As Time Goes By: Redlining, Kinship and Environmental Justice

Kaiyi Wen
Binghamton University, Department of Economics
kwen3@binghamton.edu

Neha Khanna
Binghamton University, Department of Economics
nkhanna@binghamton.edu

March 31, 2025

Declaration of Competing Interest: The authors declare no competing financial or personal interests that could have influenced the work reported in this paper.
Corresponding Author: Neha Khanna
Department of Economics, LT 1004
Binghamton University, P.O. Box 6000
Binghamton, NY 13902-6000, USA
Email: nkhanna@binghamton.edu
Acknowledgements: This work was supported by the National Science Foundation grant number 2200648. We are grateful to Richard Moser and his colleagues at the NIH/NCI who approved our use of the restricted HINTS data (HINTS 4 Cycle 1-4; HINTS 5 Cycle 1-4; HINTS 6) under a data use agreement. We also thank the Economics Department, Binghamton University, for purchasing the data from Geolytics, Inc. utilized in the analysis.

Abstract

We explore the role of historic redlining and kinship in explaining the differential in environmental pollution experienced by marginalized and non-marginalized communities in the US. Using restricted data on 20,000 survey respondents, we measure onsite toxic emissions, ambient road noise, $PM_{2.5}$ concentrations, and airborne toxicity at the proximate, neighborhood and area scales between 2014 and 2022. We find that both redlining and kinship are strongly correlated with contemporary levels of pollution, regardless of the scale of measurement. Still these factors do not fully explain the higher level of pollution that individuals identifying as Black and Hispanic experience near their place of residence as compared to White individuals, conditional on socio-economic factors. Nonetheless, measurement scale is important and our results suggest that localized pollutants should be measured at a smaller, proximate scale to avoid potential measurement errors due to spatial aggregation.

Keywords— Redlining; Kinship; Ethnic polarization; Social cohesion; Environmental justice; HINTS; TRI; Roadway noise; Fine particulate matter; RSEI; 9 digit zip code; census block group; census tract; EJScreen

JEL codes: Q53, Q56, R12, I14

1 Introduction

Environmental regulation has been tremendously successful in lowering pollution across the United States. Despite this, there is ample evidence documenting that people of color are disproportionally exposed to pollution (Banzhaf et al., 2019*b*, Currie et al., 2023). Economists explain the distribution of pollution in terms of socio-economic factors correlated with firm and residential sorting but are not able to fully account for the persistently higher pollution experienced by racial and ethnic minorities (Currie et al., 2023). Among the possible explanations for this failure are model misspecification (omitted variable bias) and measurement error. In this paper, we introduce two new factors, (i) historic redlining & (ii) kinship, as potential correlates of ambient pollution and explore their role in explaining contemporary environmental inequities in the US. To understand the role of measurement error, we estimate pollution at multiple geographic scales ranging from the proximate (or the immediate vicinity of an individual's place of residence) to the neighborhood or area (generally represented by the census block group or census tract in which a person resides).

Redlining was a federal practice during the 1930s-1960s that restricted mortgages and credit to households living in specific neighborhoods (Banzhaf et al., 2019*b*). It refers to the Home Owners Loan Corporation (HOLC) practice of demarcating in red ink neighborhoods perceived as being economically distressed and having a high credit risk. The perception of economic distress and credit risk was at least partly fueled by negative perceptions regarding the economic status of people of color.[1] The practice was especially egregious for Black, Puerto Rican, and migrant households who were systematically denied federally insured home loans (New York Times, 2017).[2]

There is emerging evidence documenting the long-term impacts of redlining. For example, children who grew up in redlined neighborhoods tend to attain lower levels of education and earn lower incomes in adulthood (Aaronson et al., 2023). As adults, they are also more likely to reside in neighborhoods with fewer amenities, higher poverty rates, lower levels of educational attainment, and a greater prevalence of single-parent households. Redlining has also been associated with long-run effects on neighborhood national income rank, the composition and characteristics

[1] For example, a government appraiser visiting the Bedford-Stuyvesant neighborhood of Brooklyn in the 1930s noted that "colored infiltration has a definitely adverse influence on neighborhood desirability" (New York Times, 2017). On the other hand, there is evidence indicating that redlining was an indication of economic distress but not race (see, for example, Shertzer et al., 2016, Shertzer and Walsh, 2019).

[2] Fishback et al. (2022) argue that the practice of redlining merely codified prevailing practices and segregation in the housing market since HOLC only refinanced existing mortgages.

of households, and geographic mobility (Aaronson et al., 2021*b*).

There is also evidence linking redlining to contemporary environmental exposure. Formerly redlined neighborhoods are significantly hotter than non-redlined areas due to less green space and more impervious surfaces (see Hoffman et al., 2020; Nardone et al., 2021), worsening the urban heat island effect and increasing heat-related risks for marginalized communities. Similarly, redlined neighborhoods in California have higher rates of asthma-related emergency visits, driven by increased exposure to air pollution (Nardone et al., 2020). And schools in historically redlined neighborhoods of New York City experience smaller air quality improvement between 2009 and 2018 than schools in non-redlined neighborhoods (Jung et al., 2022). Furthermore, there is greater disparity in $PM_{2.5}$ concentrations across redlined neighborhoods within cities compared to non-redlined neighborhoods (Lane et al., 2022). This greater disparity suggests that $PM_{2.5}$ concentrations in redlined neighborhoods are more inconsistent, with some areas experiencing much worse conditions than others, whereas $PM_{2.5}$ concentrations in non-redlined neighborhoods are more uniform. This variability is generally a negative outcome, as it indicates that residents in formerly redlined neighborhoods are more likely to be exposed to pockets of significantly poorer air quality, exacerbating environmental inequalities. Recent work also shows that historically redlined neighborhoods are disproportionately exposed to climate risks such as extreme heat and flooding (Salazar-Miranda et al., 2024). These findings highlight the persistent spatial consequences of redlining, reinforcing the link between historical housing discrimination and present-day environmental vulnerability.

There is no doubt that the Clean Air Act has significantly reduced racial disparities in pollution exposure, especially in $PM_{2.5}$ (Currie et al., 2023). While much progress has been made, people of color may still be disproportionately exposed to pollutants even after controlling for socioeconomic factors (Currie et al., 2023; Cain et al., 2024). This underscores the importance of not only quantifying exposure gaps but also understanding the mechanisms related to residential and firm sorting that sustain these disparities. For example, gentrification in cities like Seattle has exacerbated inequalities by pushing marginalized communities into more environmentally hazardous areas (Abel and White, 2015). Firm-side sorting further increases the exposure of low-income and minority communities to pollutants (Hausman and Stolper, 2021).

Our paper extends these discussions by exploring whether redlining and kinship, correlate with these sorting mechanisms to maintain or even worsen pollution gaps. Importantly, redlining has had significant and long-lasting effects by reducing neighborhood housing/rent values and increasing racial segregation (Aaronson et al., 2021*a*). We hypothesize that redlining may at least partly explain the ambient pollution gap today since redlined neighborhoods experienced under-investment in public services, including environmental amenities, which may induce sorting behaviors even conditional on respondents' income, education, and other observable socioeconomic correlates.

Kinship plays a crucial role in residential sorting, influencing where families choose to live based on support networks, cultural ties, and economic considerations (Bau, 2021, Christensen and Timmins, 2022). Very simplistically, kinship usually refers to a close connection marked by a community of interests or similarity in nature or character. Economic development and the structure of moral systems differ in societies at various levels of kinship tightness, or the extent and intensity of kinship bonds within a society (Enke, 2019). Societies with high kinship tightness have strong, extensive family networks where obligations, support, and cooperation are primarily centered around family and close relatives. In contrast, societies with low kinship tightness have weaker family bonds, with more emphasis on individualism and broader social interactions beyond the immediate family.[3]

Kinship is closely related to the idea of social cohesion which reflects *'feelings of shared commonalities, trust, reciprocity, and solidarity that generate a social environment in which people produce and share public goods and undertake collective endeavors'* (Schaeffer, 2013). Thus we expect that kinship plays a crucial role in residential sorting, influencing where families choose to live based on support networks, cultural ties, and economic considerations. We focus on the idea of kinship as a cultural system to explain the pollution gap between racial/ethnic groups (see https://www.britannica.com/topic/kinship for a brief description of the theories of kinship). Culture encompasses both moral values and routines/habits, i.e., 'ways of doing things' (Schaeffer, 2013). To this end, the current practice in the economics literature of utilizing the share of ethnic groups in the population to represent differences in pollution exposure across population groups (e.g. Brooks and Sethi, 1997; Banzhaf et al., 2019*a*) is grossly inadequate because it ignores the complex and multi-faced interaction within and across different racial groups in an area. For example, according to social identity theory, with in-group favoritism (where people trust and favor those who are like them more than others), there will be less cooperation when out-group members also benefit. What matters in this case is whether an individual belongs to the in-group or the out-group. The share of a racial/ethnic minority only reflects the majority response to minority share rather than a response in both directions, so that population share alone is insufficient to measure in-group favoritism as the channel through which diversity affects the availability of public goods (Schaeffer, 2013). There is also evidence documenting the role of local composition and social connection in shaping people's behaviors

[3] There is also evidence indicating kinship is closely related to female political participation, cultural change, and fertility (Bau, 2021; Yang and Spencer, 2022; Siriban, 2023).

toward environmental risks (Wakefield et al., 2006; Ireland and Thomalla, 2011).

Kinship-driven residential clusters can be found in both affluent and less well off areas. Affluent areas may provide better access to clean air, water, parks, and health-care facilities. In contrast, economically disadvantaged kinship clusters might face poorer infrastructure and environmental quality. These areas might be closer to industrial zones, waste disposal sites, or areas with poor air quality. Communities with strong kinship ties may organize and advocate for better environmental conditions, but they may also be overlooked by policymakers, perpetuating environmental inequities (Banzhaf et al., 2019*b*).

While economists have implicitly recognized the role of kinship, it has been represented as a community characteristic very simplistically – using the population share of racial/ethnic groups (see, for example, Brooks and Sethi, 1997, as a typical example). To capture the complex kinship dynamics within and between ethnic/racial groups, we innovatively utilize the idea of kinship from sociology, investigating how in-group favoritism and group threat, factors that are correlated with residential location decisions (Christensen and Timmins, 2022) and the potential for collective action from a community (Hamilton, 1993, Ireland and Thomalla, 2011), are correlated with the differences in environmental exposure by race/ethnicity. We draw upon three different measures of kinship (Schaeffer, 2013): the classical Hirschman-Herfindahl Index (HHI) to indicate the ethnic diversity of a community; the ethnic polarization (EP) index to predict the social cohesion within a community, and the EGI, an ethnic-group based measure of economic inequality similar to the Gini Index.

We fill the gap in the literature by identifying a strong correlation between ambient levels of different environmental pollutants, the redlining history of an individual's current neighborhood, and her community kinship, conditional on her income, education, and race. We analyze two commonly studied pollutants – onsite toxic emissions reported in the EPA's Toxic Releases Inventory (TRI) and fine particulate matter concentrations – and one relatively understudied and non-chemical pollutant – ambient roadway noise. We also consider a more directly health-based measure of environmental quality utilizing the toxicity of airborne chemicals. To account for potential measurement error, we measure the pollutants at different geographic scales, each centered at the location where an individual resides. These geographic scales are designed to reflect proximate versus community exposure, a distinction that has hithertofore not been explored in the literature.[4] We base our analysis on a novel data set that draws upon the precise residential location and

[4]This is different from the concept of ecological fallacy (Banzhaf et al., 2019*b*) since we consider proximate exposure conditional on neighborhood characteristics that are correlated with neighborhood exposure.

socio-economic characteristics of respondents from the restricted versions of the 2014, 2017-2020, and 2022 waves of the National Cancer Institute's (NCI) Health Information National Trends Survey (HINTS).[5]

Our findings highlight the significant roles that both redlining and kinship play in explaining contemporary pollution. The redlining history of the block group or census tract in which an individual currently resides is strongly correlated with higher levels of all pollutants, regardless of the geographic scale at which we measure the pollutants, and even after controlling for race/racial composition and socio-economic factors. In terms of kinship, block groups and census tracts with greater racial diversity and less social cohesion (characterized by higher levels of in-group favoritism and out-group threat) experience significantly higher levels of locally generated pollutants, such as noise and onsite emissions, but lower levels of regional pollutants, such as $PM_{2.5}$ (see Tables 6, 8, 9, and 10). These results underscore the enduring impact of historical segregation and contemporaneous social structures on environmental outcomes. Despite this, we are unable to fully account for the higher levels of ambient pollution that individuals of color, especially Blacks and Hispanics, experience as compared to the majority of White respondents in our sample. That is, the pollution gap identified by Currie et al. (2023) persists in most of our model specifications.

Importantly, we unearth different stories when we measure pollution at different scales. Conditional on an individual's income and education, as well as the socio-economic characteristics of the census block group in which they reside, we find that TRI emissions are no higher near the residences of Black and Hispanic respondents as compared to White respondents. However, Black, Hispanic and possibly Asian respondents experience significantly higher ambient road noise and $PM_{2.5}$ concentrations in the immediate vicinity of their residence relative to individuals identifying as White (see Tables 7, 8 and 9). Surprisingly, the result is reversed when we utilize traditional measures of community-level exposure: people of color tend to live in neighborhoods with lower TRI emissions and ambient road noise (Tables 5 and 6). Perhaps unsurprisingly, in the case of the more widely dispersed $PM_{2.5}$, we find that measurement scale is not as critical and that people of color experience significantly higher levels of $PM_{2.5}$ at all three geographic scales that we consider.[6] Although Currie et al. (2023) find that census tracts with larger shares of

[5] Currie et al. (2023) also analyze proximate exposure to $PM_{2.5}$ utilizing data at the census block level.

[6] The coefficients for Black individuals in Tables 7, 8 and 9 are around 0.07, suggesting that, after controlling for individual and neighborhood characteristics, Black individuals experience a 0.07 $\mu g/m^3$ higher level of $PM_{2.5}$ concentrations compared to White individuals (e.g. Table 9, column 7). In comparison, Currie et al. (2023) report a conditional Black-White difference of 0.5 $\mu g/m^3$ for 2015, using a similar approach that controls for individual and

African Americans have experienced greater reductions in the Clean Air Act-related $PM_{2.5}$, overall our results suggest that individuals of color may still experience disproportionally higher ambient pollution as compared to White individuals within the same community.

The rest of the paper is organized as follows: Section II describes our data. Section III illustrates our empirical strategy. We report our main results in Section IV and assess the robustness of these results in Section V. Section VI concludes.

2 Data Description

We utilize novel data that measure $PM_{2.5}$ concentrations, total onsite TRI emissions, airborne toxicity, and ambient roadway noise near a pooled cross-section of approximately 20,000 individuals between 2014 and 2022. A unique feature of our data is that we can link local pollution measurements to respondents' demographic information and neighborhood characteristics through relatively precise residential addresses. Under a data use agreement, we access the restricted version of HINTS which includes detailed information on individual respondents' demographic characteristics and the 9-digit zip code for their residence.[7]

Respondents' 9-digit zip code information is crucial in this study. The literature usually measures individual exposure to pollutants at the aggregated geographic level (e.g., 5-digit zip code or census tract) due to the lack of precise residential location information. The 9-digit zip code locates respondents at the "several household level" or "street level".[8] By utilizing GIS software, we can link each zip-9 centroid to its surrounding roadways, TRI facilities, and $PM_{2.5}$ concentrations, and also locate each respondent on the block group and census tract boundary maps from the US Census.

---

household characteristics. While both studies highlight disparities in exposure, the difference in magnitudes may reflect differences in sample size, time-period focus, or additional covariates included in the respective models. However, when comparing geographic scales, we observe that our estimates at the neighborhood level (block group) are much closer to the magnitude reported by Currie et al. (2023), with coefficients around 0.3 (see Table 5, Panel A). This is noteworthy given that Currie et al. measure $PM_{2.5}$ concentrations at the census block level, which is more granular than the neighborhood scale used in our study, but possibly larger than our proximate scale defined as the circular buffer of 1 km radius around an individual's place of residence (see Table 1). Our results suggest that estimated Black-White disparities in $PM_{2.5}$ concentrations are larger at broader spatial scales (e.g., neighborhood level) than at finer resolutions (e.g., proximate level).

[7] We use survey years 2014 (HINTS 4 Cycle 4), 2017-2020 (HINTS 5 Cycle 1-4), and 2022 (HINTS 6).

[8] With the majority of respondents in our sample living in relatively urbanized areas, the 9-digit zip can be as small as a single city block or even a single building.

To account for potential measurement error, we measure ambient pollution across three distinct geographic scales — proximate, neighborhood, and area – in increasing order of spatial magnitude. The proximate scale represents the immediate vicinity surrounding a respondent's residence, reflecting the most localized pollution measurement. The neighborhood scale expands this focus slightly to measure ambient pollution within defined administrative boundaries, such as block groups or census tracts. Finally, the area scale captures pollution at the broader community level by incorporating larger geographic units, such as census tracts or circular buffers extending several kilometers around respondents' residences.

The definition of each geographic scale varies depending on the dispersion properties of the pollutant in question. For example, ambient noise, which disperses very quickly and is therefore highly localized, is measured at the proximate and neighborhood scales only, whereas more broadly dispersing pollutants like $PM_{2.5}$ are also measured at the area scale. Table 1 provides an overview of the geographic definitions applied to each pollutant. In general, the proximate scale is defined by the smallest spatial unit at which data for a pollutant are available or can be reasonably measured. The neighborhood and area scales are defined by the census block group and census tract, respectively, in which each respondent resides. Most respondents in our sample live in urban areas, where block groups and census tracts tend to be smaller compared to those in suburban and rural regions. On average, block groups in our sample cover a mean area of 18.3 km^2, while census tracts cover a mean area of approximately 46.8 km^2. These sizes are relatively small, corresponding to circular areas of approximately 2.4 km and 3.9 km radii, respectively. As noted in Table 1, there are some exceptions to these general rules. For example, we measure TRI emissions at the area scale using a 5 km circular buffer around each respondent's zip-9 which corresponds to a much larger area of approximately 78.5 km^2. We explain the data sources and measurement scale for each pollutant in detail below.

We obtain noise data from the Department of Transportation's National Transportation Noise Maps for 2016, 2018 and 2020, focusing on road noise. Road noise is calculated by algorithms from the Federal Highway Administration's Traffic Noise Model version 2.5, which models road noise at a receptor height of 1.5m above ground level (DOT, 2020). These data are available on a 30-meter grid which allows us to measure ambient noise at an individual respondent's residence relatively precisely.

Ambient road noise is highly localized. To measure proximate ambient noise at the respondent's place of residence, we create a circular buffer with a radius of 1 km around each respondent, assuming that the respondent lives at the centroid of their zip-9.[9] Within a buffer, each 30 m^2 pixel area has a unique value for ambient noise. We calculate ambient noise in proximity of a respondent's residence as the average across all pixels in the buffer that have detectable noise. At the neighborhood level, we aggregate noise values within the respondent's block group. We use the 9-digit zip code to locate respondents on the DoT's National Transportation noise maps, and we overlay the block group boundary map from the US Census with the noise maps to calculate the average across all pixels that have detectable noise within the block groups where respondents reside. Because of the highly localized character of ambient noise, we do not attempt to measure it at a larger area scale due to the possibility of serious aggregation errors.

