts of historic structural racism on finding effective solutions to environmental crises and meeting the goals of environmental justice and pollution mitigation in cities.

#### 2. Materials and methods

#### 2.1. Housing and demographic data

Independent variables concerning tract-level housing characteristics and demographics come from the US census, 5 year American Community Survey. We use the 2008-2012 and 2013-2017 5-year estimates as proxies for the years 2010 and 2015. The 5 year American Community Survey estimates offer the highest accuracy for tract level estimates in the periods under consideration, and are well validated, commonly used measures. Our sample consists of 15 232 census tracts that fall within the boundaries of 196 cities across the contiguous US, as of 2010. We only include tracts within city boundaries to avoid comparing urban with suburban tracts, as development processes likely differ across such spaces. Tract-level census data are used to control for differences in both economic development and demographic indicators, and include controls for total population, number of housing units, percent of owner-occupied homes, per capita income, median home value, median rent, and percent of the population that is White (non-Hispanic). In alternate models, presented in the supplementary information, we also incorporate measures of the percent Asian, percent Black, and percent non-White Hispanic.

Total population accounts for the well-studied association between population growth and environmental impact, such as PM pollution, at a number of analytic scales (York et al 2003). Total number of housing units, in conjunction with total population size, serves as a proxy measure controlling for the typical density of development occurring within a tract. Percent of owner-occupied homes serves as a control for the relative permanence of residents within a tract, and speaks to the residents' potential interest in neighborhood development-including projects oriented towards the improvement of use-values that are promoted over those centered on the inflation of urban exchange-value (e.g. Logan and Molotch 2007). We use per capita income as a measure of economic development, and to account for the wellestablished association of affluence and pollution rate (Dietz et al 2010). Median rent and median home value account for the perceived quality of the housing stock, community amenities, and use-values in a given tract. We include both median rent and median home value in all models-where median rent is situated as a proxy for the affluence of a tract and median home value a proxy for wealth. In addition

**IOP** Publishing

to measures of development we include percent of the population that identifies as non-Hispanic White, given the highly racialized HOLC grading process (Rothstein 2017), and because racial disparities in PM pollution persist beyond what can be accounted for by HOLC score alone (Lane *et al* 2022).

#### 2.2. HOLC score data

Our key independent variable, HOLC score, was created using data from the University of Virginia's Mapping Inequality Project, which provides georeferenced HOLC codes for 202 US cities (see Nelson et al 2018). This data is based on the scanned documents from the HOLC residential security maps produced between 1935 and 1940 and rates areas based on investment risk: A is 'best', B is 'still desirable', C is 'definitely declining' and D is 'hazardous'. We assigned a numeric value to each score such that a HOLC grade of A = 1, B = 2, C = 3, and D = 4. We linked HOLC maps to census tracts using 2010 TIGER/LINE shapefiles and conducted weighted areal apportionment (e.g. Mohai and Saha 2006) to create a census tract level HOLC score. Due to the weighting scheme, the final HOLC score measure can take any continuous value between 1 and 4.

#### 2.3. Air pollution data

The dependent variable is the average annual concentration ( $\mu$ g m<sup>-3</sup>) of inhalable PM at the census tract level. Inhalable PM pollution is defined as airborne particulate pollution with an aerodynamic diameter of 10  $\mu$ m or less (henceforth PM<sub>10</sub>). PM<sub>10</sub>—which includes fine PM of 2.5 µm diameter or less-consists of aerosolized pollution from construction, road dust, automobile tire and brake pad abrasion, agricultural activity, wild and prescribed fires, waste management facilities (e.g. landfills and industrial processing plants), industrial production, and dust and pollen. Short term exposure to PM<sub>10</sub> pollution is associated with an intensification of chronic respiratory illness symptoms and related hospitalizations and emergency room visits (Hamra et al 2014). Long term exposure to PM<sub>10</sub> is associated with respiratory mortality and increased risk of lung cancer (Abbey et al 1999). The International Agency for Research on Cancer (IARC) rates outdoor PM pollution as a Group 1 carcinogen that is believed to contribute to cancer in humans (IARC 2016).

