The Spatial Relationship Between the Low-Income Housing Tax Credit Program and Industrial Air Pollution

Dana K. Goplerud
Sarah G. Gensheimer
Benjamin K. Schneider
Matthew D. Eisenberg
Genee S. Smith
Johns Hopkins Bloomberg School of Public Health

Craig Evan Pollack
Johns Hopkins Bloomberg School of Public Health
Johns Hopkins Schools of Medicine and Nursing

The views expressed in this article are those of the authors and do not represent the official positions or policies of the Office of Policy Development and Research, the U.S. Department of Housing and Urban Development, or the U.S. government.

Abstract

Housing is a key social determinant of health, but programs that create affordable housing may unintentionally concentrate residents in neighborhoods with unhealthy exposures, such as air pollution. This article examines whether neighborhoods with Low-Income Housing Tax Credit (LIHTC) properties have higher levels of industrial air pollution than comparable neighborhoods without LIHTC properties. The findings indicate that, within a given metropolitan area, more polluted neighborhoods are more likely to contain LIHTC properties (odds ratio [OR] 1.08 for 10-percentile-point increase in industrial air pollution). However, that relationship is no longer significant after accounting for neighborhood racial composition and socioeconomic status and is reversed when accounting for housing market characteristics (OR 0.95 for 10-percentile-point increase in industrial air pollution in fully adjusted model). These results provide the first estimates of the association between LIHTC properties and industrial air pollution at the national level and suggest that the disproportionate burden of air pollution exposure among LIHTC residents may be mediated by neighborhood conditions such as poverty and rental market quality.

Introduction

Living in safe and affordable housing is increasingly recognized as foundational for health and well-being (Taylor, 2018). Beyond the housing unit itself, neighborhoods can have a strong influence on long-term health outcomes by shaping access to economic and educational opportunities, as well as exposure to potential harms, such as crime or pollution (Diez Roux and Mair, 2010). Federal programs can provide residents with stable and affordable housing; however, those programs may unintentionally concentrate residents in neighborhoods with fewer resources or more harmful exposures. Thus, characterizing the neighborhoods in which these programs are built is important to fully understand their potential relationship to resident well-being.

The Low-Income Housing Tax Credit (LIHTC) is the nation's largest affordable housing program. Although previous studies of LIHTC have found that properties tend to be located in lower-income neighborhoods compared with renter households overall—and in predominantly minority neighborhoods and those with poorer schools (Ellen and Horn, 2018a; Horn and O'Regan, 2011; McClure and Johnson, 2015)—less is known about other features of LIHTC neighborhoods that may affect the health and well-being of their residents. Outdoor air pollution, specifically, has important health consequences, including increased prevalence of asthma exacerbations and incidence of heart disease, cancer, and stroke (Sun and Zhu, 2019). Few studies have examined the relationship between air pollution and the location of LIHTC properties.

The aim is to build on previous work by examining the association between industrial air pollution and the location of LIHTC properties. Industrial air pollution, rather than pollution from mobile sources such as cars or trucks, can be immediately linked to a physical location, such as a manufacturing plant. Although the distribution of pollution in the area around a point source is complex and not necessarily related to linear distance from the source (Chakraborty, Maantay, and Brender, 2011), policymakers and LIHTC developers may find that identifying point sources rather than mobile sources is easier for purposes of considering them in funding allocations. In addition, this study seeks to account for neighborhood-level characteristics, such as poverty level and racial or ethnic composition, that have been associated with the location of LIHTC properties.

Low-Income Housing Tax Credit

Administered through the Internal Revenue Service, LIHTC is the largest program designed to finance affordable housing in the United States. LIHTC awards tax credits to housing developers who build or renovate affordable housing, and it has produced more than 3 million units of affordable housing since its inception in 1986 (HUD, n.d.). Typically, these properties require that residents earn less than 50 to 60 percent of the Area Median Income. Some properties accept residents who exceed those income limits, although many residents fall well below them (O'Regan and Horn, 2013). Most properties are for general occupancy, but some have "target populations," such as families, senior residents, or formerly homeless individuals.

