

# Are Global Neighborhoods in Houston Less Polluted? A Spatial Analysis of Twenty-First-Century Urban Demographics

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## Abstract

Suburban metropolitan areas across the United States have become racially diverse. We examine this novel spatial demography in relation to pollution levels across census tracts within the greater Houston area for the year 2015. We integrate a multigroup measure of racial diversity (the Entropy Index) with information on pollution levels from the Toxics Release Inventory. Maps of these two variables show that racial diversity tends to be higher in the Houston suburbs where pollution levels tend to be lower. Indeed, across five different spatial regression models, we find that tract-level racial diversity is negatively correlated with pollution levels, controlling for a host of other factors, including population size and land area. We outline this finding as a human ecology approach to urban environmental inequality; specifically, we speculate that recent demographic shifts, like the “back-to-the-city” movement, are modifying the dynamics of environmental inequality in cities.

Keywords: environmental inequality, Houston, multigroup entropy index, spatial analysis, urban demography

## Introduction

Environmental social scientists have long drawn on the various threads of human ecology to study the ecological implications of population change (e.g., Buttel & Humphrey, 2002; Catton, 1980; Rudel, 2012). Yet the original formulations of human ecology were focused on the urban environment, using ecological forces

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as metaphors to study the demographic evolution of cities (see Michelson, 1968). In that light, some urban environmental scholars have refocused human ecology's attention back on cities to study the environmental implications of population change in terms of pollution and land use within urban spaces (e.g., Elliott & Frickel, 2013). In our study, we make use of that general framework to analyze the environmental implications of twenty-first-century urban demographics in the United States. Specifically, we look at the relationship between multigroup racial diversity and pollution levels in the context of the greater Houston area in 2015.<sup>2</sup> Given our focus on the relationship between racial demographics and pollution levels within cities, we outline our study as a human ecology approach to urban environmental inequality in line with recent scholarship on the topic (McKinney et al., 2015).

In the social sciences, much quantitative research has examined the connection between race and environmental change (Mohai et al., 2009). One track of this scholarship has relied on singular measures of the racial distribution of a community (e.g., percent black or percent white) (Crowder & Downey, 2010; Smith, 2009); another track has begun to incorporate multigroup measures of racial segregation and racial/ethnic diversity (e.g., Ard, 2016; Downey et al., 2008; Jones et al., 2014; Morello-Frosch & Jesdale, 2006). Much of the research on the environmental implications of diversity/segregation has utilized measures of evenness (e.g., Ard, 2016; Downey et al., 2008; Morello-Frosch & Jesdale, 2006), which generally represent the spatial distribution of a combination of racial groups relative to each group's proportion in the population of the urban area. While we recognize that there are many measures of evenness (see Ard, 2016), our focus is on the multigroup entropy index, a measure of evenness among racial/ethnic groups distributed across a geographic unit (Massey & Denton, 1988). We do this for two reasons: The entropy index represents an intuitive measure of the spatial evenness of racial groups; and, as the subject of news reports in the popular press, the entropy index has influenced public policy discussions of segregation (Boschma, 2016; ProPublica, 2017; Williams & Emamdjomeh, 2018).

The racial distribution of the Houston metropolitan region in the 2010s represents a unique urban demography, making the area an ideal site for investigating the relationship between racial demographics and pollution levels. During this time, Houston has become one of the most diverse urban areas in the United States (Lappie et al., 2018). In fact, according to Lappie et al. (2018), Fort Bend County, one of the nine counties making up the Houston Metropolitan Statistical Area (MSA), is the most diverse county in the United States. Moreover, over the past

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2 Throughout the manuscript, we use the term "racial diversity" to refer to the heterogeneity of racial categories in a census tract (or other areal unit). In other words, a census tract that is predominantly comprised of individuals from one racial category (i.e., a racially homogeneous tract) is less diverse than a census tract with individuals from multiple racial categories. Racial diversity does not simply mean the presence of racial minority residents.

several years, many of the city's neighborhoods have "rapidly integrated" (Williams & Emamdjomeh, 2018); their racial composition more closely resembles what urban scholars have called "global neighborhoods" (Zhang & Logan, 2016); that is, places with a relatively balanced proportion of whites, blacks, Hispanics, and Asians. While the Houston area continues to experience gentrification and still has high levels of segregation (Binkovitz, 2018; Strait & Gong, 2010), many of its residents express positive views of ethnic diversity (Klineberg, 2019). Moreover, its diverse global neighborhoods tend to be found outside of the inner urban core, especially in the western ring of suburbs (Williams & Emamdjomeh, 2018).

Houston's racial diversity makes it "one of the most ethnically and culturally diverse metro areas in the entire country" (Klineberg, 2019, p. 15). Nevertheless, some of the changes it is experiencing are also being observed in other parts of the country (Zhang & Logan, 2016). Indeed, what scholars have called the "urban revival" or "urban renaissance" is a dual spatial-demographic process unfolding around the country: the "back-to-the-city" movement is counterbalanced with the "suburbanization of poverty" (Couture & Handbury, 2017; Florida, 2016; Logan, 2014; Podagrosi et al., 2011). Not just the urban core, but metropolitan suburbs across the United States have experienced a unique transformation. In Houston, this inner-city movement has coincided with the emergence of racially diverse suburban neighborhoods. In the following study, we examine the implications of this new urban demography in terms of pollution levels, asking the question: Are these new "rapidly integrated" neighborhoods in Houston associated with higher or lower levels of pollution?