To measure $PM_{2.5}$ concentrations, we utilize satellite-based estimates provided by the Atmospheric Composition Analysis Group at Washington University in St. Louis. These data offer global and regional ground-level $PM_{2.5}$ concentration estimates derived from a combination of satellite-, simulation-, and monitor-based sources. Specifically, the dataset incorporates aerosol optical depth (AOD) measurements from multiple satellites, including NASA's MODIS, MISR, SeaWiFS, and VIIRS instruments. AOD retrievals from various methods (Dark Target, Deep Blue, and MAIAC) are integrated with simulations from the GEOS-Chem chemical transport model, calibrated using ground-based sun photometer (AERONET) observations. This multi-source approach produces highly accurate estimates that explain a substantial portion of the variation in ground-based $PM_{2.5}$ measurements (Van Donkelaar et al., 2016). While ground-based measurements of $PM_{2.5}$ concentrations provide a direct and perhaps more accurate estimate, there are only about 1000 monitors in the United States, with very limited coverage outside of major metropolitan areas. As a result, nearly a quarter of all respondents in our sample are not covered by an EPA $PM_{2.5}$ monitor and we utilize the satellite-based estimates instead as our primary measure of $PM_{2.5}$ concentrations.[10] This dataset provides annual estimates of $PM_{2.5}$ concentrations at fine spatial resolution (1km×1km).[11]

[9]Audible noise decreases non-linearly by 6 dB as the distance from the noise source is doubled. The 1 km buffer suits our study well since it captures the decay of general traffic noise (e.g. 78 dB) to a non-detectable level (e.g. 42 dB) at the margin of the buffer size (e.g. 960m). See Wen and Khanna (2024) for more justification of the buffer size.

[10]We employ version V6.GL.02.02 of this dataset, which covers the period from 1998 to 2022 (https://wustl.app.box.com/s/iwvi2avusnz3fpabl6v5ouyobavbt70a/folder/274064564959). This version extends the previous methodology by including retrievals from the Suomi National Polar-orbiting Partnership (SNPP) Visible Infrared Imaging Radiometer Suite (VIIRS) instrument, updating the ground-based calibration across the entire time series, and enhancing geophysical estimates through the use of a residual Convolutional Neural Network (CNN). See Shen et al. (2024) for details.

[11]In Appendix.C, we also exploit ground $PM_{2.5}$ monitor data from the EPA and the results are similar to those obtained using the approach described here.

To measure $PM_{2.5}$ concentrations at the proximate scale, we create a buffer with a radius of 1km surrounding the centroid of each respondent's 9-digit zip code and calculate the average $PM_{2.5}$ concentrations within the buffer. Likewise, we use the average $PM_{2.5}$ within respondents' block group boundaries as their neighborhood scale $PM_{2.5}$ concentrations. To measure ambient $PM_{2.5}$ concentrations at the area scale, we exploit the EPA's Remote Sensing Information Gateway (RSIG) which offers daily data at the census tract level for the entire US since 2002. We calculate annual $PM_{2.5}$ concentrations by averaging the daily data across each year.[12]

The third pollution source we consider is toxic emissions. The TRI records self-reported measurements of more than 700 chemicals released into the air, water and land annually by facilities in the chemical, manufacturing, metal mining, and electric power generation sectors across the US. To calculate respondents' total onsite emissions at the proximate and neighborhood levels, respectively, we overlay respondents' 9-digit zip code centroids on maps of the US block group/census tract boundaries and calculate the sum of total onsite emissions among all the facilities within the block group/census tract where the respondents' 9-digit zip code centroids are located. These definitions of the proximate and neighborhood scales encompass larger geographic areas as compared to the other pollutants in our analysis. Even with these larger geographic areas, 96% and 88% of all respondents in our sample have zero TRI emissions in the immediate proximity of their residence and neighborhood, respectively. To measure toxic emissions at the Area level, then, we follow the environmental science literature and create a circular buffer of 5 km radius around each respondent's 9-digit zip code centroid. This definition strikes a balance between capturing sufficient environmental variation and the average range of human activities and daily travel (see, for example, Zeka et al., 2006 and Brender et al., 2011). We estimate the inverse-distance-weighted (IDW) sum of total onsite emissions across all media from all the facilities within the buffer as the area-level toxic emissions.[13]

Notably, we use the inverse hyperbolic sine (IHS) transformation at all three measurement scales to address the challenges posed by our emission data, where, for example, 96% of respondents have zero emissions measured at the proximate level as measured by the block group in which they reside. We also find significant variation at the proximate level, with a mean and standard deviation of 5,625 lbs

[12] RSIG data are not available at a smaller geographic scale. While other datasets, such as Di et al. (2019), offer high-resolution $PM_{2.5}$ estimates, they only cover the period from 2000 to 2015, which does not encompass most of our survey years.

[13] We also calculate the simple sum of total onsite emissions within a 5-km buffer to ensure consistent comparison across different geographic scales. We re-estimate the models presented in Tables 5-9 using these data. Appendix D reports the results which are qualitatively similar to those in Tables 5-9.

and 233,110 lbs, respectively. The IHS transformation allows us to include observations with zero values without needing arbitrary adjustments (such as adding a small constant). Moreover, it reduces the influence of extreme values, stabilizing variance and improving the robustness of our regression estimates. This approach aligns with recent literature that prefers the IHS transformation over the standard log transformation in cases with many zero values and highly skewed distributions(Aihounton and Henningsen, 2020, Chen and Roth, 2023).

Finally, to investigate inequities in the potential health impacts associated with exposure to toxic emissions, we exploit the EPA's Risk-Screening Environmental Indicators (RSEI) datasets at various levels of aggregation. We focus on the "toxicity-weighted concentration" from RSEI's aggregated Geographic Microdata, which measures the combined effect of airborne chemical releases and their relative human health impacts, including cancer and non-cancer outcomes, within each geographic unit.[14] The RSEI model incorporates the spatial dispersion of chemicals and allows us to go beyond locally released chemicals by including the effects of airborne chemicals that may be transported over long distances. The resulting values, expressed in micrograms per cubic meter ($\mu g/m^3$), provide a standardized measure of harmful air emissions across different locations and pollutants.

The most granular files for the RSEI data are at the 810m by 810m grid cell level. We locate our HINTS respondents within these grid cells and assign the "toxicity-weighted air concentration" from the cell in which the centroid of each respondent's 9-digit zip code falls as their proximate air toxicity measurement. We assign the average block group and census tract airborne toxicity (RSEI aggregated microdata, provided by Cynthia Gould of the EPA on Aug 30, 2024) as each respondent's neighborhood and area scale toxicity, respectively. One key feature of the RSEI model is that even as geographic areas get larger (e.g., moving from grid cells to block groups and census tracts), the toxicity-weighted concentration may not increase correspondingly. This occurs because the model averages across all the land within the geographic boundary, including areas that may have lower or zero emissions.[15]

[14]In the RSEI model, the air microdata specifically includes only air emissions. These data capture air releases such as stack emissions (from facility stacks) and fugitive emissions (from leaks or non-stack releases). While the RSEI model also encompasses water and land emissions, these data were not yet available in aggregated form when we obtained the microdata from the EPA; only the air emissions data were fully prepared and ready for analysis. Consequently, our study focuses on air emissions, utilizing the data that were readily accessible and validated at the time.

[15]We include a robustness check using the inverse hyperbolic sine (IHS) transformation of RSEI toxicity to address potential concerns about outliers and the skewed distribution of the toxicity data. This transformation allows us to retain observations with small or zero values without requiring arbitrary adjustments while maintaining interpretability. The results, reported in Appendix G, are consistent with our main findings presented in Tables

For example, toxicity concentrations for a census tract are averaged from the constituent block groups, and similarly, block groups' concentrations are averaged from the grid cells.[16]

We use redlining data from the University of Richmond's *Mapping Inequality* application. These historic maps were used by the HOLC to demarcate neighborhoods into different grades, denoted by letters A through D, and color-coded as green, blue, yellow, and red, respectively, reflecting differences perceived in credit risk. Appendix Figure A.1 shows the historic redlining map for Brooklyn, NY, as an example. Households residing in areas designated as risk level D (or marked in red) were considered 'hazardous' from the perspective of underwriting home mortgages and suffered the most difficulties in the housing market. We overlay the HINTS respondents on these historic redlining maps to generate indicators that represent whether the block group or census tract of each respondent's current residence, or any part thereof, was historically redlined and coded by the letter D.

We obtain block group and census tract socio-economic data from the American Community Survey (ACS). We focus on the fraction of minority groups (African Americans, Hispanics, and Asians); the fraction of high school graduates; the fraction of population in different income ranges; the fraction of population under the poverty line; the fraction of individuals who rent their homes; and the median housing values at the block group or census tract level.[17]

We also exploit the more complex idea of a "marginalized community". The motivation for using a binary variable to differentiate "marginalized" communities from others stems from the recognition that traditionally used community characteristics may not fully capture the multifaceted nature of marginalization. Marginalization extends beyond race, encompassing economic status, environmental exposure, and other vulnerabilities. By considering a broader set of indicators, we can better understand how various environmental and socioeconomic factors interplay to impact community well-being. To construct this variable, we utilize data from EJScreen, a tool developed by the EPA that utilizes environmental and demographic information to highlight areas with potentially higher pollution burdens and vulnerable populations. EJScreen includes 13 Environmental Justice (EJ) indices, each com-

5-10, confirming the robustness of our conclusions across specifications.

[16] See https://www.epa.gov/rsei/forms/contact-us-about-rsei-model for more details to access the RSEI Geographic Microdata.

[17] Our selection of community characteristics is in the spirit of Currie et al. (2023), who include variables such as employment rates, population density, housing characteristics (e.g., the share of housing built before 1970), and income inequality, which are broader measures of socioeconomic status. In line with this, we also include housing tenure (renter vs. homeowner), which Currie et al. identify as one of the most important factors in explaining disparities in pollution exposure.

bining a specific environmental factor (e.g., traffic, air quality) with demographic data (e.g., low-income population, people of color) to assess the relative burden on communities. We define a block group as marginalized if one or more of these 13 indices exceeds the 80th percentile (i.e. falls in the last quintile), the threshold used by the EPA to highlight areas with high levels of pollution and socioeconomic vulnerability (EPA, 2020). This identifies communities facing substantial environmental and socioeconomic challenges, allowing for a more nuanced view of how these factors contribute to overall marginalization.[18]

Table 2 presents the summary statistics for our pooled cross-section sample of 20,543 observations across three different measurement scales: proximate, neighborhood, and area. Overall, our sample is quite representative of the US population, with most variables closely aligning with national averages. For instance, 13% of the individuals in our sample identify as Black, which is close to the national average of approximately 14%. Hispanic individuals constitute 14% of the sample, slightly below the national average of around 19%. Similarly, the proportion of Asian individuals is consistent with the national average. The socio-economic variables, such as median household income, the fraction of individuals living below the poverty line,[19] and housing characteristics, also closely match national figures.

Approximately 7% of individuals in our sample reside in block groups (or any part thereof) that were historically redlined, and this fraction rises to 10% if we consider that any part of the census tract was redlined. Behind these averages are notable differences in the racial composition of redlined and non-redlined neighborhoods. Specifically, 13.7% of Black respondents, 7.6% of Hispanic respondents, 7.7% of Asian respondents, and only 4.7% of White respondents in our sample live in redlined block groups.[20]

Table 3 summarizes ambient pollution by race and geographic scale. Onsite emissions are relatively modest, on average, when measured at the proximate level (5,625 lbs) but increase substantially at the neighborhood (23,522 lbs) and area levels (45,673 lbs). This pattern is largely driven by the highly skewed distribution of TRI emissions, where a significant proportion of respondents (96%) have zero

[18]Although our environmental indicators are among those utilized by EJScreen, we do not anticipate a spurious linear correlation in our OLS models for two reasons. First, we utilize a binary variable that is based on the 80th percentile of all EJ indicators. Second, EJScreen combines environmental and economic indicators in a non-linear manner.

[19]The "poverty fraction" refers to the percentage of individuals whose income falls below the poverty line, and this measure is based on the poverty threshold for each specific survey year, as reported in the annual ACS data.

[20]19.7% of Black respondents, 11.0% of Hispanic respondents, 10.8% of Asian respondents, and only 7.1% of White respondents in our sample live in historically redlined census tracts.

emissions at the proximate level, but a small number of industrial facilities release exceptionally large quantities of pollutants. As the measurement scale expands to include larger geographic areas, the likelihood of incorporating these high-emission sources increases, causing the mean to rise substantially. This reflects the concentration of emissions in specific locations rather than being evenly distributed across communities. To address the large fraction of zero TRI emissions, we present the results of a linear probability model in Appendix E and a Tobit model in Appendix F. The findings from both models are consistent with those from the main analysis (Tables 5-10). The average $PM_{2.5}$ concentration is 7.66 $\mu g/m^3$ at the proximate scale, 7.46 $\mu g/m^3$ at the neighborhood scale, and 8.54 $\mu g/m^3$ at the area scale, indicating little variation in particulate matter concentrations across spatial scales. The average ambient road noise is highest at the proximate scale (50.80 dB), decreasing to 44.45 dB at the neighborhood scale.[21]

Table 3 also indicates some disparities in ambient pollution across different racial groups. While, on average, there do not appear to be large differences in unconditional ambient $PM_{2.5}$ concentrations across the four racial/ethnic groups, Black respondents face the highest toxicity-weighted concentrations, followed by Hispanic and White respondents; Asian respondents experience the lowest toxicity-weighted ambient concentrations. TRI emissions, on the other hand, are highest near the residences of Hispanic respondents, whereas White respondents appear to live in neighborhoods with the highest onsite emissions. On the other hand, Black respondents reside in areas with the highest onsite emissions. While ambient noise is fairly uniformly distributed across the races at the neighborhood scale, there are large differences at the proximate scale with Hispanics experiencing the highest ambient roadway noise in the immediate vicinity of their residences, followed by Blacks and Hispanics, while White respondents experience significantly lower ambient noise. While a difference of 2-3 dB may seem small, prior research has shown that even a 1 dB increase in ambient noise can have measurable effects on health and well-being. For example, a 1 dB increase in roadway noise near a respondent's residence leads to a 12.7% increase in the likelihood of experiencing mild symptoms of anxiety and nervousness (Wen and Khanna, 2024). Given this, the observed disparity in ambient noise suggests significant differences in environmental stressors across racial groups.

Overall, these results suggest that people of color, particularly Black and Hispanic individuals, tend to live in more polluted environments, whether measured by fine particulate matter, onsite emissions, toxicity-weighted concentrations, or ambient road noise. Nonetheless, measurement scale also matters, and specially for locally

[21]This difference can be explained by the fact that proximate-scale measurements capture ambient noise more precisely, reflecting closer proximity to noise sources such as highways. At the neighborhood scale, noise data are averaged across a larger area, which can include quieter residential zones, leading to a lower overall average noise level.

emitted pollutants like onsite emissions reported to the TRI.

3 Empirical Strategy

Since our goal in this paper is to explore the role of omitted variables and measurement error in explaining the observed differences in ambient pollution experienced by different racial groups, we do not focus on causality. Instead, we use OLS regressions to investigate the association between redlining, kinship, racial identities, and contemporary ambient pollution. The most basic reduced-form relationship is:

$$P_{ijt} = \beta_1 + \boldsymbol{\beta_2} Race_i + \boldsymbol{\beta_3} Education_{it} + \boldsymbol{\beta_4} Income_{it} + \gamma_c + \rho_t + \epsilon_{ijt} \tag{1}$$

where pollutant P_{ijt} represents the ambient pollution individual i experiences at their place of residence due to pollutant j (i.e. ambient road noise, ambient $PM_{2.5}$ concentrations, total onsite emission, and RSEI toxicity weighted airborne toxins) in survey year t. $Race_i$ is a vector of indicator variables for non-Hispanic black, Hispanic, and Asian, with non-Hispanic White as the base group.[22] $Education$ and $Income$ represent respondents' highest completed education, and individual incomes as reported in HINTS, respectively.[23] In the first extension, we add $Redlined_{it}$, a binary variable that indicates whether the respondent resides in a census block group (or part thereof) that was historically redlined (marked with the letter D in the HOLC maps); β_5 summarizes the conditional relationship between historic redlining and contemporary pollution in respondents' current place of residence. We also control for county fixed effects γ_c and year-of-survey fixed effects ρ_t to account for factors that are invariant with time and geography which may also explain the pollution gaps between racial groups.[24]

To capture unobserved sorting behavior related to social identity, social cohesion and group dynamics, we introduce three quantitative measures of kinship.[25] The

[22]Since the fraction of other racial categories, such as American Indian and multi-racial people is very small in our sample, we include those respondents in the group of Asians. That is, we use Asians to refer Asians and other minority groups except Blacks and Hispanics.

[23]The highest level of schooling is a categorical variable that includes "less than high school"; "high school graduate"; "some college"; "college graduate"; "postgraduate". The base group is "less than high school" in our specification.

[24]The redlining dummy is based on whether a block group or census tract was historically redlined. Since redlining status varies within counties — i.e., some block groups or census tracts were redlined while others were not — this dummy variable is not perfectly collinear with county-fixed effects and captures within-county variation.

[25]Brooks and Sethi (1997) use voter turnout as an indicator of collective action among communities. However, accurate measurement of voter turnout can be challenging, and discrepancies in data quality or reporting standards across regions can introduce additional

first is the classical Hirschman-Herfindahl Index (HHI) (Hirschman, 1964), which is calculated as follows:

$$HHI = 1 - \sum_{i=1}^{k} s_i^2 \tag{2}$$

where s_i denotes the share of population group i among all k population categories within a community. This index can be interpreted as the probability of two random individuals from a community being from different racial/ethnic categories (Schaeffer, 2013), or we can simply regard it as an indicator of racial/ethnic diversity. The index, which is designed to reflect in-group favoritism, approaches 1 (absolute diversity) when there are infinite population categories while it equals 0 (no diversity) when there is only one population group in a community. The average HHI value for our sample is 0.37 at the block group level and 0.44 at the census tract level, indicating moderate levels of community diversity.

Group threat or competition for economic resources and political representation may also affect social cohesion and the generation of public goods. Here too, using the racial/ethnic share to represent kinship or social cohesion is inadequate because a completely polarized community where two equal opponents face each other will also have lower conflict. A more subtle representation of group threat is provided by the index of Ethnic Polarization (EP), which is derived as follows (Montalvo and Reynal-Querol, 2005):

$$EP = 1 - \sum_{i=1}^{k} (\frac{0.5 - s_i}{0.5})^2 s_i = 4 \sum_{i=1}^{k} s_i^2 (1 - s_i) \tag{3}$$

where s_i is the share of group i and k is the total number of groups within a community. This index ranges from 0 to 1 with a larger number indicating more ethnic polarization (or less social cohesion). The index takes a value of 0 when there is only one group in a community or where the community has an infinitely large number of groups, and a value of 1 when there are two equally sized groups. The average value of the EP index in our sample is 0.62 at the block group level and 0.64 at the census tract level, indicating relatively low social cohesion across communities.

Baldwin and Huber (2010) argue that "group-based economic differences can lead to various group needs with respect to public goods, feelings of alienation or discrimination by some groups, ..., and different 'class' identities by different groups."[26]

bias. Additionally, voter turnout data is typically collected at aggregate levels (e.g., county or precinct), while pollution exposure might need to be assessed at a more granular level (e.g., proximate or neighborhood).

[26] As quoted in Schaeffer (2013).

To reflect the economic basis for differences in social cohesion across groups, they propose an ethnic group-based index of economic inequality, EGI, that is a special case of the Gini Index where each respondent is assigned her ethnic group's income instead of her personal income. As compared to the HHI and EP, which Schaeffer (2013) describes as reflecting 'cognitive biases' – 'us' versus 'them', group threat or in-group favoritism – the EGI reflects 'asymmetrically distributed preferences' and the ability to agree upon shared goals arising out of economic inequality across racial/ethnic groups.