Air pollution data were gathered from the Center for Air, Climate, and Energy Solutions (CACES) which uses land use regression models to calculate annual mean outdoor PM<sub>10</sub> air pollution at the census tract level throughout the contiguous US for the years 1979–2015 (Kim *et al* 2018). CACES produces annual mean estimates of PM pollution (e.g. PM<sub>2.5</sub>, PM<sub>10</sub>) with spatial granularity as fine as the census block group and as coarse as the nation. We include air pollution data from 2010 and 2015 in our models. PM pollution estimates from CACES land use regression outputs have been found to have high validity in the past, tracking monitored pollution well in cross-validation analyses for a number of pollutants. CACES PM<sub>10</sub> measures used in the present study have been cross-validated with a standardized root mean squared error of 0.28 and a median  $R^2$  of 0.60. This validity has also been found to improve in more recent years, which the current analyses employ (Kim *et al* 2018). We focus analyses and discussion on PM<sub>10</sub>, as it represents a wider class of carcinogenic pollutant than PM<sub>2.5</sub>, while also including PM<sub>2.5</sub> concentrations and PM with an aerodynamic diameter between 2.5 and 10  $\mu$ m.

#### 2.4. Descriptive statistics of key variables

With the exception of period and city indicators, all variables are natural log transformed. Such transformations make coefficients interpretable as elasticities where magnitude and direction represent the proportional change in the dependent variable of interest in response to a 1% change in the independent variable under consideration. This procedure is common in stochastic impact by regression on population affluence and technology (STIRPAT) literature as it retains the multiplicative functional form of the IPAT (Impact = Population  $\times$  Affluence  $\times$  Technology) identity typically used to explore social drivers of environmental impact (Dietz and Rosa 1997). Figures 1(a)–(i) display the distributions of the key variables at the tract level for the entirety of the sample used in the analyses below.

#### 2.5. Analytic technique and model structure

The models and analysis of this study were designed with two research goals in mind. First, we wish to evaluate the role historical processes of structural racism and institutional discrimination in housing plays in contributing to contemporary environmental injustices. Specifically, we wish to explore the role HOLC grading-via subsequent access to reliable, federally insured mortgage financing and related urban development opportunities-and the phenomenon of redlining plays as a driver of  $PM_{10}$ pollution in urban space. This goal is rooted in recent scholarship in critical environmental justice that invites researchers to explore the multi-scalar nature of environmental justice problems (Pellow 2018). Second, we aim to understand how HOLC scores, serving as a proxy for racial exclusion and white privilege, have a longstanding impact on the relationships between economic development and PM pollution. Thus, we examine if and how HOLC score moderates the association of indicators representing affluence, wealth, and economic development (per capita income, median rent, and median home value) with PM<sub>10</sub> pollution in census tracts for the years 2010 and 2015.

To address the above research concerns we construct two hierarchical linear models with census



tract-years nested within cities. Intercepts vary randomly by city in order to account for city-level differences in development policy approach and other persistent city level variations that are not directly controlled for in the model. To evaluate research questions concerning the direct impact of HOLC scoring with  $PM_{10}$  outcomes, we construct a random intercept model with unconstrained co-variance structures. These models can be formally stated as follows:

$$y_{ij} = \alpha_0 + \alpha_j + \beta_i X_i + e_{ij}$$
  

$$\alpha_j = \alpha + \mu_j$$
  

$$\mu_j \sim N(0, \sigma_\mu^2)$$
  

$$e_{ij} \sim N(0, \sigma_e^2)$$
(1)

where  $y_{ij}$  is the response variable for the *i*th tractyear in the *j*th city;  $\alpha_0$  is the global mean of the tract level intercept;  $\alpha_j$  is a vector of city specific random intercepts;  $X_i$  is a vector of the additive effects of the tract-year covariates and  $\beta_i$  a vector of associated explanatory variables;  $\alpha$  is the global mean for city level intercepts;  $\mu_j$  is the city level residual term;  $e_{ij}$ is the residual for tract-year *i* nested within city *j*;  $\sigma_{\mu}^2$ is the cross-city variance term;  $\sigma_e^2$  represents withincity, tract-year, variance.