The following analysis provides a preliminary answer to this question, laying the groundwork for future scholarship to examine the environmental justice implications of the twenty-first-century urban revival. To that end, we first review the relevant literature, describing the current spatial demographics of America's cities, with an emphasis on Houston and underscoring, as mentioned above, the utility of multigroup measures of race for quantitative environmental justice scholarship. Based on this literature review, we identify a gap in the quantitative environmental justice research. On the one hand, there has been a growing inquiry into the environmental implications of multigroup measures of race and ethnic heterogeneity (Ard, 2016; Chakraborty et al., 2017; Downey et al., 2008; Jones et al., 2014; Morello-Frosch & Jesdale, 2006).<sup>3</sup> On the other hand, the Houston area has served as a case study and research site for numerous quantitative analyses, the results of which have advanced our understanding of environmental justice (Chakraborty, 2015; Collins et al., 2015; Elliott & Smiley, 2019; Hernandez et al., 2015; Linder et al., 2008). Yet the

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<sup>3</sup> Here, we simply recognize the distinction between environmental justice research addressing multigroup racial diversity (e.g., Ard, 2016) and intra-ethnic heterogeneity (e.g., Chakraborty et al., 2017). We situate our project within the former line of research, which estimates diversity strictly in terms of multiple different racial groups rather than racial variation within a single ethnicity.

studies relying on more recent data have not considered the environmental justice implications of the urban revival in Houston, with its racially diverse suburban neighborhoods. To fill this gap, we present results from a quantitative analysis, examining the relationship between racial diversity and pollution levels for the greater Houston area.

We organize our analysis as follows. First, based on 2015 data from the Toxics Release Inventory (United States Environmental Protection Agency [EPA], 2017) and the 2010–2015 five-year estimates from the United States Census American Community Survey<sup>4</sup> (US Census ACS, 2019), we juxtapose two maps displaying spatial variation in a multigroup measure of racial diversity (i.e., the entropy index) and pollution levels for all census tracts across the greater Houston area ( $n = 1,036$ ) (see Figure 1). A visual inspection of these maps suggests that pollution levels are negatively correlated with neighborhood-level diversity. Second, we integrate these variables into cross-sectional spatial regression models. In these models, we regress pollution levels (standardized by population size and land area) on the entropy index, while controlling for a host of other factors, including spatial autocorrelation. Consistent with Figure 1, we find that, across five different spatial regression models, census tracts that are comprised of increased levels of racial diversity have lower pollution levels.

In the conclusion, we emphasize the preliminary nature of these findings, and we note that, like other studies utilizing multigroup measures of racial diversity (e.g., Ard, 2016; Downey et al., 2008; Jones et al., 2014; Morello-Frosch & Jesdale, 2006), we do not examine change over time. Our cross-sectional snapshot finds a negative correlation between tract-level racial diversity and pollution levels; this negative correlation may be an artifact of the historically contingent location in which non-white populations have settled in the Houston area in the 2010s. As noted above, white residents have been moving “back to the city,” not just in Houston but in cities across the United States. Future scholarship, using longitudinal data, will be better able to address what this new geographic distribution means for conventional frameworks on environmental inequality and how it applies in emerging global neighborhoods across cities in the United States.

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<sup>4</sup> Quality concerns with both Toxics Release Inventory and ACS data sources have been raised but both provide consistent measures of the variables of interest and are commonly used across social science research.

## Twenty-first-century urban demographics and environmental inequality in Houston

Pellow (2018) notes that the “second generation” of environmental justice scholarship has evolved into a multidimensional discipline, with multiple levels of analysis and foci of investigation. Environmental justice scholars discuss and evaluate elements of inequality as related to exposure to health and natural hazards at home and in the workplace, the institutional and policy responses to environmental crises, and the structural responses to environmental crises, as well as community access to green space, to name only a few (e.g., Ard, 2016; Chakraborty et al., 2017; Chakraborty et al., 2019; Elliott & Smiley, 2019; Gould & Lewis, 2017; Liévanos, 2012). Moreover, environmental justice scholarship has kept pace with changes in the unequal exposure to pollution; one line of inquiry derives insights from the legacy of human ecology and its interest in the social and natural changes happening in urban spaces. For instance, Elliott and Frickel (2013) examine the “churning” of urban land uses, highlighting what this process means for exposure to those pollutants forgotten and often buried inside old urban cores.

Connected to this churning of land use is a recent demographic shift; although with much variation across the United States, the general trend is that white, affluent, and highly educated households are returning to the inner city (Florida, 2016). Old industrial sites, abandoned factories, and neglected commercial centers are being remodeled and redeveloped to house and accommodate the activities of these new residents. Yet, this process is two-sided. As white, affluent, and highly educated households start to reside in the inner city, poor residents and communities of color are displaced from the old urban cores (Podagrosi et al., 2011); these households then take up residence in cheaper areas outside the city (Logan, 2014).