The ethnic group-based index is defined as follows:

$$EGI = \frac{1}{2\bar{y}} \sum_{i=1}^{k} \sum_{j=1}^{k} s_i s_j |\bar{y}_i - \bar{y}_j| \tag{4}$$

where s is the share of racial/ethnic category i or j (i is not equal to j) and k is the number of racial categories. $|\bar{y}_i - \bar{y}_j|$ refers to the average income gap between racial groups i and j, which works as a weight for measuring inequality. The EGI can range from 0 to 1, similar to the traditional Gini Index, where a lower value indicates more equality in the income distribution across racial/ethnic groups, and a higher value suggests greater economic inequality between these groups. Communities with higher EGI values are less likely to agree upon social norms and, in particular, the provision of public goods. This erodes trust and, among other things, leads to underinvestment in public goods. In our sample, the EGI values are relatively low, with a mean of 0.0807 and a standard deviation of 0.0528. The kernel density estimate of EGI (Figure A.2 Panel C) shows a concentration of values towards the lower end of the scale. This suggests that most individuals in our sample live in economically homogenous block groups, where income differences between racial/ethnic groups are minimal.

To unpack these results further, we take a closer look at the distribution of kinship across racial groups. In Table 4, we divide our respondents into quartiles based on their block group level HHI, EP, and EGI, respectively. Interestingly, we find that White respondents in our sample have the largest share of the population in the first quartile and the least share in the last quartile for both HHI and EGI. In fact, more than 50% of White respondents live in neighborhoods that fall into the first two quartiles of the distribution for all indices. This is much higher than the share of minority respondents in the first two quartiles. That is, White respondents are most likely to live in communities with the least diversity, ethnic polarization, and economic inequality compared to other racial groups. In contrast, we find that Asian respondents are most likely to live in communities with the greatest diversity, as they live in neighborhoods with the smallest (largest) population share in the first (last) HHI quartile. Additionally, Black and Hispanic respondents face the most severe ethnic polarization in their neighborhoods. The share of Black respondents who live in the last EP quartile is the largest among the four racial categories, with Hispanics a close second.[27] Against the backdrop of the literature that documents that people of color are consistently exposed to more environmental pollutants (Banzhaf et al., 2019*a*), these distributions suggest that White individuals live in starkly different neighborhoods compared to people of color and that ambient pollution is higher in the more diverse neighborhoods where people of color live (lower in relatively homogenous White neighborhoods).

Given the different sociological theories underlying kinship and the role of social cohesion, we successively include the three kinship indices (HHI, EP, and EGI) in our regression model to investigate the relationship between kinship and pollution, conditional on all the aforementioned variables:

$$\begin{aligned} P_{ijt} = \beta_1 + \boldsymbol{\beta_2} Race_i + \boldsymbol{\beta_3} Education_{it} + \boldsymbol{\beta_4} Income_{it} + \beta_5 Redlined_{it} \\ + \boldsymbol{\beta_6} HHI/EP/EGI_{it} + \gamma_c + \rho_t + \epsilon_{ijt} \end{aligned} \tag{5}$$

where we calculate respondents' HHI, EP, and EGI using the group shares from the block groups in which they reside; all the other control variables are the same as those in Eq.(1). In an extended model, we include block group socio-economic characteristics as additional control variables (see section 4 for details).

Finally, we also follow the literature (see, for example, Brooks and Sethi, 1997) and regress respondents' community-level (neighborhood/area) ambient pollution on their community characteristics as follows:

$$\begin{aligned} P_{cjt} = \beta_1 + \boldsymbol{\beta_2} Race_{ct} + \beta_3 HSfrac_{ct} + \beta_4 MedHhInc_{ct} + \beta_5 MedHhInc_{ct}^2 \\ + \beta_6 Poverty_{ct} + \beta_7 Poverty_{ct}^2 + \beta_8 Rentfrac_{ct} + \beta_9 Medhousevalue_{ct} \\ + \beta_{10} Redlined_{ct} + \boldsymbol{\beta_{11}} HHI/EP/EGI_{it} + \gamma_c + \rho_t + \epsilon_{cjt} \end{aligned} \tag{6}$$

where c represents the neighborhood or area in which each respondent i resides. We use the two smallest aggregated geographic areas (i.e. block group and census tract) with publicly available data to represent each respondent's corresponding neighborhood/area (except for onsite emissions, see Table 1). $Race_{ct}$ includes the fraction of Blacks, Hispanics, and Asians from respondents' neighborhood/area c in year t. $HSfrac_{ct}$ represents the fraction of high school graduates in the neighborhood/area. β_4 and β_5 capture the association between neighborhood/area median household income while β_6 and β_7 capture the association between the fraction of people in the neighborhood/area below the poverty line and ambient neighborhood/area pollution, respectively. $Rentfrac_{ct}$ indicates the fraction of people in the neighborhood/area who rent their current residence and $Medhousevalue_{ct}$ represents the

[27] We observe similar findings in the kinship distribution at the census tract level, as reported in Appendix Table B.1.

median housing value in the neighborhood/area. Notably, $Redlined_{ct}$ represents whether the block groups or census tracts that respondents currently reside in were historically redlined. We successively introduce the three kinship measures (HHI, EP, and EGI) measured at the corresponding neighborhood/area level.

4 Results

4.1 Neighborhood and Area Scale Results

In recognition of the extant literature, we begin the discussion of our results with ambient pollution and all control variables measured at the neighborhood or area scale.

Table 5 presents the baseline results corresponding to equation (6) with and without redlining as an explanatory factor and without any measures of kinship. Focusing on the most basic specification (i.e. without either redlining or kinship controls), we find that overall, conditional on other community characteristics, neighborhoods with a larger share of racial minorities have the same or lower levels of locally generated pollution (i.e., generated within the neighborhood or area). In particular, communities with a larger fraction of Black people have lower levels of onsite emissions though the coefficient is statistically significant only at the neighborhood level. Roadway noise is also significantly lower in neighborhoods with a larger fraction of Black and Asian respondents. An exception to this pattern is that Hispanic and Asian respondents reside in areas (as defined by the buffer of a 5 km radius around the centroid of their zip-9) with statistically higher onsite emissions as compared to White respondents.

Most notably, we find that respondents who currently reside in a census block group (for neighborhood scale) or census tract (for area scale) that was historically redlined experience higher contemporary levels of all four pollutants that we analyze. This points to the enduring environmental legacy of redlining. Despite this, the redlining history of a census block group or tract is not sufficient to explain the higher ambient pollution experienced by people of color: the magnitude and statistical significance of the coefficients in the baseline model are scarcely affected by the addition of the redlining dummy.

We introduce the three measures of kinship in Table 6. We find the communities with more racial diversity (i.e. higher HHI and in-group favoritism but less social cohesion) have significantly higher levels of total onsite emissions (but, interestingly, not airborne toxicity) and lower levels of $PM_{2.5}$ concentrations measured at both neighborhood and area scales. We find similar patterns using EP: areas with greater out-group threat tend to have higher levels of locally generated pollutants but lower levels of more widespread pollution. However, for EGI, which reflects economic inequality-based differences across racial groups, we get a slightly different result. We find that EGI does not appear to be strongly correlated with locally generated pollutants (total onsite toxic emissions, airborne toxicity, and noise) when measured at either geographic scale. Nevertheless, it is significantly negatively associated with $PM_{2.5}$ concentrations at both geographic scales. This could imply that respondents living in economically unequal communities might be located in areas where broader regional or systemic factors contribute to air quality, rather than localized sources of pollution. For instance, these communities might be situated in areas with better access to air quality control measures or in regions where $PM_{2.5}$ is less of an issue, possibly due to less industrial activity or more stringent monitoring and enforcement of regulations at a broader scale.

Interestingly, Tables 5 and 6 also provides initial evidence that measurement error may bias estimates for locally generated pollutants when comparing different geographic scales. For TRI emissions, we observe that coefficients on the fractions of the minority populations tend to change signs when moving from the neighborhood level (census tract) to the area level (5 km buffer), suggesting that estimates at smaller spatial scales may be more susceptible to misclassification or incomplete reporting of emissions sources. To address the large fraction of zero TRI emissions, we present the results of a linear probability model in Appendix E and a Tobit model in Appendix F. The findings from both models are consistent with those from Tables 5 and 6. On the other hand, we consistently find that neighborhoods/areas with a larger fraction of all minorities have higher ambient concentrations of a relatively widely dispersed pollutant like $PM_{2.5}$ for which the ambient concentration recorded at a respondent's local neighborhood or area may have been generated over a much larger spatial scale. We also find that neighborhoods with a larger share of Hispanic populations experience higher toxicity concentrations of airborne pollutants, which does not appear to be the case for areas with a larger share of other minority groups. These findings underscore the importance of the geographic scale of measurement, particularly for locally generated pollutants, where aggregation may smooth out disparities or introduce bias due to the spatial distribution of pollution sources.

These results add to the mixed evidence in the literature. For example, hazardous waste handlers are more likely to be located in working-class neighborhoods with lower minority shares (Davidson and Anderton, 2000). However, conditional on different socio-economic factors, there is less consensus in the literature about the correlation between race and pollution (Banzhaf et al., 2019*a*). For example, African Americans are more likely to live in both more polluted cities and more polluted neighborhoods within those cities, while Hispanics tend to live in less polluted cities but in more polluted neighborhoods (Ash and Fetter, 2004).

4.2 Proximate Scale Results

While regression estimates using data measured at the commonly used neighborhood and area levels give us a broad idea of racial disparities in ambient pollution, we cannot draw any conclusions regarding the ambient pollution experienced by individuals within these areas, or the factors that correlate with ambient pollution in the immediate vicinity of an individual's place of residence. HINTS offers us a unique opportunity to measure pollutants at the proximate scale based on the respondents' residential addresses.

As shown in columns (1)-(4) of Table 7, we get starkly different results when we use respondent-level survey data: individuals identifying as racial minorities – Black and Hispanic and Asians alike – experience relatively higher levels of ambient road noise and $PM_{2.5}$ concentrations in the immediate vicinity of their place of residence, even conditional on their socio-economic information and county and year fixed effects, factors correlated with residential sorting. Furthermore, regardless of race, all individuals residing in a block group that was historically redlined experience higher ambient pollution, emphasizing, yet again, the persistent effects of historic practices in housing and credit markets.

However, even after accounting for the persistent effects of redlining, we find that Black, Hispanic and Asian respondents experience disproportionally higher local pollution as compared to White respondents (see Table 7, columns (6)-(7)). Overall, the lingering statistical significance of coefficients on the population share of racial minorities means that the contemporary gap in ambient pollution is not explained away by this history and that there are still some unobserved factors driving the pollution gap between individuals of color and those who identify as White.

In Table 8 we additionally control for our three measures of kinship (i.e. HHI, EP, and EGI). All three indices are calculated using block group data and therefore reflect social cohesion and kinship at the local neighborhood scale. In column (2), we find the HHI is significantly correlated with ambient roadway noise, even conditional on individual respondents' racial identities, education, income, and the redlining history of their block group. That is, compared with respondents who live within a community dominated by a single racial group (i.e. low HHI), those living in a community with greater diversity experience a higher level of ambient roadway noise. Similarly, in columns (5)-(6) and (10), we find that EP and EGI are also significantly positively related to exposure to onsite emissions and ambient road noise. Notably, we find none of the three indices is correlated with ambient $PM_{2.5}$ and airborne toxicity concentrations. That is, respondents who reside in neighborhoods with more racial diversity, ethnic polarization, and economic inequality between ethnic groups experience significantly higher levels of ambient roadway noise and possibly higher onsite emissions, but not ambient

$PM_{2.5}$ concentrations. We conclude that kinship is correlated with ambient levels of local pollutants rather than more widely dispersed pollutants. Nonetheless, the disproportionally higher ambient levels of noise and $PM_{2.5}$ for Black and Hispanic respondents (as well as ambient $PM_{2.5}$ for Asian respondents) is not explained by the addition of the kinship indices to the regression model.

To account for the possibility that the effect of residential sorting is better represented by socio-economic factors at a neighborhood scale, in another specification, we add community characteristics from the respondents' block groups as additional control variables and report the results in Table 9.[28] While the statistical significance of the estimated coefficients on some of the race variables is weakened or eroded, overall we find that our results hold: Black and Hispanic individuals experience significantly higher levels of ambient road noise and $PM_{2.5}$ concentrations, and Asian respondents to $PM_{2.5}$, even after accounting for redlining and kinship, which remain strongly correlated with our environmental outcomes.

Furthermore, to investigate how the racial composition of a respondent's neighborhood drives her own exposure to pollutants, we add the fraction of ethnic and racial minorities from respondents' neighborhoods. The results are reported in Table 10. While the disproportional exposure of Black and Hispanic individuals to locally generated pollutants (ambient roadway noise and toxic emissions) seems to be absorbed by the addition of the racial composition of their corresponding neighborhoods, we find that Black and Hispanic respondents still experience significantly higher levels of $PM_{2.5}$ concentrations.[29] This is despite the fact that there appears to be a fair degree of racial clustering in the communities where respondents reside: the correlation between being a Black respondent and the fraction of Black individuals in the block group is 0.52, and for White and Hispanic respondents, it is 0.48 and 0.46, respectively. Asian respondents display the lowest degree of racial clustering with the correlation being only 0.27.

As aforementioned, traditional measures of community characteristics may not fully capture the multifaceted nature of marginalization. To address this, we replace the neighborhood minority fraction controls with a binary variable 'marginalized BG' that identifies block groups deemed as marginalized by the EPA's EJScreen tool (see Section 2 for a detailed description of the creation of this dummy variable). As

[28]The community characteristics are those described in Eq.(6) from respondents' survey years (i.e. 2014, 2017-2020, and 2022).

[29]For consistent comparisons, we also use the inverse hyperbolic sine (IHS)-transformed, non-IDW simple sum of all emissions within the 5-km buffer as a measure of area total onsite emissions. The results remain consistent, showing similar patterns of disproportionate environmental burdens faced by people of color. These findings are reported in Appendix D Table D.1.

before, we control for redlining history and kinship.

We use two empirical specifications to assess the association between marginalized communities and ambient pollution. In the first specification, we include only the 'marginalBG' dummy without any community characteristic controls. In the second approach, we include the dummy variable along with all community characteristics noted in equation (6). Regardless of the specification, the coefficient on the 'marginalBG' dummy is positively significant for $PM_{2.5}$ concentrations and toxicity concentrations, but not for onsite emissions (see, Appendix Tables B.3 and B.4). Interestingly, the coefficient on the marginalized block group dummy variable turns out to be negatively significant in all the noise models that include the additional community characteristics (compare Appendix Tables B.3 and B.4). This differential result suggests that when controlling for the full spectrum of community characteristics, the relationship between noise (the most localized pollutant in our analysis) and marginalization is more complex. What is notable is that the coefficient on the redlining variable remains positive and significant in almost every model under both specifications (except in the noise models in Table B.4). As in Tables 8-10, the kinship indices also remain positively correlated with ambient roadway noise and negatively correlated with $PM_{2.5}$ underscoring the nuanced relationship between community and ambient pollution. Furthermore, in both Tables B.3 and B.4 the coefficients on the three variables identifying a respondent's race remain positive and statistically significant in the models for ambient roadway noise and $PM_{2.5}$ concentrations.

Our findings highlight the complexity of environmental justice issues. While $PM_{2.5}$ concentrations remain higher in marginalized communities, the lower levels of ambient roadway noise conditional on broader community characteristics suggest that localized pollutants might be sensitive to targeted interventions in marginalized communities (see Table A.4). The complex nature of environmental equity has also been noted in other contexts. For example, California's cap-and-trade program did not uniformly reduce greenhouse gas emissions across communities, often exacerbating pollution disparities in disadvantaged areas (Cushing et al., 2018), and environmental markets may unintentionally worsen environmental inequities (Hernandez-Cortes and Meng, 2023).

4.3 Discussion

There are three major takeaways from our results. First, the environmental legacy of historical practices in the housing market persists even today and is part of the complex array of factors associated with the distribution of environmental quality across neighborhoods. Second, kinship is strongly correlated with ambient pollution and people of color live in communities with very different kinship ties than the majority of White individuals. Despite these differences, we are unable to fully explain the gap in ambient pollution across neighborhoods or areas where individuals identifying as racial minorities reside as compared to the neighborhoods or areas where White individuals live. The residual (and statistically significant) coefficient on the individual race variable in our regression models is potentially suggestive of systemic racism or other structural frictions in the contemporary housing market (see also Christensen and Timmins, 2022). Without a clear measure of racial discrimination, we cannot make an unambiguous statement and this remains an open research question for economists and other social scientists to address in future work.

Third, we caution against drawing conclusions about environmental justice using pollution measured at the neighborhood or area scale alone (traditionally represented by census block groups and census tracts, areas for which socio-economic data are widely available in the public domain). Our results are sensitive to the geographic scale at which we measure ambient pollution. While Black and Hispanic respondents are exposed to significantly higher levels of ambient noise measured at the proximate scale compared to White respondents (see Tables 8 and 11), when we measure ambient road noise at an aggregated geographic scale commonly used in the literature (i.e. neighborhood or the census block group in which the respondent resides), keeping the same set of individual control variables and fixed effects (including whether the individual lives in a historically redlined neighborhood and the kinship indices), we do not find any evidence indicating people of color experience higher ambient road noise as compared to White respondents: in fact they may experience lower ambient road noise at this larger measurement scale (see Table 11).[30] On the other hand, while Hispanic respondents live in areas with higher onsite TRI emissions, this is not so when emissions are measured at the proximate and area scales. A notable exception is ambient $PM_{2.5}$ concentrations for which the coefficient on respondents of color is always positive and statistically significant regardless of the scale of measurement (see columns 3, 7 and 10 in Table 11).[31]

This variability in our results suggests that it is important to consider the relevant geographic scale at which pollutants are dispersed. For local pollutants such as ambient noise and onsite emissions, the scale of measurement should be appropriately local. For these pollutants, more spatially aggregated data can lead to misleading results due to measurement error and the potential for ecological fallacy in which an inference is mistakenly made about an individual based on aggregated data or

[30]We emphasize that ambient noise is a very localized pollutant and measurement at any aggregated geographic level may lead to significant measurement errors. This is why we do not measure ambient noise at the area level which we believe is too large to reliably reflect ambient noise measurements for individual respondents. See Wen and Khanna (2024).

[31]We show the full results in Appendix Table B.5.

group characteristics an individual shares (Banzhaf et al., 2019*a*). For more widely dispersed pollutants such as $PM_{2.5}$, the measurement scale seems to be less critical.

5 Summary and Conclusion

To the best of our knowledge, ours is the first study to establish the relationship between redlining, kinship, and environmental justice. We find redlining has a strong, positive correlation with contemporary levels of environmental pollution. As time goes by, and despite the decades of relatively successful environmental regulation, areas that were historically redlined still have significantly higher levels of onsite emissions, ambient road noise, $PM_{2.5}$ concentrations, and airborne toxicity. Likewise, we also find that kinship is strongly correlated with environmental pollution. Communities with greater racial diversity, ethnic polarization, and economic inequality between racial/ethnic groups tend to experience higher levels of local pollution, and these are the very neighborhoods where the people of color in our sample reside. Still, we are unable to explain the entire gap in ambient environmental quality between racial/ethnic minorities and the majority white population. Furthermore, our results are sensitive to the geographic scale at which we measure ambient pollution and we caution against drawing conclusions about individual exposure using pollutants measured at geographically aggregated levels.