To explore the role that HOLC scoring plays as a moderator of the association between development and  $PM_{10}$  pollution we construct random coefficient models. Random coefficients are used in order to allow the three key measures of and economic development—income per capita, median rent, and median home value—to be interacted with the tract-level, extemporaneous HOLC score measure. All models use unconstrained variance structures as likelihood ratio tests indicated such structure offered significantly improved model fit over constrained variance structures. The random coefficients model used in the analyses below can be generally expressed as:

$$y_{ij} = \alpha_0 + \alpha_j + \gamma_j \eta_i + \beta_i X_i + e_{ij}$$
  

$$\alpha_j = \alpha + \mu_j$$
  

$$\gamma_j = \gamma + \mu_{\gamma j}$$
  

$$\frac{\mu j}{[\mu \gamma j]} \sim N(0, \begin{bmatrix} \sigma_{\mu}^2 & - \\ \sigma_{\mu \mu \gamma}^2 & \sigma_{\mu \gamma}^2 \end{bmatrix}$$
  

$$e_{ij} \sim N(0, \sigma_e^2)$$
(2)

where  $y_{ij}$  is the outcome of interest for the *i*th tractyear in the *j*th city;  $\alpha_0$  is the global mean of the tract level intercepts;  $\alpha_j$  is a vector of city specific random coefficients, while  $\eta_i$  is a vector of values for the relevant development measure (i.e. income per capita, median home value, median rent);  $X_i$  is a vector of the additive effects of the tract-year covariates and  $\beta_i$  a vector of associated fixed effect parameter estimates;  $e_{ij}$ is the residual for tract-year *i* nested within city *j*;  $\alpha$ is the cross-city grand mean of the intercept;  $\mu_j$  is the city level residual term;  $\gamma$  is the cross-city grand mean of the scaling parameter for  $\eta$ ;  $\mu_{\gamma j}$  is the city level residual term for the association of *y* and  $\eta$ ;  $e_{ij}$  is



**Figure 2.** (a)–(k) Display the distributions of  $PM_{10}$  concentration, population size, number of available homes, percent of owner-occupied homes, median home value, per capita income, median rent cost, and racial composition measures for the 30, 434 census tract-year observations that compose the sample, conditioned upon HOLC grade. Black dots represent individual observations, area plots represent the probability densities of observations across tracts, conditioned on HOLC grade. Box and whisker plots represent summary statistics, with the thick vertical bar being the median value, the box the interquartile range (IQR), and the lines the 1.5 IQR extent. HOLC score is along the vertical axis of the plot.

the residual for tract-year *i* nested within city *j*;  $\sigma_{\mu}^2$  is the cross-city variance term;  $\sigma_e^2$  represents tract-level variance. As these models nest tract-years within cities, they replicate the functional logic of econometric models with fixed effect estimators for unit and year and thereby control for exogenous contemporaneous and extemporaneous factors that might influence outcomes.

#### 3. Results

Descriptive statistics, conditioned on HOLC grade, can be found in figures 2(a)-(i). Results from regression analyses are presented in table 1 and figure 3. The descriptive statistics in figure 2 suggests that both PM<sub>10</sub> and several key development and housing measures are associated with HOLC grade. Figure 2(a) indicates that a census tract's median  $PM_{10}$  value is slightly above 20  $\mu$ g m<sup>-3</sup> in neighborhoods that received a HOLC grades of C or D but is roughly 17.6  $\mu$ g m<sup>-3</sup> in ones that received a HOLC grade of A. Similarly, tracts with lower HOLC grades have substantially lower rates of homeowner occupation, median home value, median rent, and per capita income than higher graded tracts. Coupled with the sizeable disparities in White population size across A, B, C, and D scored tracts these descriptive statistics support the claim that HOLC grading is a historical process associated with systematic, racial inequalities in urban built environments-across several socioecological dimensions (e.g. Rothstein 2017, Nardone et al 2020a, Lynch et al 2021). In the statistical models below, we further explore the relationship between HOLC score and PM<sub>10</sub> pollution—including the percent of a tract identifying as non-Hispanic White. We focus on this measure of racial composition for two reasons. First, the distribution for percent of the population that is Asian, Black, and non-White Hispanic rarely surpasses 10% at the tract level. Second, many argue that the HOLC grading process was fundamentally oriented around privileging the majority White communities in the US. Or, put another way, historic US housing policy aided the generational accumulation of wealth in populations identified as White. Nonetheless, in the supplementary information we include models for all racialized groups and find that the results are consistent.