Situated within this new urban landscape, we frame our research as a human ecology approach to urban environmental inequality (McKinney et al., 2015), considering the relationship between racial demographic changes and pollution and asking generally: what are the environmental consequences of demographics in a large, diverse twenty-first-century metropolitan area? Our focus is on the racial dynamics underlying pollution levels in the Houston area in the mid-2010s. Houston has historical significance to both environmental justice scholarship and activism (Bullard, 1983), and continues to be the focus of numerous environmental justice-oriented academic studies (e.g., Chakraborty, 2015; Collins et al., 2015; Elliott & Smiley, 2019; Hernandez et al., 2015; Linder et al., 2008). Meanwhile, Houston historically has also been a segregated city (Strait & Gong, 2010), and its recent redevelopment has resulted in some of the most intensely gentrified neighborhoods

in the country (Binkovitz, 2018; Podagrosi et al., 2011).<sup>5</sup> Nevertheless, the racial composition of its neighborhoods has changed dramatically, especially in the past few years (Williams & Emamdjomeh, 2018). As of 2015, relatively speaking, while the inner city has attracted more white residents, the city's suburbs have become racially diverse (see Figure 1).

Given the experience of “urban disinvestment” and “white flight,” which continued through the end of the twentieth century, the novel spatial demographics of the twenty-first century have encouraged social scientists to develop new conceptual tools. Some scholars have described these diverse urban areas as being comprised of “global neighborhoods” (Logan & Zhang, 2010, p. 1070), which are characterized by the neighborhood-level presence of multiple racial/ethnic groups (e.g., non-Hispanic white, black, Hispanic, and Asian) in the same proportions observed in the greater metropolitan area. Houston’s “rapidly integrated” suburban neighborhoods are an expression of this “global neighborhood” phenomenon, serving as the motivation of our analysis of environmental inequality in terms of pollution levels.

## **Estimating pollution and measuring race**

A great deal of the quantitative literature on environmental inequality uses data from the Toxics Release Inventory (TRI), an annual inventory published by the Environmental Protection Agency (EPA, 2017) that documents the site-level release of pollutants known to cause harm to human health and the environment. Though the TRI only reports chemical releases, these measures are used as a way to approximate pollution levels in areas surrounding TRI sites. Scholars have found that residential proximity to a TRI site has a wide range of consequences for human health and social cohesion (Bevc et al., 2005; Johnson et al., 2014; Natural Resources Defense Council, 2004). Focused on urban areas, these scholars use methods ranging from straightforward unit hazard analysis, one of the earliest methods developed to investigate spatial proximity to pollutants, to more complex pollution plume modeling; significant research considers potential exposure to environmental toxins in relation to demographic composition of the area near or around a TRI site.

Across the environmental justice literature, there is robust evidence that race plays a primary role in structuring environmental inequality (Cushing et al., 2015; Johnston et al., 2016; Mohai & Saha, 2015). In these studies, many operational measures of race are based on single-group racial variables; there has been less quantitative work explicitly looking at the role that multigroup measures of

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<sup>5</sup> Unfortunately, we do not have the space to fully explain the legacy of segregation. However, we point interested readers to a large swatch of research that explains segregation across the United States, including in Houston (Feagin, 2000; Feagin & Sikes, 1994; Massey & Denton, 1993).

race play in pollution levels (e.g., Ard, 2016; Downey et al., 2008; Jones et al., 2014; Morello-Frosch & Jesdale, 2006).<sup>6</sup> Multigroup measures of race, measures that allow for the inclusion of multiple racial or ethnic groups in analysis, can facilitate an analysis of the relative racial/ethnic diversity of a neighborhood and help continue to incorporate a discussion of segregation into environmental justice research (Jones et al., 2014; Smith, 2007, 2009). Furthermore, including multiple group measures best represents the reality of contemporary urban demographics in metropolitan areas like Houston. To be sure, the concepts of racial/ethnic diversity and segregation figure into the theoretical frameworks of environmental inequality; for instance, scholars identify segregation as “a major contributor to the creation and maintenance of environmental inequality” (Mohai & Saha, 2015, p. 317). Yet, compared to single-group variables, in the environmental justice literature, there has been less work incorporating multigroup measures of race into quantitative analyses of pollution levels.

The evidence there is about how pollution levels vary by racial diversity/segregation is not consistent. For instance, Downey et al. (2008) find no evidence of a significant effect of segregation. While Ard (2016) was looking at the health risks of pollution exposure, she did find that these risks were exacerbated significantly by most measures of segregation, including entropy, which is the focus of our analysis; in other words, less segregation attenuates the health risk of pollution exposure, which suggests that tracts with greater racial diversity have lower levels of pollution. We note that these studies tend to analyze data from the 2000 census and Toxics Release Inventory. Yet the demographics of cities across the United States have changed since that time, especially in the greater Houston area. To assess the environmental implications of racial diversity in the Houston area we focus on the entropy index, known as Theil’s H (described below in more detail). As Ard (2016) explains, this multigroup measure of evenness allows scholars to utilize a more nuanced approach to investigate the complex and historically contested relationship between race and pollution exposure. This measure is often seen in investigations of racial residential patterns and other forms of social inequality, such as in employment (Gorelick & Bertram, 2010). Moreover, as noted above, the entropy index has been incorporated into news reports on racial/ethnic diversity and segregation by the popular press (Boschma, 2016; ProPublica, 2017; Williams & Emamdjomeh, 2018).