The location of LIHTC properties in each state is shaped by Qualified Allocation Plans (QAPs). QAPs are documents that provide guidance in how LIHTC funds should be allocated. States typically have more applications for funding than available funds, so, to prioritize applications, QAPs specify how points should be awarded for certain aspects of the development plan. Although some federal requirements are in place for QAPs, such as preferences for developing in high-poverty areas, states have considerable ability to customize and revise the QAPs to meet their own policy goals (Ellen and Horn, 2018b). For example, states may award more points to properties in low-income census tracts to promote revitalization. Alternatively, states may incentivize development in “high-opportunity” areas, such as high-income neighborhoods or areas near schools, jobs, or public transportation. LIHTC funding can also be used to revitalize existing housing and can be combined with other funding streams, such as the HOPE IV, Rental Assistance Demonstration (RAD), or Choice Neighborhoods. States recertify QAPs regularly, so priorities may change over time on the basis of the needs and interests of the state housing agency and other stakeholders. Recent initiatives across several states have attempted to prioritize LIHTC development in areas that may offer more opportunities for low-income residents (Ellen and Horn, 2018b). Various mechanisms within QAPs that incentivize developments in high-opportunity areas can effectively decrease new LIHTC development in low-income and predominantly minority neighborhoods (Ellen and Horn, 2018b).

Many states have used QAPs as mechanisms to promote the health of LIHTC residents, including environmental building standards that promote energy efficiency, avoidance of toxic materials, and lead abatement (Shi, Baum, and Pollack, 2020). QAPs may also incentivize proposals with co-located services, such as health screenings, nutrition counseling, or case management (Shi, Baum, and Pollack, 2020). Finally, QAPs may award additional points for proposals located near health-promoting services, such as community health centers, grocery stores, or parks (Shi, Baum, and Pollack, 2020). Developers recognize the inherent challenges and tradeoffs in these approaches, however; for example, building a property farther from a busy highway may decrease traffic emission exposure but also decrease the visibility of advertising about the property (Shi, Baum, and Pollack, 2020). Overall, more research is needed on how LIHTC developments can promote health beyond housing affordability alone; those data could come in the form of Health Impact Assessments to characterize the health benefits of LIHTC across sectors (Shi, Samuels, and Pollack, 2017).

Extensive literature has characterized the demographics of neighborhoods where LIHTC properties are located. LIHTC properties tend to be built in areas with higher poverty rates and greater unemployment, compared with renter households nationwide (McClure and Johnson, 2015). LIHTC properties are also constructed in areas with a higher proportion of Black residents (Horn and O’Regan, 2011). Although most units are in metropolitan areas and central cities, LIHTC properties are also increasingly being built in suburban areas (McClure, 2006).

LIHTC properties tend to be in areas with fewer resources than areas where rental properties are located overall. LIHTC households are more likely to live in neighborhoods with poor labor market engagement and worse school quality (Ellen, Horn, and Kuai, 2018). LIHTC neighborhoods, compared with other, similar neighborhoods, have poorer sidewalk completeness, which is a measure of walkability (Woo, Yu, and Lee, 2019). Compared with rental housing overall, LIHTC properties experience better transit access and affordability (Ellen, Horn, and Kuai, 2018); however, less is known about other aspects of neighborhood quality, especially those that may have an impact on health.

Air Pollution

One important feature of neighborhood quality is air pollution. Air pollution includes many different types of chemicals, often classified into criteria air pollutants and hazardous air pollutants. Criteria air pollutants—including PM2.5 (particulate matter with diameter < 2.5 microns), lead, carbon monoxide, and ozone—are present in larger quantities in the environment and are closely regulated by national emissions standards (EPA, 2021a). Hazardous air pollutants include hundreds of chemicals that have more serious health effects per "dose" but are present in smaller quantities overall (EPA, 2021b).