Table 1 presents the results of all random intercept and random coefficient regression analyses. Model 1 presents the association of urban housing, development and demographic variables, excepting HOLC grade, and  $PM_{10}$  concentrations. Results of model 1 indicate that the total number of available housing units and the percent of the population that is non-Hispanic White are both drivers of  $PM_{10}$  pollution. Conversely, increases in total population size, per capita income, and median home value, are all associated with decreases in  $PM_{10}$  values at the census tract level. Percent of owner-occupied homes and median

	Model	-	Model	5	Model	~	Model	4	Model	5	Model (	
Predictors	Estimates	Std. error	Estimates	Std. error	Estimates	Std. error	Estimates	Std. error	Estimates	Std. error	Estimates	Std. error
ntercept	3.880***	0.029	3.660***	0.032	4.338***	0.067	4.285***	0.067	4.375***	0.075	3.750***	0.031
4	(3.823 - 3.938)		(3.598 - 3.722)		(4.207 - 4.469)		(4.155 - 4.416)		(4.228 - 4.522)		(3.688 - 3.811)	
[otal	$-0.041^{***}$	0.005	$-0.033^{***}$	0.005	$-0.030^{***}$	0.004	$-0.034^{***}$	0.004	$-0.032^{***}$	0.004	$-0.049^{***}$	0.004
opulation	(-0.050 - 0.032)		(-0.042 - 0.025)		(-0.038 - 0.021)		(-0.042 - 0.025)		(-0.041 - 0.024)		(-0.057 - 0.040)	
Total housing	0.028***	0.005	$0.022^{***}$	0.005	$0.016^{***}$	0.005	$0.021^{***}$	0.005	0.019***	0.005	0.038***	0.005
units	(0.019 - 0.037)		(0.013 - 0.031)		(0.008 - 0.025)		(0.012 - 0.030)		(0.010 - 0.028)		(0.029 - 0.047)	
Per capita	$-0.058^{***}$	0.004	$-0.048^{***}$	0.004	$-0.106^{***}$	0.007	$-0.046^{***}$	0.003	$-0.035^{***}$	0.004	$-0.046^{**}$	0.004
ncome	(-0.065 - 0.051)		(-0.055 - 0.041)		(-0.120 - 0.092)		(-0.052 - 0.039)		(-0.042 - 0.028)		(-0.053 - 0.039)	
<b>Dwner</b> occupied	0.001	0.002	0.003	0.002	0.002	0.002	$0.004^{**}$	0.002	0.003	0.002	0.003	0.002
nomes (percent)	(-0.002 - 0.004)		(-0.001 - 0.006)		(-0.001 - 0.005)		(0.001 - 0.007)		(-0.000-0.006)		(-0.000-0.006)	
Median rent	-0.003	0.004	-0.002	0.003	-0.009**	0.003	$-0.095^{***}$	0.010	-0.005	0.003	-0.003	0.003
	(-0.010 - 0.004)		(-0.009 - 0.005)		(-0.015 - 0.002)		(-0.114 - 0.075)		(-0.012 - 0.001)		(-0.010 - 0.003)	
Median home	$-0.022^{***}$	0.003	$-0.018^{***}$	0.003	$-0.019^{***}$	0.003	$-0.019^{***}$	0.003	$-0.084^{***}$	0.007	$-0.021^{***}$	0.003
value	(-0.027 - 0.016)		(-0.023 - 0.012)		(-0.024 - 0.014)		(-0.024 - 0.014)		(-0.097 - 0.071)		(-0.026 - 0.015)	
White population	$0.002^{**}$	0.001	0.001	0.001	0.001	0.001	$0.001^{*}$	0.001	$0.001^{*}$	0.001	$-0.012^{***}$	0.003
(percent)	(0.001 - 0.003)		(-0.000-0.002)		(-0.000-0.002)		(0.000 - 0.002)		(0.000-0.003)		(-0.018 - 0.006)	
Holc score			$0.043^{***}$	0.002	$-0.485^{***}$	0.036	$-0.437^{* * *}$	0.034	$-0.426^{***}$	0.033	$0.015^{*}$	0.006
			(0.038 - 0.048)		(-0.555 - 0.414)		(-0.503 - 0.371)		(-0.491 - 0.361)		(0.003 - 0.028)	
Income * Holc					0.051***	0.003						
					(//////////////////////////////////////							
kent * Holc							$0.071^{***}$ ( $0.061-0.081$ )	0.005				
Home value * Holc									0.038***	0.003		
White population * Holc									( (+0.0-200.0)		$0.007^{***}$ (0.003-0.010)	0.002
7	196 <sub>city</sub>		196 <sub>city</sub>		196 <sub>city</sub>		196 <sub>city</sub>		196 <sub>city</sub>		196 <sub>city</sub>	
Observations	15232		15 232		15 232		15 232		15232		15 232	
Marginal R <sup>2</sup> / conditional R <sup>2</sup>	0.053/0.826		0.048/0.831		0.063/0.857		0.061/0.855		0.077/0.869		0.064/0.836	
Log-likelihood	15504.648		15646.983		16 706.733		$16\ 296.784$		16513.136		16225.965	