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6 To be clear, much of this literature looks at the health consequences of pollution exposure.

## Data and analysis

### Unit of analysis

For the analysis, we collect information on sociodemographic, economic, and chemical release variables at the level of the census tract across the Houston–Sugarland–Baytown MSA. The census tract is the smallest and most common unit of analysis, with readily accessible information on a variety of social and environmental variables. In the Houston–Sugarland–Baytown MSA, there are 1,070 census tracts spread across 9 counties. Of the 1,070 tracts in the greater Houston area, there are 34 tracts that are either large bodies of water, contain little or no residential population, and/or have a special function (e.g., airports, public parks, employment areas, prisons, universities, etc.). While they serve administrative purposes, these special tracts are functionally dissimilar from the standard tracts, which tend to contain thousands of non-institutionalized residents. Moreover, these special use tracts do not have complete coverage for all variables in the study (e.g., population size, racial distribution, education, home value, etc.). Rather than imputing values, we delete the 34 special use tracts from the analysis, yielding a final sample size of  $n = 1,036$ .

### Dependent variable

The data for the dependent variable come from the TRI. At the time of analysis, the most recently available and completed version of the TRI was collected in 2015 (EPA, 2017). For that year, we compute the total amount of chemical releases, measured continuously in millions of pounds, released both on- and off-site into the surrounding air, water, and land, as reported on the 2015 TRI for the Houston–Sugarland–Baytown MSA. For the analysis, we divide pounds of pollutants as reported by TRI by the number of people living in the census tract and then divide that value by the area of the tract, yielding a measure of pollution that is standardized by the population density of the census tract. As such, the dependent variable controls for variation in the population size and land area of neighborhoods across the Houston metropolitan area. Because a few tracts have very high levels of pollution, the pollution levels are positively skewed; to address this, we first compute the natural logarithm before incorporating the dependent variable into the bivariate and multivariate analyses. For the tracts that have zero values for air pollution levels, we add a constant of “1” before computing the natural logarithm, which yields a normally distributed dependent variable. All variables, their descriptions, and sources are displayed in Table 1.

## Independent variables

The primary independent variables for the study include the measure of *entropy* as well as four separate predictors for the percentage of the population that is (i) *Hispanic*, (ii) *Black*, (iii) *White*, or (iv) *Other*. The entropy index used here measures patterns of evenness among groups distributed across a geographic unit (Massey & Denton, 1988) and was calculated as follows:

where  $k$  is the number of racial/ethnic groups of interest,  $p_{ij}$  is the proportion of the  $j^{\text{th}}$  racial/ethnic group in tract  $i$ ,  $n_j$  is the total population of the  $j^{\text{th}}$  racial/ethnic group in tract  $i$ , and  $N_i$  is the total population in tract  $i$  (White, 1986). Note that the absolute value was taken from final scores generated by the entropy equation. As such, the maximum score for  $h_i$  is dependent on the number of racial ethnic groups examined, or  $\ln(k)$ , with tracts that hold higher values being more diverse, or less segregated, than tracts with lower values. For this project, the maximum value of  $h_i$  is 1.386. So, a tract with a score of 1.386 would have proportional amounts of persons from each racial/ethnic category examined, whereas a tract with a score of 0 would have only a single racial/ethnic group represented in its population.<sup>7</sup>

Race items are measured continuously from 0 to 100 percent, with (i) *Hispanic* measuring the percent of the population that self-reports as Hispanic (from any race category not already identified as non-Hispanic white, black, etc.) and (ii) *Black* reporting the percent total of non-Hispanic black persons residing in each tract. The (iii) *White* measure reports the percent total of non-Hispanic white persons residing in each tract, and (iv) *Other* reports the percent total of persons residing in each tract that fall into one or more of the following racial/ethnic groups: American Cherokee, American Chippewa, American Navajo tribal, American Sioux tribal, Asian, Native Guamanian, Native Samoan, Native Other Pacific Islander, Some Other Race, and Two or More races. The aforementioned racial/ethnic groups were combined as a result of the low population numbers of each of these groups.<sup>8</sup>

We also include the following six variables as controls: (i) percentage of the labor force that works in *Manufacturing*, (ii) percentage of the population who is *Non-Native*, (iii) *Educational Attainment*, the percentage of the population who have a high school degree or higher, (iv) percentage who live in *Poverty*, (v) median *Household Income*, and (vi) the median *Home Value*. These selected variables have been used as proxy measures of the “path of least resistance,” a perspective that supports the notion that pollutants and polluting industries, such as the industrial manufacturing industry, make siting decisions based on a combination of factors

<sup>7</sup> An alternative equation for the entropy index includes a minus sign in front of the summation command, yielding negative values for greater racial/ethnic diversity.