Air pollution has an important role in disease nationally. Outdoor air pollution has been linked with a host of adverse health outcomes, including asthma, chronic obstructive pulmonary disease (COPD), cancer, stroke, and heart disease (Adamkiewicz, Liddie, and Gaffin, 2020; Kampa and Castanas, 2008; Schraufnagel et al., 2019). In particular, PM2.5 has been widely studied as a key correlate of adverse health outcomes, including heart disease, stroke, and respiratory illness, and is a significant contributor to mortality worldwide (Bu et al., 2021; Rajagopalan, Al-Kindi, and Brook, 2018). Other types of air pollution beyond PM2.5 are also known to damage health. Exposure to hazardous air pollutants has been associated with a wide variety of acute and chronic health effects, including asthma, cancer, neurological disease, and cardiovascular dysfunction (Cicalese et al., 2017; Hill et al., 2021; Malek et al., 2015; Moore and Hotchkiss, 2016). Hazardous air pollutants have also been linked to children's educational outcomes, including reduced executive function, poorer early cognitive ability, and lower standardized test scores (Gatzke-Kopp et al., 2021; Grineski, Collins, and Adkins, 2020; Lett, Stingone, and Claudio, 2017). These effects on health and well-being persist even after controlling for race and socioeconomic status, suggesting that air pollution is independently associated with adverse outcomes rather than simply a correlate of neighborhood disadvantage.

Both criteria and hazardous air pollutants are generated from multiple sources. Industrial sites, such as factories, refineries, and power plants, produce a large component of outdoor air pollution, especially hazardous air pollutants. Other sources of air pollution include mobile sources, such as cars and trucks, and natural sources, such as forest fires (EPA, 2021d).

Recent studies suggest that industrial air pollution causes adverse health outcomes independent of other pollution sources and should be examined on its own (Persico, Figlio, and Roth, 2016; Persico and Venator, 2021). Much of this research has focused on proximity to Toxics Release Inventory (TRI) facilities. TRI sites are industrial pollution sites which release chemicals known to cause adverse health or environmental impact and have been mandated to report annual emissions data to the U.S. Environmental Protection Agency (EPA; 2021f). Geographic proximity to a TRI facility during gestation correlates with a higher rate of children dropping out of high school and with lower family income over a lifetime (Persico, Figlio, and Roth, 2016). In schools closer to TRI sites, children perform significantly worse on math and reading tests than the general population, even when accounting for race, gender, and socioeconomic status (Persico and Venator, 2021). Cognitive disabilities are also more common among populations who were closer to TRI sites during gestation (Persico, Figlio, and Roth, 2016).

Industrial air pollution, compared with that from other sources, is particularly salient to the residents of neighborhoods near these sites. Residents who live near an industrial site report a higher perception of pollution risk compared with those who live near sources of vehicular pollution (Chakraborty et al., 2017). Much environmental activism has centered around closure or decontamination of industrial sites (Allen et al., 2019; Bratspies, 2020; Knezevich and Condon, 2020). In addition, neighborhoods with TRI sites can become "corrosive communities" with decreased civic engagement and low public trust in government (Brown, 2022; Freudenburg and Jones, 1991).

Air pollution exposure—whether from industrial or other sources—disproportionately affects low-income communities and communities of color (Jones et al., 2014). Historically, Black homebuyers and renters were limited to lower quality neighborhoods by discriminatory policies, such as redlining and exclusionary zoning (Pietila, 2010). As a result of those discriminatory policies, Black Americans are more likely to live in more polluted cities overall and in more polluted neighborhoods within cities (Ash and Fetter, 2004). Areas that received the worst redlining "grade" currently experience a significantly higher burden of air pollution, as well as other environmental hazards, including extreme heat and toxic waste sites (Lane et al., 2022). Present-day residential racial segregation is linked to disparities in both criteria and hazardous air pollutants, which may contribute to well-described disparities in morbidity and mortality (Morello-Frosch and Lopez, 2006).

These disparities are particularly apparent in the distribution of industrial air pollution. Facilities that produce air pollution and other environmental hazards are more likely to have been built in low-income and majority-minority areas (Zwickl, Ash, and Boyce, 2014). Industrial air pollution also tends to be higher in cities with greater residential racial segregation (Ard, 2016). Although industrial air pollution has declined nationwide over the last several decades, racial inequities in pollution exposure persist (Salazar et al., 2019). Even in states with stronger environmental protection policies, the disproportionate burden of industrial air pollution on residents of color has not significantly decreased over the past several decades (Bullock, Ard, and Saalman, 2018).