Since we have a large number of specifications, we use a specification curve to obtain a bird's-eye view of our key results regarding the association between respondents' racial identities and different environmental pollutants across various specifications (Gao et al., 2021). The plots are made up of two parts (see Figure 1). The upper panel plots the coefficient estimates on racial identity (i.e. Black/Hispanic/Asian) in different model specifications in ascending order of magnitude and the associated 90%/95% confidence intervals. The lower panel uses black dots to indicate the choices from various specification alternatives and reports the exact specifications used in each of our regression models.

Three major patterns emerge. First, the coefficients estimated using pollution data at the proximate scale are much more precisely estimated than with pollution measured at a larger neighborhood or area scale. This pattern holds across the four pollutants in our analysis, though the difference is least marked in the case of $PM_{2.5}$. The larger standard errors in the neighborhood and area models likely result from the absence of individual-level controls. Since pollutant measurements at these broader scales are aggregated across larger geographic units, variation in exposure is primarily driven by differences between neighborhoods or areas, rather than within them. Without individual-level characteristics to help explain some of this variation, standard errors tend to be larger, leading to wider confidence intervals. Second, model specification matters. For example, Black and Hispanic respondents are exposed to significantly higher levels of onsite emissions when we measure emissions at the area scale, but the statistical significance of the coefficients tends to disappear when we include neighborhood characteristics as additional control variables. Similarly, the specification curve for RSEI toxicity concentrations shows that Hispanics experience significantly higher toxicity concentrations when pollution is measured at the area scale and without respondents' individual controls; the coefficients on the race variables in all other specifications are statistically insignificant.

Finally, these curves reiterate the importance of measurement scale and its relation to pollution dispersion. For example, people of color tend to experience higher roadway noise, the most localized of our pollutants, in the immediate vicinity of their residence, i.e., when noise is measured at the proximate scale. However, they experience lower ambient road noise when it is aggregated to the larger scale of a census block group. In contrast, the coefficients on respondents' race are almost always positive and statistically significant across all models and specifications for $PM_{2.5}$, the most widely dispersed of our pollutants.

Overall, our results reveal a nuanced picture in which racial and ethnic minorities live in census tracts or block groups that are no more (or even less) polluted than those favored by the majority White population, but within these geographic areas, Black, Hispanic, and Asian individuals reside in locations that are relatively more polluted. This underscores the need to extend the policy discussion beyond pollution measurements at a geographic scale to encompass exposure of the individual.

References

Aaronson, Daniel, Daniel Hartley, and Bhashkar Mazumder. 2021*a*. "The effects of the 1930s HOLC "redlining" maps." *American Economic Journal: Economic Policy*, 13(4): 355–392.

Aaronson, Daniel, Daniel Hartley, Bhashkar Mazumder, and Martha Stinson. 2023. "The long-run effects of the 1930s redlining maps on children." *Journal of Economic Literature*, 61(3): 846–862.

Aaronson, Daniel, Jacob Faber, Daniel Hartley, Bhashkar Mazumder, and Patrick Sharkey. 2021*b*. "The long-run effects of the 1930s HOLC "redlining" maps on place-based measures of economic opportunity and socioeconomic success." *Regional Science and Urban Economics*, 86: 103622.

Abel, Troy D, and Jonah White. 2015. "Gentrified sustainability: inequitable development and Seattle's skewed riskscape." *Interdisciplinary Environmental Review*, 16(2-4): 124–157.

Aihounton, Ghislain B D, and Arne Henningsen. 2020. "Units of measurement and the inverse hyperbolic sine transformation." *The Econometrics Journal*, 24(2): 334–351.

Ash, Michael, and T Robert Fetter. 2004. "Who lives on the wrong side of the environmental tracks? Evidence from the EPA's risk-screening environmental indicators model." *Social Science Quarterly*, 85(2): 441–462.

Baldwin, Kate, and John D Huber. 2010. "Economic versus cultural differences: Forms of ethnic diversity and public goods provision." *American Political Science Review*, 104(4): 644–662.

Banzhaf, H Spencer, Lala Ma, and Christopher Timmins. 2019*a*. "Environmental justice: Establishing causal relationships." *Annual Review of Resource Economics*, 11: 377–398.

Banzhaf, Spencer, Lala Ma, and Christopher Timmins. 2019*b*. "Environmental justice: The economics of race, place, and pollution." *Journal of Economic Perspectives*, 33(1): 185–208.

Bau, Natalie. 2021. "Can policy change culture? Government pension plans and traditional kinship practices." *American Economic Review*, 111(6): 1880–1917.

Brender, Jean D, Juliana A Maantay, and Jayajit Chakraborty. 2011. "Residential proximity to environmental hazards and adverse health outcomes." *American journal of public health*, 101(S1): S37–S52.

Brooks, Nancy, and Rajiv Sethi. 1997. "The Distribution of Pollution: Community Characteristics and Exposure to Air Toxics." *Journal of Environmental Economics and Management*, 32(2): 233–250.

Cain, Lucas, Danae Hernandez-Cortes, Christopher Timmins, and Paige Weber. 2024. "Recent findings and methodologies in economics research in environmental justice." *Review of Environmental Economics and Policy*, 18(1): 116–142.

Chen, Jiafeng, and Jonathan Roth. 2023. "Logs with Zeros? Some Problems and Solutions." *The Quarterly Journal of Economics*, 139(2): 891–936.

Christensen, Peter, and Christopher Timmins. 2022. "Sorting or steering: The effects of housing discrimination on neighborhood choice." *Journal of Political Economy*, 130(8): 2110–2163.

Currie, Janet, John Voorheis, and Reed Walker. 2023. "What caused racial disparities in particulate exposure to fall? New evidence from the Clean Air Act and satellite-based measures of air quality." *American Economic Review*, 113(1): 71–97.

Cushing, Lara, Dan Blaustein-Rejto, Madeline Wander, Manuel Pastor, James Sadd, Allen Zhu, and Rachel Morello-Frosch. 2018. "Carbon trading, copollutants, and environmental equity: Evidence from California's cap-and-trade program (2011–2015)." *PLoS medicine*, 15(7): e1002604.

Davidson, Pamela, and Douglas L Anderton. 2000. "Demographics of dumping II: A national environmental equity survey and the distribution of hazardous materials handlers." *Demography*, 37: 461–466.

Di, Qian, Heresh Amini, Liuhua Shi, Itai Kloog, Rachel Silvern, James Kelly, M Benjamin Sabath, Christine Choirat, Petros Koutrakis, Alexei Lyapustin, et al. 2019. "An ensemble-based model of PM2. 5 concentration across the contiguous United States with high spatiotemporal resolution." *Environment international*, 130: 104909.

DOT. 2020. "National Transportation Noise Map Document." *Bureau of Transportation Statistics*.

Enke, Benjamin. 2019. "Kinship, cooperation, and the evolution of moral systems." *The Quarterly Journal of Economics*, 134(2): 953–1019.

EPA. 2020. "EJSCREEN: Environmental Justice Screening and Mapping Tool."

Fishback, Price, Jonathan Rose, Kenneth A Snowden, and Thomas Storrs. 2022. "New evidence on redlining by federal housing programs in the 1930s." *Journal of Urban Economics*, 103462.

Gao, Mingze, Henry Leung, and Buhui Qiu. 2021. "Organization capital and executive performance incentives." *Journal of Banking & Finance*, 123: 106017.

Hamilton, James T. 1993. "Politics and social costs: estimating the impact of collective action on hazardous waste facilities." *The RAND journal of economics*, 101–125.

Hausman, Catherine, and Samuel Stolper. 2021. "Inequality, information failures, and air pollution." *Journal of Environmental Economics and Management*, 110: 102552.

Hernandez-Cortes, Danae, and Kyle C Meng. 2023. "Do environmental markets cause environmental injustice? Evidence from California's carbon market." *Journal of Public Economics*, 217: 104786.

Hirschman, Albert Otto. 1964. "The paternity of an index." *The American Economic Review*, 54(5): 761–762.

Hoffman, Jeremy S, Vivek Shandas, and Nicholas Pendleton. 2020. "The effects of historical housing policies on resident exposure to intra-urban heat: a study of 108 US urban areas." *Climate*, 8(1): 12.

Ireland, Philip, and Frank Thomalla. 2011. "The role of collective action in enhancing communities' adaptive capacity to environmental risk: an exploration of two case studies from Asia." *PLoS currents*, 3.

Jung, Kyung Hwa, Zachary Pitkowsky, Kira Argenio, James W Quinn, Jean-Marie Bruzzese, Rachel L Miller, Steven N Chillrud, Matthew Perzanowski, Jeanette A Stingone, and Stephanie Lovinsky-Desir. 2022. "The effects of the historical practice of residential redlining in the United States on recent temporal trends of air pollution near New York City schools." *Environment international*, 169: 107551.

Lane, Haley M, Rachel Morello-Frosch, Julian D Marshall, and Joshua S Apte. 2022. "Historical redlining is associated with present-day air pollution disparities in US cities." *Environmental science & technology letters*, 9(4): 345–350.

Montalvo, Jose G, and Marta Reynal-Querol. 2005. "Ethnic diversity and economic development." *Journal of Development Economics*, 76(2): 293–323.

Nardone, Anthony, Joan A Casey, Rachel Morello-Frosch, Mahasin Mujahid, John R Balmes, and Neeta Thakur. 2020. "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." *The Lancet Planetary Health*, 4(1): e24–e31.

Nardone, Anthony, Kara E Rudolph, Rachel Morello-Frosch, and Joan A Casey. 2021. "Redlines and greenspace: the relationship between historical redlining and 2010 greenspace across the United States." *Environmental health perspectives*, 129(1): 017006.

New York Times. 2017. "How Redlining's Racist Effects Lasted for Decades." *New York Times*. Accessed: July 15, 2024.

Salazar-Miranda, Arianna, Claire Conzelmann, Toàn Phan, and Jeremy Hoffman. 2024. "Long-term effects of redlining on climate risk exposure." *Nature Cities*, 1(6): 436–444.

Schaeffer, Merlin. 2013. "Can competing diversity indices inform us about why ethnic diversity erodes social cohesion? A test of five diversity indices in Germany." *Social Science Research*, 42(3): 755–774.

Shen, Siyuan, Chi Li, Aaron van Donkelaar, Nathan Jacobs, Chenguang Wang, and Randall V Martin. 2024. "Enhancing Global Estimation of Fine Particulate Matter Concentrations by Including Geophysical a Priori Information in Deep Learning." *ACS ES&T Air*, 1(5): 332–345.

Shertzer, Allison, and Randall P Walsh. 2019. "Racial sorting and the emergence of segregation in American cities." *Review of Economics and Statistics*, 101(3): 415–427.

Shertzer, Allison, Tate Twinam, and Randall P Walsh. 2016. "Race, ethnicity, and discriminatory zoning." *American Economic Journal: Applied Economics*, 8(3): 217–246.

Siriban, Charles Irvin S. 2023. "Kinship ties and female political participation: The case of Philippine mayors." *European Journal of Political Economy*, 80: 102419.

Van Donkelaar, Aaron, Randall V Martin, Michael Brauer, N Christina Hsu, Ralph A Kahn, Robert C Levy, Alexei Lyapustin, Andrew M Sayer, and David M Winker. 2016. "Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors." *Environmental science & technology*, 50(7): 3762–3772.

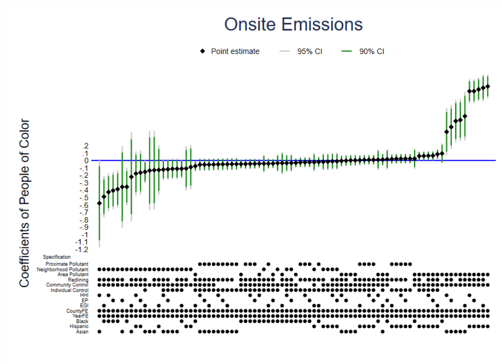
Wakefield, Sarah EL, Susan J Elliott, John D Eyles, and Donald C Cole. 2006. "Taking environmental action: The role of local composition, context, and collective." *Environmental Management*, 37: 40–53.

Wen, Kaiyi, and Neha Khanna. 2024. "Beyond the Haze of Air Pollution: Traffic Noise and Mental Health." *https://ssrn.com/abstract=4771912 or http://dx.doi.org/10.2139/ssrn.4771912*, Available at SSRN.

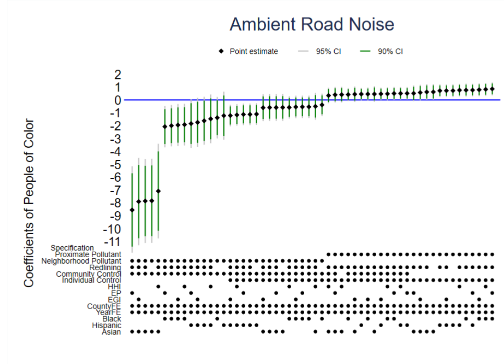
Yang, Wei, and Byron G Spencer. 2022. “Kinship and fertility: Brother and sibling effects on births in a patrilineal system.” *Journal of Economic Behavior & Organization*, 195: 158–170.

Zeka, Ariana, Antonella Zanobetti, and Joel Schwartz. 2006. “Individual-level modifiers of the effects of particulate matter on daily mortality.” *American journal of epidemiology*, 163(9): 849–859.

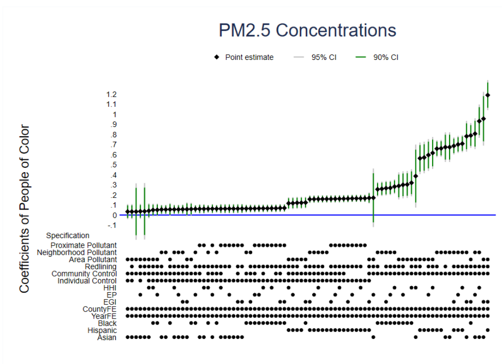
Figures



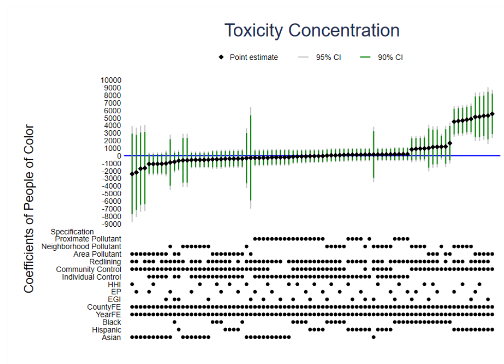
(a) Onsite Emissions



(b) Ambient Road Noise



(c) $PM_{2.5}$ Concentrations



(d) Toxicity Concentrations

Figure 1: Specification Curves for Four Pollution Measures

Tables

Table 1: Geographic Definitions for Pollution Measurement Scales

Pollutant	Proximate	Neighborhood	Area
TRI Emissions	Block Group	Census Tract	5-km Buffer
Ambient Road Noise	1-km Buffer	Block Group	Not Measured
$PM_{2.5}$ Concentrations	1-km Buffer	Block Group	Census Tract
Airborne Toxicity	810m Grid Cell	Block Group	Census Tract

Notes: In this and all subsequent tables, TRI Emissions refer to on-site TRI emissions measured by the inverse hyperbolic sine transformation; toxicity refers to toxicity weighted concentration of airborne chemical releases.

Table 2: Summary Statistics: Socio-economics

	Measurement Scale			National Average
	Proximate	Neighborhood	Area	
	Mean (*SD*)	*Mean* (*SD*)	*Mean* (*SD*)	
	(1)	(2)	(3)	(4)
Black (%)	0.13	0.18	0.19	0.14
	(0.33)	(0.26)	(0.25)	
Hispanic (%)	0.14	0.22	0.23	0.19
	(0.35)	(0.25)	(0.24)	
Asian (%)	0.07	0.08	0.08	0.06
	(0.26)	(0.10)	(0.09)	
High school graduate (%)		0.23	0.23	0.26
		(0.11)	(0.09)	
Median household income (1,000$)		68.2	67.0	68.7
		(35.6)	(32.2)	
Fraction below poverty		0.11	0.11	0.123
		(0.13)	(0.10)	
House renter (%)		0.36	0.38	0.36
		(0.25)	(0.22)	
Median housing value (1,000$)		264.8	267.8	293.0
		(226.3)	(220.8)	
Redlined (%)		0.07	0.10	
		(0.25)	(0.30)	
Marginalized block group (%)		0.63		
		(0.48)		
N	20,543	20,543	20,543	20,543

*Notes:*The race variables at the neighborhood/area scale refer to the fraction of the population within each respective category. Whereas at the proximate scale, they refer to the fraction of individuals in the HINTS sample. National averages are obtained from the US Census. All other socio-economic variables, including Redlined, are measured at the block group (neighborhood) or census tract (area) scale. For consistency, onsite emissions at the area level are summarized as the simple sum of emissions within the 5 km buffer surrounding each respondent.

Table 3: Pollution Summary Statistics by Race Across Geographic Scales

Panel A: Proximate

Race	$PM_{2.5}$ ($\mu g/m^3$)	TRI Emissions (1,000 lbs)	Toxicity ('000 $\mu g/m^3$)	Road Noise (dB)
White	7.40 (1.52)	4.39 (90.94)	4.48 (22.35)	49.67 (14.22)
Black	7.84 (1.25)	4.75 (95.39)	7.29 (21.63)	52.23 (9.49)
Hispanic	8.34 (2.17)	10.67 (51.26)	5.09 (17.94)	53.07 (7.97)
Asian	8.06 (1.93)	2.31 (53.19)	4.78 (18.87)	52.19 (10.11)
Overall mean (SD)	7.66 (1.68)	5.63 (233.11)	5.14 (22.02)	50.80 (12.53)

Panel B: Neighborhood

Race	$PM_{2.5}$ ($\mu g/m^3$)	TRI Emissions (1,000 lbs)	Toxicity ('000 $\mu g/m^3$)	Road Noise (dB)
White	7.39 (1.52)	30.04 (1254.32)	4.62 (21.79)	44.20 (20.42)
Black	7.84 (1.25)	10.06 (122.97)	7.07 (24.55)	44.95 (19.72)
Hispanic	8.34 (2.18)	15.78 (519.94)	5.35 (20.93)	44.25 (20.58)
Asian	8.05 (1.93)	5.03 (65.35)	4.22 (14.26)	44.41 (20.51)
Overall mean (SD)	7.46 (1.59)	23.52 (976.86)	5.11 (21.33)	44.45 (20.25)

Panel C: Area

Race	$PM_{2.5}$ ($\mu g/m^3$)	TRI Emissions (1,000 lbs)	Toxicity ('000 $\mu g/m^3$)
White	8.29 (1.85)	40.97 (434.11)	4.81 (29.47)
Black	8.79 (1.53)	57.39 (314.70)	7.52 (26.17)
Hispanic	9.08 (2.54)	43.61 (557.84)	5.38 (20.24)
Asian	8.90 (2.16)	23.24 (120.87)	4.32 (15.80)
Overall mean (SD)	8.54 (1.98)	45.67 (483.15)	5.39 (28.40)
N (White)		11,616	
N (Black)		2,584	
N (Hispanic)		2,916	
N (Asian)		1,448	

Notes: The total number of observations reported in this table (18,564) does not match the total sample size used in the regressions (19,910) because respondents with missing ethnicity information are excluded from the group-specific summaries shown here. In the regressions, these respondents are included as part of the base category, along with White respondents.