<sup>8</sup> For a sensitivity check, in a supplemental analysis, we also computed a variable for the percent of the population who is non-white. In two additional spatial error models, displayed in the appendix in Table 3S, we find that the slope estimate for this variable is non-significant, which is consistent with the results displayed in Table 3.

that present the least resistance to their efforts (Anderton et al., 1994; Schelly & Stretesky, 2009). This perspective considers environmental inequality as arising from a variety of political, social, and economic forces. *Manufacturing* scores per tract percentages of persons above the age of 16 employed in a manufacturing job in any industry, while *Non-Native* reports the tract-level composition of all persons reported as being US citizens by naturalization or who report not being a US citizen. *Poverty* is measured as a percent total per tract of persons for whom poverty status has been determined in the 12 months prior. Finally, median *Household Income* and median *Home Value* are measured continuously in US dollars based on 2015 estimates and are reported per tract by the Census (US Census ACS, 2019). All variables have been logged, which facilitates interpretation of the slope estimates in the spatial regression models. The slope estimate is interpreted roughly as the percent change in the dependent variable for every 1 percent change in the predictor variable, holding the rest of the factors constant (see York et al., 2003).

**Table 1. Variables, descriptions, and sources.**

Variable	Description	Source
1. Pollution	Pollution standardized by the population density of the census tract; pollution level per person per area	Toxics Release Inventory (TRI)
2. Entropy	Measure of diversity, representing the distribution of the racial groups relative to their population proportion in the metropolitan area	US Census
3. Hispanic	Percentage who are Hispanic	US Census
4. Black	Percentage who are Black	US Census
5. White	Percentage who are White	US Census
6. Other	Percentage who are Other	US Census
7. Manufacturing	Percentage of labor force employed in manufacturing	US Census
8. Non-Native	Percentage of the population who were not born in the United States	US Census
9. Educational Attainment	Percentage of the population who have a high school degree or higher	US Census
10. Poverty	Percentage of the population who live in poverty	US Census
11. Household Income	Median household income	US Census
12. Home Value	Median home value	US Census

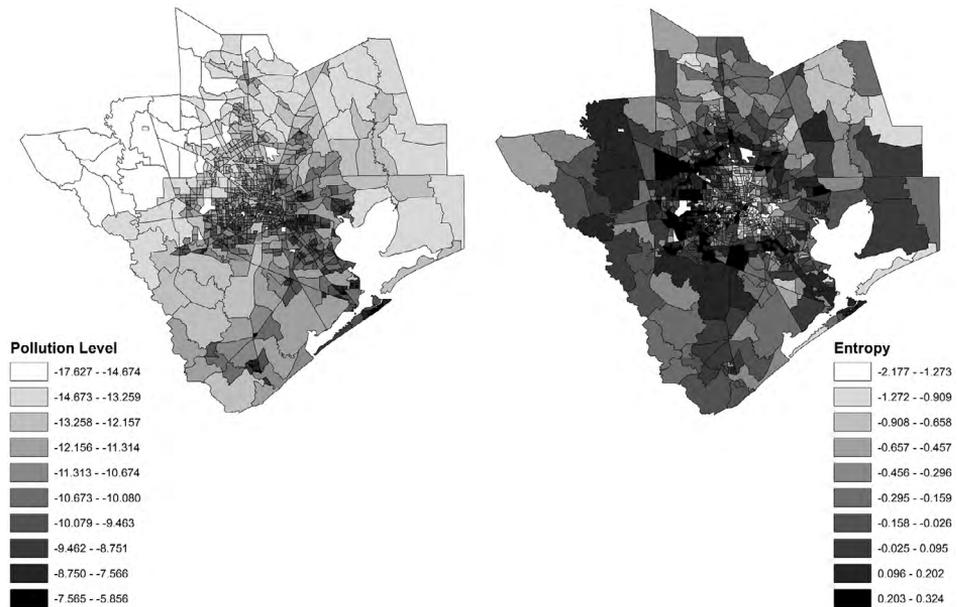
Note: All variables measured in 2015; all values have been logged.

Source: Toxics Release Inventory 2015 (EPA, 2017; US Census ACS, 2019).

**Table 2. Univariate and bivariate statistics.\***

Variable	Mean Unlogged	Mean Logged	SD Logged	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Pollution	0.000	-10.660	1.697	1.000											
2. Entropy	0.868	-0.141	0.356	-0.078	1.000										
3. Hispanic	28.991	3.367	0.741	0.158	-0.066	1.000									
4. Black	10.186	2.321	1.148	0.092	0.474	0.057	1.000								
5. White	23.406	3.153	1.242	-0.233	0.287	-0.467	-0.521	1.000							
6. Other	5.871	1.770	0.936	-0.100	0.614	-0.396	0.024	0.347	1.000						
7. Manufacturing	9.365	2.237	0.538	-0.179	-0.148	0.128	-0.263	0.131	-0.144	1.000					
8. Non-Native	18.120	2.897	0.710	0.128	0.143	0.581	0.030	-0.326	0.230	-0.112	1.000				
9. Educational Attainment	9.699	2.272	0.920	-0.144	0.391	-0.671	-0.119	0.601	0.620	-0.167	-0.201	1.000			
10. Poverty	12.268	2.507	0.924	0.183	-0.124	0.599	0.347	-0.593	-0.416	-0.115	0.282	-0.658	1.000		
11. Household Income	55,714.739	10.928	0.689	-0.158	0.142	-0.364	-0.253	0.451	0.310	0.089	-0.165	0.479	-0.555	1.000	
12. Home Value	138,551.863	11.839	0.593	-0.163	0.140	-0.596	-0.373	0.611	0.486	-0.079	-0.124	0.757	-0.647	0.418	1.000

\* Note: For consistency with the results from the spatial error models, we report the bivariate statistics using logged values for all variables. All bivariate correlations are significant ( $p < 0.05$ ) except the correlations between *Black* and *Other*, and *Black* and *Non-Native*.  
Source: Authors' summary of findings.