Air Pollution and Public Housing

Limited literature exists to describe the burden of air pollution among recipients of housing assistance programs. Most studies focus on indoor air pollution, especially that from secondhand smoke, given recent legislation banning smoking in public housing developments (Anastasiou et al., 2020; Galiatsatos et al., 2020). Relatively few studies examine outdoor air pollution exposure among federally assisted households, however. Recent attention has focused on the proximity of public housing developments to Superfund sites or hazardous waste sites in need of remediation. Reports from EPA and the U.S. Department of Housing and Urban Development (HUD) estimate that approximately 77,000 federally assisted households are living within 1 mile of the most polluted Superfund sites (Coffey et al., 2020). These figures provide a conservative estimate of the burden of environmental contamination on federally assisted households, as this number does not include all hazardous waste sites or other housing programs. Extensive organizing by community members and advocacy organizations has shone a spotlight on the health hazards of living near these toxic waste sites, as well as poor coordination between federal, state, and local agencies responsible for housing, pollution, and health (Coffey et al., 2020).

Other analyses examine the location of public housing in relationship to major roadways. In New York State, a significant proportion of public housing developments are in close proximity to major roadways, which may confer greater risk for morbidity and mortality due, in part, to air pollution from mobile sources (Krisko, 2021). Almost 2 percent of public housing developments in the state are in census tracts where PM2.5-related mortality is twice the state average (Krisko, 2021).

Previous Work on LIHTC and Air Pollution

Air pollution is an important but understudied aspect of the neighborhood environment where LIHTC properties are located. One key study describing air pollution exposure among LIHTC properties is that of Ellen, Horn, and Kuai (2018). In that study, Ellen and colleagues used a sample of 12 states for which they were able to obtain individual-level data on LIHTC households. The study included all LIHTC units built up until 2011 or 2012, depending on the quality of state-level data. The sample was constructed with each observation representing either an LIHTC unit or a rental unit. Then, the authors used multiple measures of neighborhood opportunity from the HUD Affirmatively Furthering Fair Housing dataset, including the HUD environmental health index, as dependent variables to describe differences in the neighborhood conditions of LIHTC units compared with other rental units. The authors found that LIHTC units were in neighborhoods with higher poverty rates, worse schools, and lower labor engagement. LIHTC units were also found in neighborhoods with poorer environmental quality, although the magnitude of this difference (1 percentile point) was lower than the difference in other percentile-based indices. By contrast, LIHTC units were found in neighborhoods with a greater percentage of tenants using public transportation and more affordable transportation for low-income residents. Using tenant-level data, the authors also found that, compared with non-poor LIHTC tenants, low-income LIHTC households lived in neighborhoods with greater air pollution. Similarly, Black and Hispanic LIHTC households lived in neighborhoods with greater air pollution than White LIHTC households, even after controlling for household poverty status. Notably, their regressions included fixed effects for the metropolitan statistical area (MSA) but no other neighborhood-level covariates. Thus, the primary findings represent average differences within an MSA and do not account for possible confounders, such as neighborhood poverty level, racial segregation, or other factors that may influence LIHTC siting decisions and the burden of air pollution.

In another analysis focusing on traffic exposure, transit access, and walkability, LIHTC properties were compared with housing choice voucher units in Orange County, California (Houston, Basolo, and Yang, 2013). Compared with voucher units, LIHTC properties were more likely to be found in neighborhoods with commercial, transportation, utilities, or vacant land use and less likely to be found in residential areas. When adjusted for block group demographics and land use, LIHTC properties were less likely than voucher units to be found in high-traffic areas and were thus less exposed to vehicular air pollution. That relationship was not significant when adjusting for walkability and transit characteristics of the neighborhood, however. Similar to trends described above in the characteristics of LIHTC neighborhoods, the findings from Ellen, Horn, and Kuai

(2018) and Houston, Basolo, and Yang (2013) suggest that LIHTC units may experience more air pollution than rental units overall but less than voucher units.

Present Study

This study compares industrial air pollution exposure in neighborhoods with LIHTC properties with neighborhoods without LIHTC properties, although how neighborhood conditions may be contributing to this relationship is unclear. Given racial and economic disparities in both the location of LIHTC properties and the distribution of industrial air pollution, it is hypothesized that neighborhoods with LIHTC properties will be exposed to a higher level of industrial air pollution than neighborhoods without LIHTC. Finally, it is hypothesized that these disparities will persist even after controlling for neighborhood characteristics.