Figure 3. (a)–(d) Display the estimated outcomes of the interactions presented in models 3–6 of table 1. Solid lines represent estimates. Shaded area represents 95% confidence intervals. For ease of interpretation we only show estimates for tracts with HOLC scores of A (green) and D (red).

rent cost are both found to have no statistically significant association with PM<sub>10</sub>.

Model 2 extends model 1 by incorporating the HOLC score variable. Results of model 2 are consistent with those of model one, with the exception that controlling for HOLC score renders the association between percent of the population that is non-Hispanic White and  $PM_{10}$  statistically indistinguishable from 0. Model 2 results also indicate that a 1% increase in HOLC score is associated with a .043% increase in  $PM_{10}$  pollution. The association between HOLC score and  $PM_{10}$  pollution is only surpassed in magnitude by that of per capita income which appears to reduce  $PM_{10}$  by .048% for every 1% increase in its value.

Models 3–6 expand on model 2 by incorporating interactions between HOLC score and per capita income, median rent, median home value, and the percent of the population that identifies as non-Hispanic White, respectively. As models 3–6 display results for the interaction of two continuous variables, the coefficients for the main effects represent the association of one variable in the interaction when the other is equivalent to 0. Thus, to better understand the results we turn to figures 3(a)-(d).

Figure 3(a) presents results of the interaction between income per capita and HOLC score in model 3 of table 1. As figure 3(a) indicates, tracts with a HOLC grade of A are likely to have greater concentrations of PM<sub>10</sub> pollution when per capita income is lower than roughly US \$7000. However, as can be seen in figure 2(f), there are no tracts that were observed to have a HOLC grade of A *and* less than roughly US \$12 000 per capita income. Conversely, beyond a per capita income of about US \$30 000, which represents the 65th percentile of D-graded tracts,  $PM_{10}$  pollution is likely to be greater in D than A-graded areas—all else being equal. This suggests that the forms of economic development available to historically redlined neighborhoods, D graded tracts, are likely to result in exposure to greater concentrations of  $PM_{10}$  than in other neighborhoods, especially those with a HOLC score of A or B.