Table 4: Block Group Level Kinship Distribution by Quartile and Race/Ethnicity

Panel A: HHI	Hirschman-Herfindahl Index Quartile Range			
	0–Q1	Q1–Q2	Q2–Q3	Q3–1
Population Group (%)		Q1: 0.2401	Q2: 0.4627	Q3: 0.5893
White	28.6	26.6	23.6	21.2
Black	22.9	22.6	26.7	27.7
Hispanic	18.5	24.6	27.9	29.0
Asian	11.6	19.9	26.5	42.1
Panel B: EP	Ethnic Polarization Quartile Range			
	0–Q1	Q1–Q2	Q2–Q3	Q3–1
		Q1: 0.4350	Q2: 0.7284	Q3: 0.8269
White	28.8	26.2	21.7	23.2
Black	22.6	21.2	27.4	28.8
Hispanic	18.0	24.0	29.5	28.5
Asian	11.6	25.4	38.3	24.7
Panel C: EGI	Ethnic Group-based Index Quartile Range			
	0–Q1	Q1–Q2	Q2–Q3	Q3–1
		Q1: 0.038	Q2: 0.071	Q3: 0.111
White	26.4	26.0	25.2	22.5
Black	25.2	23.3	25.7	25.8
Hispanic	22.1	24.6	25.0	28.4
Asian	13.7	24.2	28.2	33.8

Note: Sample size across all panels is $N = 20{,}543$.

Table 5: Neighborhood/Area OLS Results with Redlining

Panel A: Neighborhood Level	Dependent Variable							
	TRI Emissions	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Neighborhood Black Fraction	-0.356***	-1.378*	0.260***	1186.525	-0.387***	-1.999**	0.255***	935.531
	(0.130)	(0.822)	(0.037)	(869.430)	(0.130)	(0.821)	(0.037)	(871.110)
Neighborhood Hispanic Fraction	-0.090	-1.222	0.661***	4762.685***	-0.108	-1.617*	0.657***	4591.230***
	(0.152)	(0.953)	(0.043)	(1017.574)	(0.152)	(0.950)	(0.043)	(1017.926)
Neighborhood Asian Fraction	-0.137	-7.834***	0.673***	-607.056	-0.131	-7.852***	0.673***	-609.854
	(0.272)	(1.669)	(0.075)	(1794.135)	(0.272)	(1.663)	(0.075)	(1793.283)
Neighborhood Redlined					0.197***	6.131***	0.048*	2449.587***
					(0.069)	(0.565)	(0.025)	(588.998)
Constant	0.573**	49.469***	7.246***	4158.460***	0.563**	49.277***	7.245***	4070.349***
	(0.229)	(1.252)	(0.056)	(1339.307)	(0.229)	(1.248)	(0.056)	(1338.838)
Community Characteristics	X***	X***	X***	X*	X**	X***	X***	X
County FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
R^2	0.232	0.259	0.782	0.317	0.233	0.263	0.782	0.318
Observations	19,802	19,910	19,910	18,455	19,802	19,910	19,910	18,455

Panel B: Area Level	Dependent Variable					
	TRI Emissions	*PM2.5*	*Toxicity*	*TRI Emissions*	*PM2.5*	*Toxicity*
	(1)	(2)	(3)	(4)	(5)	(6)
Area Black Fraction	0.094	0.303***	1662.594	0.024	0.288***	1216.631
	(0.070)	(0.068)	(1384.029)	(0.070)	(0.068)	(1388.511)
Area Hispanic Fraction	1.000***	0.570***	5537.634***	0.959***	0.562***	5274.960***
	(0.082)	(0.080)	(1623.730)	(0.082)	(0.080)	(1624.615)
Area Asian Fraction	0.532***	0.034	-1714.507	0.546***	0.037	-1628.554
	(0.147)	(0.143)	(2903.505)	(0.146)	(0.143)	(2902.536)
Area Redlined				0.437***	0.088**	2795.929***
				(0.037)	(0.036)	(737.057)
Constant	0.361***	8.335***	-493.155	0.340***	8.331***	-628.841
	(0.124)	(0.120)	(2448.387)	(0.123)	(0.120)	(2447.757)
Community Characteristics	X***	X***	X***	X***	X***	X***
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.263	0.605	0.229	0.269	0.606	0.230
Observations	19,802	19,798	19,747	19,802	19,798	19,747

The number of observations varies across columns because (i) some community characteristics are missing at the census tract level in the ACS; (ii) several block group/census tracts' $PM_{2.5}$/toxicity concentrations are not reported in the RSIG/RSEI data across our survey years. We also report the joint significance test (F-test) for community characteristics, which include high school graduate fraction, median household income and its square, poverty fraction and its square, house renter fraction, and median house value.

Table 6: Neighborhood/Area OLS Results with Redlining and Kinship

Panel A: Neighborhood Level	Dependent Variable											
	TRI Emissions	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Neighborhood Black Fraction	-0.427***	-1.918**	0.282***	963.460	-0.406***	-2.071**	0.269***	909.844	-0.489***	-1.948**	0.266***	831.956
	(0.131)	(0.826)	(0.037)	(875.678)	(0.130)	(0.823)	(0.037)	(872.462)	(0.142)	(0.834)	(0.038)	(888.129)
Neighborhood Hispanic Fraction	-0.177	-1.468	0.707***	4647.236***	-0.164	-1.836*	0.700***	4504.236***	-0.129	-1.738*	0.685***	4863.102***
	(0.153)	(0.965)	(0.043)	(1033.515)	(0.153)	(0.962)	(0.043)	(1030.967)	(0.172)	(0.969)	(0.044)	(1040.954)
Neighborhood Asian Fraction	-0.578*	-7.082***	0.930***	-316.947	-0.357	-8.546***	0.806***	-888.193	-0.221	-7.898***	0.780***	161.021
	(0.303)	(1.874)	(0.084)	(2022.193)	(0.282)	(1.731)	(0.078)	(1867.910)	(0.307)	(1.730)	(0.078)	(1870.195)
Neighborhood Redlined	0.195***	6.135***	0.049*	2450.906***	0.195***	6.123***	0.050*	2446.548***	0.180**	6.180***	0.050*	2398.232***
	(0.069)	(0.565)	(0.025)	(589.028)	(0.069)	(0.565)	(0.025)	(589.038)	(0.072)	(0.572)	(0.026)	(598.568)
Neighborhood HHI	0.456***	-0.816	-0.273***	-305.408								
	(0.137)	(0.915)	(0.041)	(974.350)								
Neighborhood EP					0.320***	0.951	-0.183***	373.794				
					(0.106)	(0.659)	(0.030)	(701.797)				
Neighborhood EGI									0.082	-0.863	-0.653***	-4975.738
									(0.551)	(2.898)	(0.130)	(3136.291)
Constant	0.462**	49.438***	7.299***	4131.616***	0.412*	48.856***	7.326***	3904.427***	0.717***	49.469***	7.279***	4342.685***
	(0.231)	(1.261)	(0.057)	(1353.066)	(0.234)	(1.281)	(0.057)	(1374.630)	(0.261)	(1.268)	(0.057)	(1366.540)
R^2	0.233	0.263	0.782	0.318	0.233	0.263	0.782	0.318	0.244	0.262	0.781	0.316
Observations	19,802	19,910	19,910	18,455	19,802	19,910	19,910	18,455	16,774	19,589	19,589	18,159

Panel B: Area Level	Dependent Variable								
	TRI Emissions	*PM2.5*	*Toxicity*	*TRI Emissions*	*PM2.5*	*Toxicity*	*TRI Emissions*	*PM2.5*	*Toxicity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Area Black Fraction	0.010	0.319***	1146.583	0.017	0.299***	1170.047	-0.036	0.788***	1014.300
	(0.070)	(0.068)	(1394.495)	(0.070)	(0.068)	(1390.046)	(0.077)	(0.063)	(1574.092)
Area Hispanic Fraction	0.934***	0.615***	5154.317***	0.936***	0.595***	5132.932***	0.980***	1.188***	5307.031***
	(0.083)	(0.080)	(1639.713)	(0.082)	(0.080)	(1636.645)	(0.094)	(0.076)	(1910.910)
Area Asian Fraction	0.386**	0.386**	-2411.739	0.451***	0.171	-2202.910	0.597***	0.954***	-288.962
	(0.163)	(0.159)	(3240.015)	(0.152)	(0.148)	(3010.878)	(0.167)	(0.136)	(3422.043)
Area Redlined	0.436***	0.091**	2791.085***	0.436***	0.090**	2788.759***	0.411***	0.071**	2840.381***
	(0.037)	(0.036)	(737.125)	(0.037)	(0.036)	(737.135)	(0.039)	(0.032)	(797.798)
Area HHI	0.163**	-0.355***	798.351						
	(0.074)	(0.072)	(1467.550)						
Area EP				0.133**	-0.188***	809.614			
				(0.057)	(0.055)	(1128.076)			
Area EGI							-0.276	-0.423*	-8345.440
							(0.300)	(0.243)	(6134.440)
Constant	0.304**	8.409***	-806.268	0.277**	8.420***	-1013.112	0.289**	7.404***	-1685.604
	(0.124)	(0.121)	(2469.437)	(0.126)	(0.123)	(2505.664)	(0.142)	(0.115)	(2910.391)
R^2	0.269	0.606	0.230	0.269	0.606	0.230	0.277	0.716	0.228
Observations	19,802	19,798	19,747	19,802	19,798	19,747	16,774	16,770	16,727

Both panels control for community characteristics, which include high school graduate fraction, median household income and its square, poverty fraction and its square, house renter fraction, and median house value, as well as county and year fixed effects. The number of observations varies across columns because (i) some community characteristics are missing at the census tract level in the ACS; (ii) several block group/census tracts' $PM_{2.5}$/toxicity concentrations are not reported in the RSIG/RSEI data across our survey years.

Table 7: Proximate OLS Results with Redlining

	Dependent Variable (Proximate Level)							
	TRI Emissions	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	-0.020	0.793^{***}	0.070^{***}	284.399	-0.026	0.767^{***}	0.066^{***}	204.989
	(0.036)	(0.255)	(0.020)	(472.053)	(0.036)	(0.255)	(0.020)	(472.525)
Hispanic	0.024	0.726^{***}	0.166^{***}	153.560	0.023	0.719^{***}	0.165^{***}	131.949
	(0.035)	(0.248)	(0.019)	(459.943)	(0.035)	(0.248)	(0.019)	(459.863)
Asian	-0.048	0.625^{**}	0.063^{***}	-206.925	-0.049	0.621^{**}	0.063^{***}	-216.901
	(0.044)	(0.310)	(0.024)	(574.281)	(0.044)	(0.309)	(0.024)	(574.132)
Redlined					0.145^{***}	0.667^{**}	0.091^{***}	2008.312^{***}
					(0.046)	(0.325)	(0.025)	(602.399)
Constant	0.343^{***}	51.428^{***}	7.646^{***}	6422.816^{***}	0.324^{***}	51.345^{***}	7.635^{***}	6171.861^{***}
	(0.049)	(0.351)	(0.027)	(650.426)	(0.050)	(0.353)	(0.027)	(654.591)
Education	X^{***}	X	X^{**}	X	X^{**}	X	X^{**}	X
Income	X^{***}	X^{***}	X	X^{***}	X^{***}	X^{***}	X	X^{**}
County FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
R^2	0.163	0.282	0.779	0.282	0.163	0.282	0.779	0.283
Observations	19,910	19,910	19,910	19,828	19,910	19,910	19,910	19,828
Note:								*p<0.1; **p<0.05; ***p<0.01

Emissions refer to on-site TRI emissions and are measured by the inverse hyperbolic sine transformation. The number of observations varies across columns because several block groups' toxicity concentrations are not reported in the RSEI data across our survey years. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the F-test for joint significance for control variables.

Table 8: Proximate OLS Results with Redlining and Kinship

	Dependent Variable (Proximate Level)											
	TRI Emissions	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Black	-0.025	0.825***	0.067***	201.229	-0.023	0.859***	0.066***	209.264	-0.021	0.795***	0.070***	190.935
	(0.036)	(0.254)	(0.020)	(472.640)	(0.036)	(0.255)	(0.020)	(472.828)	(0.036)	(0.254)	(0.020)	(479.271)
Hispanic	0.023	0.763***	0.165***	129.253	0.024	0.770***	0.164***	134.229	0.018	0.725***	0.163***	130.977
	(0.035)	(0.247)	(0.019)	(459.928)	(0.035)	(0.247)	(0.019)	(459.959)	(0.035)	(0.245)	(0.020)	(464.108)
Asian	-0.052	0.415	0.061**	-203.687	-0.051	0.517*	0.063***	-221.699	-0.051	0.575*	0.064***	-209.680
	(0.044)	(0.309)	(0.024)	(575.206)	(0.044)	(0.309)	(0.024)	(574.448)	(0.044)	(0.307)	(0.024)	(579.791)
Redlined(BG)	0.143***	0.532	0.090***	2017.037***	0.142***	0.544*	0.091***	2002.603***	0.151***	0.498	0.090***	1952.557***
	(0.046)	(0.325)	(0.025)	(602.854)	(0.046)	(0.325)	(0.025)	(602.822)	(0.046)	(0.325)	(0.025)	(613.520)
HHI(BG)	0.083	5.003***	0.038	-322.580								
	(0.065)	(0.458)	(0.035)	(852.574)								
EP(BG)					0.087*	3.723***	-0.015	172.857				
					(0.051)	(0.361)	(0.028)	(670.996)				
EGI(BG)									-0.060	12.849***	0.045	-2446.816
									(0.226)	(1.582)	(0.124)	(2990.694)
Constant	0.291***	49.330***	7.614***	6301.882***	0.271***	49.067***	7.644***	6066.088***	0.338***	50.454***	7.633***	6367.894***
	(0.056)	(0.397)	(0.031)	(739.324)	(0.059)	(0.415)	(0.032)	(772.720)	(0.053)	(0.374)	(0.029)	(708.092)
Education	X***	X	X**	X	X***	X***	X**	X	X***	X	X**	X
Income	X***	X***	X	X**	X***	X***	X	X**	X***	X	X	X**
County FE	X	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X	X	X
R^2	0.163	0.287	0.779	0.283	0.163	0.286	0.779	0.283	0.161	0.282	0.779	0.282
Observations	19,910	19,910	19,910	19,828	19,910	19,910	19,910	19,828	19,589	19,589	19,589	19,509

Note: *p<0.1; **p<0.05; ***p<0.01

Emissions refer to on-site TRI emissions and are measured by the inverse hyperbolic sine transformation. The number of observations varies across columns because several block groups' toxicity concentrations are not reported in the RSEI data across our survey years. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the F-test for joint significance for control variables.

Table 9: Proximate OLS Results with Redlining, Kinship and Community Characteristics

	Dependent Variable (Proximate Level)															
	TRI Emissions (1)	*Noise* (2)	*PM2.5* (3)	*Toxicity* (4)	*TRI Emissions* (5)	*Noise* (6)	*PM2.5* (7)	*Toxconc* (8)	*TRI Emissions* (9)	*Noise* (10)	*PM2.5* (11)	*Toxicity* (12)	*TRI Emissions* (13)	*Noise* (14)	*PM2.5* (15)	*Toxicity* (16)
Black	-0.047	0.423*	0.067**	-101.519	-0.046	0.479*	0.066***	-107.166	-0.045	0.507**	0.065***	-97.328	-0.042	0.463*	0.069***	-131.312
	(0.036)	(0.256)	(0.020)	(478.690)	(0.036)	(0.256)	(0.020)	(478.958)	(0.037)	(0.256)	(0.020)	(479.240)	(0.037)	(0.255)	(0.020)	(485.622)
Hispanic	0.008	0.459*	0.162***	-48.446	0.009	0.510**	0.161***	-53.477	0.010	0.515**	0.160***	-45.691	0.004	0.474*	0.159***	-57.615
	(0.035)	(0.247)	(0.019)	(462.002)	(0.035)	(0.247)	(0.019)	(462.224)	(0.035)	(0.247)	(0.019)	(462.255)	(0.035)	(0.245)	(0.019)	(466.321)
Asian	-0.055	0.463	0.061***	-285.563	-0.057	0.346	0.063***	-273.891	-0.057	0.404	0.062***	-288.491	-0.056	0.447	0.063***	-274.840
	(0.044)	(0.307)	(0.024)	(574.428)	(0.044)	(0.307)	(0.024)	(575.355)	(0.044)	(0.307)	(0.024)	(574.662)	(0.044)	(0.304)	(0.024)	(580.000)
Redlined(BG)	0.131***	-0.125	0.060**	1865.663***	0.131***	-0.151	0.061**	1868.258***	0.130***	-0.159	0.061**	1863.976***	0.138***	-0.198	0.061**	1798.171***
	(0.047)	(0.327)	(0.025)	(611.034)	(0.047)	(0.327)	(0.025)	(611.091)	(0.047)	(0.327)	(0.025)	(611.118)	(0.047)	(0.327)	(0.026)	(621.742)
HHI(BG)					0.063	3.171***	-0.042	-318.399								
					(0.067)	(0.472)	(0.037)	(883.812)								
EP(BG)									0.074	2.544***	-0.062**	126.691				
									(0.052)	(0.366)	(0.028)	(685.979)				
EGI(BG)													-0.167	8.727***	-0.127	-3024.382
													(0.229)	(1.596)	(0.126)	(3042.267)
Constant	0.161	51.452***	7.443***	5104.192***	0.143	50.547***	7.454***	5194.960***	0.122	50.116***	7.481***	5037.622***	0.193*	51.124***	7.464***	5197.709***
	(0.108)	(0.756)	(0.060)	(1416.398)	(0.109)	(0.767)	(0.061)	(1438.666)	(0.111)	(0.779)	(0.061)	(1461.579)	(0.109)	(0.761)	(0.060)	(1452.258)
Education	X	X	X*	X	X	X	X**	X	X	X	X**	X	X	X	X**	X
Income	X	X***	X	X*	X	X***	X	X	X	X***	X	X	X	X	X	X*
Community Characteristics	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***
County FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
R^2	0.164	0.296	0.781	0.284	0.164	0.298	0.781	0.284	0.164	0.298	0.781	0.284	0.162	0.294	0.780	0.283
Observations	19,910	19,910	19,910	19,828	19,910	19,910	19,910	19,828	19,910	19,910	19,910	19,828	19,589	19,589	19,589	19,509

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Emissions refer to on-site TRI emissions and are measured by the inverse hyperbolic sine transformation. The number of observations varies across columns because several block groups' toxicity concentrations are not reported in the RSEI data across our survey years. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the F-test for joint significance for education, income, and community characteristics.