Methods

LIHTC

A publicly available database of LIHTC properties built from 1986 to 2018 was obtained from HUD. Available data include property address, coordinates, and census tract, as well as number of rental units. Properties that were listed as “no longer monitored” by the LIHTC program (~15 percent) were retained because they may still be low-income properties (Ellen, Horn, and Kuai, 2018).

The initial dataset was restricted to 48,278 properties in the 50 states and Washington, D.C. Properties that could be successfully geocoded were retained (n=46,296). Entries corresponding to multiple buildings within the same property were merged into one observation, and duplicate entries were removed, leaving 43,044 properties. Properties were dropped if they were put into service after 2018 or contained 0 or missing units (n=314). For properties with missing year put into service (n=3,306), the value was replaced with the year that funds were allocated plus 1 year, representing the average difference between the year put in service and the year funds were allocated among properties that had both values. Properties missing both the year put in service and the year of funding allocation were dropped (n=1,733). Properties were categorized by year put into service into three time periods: early years (1987–1999), housing bubble era (2000–2007), and crash and recovery period (2008–2018), following the approach of McClure and Schwartz (2021).

Census tracts were designated as having no LIHTC units or least one LIHTC unit. Tracts that could not contain LIHTC properties were removed, including tracts that completely cover bodies of water (n=317); other nonhabitable areas, such as airports (n=423); and tracts with no inhabitants (n=47). Tracts were also removed if they did not contain any multifamily units, defined as a building containing two or more housing units, based on the 2014–2018 American Community Survey 5-year estimates (n=4,709, or 6.5 percent of all remaining tracts). Finally, following the approach of Ellen, Horn, and Kuai (2018), the dataset was restricted to those tracts with greater than 200 inhabitants located in metropolitan areas, as defined by the U.S. Census Bureau 2018 metropolitan divisions (U.S. Census Bureau, 2021).

The final dataset includes 56,379 tracts overall and 16,406 tracts containing LIHTC properties. These metropolitan LIHTC tracts include 32,332 properties and 2.6 million units, or ~67 percent of the entire LIHTC stock.

Industrial Air Pollution

Industrial air pollution was described using the 2018 Risk-Screening Environmental Indicators (RSEI) data (EPA, 2021e). RSEI compiles information reported annually to the Environmental Protection Agency on the release of more than 700 toxic substances, including all hazardous air pollutants, from Toxics Release Inventory (TRI) sites (EPA, 2021f). The RSEI score incorporates dispersion variables such as height of pollutant emission and wind direction to model the pollutant exposure “dose” in the area surrounding each release site. It then adds a “toxicity weight” to each compound released, which represents its relative effect on human health in terms of cancer and non-cancer health outcomes. The RSEI geographic microdata then construct a “toxicity-weighted concentration,” which accounts for both dose and toxicity weight and allows a comparison across geographic areas. These toxicity-weighted concentrations are then scaled on a national percentile in which all census tracts are ranked from 0 to 100 in order of toxicity-weighted concentration, with higher numbers reflecting higher levels of harmful toxic exposures.

The RSEI measure was chosen for several reasons. First, RSEI describes aggregate exposure to hundreds of toxic chemicals rather than focusing on individual pollutants. Those data more accurately model exposure to air pollution than does the simple linear distance to a point source (Chakraborty, Maantay, and Brender, 2011). Second, although the RSEI measure does not model the precise health impact of air pollution (for example, number of excess cancer cases per year), it serves as a screening tool that can describe general trends in burden of air pollution exposure. Third, RSEI models are released yearly, which allows for up-to-date estimates of local sources of air pollution. Area-level measures in the RSEI model are designed to be compared with each other across space and across time (EPA, 2021e). Fourth, the geographic microdata, including toxicity-weighted concentration, are available at the census tract level and can be easily merged with other census-tract level datasets. Finally, the releases relate to specific physical sites, which are identified in the EPA database. State LIHTC allocation agencies and LIHTC developers could locate those sites through the EasyRSEI dashboard and by their RSEI score to help make decisions about where to incentivize and propose new LIHTC properties (EPA, 2020).