**Figure 1. Pollution levels and racial diversity across the Houston Metropolitan Area, 2015.**

Note: Units are census tracts ( $n = 1,036$ ). Values are logged. Pollution level equals pounds of pollutants as reported by TRI divided by the number of people living in the census tract and by the area of the tract, yielding a measure of pollution that is standardized by the population density of the census tract. Racial diversity is measured in terms of entropy, representing the spatial distribution of four racial categories, relative to their proportions in the population. The higher the entropy, the greater the racial diversity of the census tract.

Source: EPA (2017); US Census ACS (2019).

## Bivariate analysis and results

Table 2 reports the univariate and bivariate statistics. Looking at Table 2, we note that the bivariate correlation between pollution and entropy is negative ( $r = -0.078$ ;  $p < 0.05$ ). Figure 1 displays spatial variation in our dependent variable and the entropy index across the greater Houston area. A visual inspection of these maps suggests a negative correlation between pollution level and racial diversity. Generally speaking, as one moves from the city center in a west and northwest direction, racial diversity goes up and pollution levels decrease. Likewise, the area immediately southeast of the city center is characterized by low racial diversity and high pollution levels. In a supplemental analysis, we also estimated the bivariate Moran's I between these two variables ( $I = -0.051$ ;  $p < 0.01$ ), which shows that pollution and entropy are negatively correlated across space. Taken together, these results suggest the following exploratory hypothesis:

*Hypothesis: At the tract level, there is a negative association between the racial diversity of the tract and its pollution level. In other words, tracts with greater racial diversity have lower pollution levels.*

**Table 3. Results from spatial error model.**

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	b	SE								
<b>Primary Variables</b>										
Entropy	-0.437	**0.140	-0.440	**0.142	-0.497	**0.181	-0.428	**0.142	-0.308	*0.155
Hispanic			0.011	0.103						
Black					0.030	0.058				
White							-0.020	0.059		
Other									-0.133	0.071
<b>Controls</b>										
Manufacturing	-0.282	**0.083	-0.282	**0.084	-0.277	**0.084	-0.279	**0.084	-0.273	**0.083
Non-Native	-0.016	0.075	-0.021	0.089	0.000	0.081	-0.017	0.075	0.020	0.077
Educational Attainment	0.073	0.085	0.076	0.088	0.075	0.085	0.078	0.086	0.104	0.086
Poverty	-0.115	0.065	-0.117	0.066	-0.120	0.066	-0.118	0.066	-0.133	*0.066
Household Income	-0.018	0.064	-0.018	0.065	-0.013	0.065	-0.015	0.065	-0.015	0.064
Home Value	-0.508	***0.115	-0.505	***0.118	-0.492	***0.119	-0.496	***0.120	-0.472	***0.116
Constant	-0.352	2.154	-0.405	2.207	-0.739	2.257	-0.499	2.171	-0.675	2.163
$\lambda$	0.977	***0.013	0.977	***0.013	0.977	***0.013	0.977	***0.013	0.977	***0.013
Moran's I (Residuals)	0.008	0.007	0.008	0.006	0.008	0.007	0.008	0.006	0.008	0.006
Max/Mean VIF	3.71/2.02		4.16/2.37		3.72/2.17		3.72/2.14		4.02/2.26	
N	1,036		1,036		1,036		1,036		1,036	

Note: In order to minimize spatial autocorrelation in the residuals to non-significant levels, the spatial parameter  $\lambda$  was estimated using a 3rd order queen contiguity weights matrix. VIF (variation influence factor) values were derived from separate OLS (ordinary least squares) models. SE: standard error. \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001.

Source: Authors' summary of findings.

## Spatial regression analysis and results

To evaluate our exploratory hypothesis, we turn to results from a multivariate analysis. Here, we regress our dependent variable on the primary predictors as well as the control variables in a spatial error model, which controls for spatial dependence in the error term. The generic equation for a spatial error model is written as follows:

$$y_i = x_{ik}\beta_k + v_i$$

$$v_i = \lambda Wv_i + \varepsilon_i$$

wherein  $y_i$  indicates the value of the dependent variable for the  $i^{\text{th}}$  census tract;  $x_{ik}$  indicates the value of the  $k^{\text{th}}$  predictor for the  $i^{\text{th}}$  tract, with  $\beta_k$  representing the effect of the  $k^{\text{th}}$  predictor on the dependent variable. Because we have logged both the dependent and independent variables, the estimate for  $\beta_k$  represents, generally speaking, the percent change in pollution levels for every one percent change in the predictor, all else equal. The error term  $v_i$  is decomposed into two parts. The first part estimates the spatial error term  $\lambda$ , which is based on a queen 3rd order contiguity weights matrix  $W$ , and the second part  $\varepsilon_i$  represents all the leftover unobserved variation in the dependent variable.<sup>9</sup>