Table 10: Proximate OLS Results with Redlining, Kinship, Community Characteristics and Minority Fraction

	Dependent Variable (Proximate Level)															
	TRI Emissions (1)	*Noise* (2)	*PM2.5* (3)	*Toxicity* (4)	*TRI Emissions* (5)	*Noise* (6)	*PM2.5* (7)	*Toxicity* (8)	*TRI Emissions* (9)	*Noise* (10)	*PM2.5* (11)	*Toxicity* (12)	*TRI Emissions* (13)	*Noise* (14)	*PM2.5* (15)	*Toxicity* (16)
Black	-0.037	0.140	0.047^{**}	-248.341	-0.033	0.207	0.038^{*}	-266.233	-0.033	0.222	0.039^{*}	-252.428	-0.034	0.190	0.045^{**}	-254.003
	(0.039)	(0.274)	(0.021)	(512.911)	(0.039)	(0.275)	(0.021)	(513.887)	(0.039)	(0.274)	(0.021)	(513.811)	(0.039)	(0.273)	(0.021)	(519.161)
Hispanic	0.004	0.245	0.104^{***}	-390.193	0.009	0.315	0.095^{***}	-408.665	0.009	0.333	0.096^{***}	-394.580	-0.001	0.286	0.098^{***}	-421.342
	(0.036)	(0.253)	(0.020)	(473.325)	(0.036)	(0.253)	(0.020)	(474.450)	(0.036)	(0.253)	(0.020)	(474.443)	(0.036)	(0.251)	(0.020)	(478.175)
Asian	-0.044	0.113	0.022	-318.697	-0.042	0.137	0.019	-325.506	-0.042	0.142	0.019	-320.216	-0.045	0.160	0.021	-335.038
	(0.044)	(0.310)	(0.024)	(581.785)	(0.044)	(0.310)	(0.024)	(581.919)	(0.044)	(0.310)	(0.024)	(581.908)	(0.044)	(0.308)	(0.024)	(587.555)
BG Black Fraction	-0.044	1.965^{***}	0.232^{***}	1430.241	-0.061	1.706^{***}	0.266^{***}	1499.374	-0.055	1.756^{***}	0.252^{***}	1440.673	-0.033	1.760^{***}	0.245^{***}	1334.420
	(0.072)	(0.508)	(0.039)	(951.549)	(0.073)	(0.512)	(0.040)	(959.328)	(0.073)	(0.510)	(0.039)	(954.684)	(0.073)	(0.509)	(0.040)	(970.434)
BG Hispanic Fraction	0.030	2.518^{***}	0.610^{***}	3513.705^{***}	0.001	2.083^{***}	0.666^{***}	3630.621^{***}	0.003	2.010^{***}	0.657^{***}	3539.217^{***}	0.034	2.115^{***}	0.637^{***}	3741.402^{***}
	(0.081)	(0.567)	(0.044)	(1062.138)	(0.082)	(0.577)	(0.045)	(1081.940)	(0.082)	(0.575)	(0.044)	(1078.726)	(0.082)	(0.572)	(0.045)	(1090.604)
BG Asian Fraction	-0.226	6.355^{***}	0.656^{***}	-265.857	-0.360^{**}	4.335^{***}	0.917^{***}	276.421	-0.301^{**}	4.911^{***}	0.791^{***}	-193.391	-0.222	5.316^{***}	0.758^{***}	386.343
	(0.139)	(0.975)	(0.075)	(1827.811)	(0.157)	(1.099)	(0.085)	(2062.402)	(0.145)	(1.015)	(0.078)	(1904.492)	(0.144)	(1.002)	(0.078)	(1913.627)
Redlined(BG)	0.132^{***}	-0.193	0.049^{*}	1778.148^{***}	0.131^{***}	-0.205	0.050^{**}	1781.501^{***}	0.131^{***}	-0.212	0.051^{**}	1779.134^{***}	0.138^{***}	-0.241	0.052^{**}	1724.866^{***}
	(0.047)	(0.327)	(0.025)	(612.117)	(0.047)	(0.327)	(0.025)	(612.157)	(0.047)	(0.327)	(0.025)	(612.177)	(0.047)	(0.327)	(0.026)	(622.670)
HHI(BG)					0.141^{*}	2.121^{***}	-0.274^{***}	-567.016								
					(0.076)	(0.533)	(0.041)	(998.819)								
EP(BG)									0.102^{*}	1.949^{***}	-0.182^{***}	-97.354				
									(0.055)	(0.383)	(0.030)	(718.484)				
EGI(BG)													-0.095	6.105^{***}	-0.615^{***}	-4302.526
													(0.239)	(1.663)	(0.130)	(3172.433)
Constant	0.172	50.151^{***}	7.224^{***}	3926.888^{***}	0.148	49.782^{***}	7.272^{***}	4025.500^{***}	0.130	49.348^{***}	7.299^{***}	3966.993^{***}	0.197^{*}	50.144^{***}	7.253^{***}	4038.472^{***}
	(0.113)	(0.789)	(0.061)	(1479.496)	(0.113)	(0.794)	(0.061)	(1489.686)	(0.115)	(0.804)	(0.062)	(1508.850)	(0.114)	(0.791)	(0.062)	(1509.539)
Education	X	X	X^{**}	X	X	X	X^{**}	X	X	X	X^{**}	X	X	X	X^{**}	X
Income	X	X^{***}	X	X^{*}	X	X^{***}	X	X^{*}	X	X^{***}	X	X^{*}	X	X^{***}	X	X^{*}
Community Characteristics	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}	X^{***}
County FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
R^2	0.164	0.298	0.783	0.284	0.165	0.299	0.784	0.284	0.165	0.299	0.784	0.284	0.162	0.296	0.783	0.284
Observations	19,910	19,910	19,910	19,828	19,910	19,910	19,910	19,828	19,910	19,910	19,910	19,828	19,589	19,589	19,589	19,509

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Emissions refer to on-site TRI emissions and are measured by the inverse hyperbolic sine transformation. The number of observations varies across columns because several block groups' toxicity concentrations are not reported in the RSEI data across our survey years. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the F-test for joint significance for education, income, and community characteristics.

Table 11: OLS Results with Different Pollutant Measurements

	Dependent Variable Measurement Scale										
	Proximate				Neighborhood				Area		
	TRI Emissions	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*PM2.5*	*Toxicity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Black	-0.046	0.479*	0.066***	-107.166	-0.035	-0.578	0.062***	54.843	-0.043	0.069**	-474.305
	(0.036)	(0.256)	(0.020)	(478.958)	(0.061)	(0.442)	(0.020)	(470.359)	(0.033)	(0.032)	(648.461)
Hispanic	0.009	0.510**	0.161***	-53.477	-0.011	-1.160***	0.158***	162.461	0.064**	0.127***	-400.740
	(0.035)	(0.247)	(0.019)	(462.224)	(0.058)	(0.427)	(0.019)	(456.314)	(0.031)	(0.030)	(622.682)
Asian	-0.057	0.346	0.063***	-273.891	-0.124*	-0.494	0.056**	-550.804	-0.006	0.039	-1092.199
	(0.044)	(0.307)	(0.024)	(575.355)	(0.072)	(0.531)	(0.024)	(567.768)	(0.039)	(0.038)	(774.466)
Redlined(BG/CT)	0.131***	-0.151	0.061**	1868.258***	0.179***	6.104***	0.061**	2507.294***	0.437***	0.125***	2826.725***
	(0.047)	(0.327)	(0.025)	(611.091)	(0.069)	(0.565)	(0.025)	(588.540)	(0.037)	(0.036)	(735.620)
HHI(BG/CT)	0.063	3.171***	-0.042	-318.399	0.358***	-2.475***	-0.032	-28.300	0.257***	-0.221***	538.378
	(0.067)	(0.472)	(0.037)	(883.812)	(0.124)	(0.816)	(0.037)	(868.339)	(0.067)	(0.063)	(1321.472)
Constant	0.143	50.547***	7.460***	5194.960***	0.516**	48.895***	7.426***	5494.201***	0.528***	8.444***	1297.512
	(0.109)	(0.767)	(0.060)	(1438.666)	(0.237)	(1.327)	(0.060)	(1424.155)	(0.128)	(0.096)	(2529.300)
County FE	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X	X
Community Characteristics	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***
R^2	0.164	0.298	0.781	0.284	0.233	0.263	0.779	0.317	0.263	0.605	0.230
Observations	19,910	19,910	19,910	19,828	19,802	19,910	19,910	18,455	19,802	19,906	19,747

Note: *p<0.1; **p<0.05; ***p<0.01

Emissions refer to on-site TRI emissions and are measured by the inverse hyperbolic sine transformation. The number of observations varies across columns because (i) some neighborhoods' shapefiles do not include any centroids of the satellite $PM_{2.5}$ pixels which contributes to fewer observations; (ii) some community characteristics are missing at the census tract level in the ACS; (iii) there are several block group/census tracts' $PM_{2.5}$/toxicity concentrations are not reported in the RSIG/RSEI data across our survey years.

For Online Publication

Appendix

A Figures

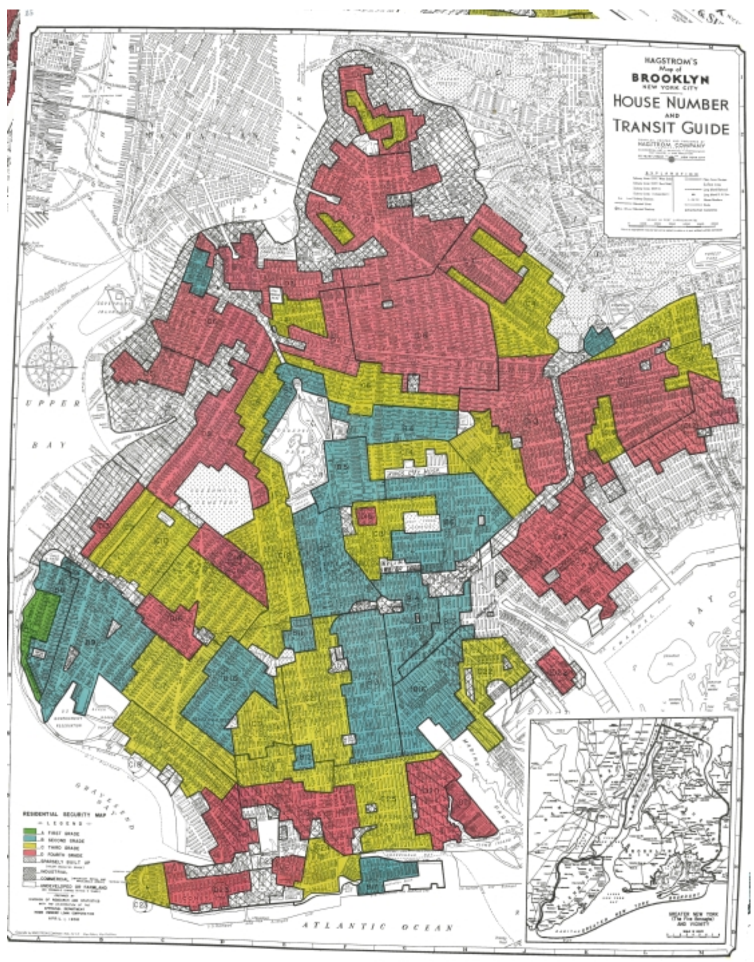
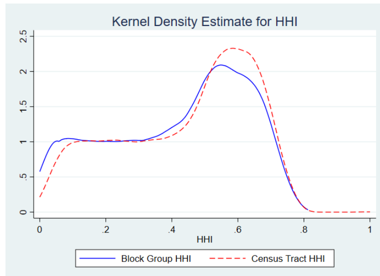
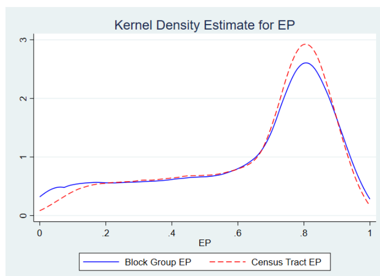


Figure A.1: Redlining Map for Brooklyn, NY

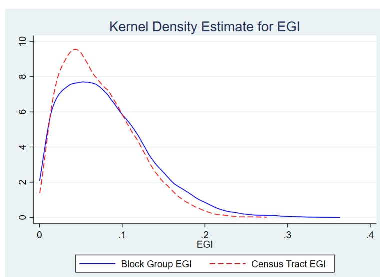
Source: https://dsl.richmond.edu/panorama/redlining



Panel A: HHI Distribution



Panel B: EP Distribution



Panel C: EGI Distribution

Figure A.2: Block Group/Census Tract Kinship Distribution

B Tables

Table B.1: Kinship Distribution at the Census Tract Level by Quartile and Race/Ethnicity

Panel A: *(N=20,543)*	HHI			
	0-Q1	Q1-Q2	Q2-Q3	Q3-1
Fraction of Ethnic Group(%)		Q1: 0.276	Q2: 0.497	Q3: 0.609
White	29.3	25.7	23.4	21.6
Black	21.6	24.1	27.7	26.7
Hispanic	18.1	25.2	28.7	28.0
Asian	6.2	19.5	25.2	49.1
Panel B: *(N=20,543)*	EP			
	0-Q1	Q1-Q2	Q2-Q3	Q3-1
		Q1: 0.482	Q2: 0.739	Q3: 0.826
White	29.4	25.5	21.4	23.7
Black	21.3	21.3	29.1	28.3
Hispanic	17.6	25.3	29.5	27.7
Asian	6.3	29.4	41.6	22.6
Panel C: *(N=20,543)*	EGI			
	0-Q1	Q1-Q2	Q2-Q3	Q3-1
		Q1: 0.023	Q2: 0.055	Q3: 0.093
White	26.4	28.3	24.0	21.3
Black	24.5	24.7	25.3	25.5
Hispanic	23.0	17.2	25.3	34.5
Asian	19.6	20.5	28.0	31.9

Table B.2: Population Fractions by Race at Block Group and Census Tract Levels

	Panel A: Block Group Level			
	White (1)	Black (2)	Hispanic (3)	Asian (4)
White Fraction	0.6460	0.2543	0.3007	0.4351
Black Fraction	0.1126	0.5339	0.1150	0.1564
Hispanic Fraction	0.1661	0.1490	0.5034	0.2443
Asian Fraction	0.0753	0.0628	0.0809	0.1642
N	11,616	2,584	2,916	1,448
	Panel B: Census Tract Level			
	White (1)	Black (2)	Hispanic (3)	Asian (4)
White Fraction	0.6272	0.2608	0.2993	0.4351
Black Fraction	0.1208	0.5204	0.1168	0.1564
Hispanic Fraction	0.1749	0.1542	0.5009	0.2443
Asian Fraction	0.0769	0.0642	0.0830	0.1642
N	11,616	2,584	2,916	1,448

Table B.3: Proximate OLS Results with Redlining, Kinship, and Marginalized Block Group Dummy

	Dependent Variable (Proximate Level)															
	TRI Emissions	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Black	-0.030	0.689***	0.054**	77.972	-0.028	0.835***	0.054**	56.058	-0.027	0.849***	0.052**	74.176	-0.026	0.754***	0.057***	51.403
	(0.036)	(0.257)	(0.020)	(476.800)	(0.036)	(0.257)	(0.020)	(477.481)	(0.036)	(0.257)	(0.020)	(477.725)	(0.037)	(0.256)	(0.020)	(483.853)
Hispanic	0.020	0.670***	0.157***	51.295	0.021	0.770***	0.157***	36.658	0.022	0.764***	0.156***	49.106	0.015	0.699***	0.155***	42.900
	(0.035)	(0.249)	(0.019)	(461.617)	(0.035)	(0.248)	(0.019)	(461.933)	(0.035)	(0.248)	(0.019)	(461.943)	(0.035)	(0.247)	(0.019)	(465.974)
Asian	-0.051	0.586*	0.057**	-275.600	-0.053	0.418	0.057**	-250.740	-0.053	0.513*	0.058**	-273.909	-0.053	0.558*	0.059**	-267.333
	(0.044)	(0.310)	(0.024)	(574.847)	(0.044)	(0.309)	(0.024)	(575.575)	(0.044)	(0.309)	(0.024)	(575.013)	(0.044)	(0.307)	(0.024)	(580.393)
Redlined(BG)	0.142***	0.615*	0.082***	1921.944***	0.141***	0.538*	0.082***	1933.441***	0.140***	0.539*	0.083***	1923.746***	0.148***	0.474	0.082***	1871.549***
	(0.046)	(0.326)	(0.025)	(603.920)	(0.046)	(0.325)	(0.025)	(604.072)	(0.046)	(0.325)	(0.025)	(604.099)	(0.046)	(0.326)	(0.025)	(614.686)
HHI(BG)					0.073	5.033***	0.001	-754.806								
					(0.067)	(0.471)	(0.036)	(876.297)								
EP(BG)									0.081	3.705***	-0.041	-87.924				
									(0.052)	(0.368)	(0.028)	(683.845)				
EGI(BG)													-0.097	12.542***	-0.050	-3501.859
													(0.229)	(1.604)	(0.126)	(3032.714)
MarginalizedBG	0.026	0.433**	0.068***	713.534**	0.019	-0.056	0.068***	787.210**	0.018	0.050	0.072**	722.640**	0.027	0.225	0.069***	771.541**
	(0.027)	(0.194)	(0.015)	(359.436)	(0.028)	(0.199)	(0.015)	(369.476)	(0.028)	(0.197)	(0.015)	(366.358)	(0.028)	(0.195)	(0.015)	(369.110)
Constant	0.305***	51.025***	7.585***	5644.625***	0.281***	49.359***	7.585***	5894.422***	0.262***	49.041***	7.607***	5691.698***	0.321***	50.311***	7.592***	5877.778***
	(0.048)	(0.381)	(0.051)	(706.370)	(0.052)	(0.410)	(0.055)	(763.589)	(0.061)	(0.428)	(0.033)	(795.631)	(0.056)	(0.394)	(0.031)	(745.841)
Education	X	X	X*	X	X	X	X**	X	X	X	X**	X	X*	X	X**	X
Income	X	X***	X	X**	X	X***	X	X**	X	X***	X	X**	X***	X***	X	X**
County FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
R^2	0.163	0.283	0.779	0.283	0.163	0.287	0.779	0.283	0.163	0.286	0.779	0.283	0.161	0.282	0.779	0.282
Observations	19,910	19,910	19,910	19,828	19,910	19,910	19,910	19,828	19,910	19,910	19,910	19,828	19,589	19,589	19,589	19,509

Note: *p<0.1; **p<0.05; ***p<0.01

*Emissions refer to on-site TRI emissions and are measured by the inverse hyperbolic sine transformation. The number of observations varies across columns because several block groups' toxicity concentrations are not reported in the RSEI data across our survey years. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).*

Table B.4: Proximate OLS Results with Redlining, Kinship, Community Characteristics, and Marginalized Block Group Dummy

	Dependent Variable (Proximate Level)															
	TRI Emissions	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Black	-0.045	0.479*	0.061***	-125.263	-0.043	0.572**	0.059***	-136.838	-0.042	0.594**	0.057***	-122.725	-0.041	0.531**	0.062***	-158.842
	(0.037)	(0.257)	(0.020)	(480.183)	(0.037)	(0.257)	(0.020)	(480.767)	(0.037)	(0.257)	(0.020)	(481.066)	(0.037)	(0.256)	(0.020)	(487.302)
Hispanic	0.009**	0.495**	0.158***	-63.726	0.011**	0.572**	0.156***	-73.122	0.012	0.572**	0.157***	-62.065	0.005	0.517**	0.155***	-75.214
	(0.035)	(0.247)	(0.019)	(462.648)	(0.035)	(0.247)	(0.019)	(463.050)	(0.035)	(0.247)	(0.019)	(463.047)	(0.035)	(0.245)	(0.019)	(467.041)
Asian	-0.054	0.501	0.057**	-301.633	-0.056	0.389	0.059**	-287.864	-0.055	0.452	0.058**	-302.688	-0.055	0.488	0.059**	-291.399
	(0.044)	(0.307)	(0.024)	(575.005)	(0.044)	(0.307)	(0.024)	(575.696)	(0.044)	(0.307)	(0.024)	(575.146)	(0.044)	(0.304)	(0.024)	(580.516)
Redlined(BG)	0.132***	-0.099	0.057**	1854.818***	0.132***	-0.115	0.058**	1856.746***	0.131***	-0.125	0.058**	1854.245***	0.139***	-0.172	0.058**	1787.777***
	(0.047)	(0.327)	(0.025)	(611.287)	(0.047)	(0.327)	(0.026)	(611.312)	(0.047)	(0.327)	(0.025)	(611.338)	(0.047)	(0.327)	(0.026)	(621.938)
HHI(BG)					0.073	3.561***	-0.073*	-443.937								
					(0.069)	(0.481)	(0.037)	(901.176)								
EP(BG)									0.080	2.769***	-0.082***	60.942				
									(0.053)	(0.371)	(0.029)	(694.465)				
EGI(BG)													-0.152	9.374***	-0.193	-3285.691
													(0.231)	(1.608)	(0.127)	(3066.323)
MarginalizedBG	-0.017	-0.583***	0.064***	247.218	-0.023	-0.891***	0.070***	285.758	-0.024	-0.829***	0.071***	241.782	-0.015	-0.677***	0.069***	273.818
	(0.030)	(0.210)	(0.016)	(392.885)	(0.030)	(0.214)	(0.017)	(400.607)	(0.030)	(0.212)	(0.016)	(397.749)	(0.030)	(0.210)	(0.017)	(401.317)
Constant	0.174	51.922***	7.397***	4904.826***	0.158	51.155***	7.413***	5000.302***	0.138	50.667***	7.434***	4877.188***	0.205*	51.636***	7.412***	4991.092***
	(0.110)	(0.775)	(0.060)	(1451.425)	(0.111)	(0.781)	(0.061)	(1464.338)	(0.113)	(0.792)	(0.062)	(1485.242)	(0.112)	(0.778)	(0.061)	(1483.516)
Education	X	X	X*	X	X	X	X**	X	X	X	X**	X	X	X	X**	X
Income	X	X***	X	X*	X	X***	X	X*	X	X***	X	X*	X	X	X	X*
Community Characteristics	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***	X***
County FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
R^2	0.164	0.297	0.781	0.284	0.164	0.299	0.781	0.284	0.164	0.299	0.781	0.284	0.162	0.295	0.780	0.283
Observations	19,910	19,910	19,910	19,828	19,910	19,910	19,910	19,828	19,910	19,910	19,910	19,828	19,589	19,589	19,589	19,509