Sensitivity analyses that compare this approach to that of Ellen, Horn, and Kuai (2018) use the HUD Affirmatively Furthering Fair Housing (AFFH) environmental health index (HUD PD&R, 2020). This index is constructed from the National Air Toxics Assessment (NATA), another commonly used environmental health index, which models the health risks from hazardous air pollutants (EPA, 2021c). These data model health risk from TRI industrial sites, as well as from mobile sources, such as cars and trucks. An important consideration is that NATA estimates may include different chemicals across years and are thus not intended to be compared across time periods. NATA estimates are also not intended to be compared across geographic areas but rather as a screening tool to highlight areas that may require further study. Higher values on the HUD AFFH environmental health index correspond to better air quality, to compare with other AFFH indices in which higher scores represent better neighborhood conditions, such as improved school quality or higher employment. For ease of comparison with the RSEI percentile, the HUD AFFH environmental health index was inverted so that higher scores on both indices represent increasing burden of air pollution. Ellen, Horn, and Kuai (2018) use the 2012 AFFH index, which uses data from the 2005 NATA release. Models were run with the 2012 AFFH index as well as the more recent 2018 index, based on the 2014 NATA release (HUD, 2020).

Neighborhood Characteristics

Census tract level variables were obtained from the American Community Survey 5-year estimates from 2014 through 2018 for all census tracts in the 50 states and Washington, D.C. Data were retrieved from the IPUMS National Historical Geographic Information System (Manson et al., 2020). Included are several groups of variables known to be associated with both LIHTC location and air pollution exposure. Those factors include data related to the housing market (median rent, percent renter occupancy, percent of rental units left vacant), factors related to socioeconomic status (percent unemployed and percent below federal poverty level), and demographic characteristics (percent Black residents and percent Hispanic residents). Population density and urbanicity are also included. Urbanicity was described using Rural-Urban Commuting Area (RUCA) codes, which categorize tracts on the basis of population density, urbanization, and commuting patterns within metropolitan areas (U.S. Department of Agriculture, Economic Research Service, 2020). Tracts were categorized as urban, suburban, large rural, or small rural (Washington State Department of Health, 2016).

Analysis Methods

The analysis began by describing differences between census tracts that contain LIHTC properties and census tracts that do not, using one-way analysis of variance or Chi^2 tests. Next, several logistic regression models were estimated in which the RSEI toxicity-weighted concentration nationally ranked percentile was the independent variable and the presence of any LIHTC property was the dependent variable. Each regression model included a fixed effect for the MSA in which each tract is located. For MSAs that cover multiple states, a fixed effect was used, which referred to the combination of MSA and state that applied to a given census tract. For adjusted models, covariates were added to the model by category of covariates (urbanicity, housing market characteristics, socioeconomic status, race and ethnicity). Thus, these models describe the independent association of industrial air pollution with the presence of LIHTC in a tract while controlling for variables that may be associated both with LIHTC location and burden of air pollution. The regression equation is shown below:

$$Log\ Odds(LIHTC) = \beta_0 + \beta_1 * RSEI_i + \beta_2 * X_i + \sigma_j + \varepsilon_j$$

In this equation, $LIHTC_i$ is an indicator variable for the presence or absence of at least one LIHTC unit in census tract *i*. $RSEI_i$ is the inverted nationally ranked percentile of the RSEI industrial air pollution toxicity-weighted concentration for a given census tract. β_0 is the intercept. β_1 is the regression coefficient; when exponentiated, this variable represents the odds ratio for each 10-percentile-point increase in the RSEI industrial air pollution score. β_2 is a vector of estimated coefficients, and X_i is an array of tract-level variables. σ_j is the state or MSA fixed effect. ε_j represents standard errors clustered by MSA. Results are presented as odds ratios, or the exponentiated forms of the coefficients in this equation.