Table 3 displays the results from the spatial error model. Our primary focus is on the association between *Pollution* and *Entropy*. Given the results from the bivariate analyses, the results from the multivariate analysis will indicate whether the negative bivariate association holds after controlling for potentially confounding variables, including spatial autocorrelation. Looking at Table 3, we first note the significant positive estimates for the spatial error parameter  $\lambda$  in all five models, indicating that there is positive spatial dependency in the error term. While there is not an intuitive interpretation of the estimate for  $\lambda$ , its inclusion in the model has helped reduce spatial autocorrelation of the residuals to non-significant levels (as seen in the values for Moran's I) and minimize any spatially induced bias in the slope estimates of the predictor variables.<sup>10</sup>

Model 1 includes the measure of *Entropy* along with the five non-racial control variables; Models 2–5 then incorporate an additional variable separately for *Hispanic*, *Black*, *White*, and *Other*. While *Entropy* is a multigroup measure of racial diversity, we include separate variables for the other racial groups as a sensitivity check and to ensure that the estimate for *Entropy* is not being influenced by any one particular racial category. Indeed, across all five models, the slope estimate for *Entropy* is consistently negative and significant. In Models 1–4, a 1 percent increase in the entropy of

9 We also estimated spatial error models with spatial weights based on queen 1st and 2nd order contiguity as well as inverse distance; while the slope estimates from these supplemental models (available upon request) were substantively identical, the model residuals using these lower orders still exhibited significant spatial autocorrelation.

10 In Table 3, we also report the max/mean VIFs (variance inflation factors). In all the models, the VIFs are well below the threshold of 10, indicating that there is no problem with multicollinearity.

a census tract is approximately associated with a 0.4 percent decrease in pollution levels ( $p < 0.01$ ); in Model 5, the magnitude of the slope estimate declines slightly but is still significantly negative ( $b = -0.308$ ;  $p < 0.05$ ). Given that the dependent and independent variables have been logged, the slope estimate for the entropy variable is interpreted roughly as follows: For every 1 percent increase in entropy at the level of the census tract, there is between 0.497 percent and 0.308 percent decrease in density-standardized pollution levels across the Houston area.

There are two points to make regarding these results. First, the significant, negative coefficient for *Entropy* is not substantively moderated by the inclusion of any of the single-group race variables, which indicates that it is a robust finding. Second, controlling for multigroup racial/ethnic diversity, none of the slopes estimates for the single-group race variables are significant. To be clear, we included the single-race measures as a sensitivity check to observe whether the estimate for *Entropy* was being influenced by a particular racial category. With this caveat in mind, we speculate whether the cross-sectional effect of race is most evident not with single-group measures but with multigroup diversity measures; we encourage future scholarship to consider incorporating a multigroup measure of racial/ethnic diversity when assessing the effect of race on pollution exposure.

Before we turn to a discussion of these results in the conclusion, we briefly report the results from two control variables that are consistently significant across the five different models. First, while the negative slope estimate for *Manufacturing* may seem contradictory, this variable measures the percentage of the residents of the census tract who are employed in manufacturing industries; it does not directly represent the level of manufacturing activity within the census tract. Either way, the negative slope estimate is inconsistent with previous work by Elliott and Smiley (2019), who also conducted a cross-sectional snapshot analysis of pollution levels within the Houston area. Aside from a different research question, Elliott and Smiley analyzed data for the year 2010 and did not control for land area, as we did. Future research can delve into whether the inconsistency for *Manufacturing* is the result of differences in the year analyzed and/or differences in the operational measures used in the analysis. Second, the estimate for median *Home Value* is significantly negative. In other words, neighborhoods with higher property values are associated with lower pollution levels. This result is consistent with previous analyses looking at the independent effect of socioeconomic status on exposure to environmental pollutants (Crowder & Downey, 2010).

## Discussion and conclusion

Given our interest in changing urban demographics, we frame the above project as a human ecology approach to urban environmental inequality (Elliott & Frickel, 2013; McKinney et al., 2015). Specifically, we look at the relationship between multigroup racial diversity and pollution levels in the context of the greater Houston area in 2015. While many quantitative environmental justice scholars utilize single-group measures of race, there is also a growing body of research incorporating multigroup measures of racial diversity and ethnic heterogeneity (e.g., Ard, 2016; Chakraborty et al., 2017; Downey et al., 2008; Jones et al., 2014; Morello-Frosch & Jesdale, 2006). This academic trend is concurrent with the increasing diversity of the American population. In fact, not just environmental scholars, but social scientists in general have been building analytic techniques and conceptual frameworks to study the novel demographics of America's urban areas, especially with the emergence of "multi-ethnic" "global neighborhoods" (Zhang & Logan, 2016). In this new metropolitan landscape, Logan and Zhang (2010) argue that "the simple place categories of predominantly white, predominantly black, or racially mixed are no longer adequate" (p. 1070). Instead, operational measures of race should adequately capture the demographic diversity of the unit of analysis. One contribution of our analysis is that we utilize a multigroup measure of race to assess the role that neighborhood diversity plays in pollution levels within a "multi-ethnic" "rapidly integrated" metropolitan region.