Figure 3(b) displays the results of model 4 from table 1. The interaction between median rent and HOLC score reveals that in A-graded tracts there is a reduction in expected PM<sub>10</sub> concentrations. In D-graded tracts the opposite is true, however, and increases in median rent are associated with increased concentrations of PM<sub>10</sub>. The result is that, on average, D-graded tracts have significantly higher concentrations of PM10 once median rent reaches \$800 a month or more. As seen in figure 1, median rent cost for all tracts is US \$813 a month. Turning to figure 2 it can be seen that \$800 is the 56th percentile of rent cost for D-graded tracts and the 35th percentile for A-graded tracts. This suggests that as the expected affluence of occupants in a given tract increases, and the cost of living associated with those increases rise as well, neighborhoods that were graded A, B, and C by the HOLC organization experienceby descending degree-declines in PM<sub>10</sub> concentrations as rents rise. In D-graded tracts the opposite is true.

Figure 3(c) displays the results of the interaction between median home value and HOLC score from model 5. Figure 3(c) suggests that increasing median home values results in a decline of PM<sub>10</sub> concentrations for all neighborhoods. However, the reduction is of a greater magnitude in census tracts with a lower HOLC grade. The result is that D-graded tracts would need to achieve much higher median home values in order to lower PM<sub>10</sub> concentrations to match those of their A-graded counterparts. For instance, at the overall median home value of US \$207 650 an A-graded tract is estimated to have a PM<sub>10</sub> concentration of roughly 17.5  $\mu$  m<sup>-3</sup>. In a D-graded neighborhood, however, PM<sub>10</sub> concentrations are not estimated to descend to 17.5  $\mu$  m<sup>-3</sup> until median housing values reach nearly US \$850 000-which is the 95th percentile of median home values across all tracts, and the 97th percentile of D-graded tracts.

To explore the interaction of racial composition and historical HOLC grade we turn to figure 3(d)which presents the results of model 6. The interaction between percent of the population that identifies as non-Hispanic White and HOLC score demonstrates that in D-graded neighborhoods there is little change in PM<sub>10</sub> pollution associated with change in percent of non-Hispanic White population. However, in A-graded neighborhoods increasing the percent of the population that identifies as non-Hispanic White is associated with notable declines in PM<sub>10</sub> concentration. As can be seen in figure 3(d), when non-Hispanic White population size declines below roughly 17.5% there is no statistically significant difference between PM<sub>10</sub> pollution in A or D-graded neighborhoods. This suggests that, while HOLC grading does indeed play a role in contemporary PM<sub>10</sub> outcomes, there are also contemporary racial dynamics at work that influence which neighborhoods are most regularly polluted-such that predominantly White tracts are exposed to less pollution overall.

#### 4. Discussion and conclusion

The discriminatory practice of redlining not only prevented Black Americans and other historically marginalized groups from building generational wealth, or affluence, through homeownership, but it has also played a role in the inequitable distribution of environmental externalities in cities across the US (Nardone et al 2021, Lane et al 2022, Nowak et al 2022). As with previous research concerned with PM<sub>2.5</sub> distributions (Lane et al 2022), we find that there are differential patterns of PM<sub>10</sub> concentration across neighborhoods and that these differences relate to historic HOLC grading. Similarly, as with existing research into social drivers of PM2.5 concentrations, contemporary racial compositions of neighborhoods are also found to be an important driver of differential patterns in PM<sub>10</sub> pollution (Tessum et al 2021, Lane et al 2022). The results presented above build

upon these findings, and demonstrate how economic development, or growing affluence, does not lead to a reduction in PM<sub>10</sub> concentration equally across neighborhoods. Even as D-graded neighborhoods develop or gain affluence-measured as per capita income, median rent, and median home valueair pollution levels remain static, never significantly decreasing. This finding is striking when compared to the relationships uncovered in A-graded neighborhoods, where measures of economic development are associated with a reduction in PM<sub>10</sub> concentration. Taken together, these results support prior research that explores how racial inequality diminishes the negative association between economic development and harmful environmental externalities in urban areas (McGee et al 2018).