In secondary analyses, separate unadjusted and fully adjusted regressions were run, in which the dependent variable was the presence of LIHTC units built in each of the three time periods (1987–1999, 2000–2007, 2008–2018). Separate regression models for each state and Washington, D.C., were run, to explore whether the relationship between industrial air pollution and the presence of LIHTC units differed across jurisdictions. For the final secondary analysis, the sample was restricted to those tracts that contain at least one LIHTC unit. This analysis used a linear regression model in which the dependent variable was the number of LIHTC units in the tract, and the independent variables were the RSEI percentile and covariates as described above. In this analysis, the dependent variable (number of LIHTC units) was highly positively skewed, so tracts with greater than 1,000 units were "top coded" (n=125, or 0.7 percent of all LIHTC tracts).

A series of sensitivity analyses were performed to explicitly compare the findings with those of Ellen, Horn, and Kuai (2018), which describes the differences in neighborhood conditions between LIHTC units and rental units in 12 states. First, the sample was limited to the LIHTC units that had been built in those 12 states in or before 2012. Next, a primary regression was performed (odds of LIHTC properties in the tract versus air pollution index) using four separate models, each using a different air pollution index as the independent variable: (1) the HUD environmental health index from 2012, as used by Ellen and colleagues; (2) an updated HUD environmental health index from 2018; (3) the RSEI index from 2012; and (4) the RSEI index from 2018 as used in the rest of this analysis. Then, the four models were estimated in the main sample, which includes all 50 states and all LIHTC units through 2018. The correlation coefficients between these four air pollution measures are also presented.

Finally, two other sensitivity analyses were included to test several assumptions in the modeling. Included first is a regression in which the independent variable is the RSEI measure categorized into quartiles, which allows a test of the assumption that the relationship between air pollution and the odds of LIHTC is linear. Second, a comparison was made between regressions in which the sample excludes tracts without multifamily units (the main cohort) versus regressions that include those tracts.

Results

LIHTC properties were found in 29 percent of metropolitan census tracts (exhibit 1). About one-fourth of LIHTC tracts had 50 units or less, whereas another one-fourth contained more than 200 units. Tracts with LIHTC properties differed in several key characteristics from tracts without LIHTC properties. Compared with non-LIHTC tracts, LIHTC tracts had higher proportions of Black residents (22.6 percent versus 12.3 percent, $p<0.001$) and Hispanic residents (20.1 percent versus 17.7 percent, $p<0.001$). Socioeconomic disadvantage was greater in LIHTC tracts, with an average poverty rate of 20.4 percent. LIHTC tracts were more densely populated and had greater proportions of renters (50.8 percent versus 35.7 percent, $p<0.001$). On a national level, LIHTC tracts in metropolitan areas experienced 1.7 percentile points higher industrial air pollution than non-LIHTC tracts (55.6 versus 53.9, $p<0.001$).

Exhibit 1

Bivariate Analysis of Census Tract Characteristics by Presence of LIHTC Properties

	Census Tracts With LIHTC Properties N (%) or Mean (SD)	**Census Tracts Without LIHTC Properties** N (%) or Mean (SD)
Total	16,406 (100%)	39,973 (100%)
Number of LIHTC Units per Tract		
1 to 50	4,437 (27.0%)	---
51 to 100	3,839 (23.4%)	---
101 to 200	4,103 (25.0%)	---
201+	4,027 (24.6%)	---
Population Density, in People per Mi²	7,886 (16,028)	6,270 (12,297)
Urbanicity		
Urban	14,060 (85.7%)	34,792 (87.1%)
Suburban	1,299 (7.9%)	3,873 (9.7%)
Large Rural	590 (3.6%)	735 (1.8%)
Small Rural	457 (2.8%)	552 (1.4%)
Median Rent, in $	1,007 (372)	1,228 (485)
% Renter Occupied	50.8 (22.6)	35.7 (22.4)
% Vacancy	11.2 (8.5)	10.1 (9.4)
% Unemployment	7.7 (5.5)	5.9 (4.1)
% Below Poverty	20.7 (13.4)	13.0 (10.9)
% Black	22.6 (27.5)	12.3 (20.0)
% Hispanic	20.1 (23.8)	17.7 (21.8)
RSEI Industrial Air Pollution Percentile	55.6 (27.9)	53.9 (27.9)

LIHTC = Low-Income Housing Tax Credit. RSEI = Risk-Screening Environmental Indicators.