Note: *p<0.1; **p<0.05; ***p<0.01

*Emissions refer to on-site TRI emissions and are measured by the inverse hyperbolic sine transformation. The number of observations varies across columns because several block groups' toxicity concentrations are not reported in the RSEI data across our survey years. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).*

Table B.5: OLS Results with Different Pollutant Measurements

	Dependent Variable Measurement Scale										
	Proximate				Neighborhood				Area		
	TRI Emissions	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*Noise*	*PM2.5*	*Toxicity*	*TRI Emissions*	*PM2.5*	*Toxicity*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Black	-0.046	0.479*	0.066***	-107.166	-0.035	-0.578	0.062***	54.843	-0.043	0.069**	-474.305
	(0.036)	(0.256)	(0.020)	(478.958)	(0.061)	(0.442)	(0.020)	(470.359)	(0.033)	(0.032)	(648.461)
Hispanic	0.009	0.510**	0.161***	-53.477	-0.011	-1.160***	0.158***	162.461	0.064**	0.127***	-400.740
	(0.035)	(0.247)	(0.019)	(462.224)	(0.058)	(0.427)	(0.019)	(456.314)	(0.031)	(0.030)	(622.682)
Asian	-0.057	0.346	0.063***	-273.891	-0.124*	-0.494	0.056**	-550.804	-0.006	0.039	-1092.199
	(0.044)	(0.307)	(0.024)	(575.355)	(0.072)	(0.531)	(0.024)	(567.768)	(0.039)	(0.038)	(774.466)
eduHS	-0.082	0.294	0.033	772.785	-0.189**	-0.083	0.033	322.519	-0.046	-0.041	758.867
	(0.051)	(0.355)	(0.028)	(665.409)	(0.084)	(0.614)	(0.028)	(651.335)	(0.045)	(0.044)	(898.145)
eduvocational	-0.170***	0.494	-0.010	779.858	-0.218**	0.031	-0.007	506.793	-0.076	-0.093*	571.255
	(0.060)	(0.424)	(0.033)	(794.414)	(0.100)	(0.733)	(0.033)	(779.046)	(0.054)	(0.052)	(1071.159)
edusomecollege	-0.114**	-0.184	0.027	73.487	-0.142*	-0.126	0.028	34.987	-0.085*	-0.070	181.883
	(0.050)	(0.352)	(0.027)	(658.963)	(0.083)	(0.608)	(0.027)	(644.445)	(0.045)	(0.043)	(889.526)
educollege	-0.138***	-0.225	0.017	-173.915	-0.250***	-0.459	0.020	-571.902	-0.087*	-0.025	-107.615
	(0.051)	(0.356)	(0.028)	(667.662)	(0.084)	(0.616)	(0.028)	(653.863)	(0.046)	(0.044)	(901.731)
edupost	-0.148***	0.022	0.003	612.505	-0.323***	0.174	0.009	224.555	-0.091*	-0.049	1256.413
	(0.054)	(0.379)	(0.029)	(709.588)	(0.090)	(0.655)	(0.030)	(694.950)	(0.048)	(0.047)	(957.471)
inc19999	0.073	-0.118	0.060*	-171.385	-0.009	1.179*	0.064**	604.254	-0.121**	0.053	-1037.563
	(0.056)	(0.392)	(0.030)	(734.765)	(0.093)	(0.678)	(0.031)	(716.872)	(0.050)	(0.048)	(989.563)
inc34999	0.094**	0.407	0.025	-1434.352**	-0.025	0.464	0.022	-863.534	0.013	0.034	-1784.700**
	(0.044)	(0.306)	(0.024)	(573.665)	(0.072)	(0.529)	(0.024)	(559.274)	(0.039)	(0.038)	(773.277)
inc49999	0.073*	0.162	0.019	-770.305	-0.056	0.160	0.020	-309.260	0.000	0.020	-1209.716
	(0.044)	(0.307)	(0.024)	(575.096)	(0.072)	(0.531)	(0.024)	(563.213)	(0.039)	(0.038)	(774.129)
inc74999	0.080*	0.389	0.008	-563.851	0.044	0.632	0.007	-224.309	0.003	0.013	-1365.228*
	(0.043)	(0.299)	(0.023)	(560.389)	(0.070)	(0.517)	(0.023)	(548.282)	(0.038)	(0.037)	(752.296)
inc99999	0.117**	0.072	0.012	-1298.839**	0.030	-0.523	0.014	-514.912	0.023	-0.015	-1916.355**
	(0.047)	(0.328)	(0.025)	(614.041)	(0.077)	(0.566)	(0.026)	(601.177)	(0.042)	(0.040)	(823.875)
inc199999	0.101**	-0.234	0.006	-1434.665**	0.102	-0.317	0.009	-711.995	-0.020	-0.023	-2096.498***
	(0.045)	(0.313)	(0.024)	(586.937)	(0.073)	(0.541)	(0.024)	(575.439)	(0.040)	(0.039)	(784.638)
incmore	0.085	-1.119**	-0.020	-1738.092**	0.013	-0.105	-0.020	-879.608	-0.049	-0.076	-2356.989**
	(0.058)	(0.405)	(0.032)	(759.370)	(0.095)	(0.701)	(0.032)	(750.784)	(0.051)	(0.050)	(1015.041)
HSfrac	0.235*	-4.848***	-0.041	6532.740***	1.382***	4.028**	-0.038	4371.661**	0.569***	0.558***	12537.658***
	(0.133)	(0.934)	(0.073)	(1750.637)	(0.307)	(1.615)	(0.073)	(1731.966)	(0.166)	(0.115)	(3284.435)
medHhinc	0.000	-0.000**	0.000***	-0.017	0.000	-0.000***	0.000***	-0.025	-0.000***	-0.000	0.013
	(0.000)	(0.000)	(0.000)	(0.018)	(0.000)	(0.000)	(0.000)	(0.018)	(0.000)	(0.000)	(0.032)
medHhincsq	-0.000	0.000**	-0.000***	0.000	-0.000	0.000***	-0.000***	0.000	0.000***	-0.000	0.013
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
povertyfrac	0.539**	-2.080	-0.383***	1590.354	1.646***	7.745***	-0.384***	3739.640	1.412***	-0.221	9832.390
	(0.246)	(1.728)	(0.134)	(3238.632)	(0.573)	(2.988)	(0.135)	(3183.999)	(0.309)	(0.213)	(6123.994)
povertysq	-0.415	1.811	0.662***	-802.404	-2.225**	-18.098***	0.656***	-6904.798	-0.830	0.530	-13343.753
	(0.458)	(3.213)	(0.250)	(6019.778)	(1.131)	(5.555)	(0.251)	(5859.225)	(0.611)	(0.396)	(12083.029)
renterfrac	0.017	5.395***	0.282***	-17.667	-0.359***	-1.984**	0.319***	410.100	0.477***	0.091	1387.290
	(0.065)	(0.459)	(0.036)	(860.398)	(0.138)	(0.794)	(0.036)	(850.139)	(0.075)	(0.056)	(1479.090)
medhousevalue	-0.000*	-0.000***	0.000***	-0.001	-0.000	0.000	0.000***	-0.001	-0.000***	0.000***	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)
Redlined(BG/CT)	0.131***	-0.151	0.061**	1868.258***	0.179***	6.104***	0.061**	2507.294***	0.437***	0.125***	2826.725***
	(0.047)	(0.327)	(0.025)	(611.091)	(0.069)	(0.565)	(0.025)	(588.540)	(0.037)	(0.036)	(735.620)
HHI(BG/CT)	0.063	3.171***	-0.042	-318.399	0.358***	-2.475***	-0.032	-28.300	0.257***	-0.221***	538.378
	(0.067)	(0.472)	(0.037)	(883.812)	(0.124)	(0.816)	(0.037)	(868.339)	(0.067)	(0.063)	(1321.472)
Constant	0.143	50.547***	7.460***	5194.960***	0.516**	48.895***	7.426***	5494.201***	0.528***	8.444***	1297.512
	(0.109)	(0.767)	(0.060)	(1438.666)	(0.237)	(1.327)	(0.060)	(1424.155)	(0.128)	(0.096)	(2529.300)
County FE	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X	X
R^2	0.164	0.298	0.781	0.284	0.233	0.263	0.779	0.317	0.263	0.605	0.230
Observations	19,910	19,910	19,910	19,828	19,802	19,910	19,910	18,455	19,802	19,906	19,747

Note: *p<0.1; **p<0.05; ***p<0.01

Emissions refer to on-site TRI emissions and are measured by the inverse hyperbolic sine transformation. The number of observations varies across columns because (i) some neighborhoods' shapefiles do not include any centroids of the satellite $PM_{2.5}$ pixels which contributes to fewer observations; (ii) some community characteristics are missing at the census tract level in the ACS; (iii) there are several block group/census tracts' $PM_{2.5}$/toxicity concentrations are not reported in the RSIG/RSEI data across our survey years.

C Exploiting Ground $PM_{2.5}$ Monitor Data

For $PM_{2.5}$, which can travel much larger distances than roadway noise, the EPA documents the measurement scale of each $PM_{2.5}$ monitor as micro, middle, neighborhood, urban, and regional.[32] We create buffers with different radii centered at monitors, where the buffer sizes are set as the upper bounds of the measurement scales of the different monitor types. In other words, we create buffer sizes of 50m, 100m, 4km, 50km, and 100km for micro, middle, neighborhood, urban, and regional monitors, respectively. We then drop each HINTS respondent into the map of monitor buffers and assign the $PM_{2.5}$ concentrations from the most locally precise monitor to this respondent as her individual level ambient $PM_{2.5}$ concentration. For instance, assume we have a respondent who lives within the buffers of three monitors, which are middle, neighborhood, and urban levels, respectively. We will assign the $PM_{2.5}$ concentration from the "middle type" monitor to this respondent as her individual level ambient $PM_{2.5}$ concentration. It is quite common that some respondents live within the buffers of several monitors of the same type and we assign the average $PM_{2.5}$ values across these monitors to such respondents.

There are only about 1,000 $PM_{2.5}$ monitors in the US. Not surprisingly, then, some HINTS respondents live in areas with no intersections with any of the monitor buffers that we create. To include these respondents (around 21% of all respondents) in our analysis sample, we resize the regional buffer to a 500 km radius and we estimate the individual-level exposure as the average regional $PM_{2.5}$ exposure among all the buffers she is located in.

We follow a similar methodology to estimate ambient $PM_{2.5}$ concentrations at the block group level. That is, we calculate the average $PM_{2.5}$ concentration from each monitor type across all monitor buffers that intersect with each block group. If a block group intersects with the buffers of multiple monitor types, we use the average of the most locally precise monitor to approximate the ambient $PM_{2.5}$ concentrations in this block group. For the block groups with missing $PM_{2.5}$ measurements (around 20%), we use the same strategy as for the individual-level measurement by assuming that the regional monitors measure concentrations up to 500 km. To measure ambient $PM_{2.5}$ concentrations at the census tract level, we exploit the EPA's Remote Sensing Information Gateway (RSIG) which offers daily data at the census tract level for the entire US since 2002. We calculate annual $PM_{2.5}$ concentrations by averaging the daily data across each year.

We attempted to assign block groups (BGs) the corresponding census tract (CT) level data from the RSIG for $PM_{2.5}$. Since BGs are subsets of CTs, this was intended

[32] See "Site and Monitor Descriptions" at https://aqs.epa.gov/aqsweb/airdata/download_files.html#Meta for detail.

as a consistency check. However, we had an almost 1-to-1 correlation between BGs and CTs in our sample, meaning each census tract corresponds to a single block group. As a result, this approach would not introduce any variation in the $PM_{2.5}$ data, making it uninformative for our analysis.[33]

[33] See https://aqs.epa.gov/aqsweb/airdata/download_files.html#Meta for more details about the RSIG data.

Table C.1: OLS Results with Redlining

	Dependent Variable ($PM_{2.5}$)					
	Proximate (1)	*Neighborhood* (2)	*Area* (3)	*Proximate* (4)	*Neighborhood* (5)	*Area* (6)
Black	0.104***	0.108***	0.088***	0.091***	0.094***	0.079**
	(0.034)	(0.034)	(0.031)	(0.034)	(0.034)	(0.031)
Hispanic	0.114***	0.123***	0.135***	0.110***	0.118***	0.133***
	(0.034)	(0.034)	(0.030)	(0.034)	(0.034)	(0.030)
Asian	0.002	-0.021	0.034	-0.002	-0.024	0.033
	(0.043)	(0.043)	(0.038)	(0.043)	(0.043)	(0.038)
Redlined				0.347***	0.372***	0.144***
				(0.043)	(0.044)	(0.035)
Constant	7.611***	7.653***	8.610***	7.567***	7.606***	8.586***
	(0.047)	(0.048)	(0.043)	(0.047)	(0.048)	(0.043)
Education	X**	X***	X**	X**	X***	X*
Income	X	X	X***	X	X	X***
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.544	0.534	0.603	0.545	0.536	0.603
Observations	18,717	18,766	19,906	18,717	18,766	19,906

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

$PM_{2.5}$ refers to $PM_{2.5}$ concentrations measured by ground monitors. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).

Table C.2: OLS Results with Redlining and Kinship

	Dependent Variable ($PM_{2.5}$)					
	Proximate (1)	*Neighborhood* (2)	*Area* (3)	*Proximate* (4)	*Neighborhood* (5)	*Area* (6)
Black	0.091^{***}	0.094^{***}	0.079^{**}	0.090^{***}	0.092^{***}	0.076^{**}
	(0.034)	(0.034)	(0.031)	(0.034)	(0.034)	(0.031)
Hispanic	0.110^{***}	0.118^{***}	0.133^{***}	0.109^{***}	0.117^{***}	0.130^{***}
	(0.034)	(0.034)	(0.030)	(0.034)	(0.034)	(0.030)
Asian	-0.002	-0.024	0.033	-0.000	-0.019	0.041
	(0.043)	(0.043)	(0.038)	(0.043)	(0.043)	(0.038)
Redlined	0.347^{***}	0.372^{***}	0.144^{***}	0.348^{***}	0.375^{***}	0.149^{***}
	(0.043)	(0.044)	(0.035)	(0.043)	(0.044)	(0.035)
HHI				-0.039	-0.124^{**}	-0.222^{***}
				(0.062)	(0.062)	(0.062)
Constant	7.567^{***}	7.606^{***}	8.586^{***}	7.583^{***}	7.655^{***}	8.681^{***}
	(0.047)	(0.048)	(0.043)	(0.053)	(0.054)	(0.051)
Education	X^{**}	X^{***}	X^{**}	X^{**}	X^{***}	X^{*}
Income	X	X	X^{***}	X	X	X^{***}
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.545	0.536	0.603	0.545	0.536	0.603
Observations	18,717	18,766	19,906	18,717	18,766	19,906
Note:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

$PM_{2.5}$ refers to $PM_{2.5}$ concentrations measured by ground monitors. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).

Table C.3: OLS Results with Redlining and Kinship

	Dependent Variable ($PM_{2.5}$)					
	Proximate (1)	*Neighborhood* (2)	*Area* (3)	*Proximate* (4)	*Neighborhood* (5)	*Area* (6)
Black	0.091***	0.094***	0.079**	0.089***	0.091***	0.077**
	(0.034)	(0.034)	(0.031)	(0.034)	(0.034)	(0.031)
Hispanic	0.110***	0.118***	0.133***	0.109***	0.117***	0.131***
	(0.034)	(0.034)	(0.030)	(0.034)	(0.034)	(0.030)
Asian	-0.002	-0.024	0.033	-0.000	-0.021	0.036
	(0.043)	(0.043)	(0.038)	(0.043)	(0.043)	(0.038)
Redlined	0.347***	0.372***	0.144***	0.349***	0.375***	0.147***
	(0.043)	(0.044)	(0.035)	(0.043)	(0.044)	(0.035)
EP				-0.053	-0.100**	-0.108**
				(0.048)	(0.049)	(0.052)
Constant	7.567***	7.606***	8.586***	7.599***	7.666***	8.654***
	(0.047)	(0.048)	(0.043)	(0.056)	(0.056)	(0.054)
Education	X**	X***	X**	X**	X***	X*
Income	X	X	X***	X	X	X***
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.545	0.536	0.603	0.545	0.536	0.603
Observations	18,717	18,766	19,906	18,717	18,766	19,906
Note:						*p<0.1; **p<0.05; ***p<0.01

*$PM_{2.5}$ refers to $PM_{2.5}$ concentrations measured by ground monitors. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).*

Table C.4: OLS Results with Redlining and Kinship

	Dependent Variable ($PM_{2.5}$)					
	Proximate (1)	*Neighborhood* (2)	*Area* (3)	*Proximate* (4)	*Neighborhood* (5)	*Area* (6)
Black	0.091***	0.094***	0.079**	0.092***	0.094***	0.103**
	(0.034)	(0.034)	(0.031)	(0.034)	(0.035)	(0.029)
Hispanic	0.110***	0.118***	0.133***	0.107***	0.114***	0.155***
	(0.034)	(0.034)	(0.030)	(0.034)	(0.034)	(0.028)
Asian	-0.002	-0.024	0.033	0.002	-0.020	0.054
	(0.043)	(0.043)	(0.038)	(0.043)	(0.043)	(0.035)
Redlined	0.347***	0.372***	0.144***	0.343***	0.371***	0.103***
	(0.043)	(0.044)	(0.035)	(0.044)	(0.044)	(0.031)
EGI				-0.310	-0.380*	0.396*
				(0.217)	(0.219)	(0.226)
Constant	7.567***	7.606***	8.586***	7.590***	7.635***	8.689***
	(0.047)	(0.048)	(0.043)	(0.051)	(0.052)	(0.043)
Education	X**	X***	X**	X**	X***	X*
Income	X	X	X***	X	X	X***
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.545	0.536	0.603	0.543	0.533	0.710
Observations	18,717	18,766	19,906	18,398	18,447	16,811
Note:						*p<0.1; **p<0.05; ***p<0.01

*$PM_{2.5}$ refers to $PM_{2.5}$ concentrations measured by ground monitors. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).*

Table C.5: OLS Results with Redlining, Kinship, and Community Characteristics

	Dependent Variable ($PM_{2.5}$)					
	Proximate (1)	*Neighborhood* (2)	*Area* (3)	*Proximate* (4)	*Neighborhood* (5)	*Area* (6)
Black	0.090***	0.092***	0.076**	0.086**	0.082**	0.050
	(0.034)	(0.034)	(0.031)	(0.034)	(0.035)	(0.032)
Hispanic	0.109***	0.117***	0.130***	0.106***	0.111***	0.116***
	(0.034)	(0.034)	(0.030)	(0.034)	(0.034)	(0.031)
Asian	-0.000	-0.019	0.041	0.001	-0.018	0.042
	(0.043)	(0.043)	(0.038)	(0.043)	(0.043)	(0.038)
Redlined	0.348***	0.375***	0.149***	0.316***	0.341***	0.102***
	(0.043)	(0.044)	(0.035)	(0.044)	(0.044)	(0.036)
HHI	-0.039	-0.124**	-0.222***	-0.085	-0.168***	-0.258***
	(0.062)	(0.062)	(0.062)	(0.064)	(0.064)	(0.065)
Constant	7.583***	7.655***	8.681***	7.501***	7.566***	8.576***
	(0.053)	(0.054)	(0.051)	(0.105)	(0.105)	(0.124)
Education	X**	X***	X**	X**	X***	X*
Community Characteristics				X***	X***	X***
Income	X	X	X***	X	X	X***
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.545	0.536	0.603	0.546	0.537	0.605
Observations	18,717	18,766	19,906	18,717	18,766	19,798

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

$PM_{2.5}$ refers to $PM_{2.5}$ concentrations measured by ground monitors. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).