While it is true that predominately White tracts are exposed to less PM<sub>10</sub> pollution overall, the results reveal that the current racial composition of neighborhoods is not necessarily a proxy for redlining, which Lane et al also found with respect to PM<sub>2.5</sub> (2022). Here, as the percentage of non-Hispanic Whites increases in D-graded neighborhoods, we find there is no significant decrease in air pollution. Further research should explore how the racial composition of these neighborhoods has changed in the decades since the period of HOLC grading to determine whether or not changes in the racial composition of neighborhoods influence the relationship between pollution levels and HOLC grade. Such a study could uncover the long-lasting environmental impact of disinvestment in spaces occupied by historically marginalized groups, or the privileging of White spaces, even in the context of long-term change in racial composition across urban areas. The models here rely on well validated estimates of air pollution in urban environments. There is ample room to expand upon the present inquiry by exploring how the patterns identified here function outside of urban space, as rural and suburban areas often follow alternative development logics. Future research might also better uncover mechanisms of air pollution concentration by relying on direct measures of both population characteristics and pollution outcomes.

Our research demonstrates how the temporal scale of environmental justice concerns can span decades (Pellow 2018), and importantly, how these disparities in environmental externalities are embedded within historic policies, whether informal or formal, geared towards maintaining racial segregation and expanding White affluence and wealth. The environmental ramifications of inequitable housing policy dating back to the late 1930s reveals how the push for development, absent of a historical analysis of racism, is likely not enough to solve the myriad environmental crises, including air pollution, plaguing US cities. Although redlining is understood as racial gatekeeping to mortgage financing, the disinvestment in these 'hazardous' areas also involved altering the physical space of these neighborhoods. In this sense, the racism of the past can be said to have its own inertia—impacting a population's quality of life and the likely development trajectories open to their neighborhoods decades after the initial institution of this racialized policy program. A city level approach to climate justice requires addressing the socio-environmental damage caused by industrial development and pollution, destruction of trees and greenspace, and other environmental issues plaguing formerly redlined areas.

## Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

## Acknowledgment

We thank the anonymous reviewers for their helpful comments throughout the review process.

## ORCID iDs

Patrick Trent Greiner 
https://orcid.org/0000-0001-5833-2807

Rachel G McKane https://orcid.org/0000-0002-5295-8611

#### References

- Abbey D E, Nishino N, McDonnell W F, Burchette R J, Knutsen S F, Beeson W L and Yang J X 1999 Long-term inhalable particles and other air pollutants related to mortality in nonsmokers Am. J. Respir. Crit. Care Med. 159 373–99
- Daouda M, Henneman L, Kioumourtzoglou M A, Gemmill A, Zigler C and Casey J A 2021 Association between county-level coal-fired power plant pollution and racial disparities in preterm births from 2000 to 2018 *Environ. Res. Lett.* **16** 034–055
- Dietz T and Rosa E A 1994 Rethinking the environmental impacts of population affluence and technology *Hum. Ecol. Rev.* 1 277–300 (available at: www.jstor.org/stable/24706840)
- Dietz T and Rosa E A 1997 Effects of population and affluence on CO<sub>2</sub> emissions *Proc. Natl Acad. Sci.* **94** 175–9
- Dietz T, Rosa E A and York R 2010 Human driving forces of global change: dominant perspectives *Human Footprints on the Global Environment: Threats to Sustainability* (Cambridge, MA: MIT Press) ed E A Rosa, Diekmann A, T Dietz and C Jaeger pp 83–134
- Fishback P V, Rose J, Snowden K and Storrs T 2021 New evidence on redlining by federal housing programs in the 1930s *NBER Working Paper No.* w29244
- Hamra G B *et al* 2014 Outdoor particulate matter exposure and lung cancer: a systematic review and meta-analysis *Environ*. *Health Perspect.* **122** 906–11
- Hiller A 2003 Who received loans? Home owners' loan corporation lending and discrimination in Philadelphia in the 1930s J. Plan. Hist. 2 3–24
- Hoffman J S, Shandas V and Pendleton N 2020 The effects of historical hosuing policies on resident exposure to intra-urban heat: a study of 108 US urban areas *Climate* **8** 12 International Agency for Reaserch on Cancer Working Group on
  - the Evaluation of Carcinogenic Risks to Humans [IARC]