As mentioned above, some scholars have found that higher levels of segregation are associated with more toxic industries and increased health risk from air pollution (Ard, 2016; Smith, 2009). To be clear, these findings do not contradict the results of our study; instead, they reflect the obverse of what we observe: lower diversity is associated with higher pollution levels, and greater diversity is associated with lower pollution levels. In other words, those locations with the highest levels of diversity have the lowest TRI levels and vice versa. Yet, in another way, the results of the models presented above do run counter to quantitative work on environmental inequality, at least with respect to the use of single-group race variables. Again, much of this research has demonstrated that single-group measures of race are reliable predictors of a wide range of environmental contaminants (Brulle & Pellow, 2006; Mohai et al., 2009). However, in our analysis, given that the slope estimates for the single-group variables are non-significant, the multigroup variable is a more consistent predictor of pollution levels than the single-group measures. This finding could point to emergent trends that researchers should be mindful of in their future research.

Nevertheless, we underscore that the results of our study are based on a single metropolitan area (Houston, Texas) using cross-sectional data for the year 2015. We are careful in drawing conclusions about the mechanism involved here and we seek to provide suggested reasons for this finding, pointing to two limitations of this work while highlighting fruitful opportunities for future research.

First, we reiterate that, not just Houston, but other diverse cities, such as Chicago, continue to have large pockets of neighborhoods, especially in the urban core, that remain highly segregated (e.g., Podagrosi et al., 2011). Yet, these cities' suburban neighborhoods are the places that are undergoing "rapid" integration (Williams & Emamdjomeh, 2018). This is important as the shifts in environmental inequality highlighted in this research may point to quickly changing demographic trends that require not only new theoretical lenses (e.g., global neighborhoods) but also innovative methodological strategies that incorporate longitudinal data. To be clear, previous environmental research on diversity/segregation also tends to rely on cross-sectional snapshots (e.g., Ard, 2016; Downey et al., 2008; Jones et al., 2014; Morello-Frosch & Jesdale, 2006). Likewise, since we do not have longitudinal data, we can only identify a cross-sectional relationship between racial/ethnic diversity and pollution levels in Houston. Our cross-sectional analysis captures the spatial but not the temporal dimension of variation; as such, our models do not adequately analyze processes like gentrification.

On that note, as seen in Figure 1, much of the pollution associated with TRI levels in Houston is located in the southeastern parts of the city, while the suburban areas west of the city are less polluted (cf. Downey, 2005). Again, it is these suburban areas that are also undergoing rapid integration as the central part of the city is gentrifying. We suspect that as affluent, white households abandon the suburbs for the inner city, the suburbs of Houston are undergoing a transformation in which a more diverse, non-white population is becoming more commonplace. Hence, it is in these suburban areas where there is a confluence of increased racial/ethnic diversity and decreased levels of pollution. Yet, while our cross-sectional analysis, controlling for spatial autocorrelation as well as a host of potentially confounding variables, reveals an inverse correlation between racial/ethnic diversity and pollution levels, it precludes a more thorough evaluation of whether and how over time these demographic shifts are contributing to temporal changes in pollution levels. As the shift towards multi-ethnic neighborhoods continues across American cities, environmental justice scholarship would benefit from the incorporation of longitudinal data to test whether the results we observe for the Houston area in 2015 are generalizable across time and space.

Secondly, among other strategies, Pellow (2018) argues that environmental justice research should include multiple levels of analysis and foci of investigation. To that end, we recognize that inequality in pollution levels is experienced in many settings, not just where people live but also where they spend their time in leisure, their daily rounds, and work (e.g., Bullard, 1996). Our focus was on the racial dynamics of pollution level within the neighborhood of residence. Nevertheless, following the lead of previous research (e.g., Elliott & Smiley, 2019), future scholarship can consider whether the daily rounds of residents and workers might also play a role in pollution exposure within the context of the shifting demographics of American

cities. Perhaps, while diverse neighborhoods experience lower levels of pollution, the residents of these neighborhoods may be working in toxic conditions. As noted by other social scientists utilizing spatial data (Anderson, 2018), answering these questions will require not only longitudinal data but also multilevel methods to assess the neighborhood and workplace impacts on individuals.

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## Appendix: Supplemental results

**Table 3S. Supplemental results from spatial error model.**

Variable	Model 1S		Model 2S	
	b	SE	B	SE
<b>Primary Variables</b>				
Entropy	-0.385	**0.132		
Black				
Hispanic (Non-White)				
Other				
All Non-White	0.222	0.135	0.039	0.120
White				
<b>Controls</b>				
Manufacturing	-0.241	**0.070	-0.237	**0.084
Non-Native	0.014	0.068	0.003	0.068

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	<b>Model 1S</b>		<b>Model 2S</b>	
Educational Attainment	0.078	0.073	-0.079	0.067
Poverty	-0.116	*0.056	-0.124	*0.056
Household Income	-0.014	0.054	0.012	0.054
Home Value	-0.354	***0.102	-0.371	***0.102
Constant	0.960	2.506	2.466	2.514
$\lambda$	0.985	***0.009	0.985	***0.009
Moran's I (Residuals)	0.018	**0.006	0.018	**0.006
Max/Mean VIF	3.80/2.38		3.20/2.33	
N	1,036		1,036	

Note: In order to minimize spatial autocorrelation in the residuals to non-significant levels, the spatial parameter  $\lambda$  was estimated using a 3rd order queen contiguity weights matrix. VIF (variance inflation factor) values were derived from separate OLS (ordinary least squares) models. SE: standard error. \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001.

Source: Authors' summary.

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