D Results using Simple Sum of Total Onsite Emissions

Table D.1: OLS Results with Redlining, Kinship, and Community Characteristics

	Simple Sum Emission					
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.527***	0.386***	0.426***	0.432***	0.301***	-0.008
	(0.104)	(0.104)	(0.103)	(0.103)	(0.112)	(0.103)
Hispanic	0.513***	0.471***	0.498***	0.499***	0.474***	0.229**
	(0.102)	(0.101)	(0.100)	(0.100)	(0.109)	(0.099)
Asian	0.223*	0.216*	0.140	0.172	0.240*	0.056
	(0.127)	(0.126)	(0.125)	(0.125)	(0.137)	(0.123)
Redlined		2.258***	2.200***	2.205***	2.051***	1.647***
		(0.116)	(0.116)	(0.116)	(0.121)	(0.117)
HHI			2.282***			1.207***
			(0.204)			(0.211)
EP				1.842***		
				(0.171)		
EGI					8.522***	
					(0.885)	
Constant	5.012***	4.634***	3.653***	3.468***	4.226***	2.769***
	(0.144)	(0.144)	(0.168)	(0.179)	(0.167)	(0.403)
Education	X***	X***	X***	X***	X***	X
Income	X***	X***	X***	X***	X***	X**
Community Characteristics						X***
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.262	0.277	0.281	0.281	0.288	0.309
Observations	19,910	19,910	19,910	19,910	16,815	19,802
Note:				*p<0.1; **p<0.05; ***p<0.01		

*Emissions refer to on-site TRI emissions and are measured by the simple summation of onsite emissions within respondents' 5-km buffer, without inverse distance weights. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).*

E Results using Linear Probability Model for Total Onsite Emissions

Table E.1: Linear Probability Results with Redlining

	Dependent Variable (Onsite Emissions)					
	Proximate (1)	*Neighborhood* (2)	*Area* (3)	*Proximate* (4)	*Neighborhood* (5)	*Area* (6)
Black	-0.004	0.004	0.071***	-0.005	-0.003	0.059***
	(0.004)	(0.007)	(0.011)	(0.004)	(0.007)	(0.011)
Hispanic	0.001	-0.002	0.047***	0.001	-0.002	0.043***
	(0.004)	(0.007)	(0.011)	(0.004)	(0.007)	(0.011)
Asian	-0.009*	-0.011	0.017	-0.010*	-0.011	0.017
	(0.005)	(0.009)	(0.013)	(0.005)	(0.009)	(0.013)
Redlined				0.016***	0.021***	0.196***
				(0.006)	(0.008)	(0.012)
Constant	0.046***	0.144***	0.605***	0.044***	0.141***	0.572***
	(0.006)	(0.010)	(0.015)	(0.006)	(0.010)	(0.015)
Education	X**	X***	X**	X**	X***	X*
Income	X	X	X***	X	X	X***
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.143	0.195	0.239	0.143	0.195	0.249
Observations	19,910	19,910	19,910	19,910	19,910	19,910
Note:						*p<0.1; **p<0.05; ***p<0.01

*Emissions refer to on-site TRI emissions and are measured by the dummy variables to indicate whether there are positive emissions within the area. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).*

Table E.2: Linear Probability Results with Redlining and Kinship

	Dependent Variable (Onsite Emissions)					
	Proximate	*Neighborhood*	*Area*	*Proximate*	*Neighborhood*	*Area*
	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.005	0.003	0.059^{***}	-0.005	0.004	0.063^{***}
	(0.004)	(0.007)	(0.011)	(0.004)	(0.007)	(0.011)
Hispanic	0.001	-0.002	0.043^{***}	0.001	-0.002	0.046^{***}
	(0.004)	(0.007)	(0.011)	(0.004)	(0.007)	(0.010)
Asian	-0.010^{*}	-0.011	0.017	-0.010^{*}	-0.013	0.008
	(0.005)	(0.009)	(0.013)	(0.005)	(0.009)	(0.013)
Redlined	0.016^{***}	0.021^{***}	0.196^{***}	0.015^{***}	0.019^{**}	0.189^{***}
	(0.006)	(0.008)	(0.012)	(0.006)	(0.008)	(0.012)
HHI				0.011	0.052^{***}	0.267^{***}
				(0.008)	(0.014)	(0.021)
Constant	0.044^{***}	0.141^{***}	0.572^{***}	0.040^{***}	0.118^{***}	0.457^{***}
	(0.006)	(0.010)	(0.015)	(0.007)	(0.012)	(0.017)
Education	X^{**}	X^{***}	X^{*}	X^{**}	X^{***}	X^{**}
Income	X	X	X^{***}	X	X	X^{***}
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.143	0.195	0.249	0.143	0.196	0.256
Observations	19,910	19,910	19,910	19,910	19,910	19,910
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

*Emissions refer to on-site TRI emissions and are measured by the dummy variables to indicate whether there are positive emissions within the area. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).*

Table E.3: Linear Probability Results with Redlining and Kinship

	Dependent Variable (Onsite Emissions)					
	Proximate (1)	*Neighborhood* (2)	*Area* (3)	*Proximate* (4)	*Neighborhood* (5)	*Area* (6)
Black	-0.005	0.003	0.059***	-0.004	0.004	0.064***
	(0.004)	(0.007)	(0.011)	(0.004)	(0.007)	(0.011)
Hispanic	0.001	-0.002	0.043***	0.001	-0.002	0.046***
	(0.004)	(0.007)	(0.011)	(0.004)	(0.007)	(0.010)
Asian	-0.010*	-0.011	0.017	-0.010*	-0.012	0.0012
	(0.005)	(0.009)	(0.013)	(0.005)	(0.009)	(0.013)
Redlined	0.016***	0.021***	0.196***	0.012***	0.019**	0.190***
	(0.006)	(0.008)	(0.012)	(0.006)	(0.008)	(0.012)
EP				0.012*	0.043***	0.205***
				(0.006)	(0.012)	(0.018)
Constant	0.044***	0.141***	0.572***	0.037***	0.113***	0.442***
	(0.006)	(0.010)	(0.015)	(0.007)	(0.012)	(0.019)
Education	X**	X***	X*	X**	X***	X**
Income	X	X	X***	X	X	X***
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.143	0.195	0.249	0.143	0.196	0.255
Observations	19,910	19,910	19,910	19,910	19,910	19,910
Note:						*p<0.1; **p<0.05; ***p<0.01

*Emissions refer to on-site TRI emissions and are measured by the dummy variables to indicate whether there are positive emissions within the area. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).*

Table E.4: Linear Probability Results with Redlining and Kinship

	Dependent Variable (Onsite Emissions)					
	Proximate	*Neighborhood*	*Area*	*Proximate*	*Neighborhood*	*Area*
	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.005	0.003	0.059***	-0.004	-0.004	0.056***
	(0.004)	(0.007)	(0.011)	(0.004)	(0.008)	(0.012)
Hispanic	0.001	-0.002	0.043***	0.001	-0.004	0.041***
	(0.004)	(0.007)	(0.011)	(0.004)	(0.007)	(0.011)
Asian	-0.010*	-0.011	0.017	-0.010*	-0.014	0.019
	(0.005)	(0.009)	(0.013)	(0.005)	(0.009)	(0.014)
Redlined	0.016***	0.021***	0.196***	0.016***	0.019**	0.189***
	(0.006)	(0.008)	(0.012)	(0.006)	(0.008)	(0.013)
EGI				-0.020	0.077	0.929***
				(0.028)	(0.060)	(0.092)
Constant	0.044***	0.141***	0.572***	0.047***	0.135***	0.525***
	(0.006)	(0.010)	(0.015)	(0.007)	(0.011)	(0.017)
Education	X**	X***	X*	X**	X***	X**
Income	X	X	X***	X	X	X***
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.143	0.195	0.249	0.143	0.205	0.259
Observations	19,910	19,910	19,910	19,589	16,815	16,815

Note: *p<0.1; **p<0.05; ***p<0.01

Emissions refer to on-site TRI emissions and are measured by the dummy variables to indicate whether there are positive emissions within the area. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).

Table E.5: Linear Probability Results with Redlining, Kinship, and Community Characteristics

	Dependent Variable (Onsite Emissions)					
	Proximate	*Neighborhood*	*Area*	*Proximate*	*Neighborhood*	*Area*
	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.005	0.004	0.063***	-0.008*	-0.003	0.020*
	(0.004)	(0.007)	(0.011)	(0.005)	(0.007)	(0.011)
Hispanic	0.001	-0.002	0.046***	-0.001	-0.005	0.019*
	(0.004)	(0.007)	(0.010)	(0.004)	(0.007)	(0.010)
Asian	-0.010*	-0.013	0.008	-0.011**	-0.014*	0.001
	(0.005)	(0.009)	(0.013)	(0.005)	(0.009)	(0.013)
Redlined	0.015***	0.019***	0.189***	0.014**	0.019**	0.132***
	(0.006)	(0.008)	(0.012)	(0.006)	(0.008)	(0.012)
HHI	0.011	0.052***	0.267***	0.007	0.056***	0.138***
	(0.008)	(0.014)	(0.021)	(0.008)	(0.015)	(0.022)
Constant	0.040***	0.118***	0.457***	0.026*	0.062**	0.406***
	(0.007)	(0.012)	(0.017)	(0.013)	(0.028)	(0.042)
Education	X**	X***	X**	X*	X***	X
Income	X	X	X***	X*	X	X**
Neighborhood Characteristics	X	X	X	X***	X***	X***
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.143	0.196	0.256	0.145	0.200	0.285
Observations	19,910	19,910	19,910	19,910	19,802	19,802
Note:						*p<0.1; **p<0.05; ***p<0.01

*Emissions refer to on-site TRI emissions and are measured by the dummy variables to indicate whether there are positive emissions within the area. Race, education, and income are at the individual level, as reported in the HINTS survey. We also report the joint significance test (F-test) for control variables (i.e. *** on Education etc.).*

F Results using Tobit Model for Total Onsite Emissions

Table F.1: Neighborhood Scale Tobit Results

	Dependent Variable (TRI Emissions)				
	(1)	(2)	(3)	(4)	(5)
Neighborhood Black Fraction	-6.482***	-6.519***	-7.767***	-7.911***	-7.221***
	(1.046)	(1.041)	(1.151)	(1.138)	(1.129)
Neighborhood Hispanic Fraction	-7.276***	-7.281***	-8.687***	-8.892***	-8.264***
	(1.326)	(1.320)	(1.558)	(1.531)	(1.526)
Neighborhood Asian Fraction	-6.762**	-6.769**	-12.776***	-10.575***	-9.535***
	(2.799)	(2.798)	(3.777)	(3.195)	(3.428)
Neighborhood Redlined		0.228	0.327	0.353	0.050
		(0.832)	(0.841)	(0.839)	(0.867)
Neighborhood HHI			4.569***		
			(1.447)		
Neighborhood EP				3.963***	
				(0.988)	
Neighborhood EGI					13.709***
					(5.986)
Constant	-15.661***	-15.659***	-16.386***	-17.431***	-14.367***
	(1.937)	(1.938)	(1.903)	(1.926)	(2.095)
Community Characteristics	X	X	X	X	X
Observations	20,435	20,435	20,435	20,435	17,442
Note:					*p<0.1; **p<0.05; ***p<0.01

The Tobit model is left-censored at 0 to account for the large number of zero TRI emissions, and standard errors are clustered at the county level.

Table F.2: Area Scale Tobit Results

	Dependent Variable (TRI Emissions)				
	(1)	(2)	(3)	(4)	(5)
Area Black Fraction	0.521**	0.322	0.285	0.271	0.249
	(0.210)	(0.202)	(0.221)	(0.217)	(0.223)
Area Hispanic Fraction	0.617*	0.617**	0.575*	0.552*	0.607*
	(0.326)	(0.302)	(0.335)	(0.330)	(0.355)
Area Asian Fraction	1.056**	1.060**	0.864	0.896	1.056*
	(0.534)	(0.515)	(0.670)	(0.586)	(0.593)
Area Redlined		1.043***	1.047***	1.049***	0.991***
		(0.135)	(0.137)	(0.137)	(0.142)
Area HHI			0.190		
			(0.264)		
Area EP				0.224	
				(0.177)	
Area EGI					-0.121
					(0.985)
Constant	-1.468***	-1.403***	-1.433***	-1.502***	-1.194***
	(0.302)	(0.295)	(0.296)	(0.300)	(0.317)
Community Characteristics	X	X	X	X	X
Observations	20,435	20,435	20,435	20,435	17,442
Note:					*p<0.1; **p<0.05; ***p<0.01

The Tobit model is left-censored at 0 to account for the large number of zero TRI emissions, and standard errors are clustered at the county level.

Table F.3: Proximate Scale Tobit Results

	Dependent Variable (TRI Emissions)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black	-1.963**	-2.060**	-1.807**	-1.878***	-1.788**	-2.609***	-1.156
	(0.854)	(0.864)	(0.880)	(0.877)	(0.872)	(0.872)	(0.959)
Hispanic	-3.035***	-3.043***	-2.693***	-2.786***	-2.948***	-2.276**	-0.360
	(0.869)	(0.868)	(0.885)	(0.874)	(0.890)	(0.891)	(0.929)
Asian	-3.587***	-3.611***	-3.010***	-3.285***	-3.453***	-2.266**	-1.382
	(1.113)	(1.116)	(1.114)	(1.114)	(1.111)	(1.098)	(1.108)
Redlined		1.210	1.488	1.400	1.592	2.044*	2.450**
		(1.191)	(1.185)	(1.188)	(1.183)	(1.151)	(1.172)
HHI(BG)			-5.345***			-3.574**	1.073
			(1.504)			(1.510)	(1.926)
EP(BG)				-3.149***			
				(1.159)			
EGI(BG)					-17.624***		
					(6.009)		
Neighborhood Black Fraction							-5.808***
							(1.441)
Neighborhood Hispanic Fraction							-7.753***
							(1.673)
Neighborhood Asian Fraction							-12.355***
							(4.365)
Constant	-25.211***	-25.356***	-23.357***	-23.510***	-23.800***	-28.306***	-27.960***
	(1.332)	(1.341)	(1.379)	(1.409)	(1.389)	(2.559)	(2.515)
Education	X	X	X	X	X	X	X
Income	X	X	X	X	X	X	X
Community Characteristics						X	X
Observations	20,543	20,543	20,543	20,543	20,236	20,543	20,543
Note:							*p<0.1; **p<0.05; ***p<0.01

The Tobit model is left-censored at 0 to account for the large number of zero TRI emissions, and standard errors are clustered at the county level.

G Results using IHS-transformed Toxicity Concentrations

Table G.1: Neighborhood Scale Results

	Dependent Variable (Toxicity)				
	(1)	(2)	(3)	(4)	(5)
Neighborhood Black Fraction	0.532***	0.506***	0.504***	0.503***	0.491***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.054)
Neighborhood Hispanic Fraction	0.718***	0.700***	0.697***	0.688***	0.689***
	(0.062)	(0.062)	(0.063)	(0.062)	(0.063)
Neighborhood Asian Fraction	0.614***	0.614***	0.595***	0.575***	0.601***
	(0.109)	(0.109)	(0.122)	(0.113)	(0.113)
Neighborhood Redlined		0.247***	0.247***	0.247***	0.238***
		(0.036)	(0.036)	(0.036)	(0.036)
Neighborhood HHI			0.020		
			(0.059)		
Neighborhood EP				0.052	
				(0.042)	
Neighborhood EGI					0.080
					(0.189)
Constant	6.679***	6.670***	6.666***	6.647***	6.684***
	(0.081)	(0.081)	(0.082)	(0.083)	(0.082)
Community Characteristics	X	X	X	X	X
Observations	18,455	18,455	18,455	18,455	18,159
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table G.2: Area Scale Results

	Dependent Variable (Toxicity)				
	(1)	(2)	(3)	(4)	(5)
Area Black Fraction	0.623***	0.581***	0.580***	0.579***	0.610***
	(0.060)	(0.060)	(0.061)	(0.060)	(0.064)
Area Hispanic Fraction	0.903***	0.878***	0.876***	0.872***	1.028***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.078)
Area Asian Fraction	0.762***	0.770***	0.755***	0.746***	1.067***
	(0.126)	(0.126)	(0.141)	(0.131)	(0.140)
Area HHI			0.016		
			(0.064)		
Area EP				0.035	
				(0.049)	
Area EGI					-0.687***
					(0.250)
Constant	6.511***	6.499***	6.495***	6.482***	6.459***
	(0.106)	(0.106)	(0.107)	(0.109)	(0.119)
Community Characteristics	X	X	X	X	X
Observations	19,747	19,747	19,747	19,747	16,727
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table G.3: Proximate Scale Results

	Dependent Variable (Toxicity)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black	0.122***	0.110***	0.114***	0.115***	0.112***	0.097***	0.020
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.031)
Hispanic	0.052*	0.049*	0.051*	0.051*	0.050*	0.038	-0.027
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)
Asian	0.007	0.006	-0.006	0.000	0.007	-0.010	-0.046
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Redlined		0.303***	0.295***	0.297***	0.286***	0.257***	0.235***
		(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
HHI(BG)			0.291***			0.197***	0.022
			(0.052)			(0.054)	(0.061)
EP(BG)				0.199***			
				(0.041)			
EGI(BG)					0.700***		
					(0.182)		
Neighborhood Black Fraction							0.510***
							(0.058)
Neighborhood Hispanic Fraction							0.696***
							(0.066)
Neighborhood Asian Fraction							0.630***
							(0.125)
Constant	7.165***	7.127***	7.010***	7.005***	7.076***	6.946***	6.683***
	(0.040)	(0.040)	(0.045)	(0.047)	(0.043)	(0.088)	(0.091)
Education	X	X	X	X	X	X	X
Income	X	X	X	X	X	X	X
Community Characteristics						X	X
Observations	19,828	19,828	19,828	19,828	19,509	19,828	19,828

Note: *p<0.1; **p<0.05; ***p<0.01