2016 Outdoor air pollution *IARC Monographs on the Evaluation of Carcinogenic Risks to Humans* **109** 9

- Jackson K T 1985 Crabgrass Frontier: The Suburbanization of the United States (New York: Oxford University Press)
- Jorgenson A K, Thombs R P, Clark B, Givens J E, Hill T D, Huang X, Kelly O M and Fitzgerald J B 2020 Inequality amplifies the negative association between life expectancy and air pollution: a cross-national longitudinal study *Sci. Total Environ.* **758** 143705
- Kim S Y, Bechle M, Hankey S, Sheppard L, Szpiro A A and Marshall J D 2018 Concentrations of criteria pollutants in the contiguous US, 1979–2015: role of prediction model parsimony in integrated empirical geographic regression *PLoS One* 15 e0228535
- Lane H M, Morello-Frosch R, Mashall J D and Apte J S 2022
  Historical redlining is associated with present-day air pollution disparities in US cities *Environ. Sci. Technol. Lett.* 9 345–50
- Logan J R and Molotch H L 2007 Urban Fortunes: The Political Economy of Place (Berkeley, CA: University of California Press)
- Lynch E E, Malcoe L H, Laurent S E, Richardson J, Mitchell B C and Meier C S H 2021 The legacy of structural racism: associations between historic redlining, current mortgage lending, and health *SSM-Population Health* **14** 100793
- Marshall J D 2008 Environmental inequality: air pollution exposures in California's South Coast air basin *Atmos. Environ.* **42** 5499–503
- McGee J A, Ergas C and Clement M T 2018 Racing to Reduce Emissions: Assessing the relationship between race and carbon dioxide emissions from on-road travel *Sociol. Dev.* 4 217–36
- Mohai P and Saha R 2006 Reassessing racial and socioeconomic disparities in environmental justice research *Demography* **43** 383–99
- Nardone A, Casey J A, Morello-Frosch R, Mujahid M, Balmes J R and Thakur N 2020b Associations between historical residential redlining and current age-adjusted rates of emergency department visits due to asthma across eight cities in California: an ecological study *Lancet Plan. Health* 4 e24–231
- Nardone A, Chiang J and Corburn J 2020a Historic redlining and urban health today in US cities *Environ. Justice* **13** 109–19
- Nardone A, Rudolph K E, Morello-Frosch R and Casey J A 2021 Redlines and greenspace: the relationship between historical redlining and 2010 greenspace access in the United States *Environ. Health Perspect.* **129** 1–9
- Nelson R K, Winling L, Marciano R and Connolly N Mapping Inequality 2018 *American Panorama* ed K N Robert and L A Edward (available at: https://dsl.richmond.edu/ panorama/redlining/)
- Nowak D J, Ellis A and Greenfield E J 2022 The disparity in tree cover and ecosystem service values among redlining classes in the United States *Landsc Urban Plan.* **221** 104370
- O'Neil M S, Jerrett M, Kawachi I, Levy J I, Cohen A J, Gouveia N, Wilkinson P, Fletcher T, Cifuentes L and Schwartz J 2003 Health, wealth, and air pollution: advancing theory and methods *Environ. Health Perspect.* **111** 1861–79
- Pellow D 2018 What is Critical Environmental Justice? (Cambridge: Polity Press)
- Rothstein R 2017 *The Color of Law* (New York: Liveright) Shah R U, Robinson E S, Gu P, Apte J S, Marshall J D, Robinson A L and Presto A A 2020 Socio-economic disparities in exposure to urban restaurant emissions are larger than for traffic *Environ. Res. Lett.* **15** 114039
- Tessum C W, Paoella D A, Chambliss S E, Apte J S, Hill J D and Marshall J D 2021 PM<sub>2.5</sub> polluters disproportionately and systemically affect people of color in the United States Sci. Adv. 7 eabf4491
- Wilson B 2020 Urban heat management and the legacy of redlining J. Am. Plan. Assoc. 86 443–57
- York R, Rosa E A and Dietz T 2003 STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts *Ecol. Econ.* **46** 351–65