Notes: Includes all metropolitan tracts nationwide with >200 residents and multifamily housing. Sample includes metropolitan tracts nationwide with >200 residents and multifamily housing. All differences significant at p <0.01.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Industrial air pollution was associated with the presence of LIHTC in a tract (exhibit 2). In the initial model, a 10-percentile-point increase in industrial air pollution was associated with 8-percent higher odds of LIHTC properties being located in that tract (OR 1.08, 95 percent CI [1.04, 1.12]).[1] This relationship was similar in the model that then adjusted for population density and urbanicity (OR 1.05, 95 percent CI [1.02, 1.09]). However, in the model that adjusted for housing market characteristics—including median rent, proportion of renters, and proportion of vacant properties—the relationship between industrial air pollution and the presence of LIHTC in a tract was inverted: a 10-percentile-point increase in industrial air pollution was significantly associated with lower odds of LIHTC properties being located in a tract (OR 0.96, 95 percent CI [0.93, 0.98]). The industrial air pollution percentile was not significantly associated with LIHTC in models that controlled for socioeconomic status or for those that accounted for area-level race and ethnicity. In the fully adjusted model, similar to the model adjusted only for housing market characteristics, a 10-percentile-point increase in industrial air pollution was associated with

[1] CI = confidence interval. OR = odds ratio.

5-percent lower odds of LIHTC properties being located in a tract, all else being equal (OR 0.95, 95 percent CI [0x.93, 0.98]).

Exhibit 2

Logistic Regression for Odds of LIHTC in a Tract Associated with a 10-Point Increase in RSEI Industrial Air Pollution Percentile

	Unadjusted	Urbanicity	Housing Market	Socioeconomic Status	Race & Ethnicity	Full Model
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
RSEI Industrial Air Pollution Percentile (10-point increase)	1.08*** (1.04, 1.12)	1.05*** (1.02, 1.09)	0.96*** (0.93, 0.98)	0.99 (0.96, 1.02)	0.97 (0.93, 1.01)	0.95** (0.93, 0.98)
Population Density, in 100 Persons/Mi²	---	1.00*** (1.00, 1.00)	---	---	---	1.00 (1.00, 1.00)
Urbanicity (ref: Urban)	---	Ref.	---	---	---	Ref.
- Suburban	---	0.77*** (0.69, 0.87)	---	---	---	1.22** (1.05, 1.41)
- Large Rural	---	1.91*** (1.67, 2.19)	---	---	---	2.01*** (1.71, 2.37)
- Small Rural	---	1.95*** (1.66, 2.29)	---	---	---	2.15*** (1.78, 2.59)
Median Rent, in $100	---	---	0.85*** (0.82, 0.88)	---	---	0.89*** (0.86, 0.92)
% Renters^	---	---	1.03*** (1.03, 1.03)	---	---	1.03*** (1.02, 1.03)
% Vacant^	---	---	1.00 (0.99, 1.00)	---	---	0.98*** (0.98, 0.99)
% Unemployment^	---	---	---	1.02*** (1.01, 1.03)	---	1.01 (1.00, 1.02)
% Below Poverty^	---	---	---	1.06*** (1.05, 1.06)	---	1.01*** (1.00, 1.01)
% Black^	---	---	---	---	1.03*** (1.03, 1.03)	1.01*** (1.01, 1.02)
% Hispanic^	---	---	---	---	1.02*** (1.02, 1.03)	1.00 (1.00, 1.01)
Number of Tracts	56,361	56,357	55,729	56,358	56,360	55,726

CI = confidence interval. OR = odds ratio. RSEI = Risk-Screening Environmental Indicators.

** p < 0.05. ** p < 0.01. *** p < 0.001.*

Notes: Sample includes metropolitan tracts nationwide with >200 residents and multifamily housing. All models include MSA fixed effects. ^ signifies change in odds ratio, ceteris paribus, associated with a 1-point increase in the independent variable from its mean.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Several tract-level characteristics were also associated with the odds of LIHTC in the tract (exhibit 2). In fully adjusted models, suburban and rural tracts were more likely to contain LIHTC properties compared with urban tracts. Tracts with lower rents and a greater proportion of renters were more likely to contain LIHTC, whereas tracts with higher vacancy rates were less likely to contain LIHTC. Tracts with higher poverty rates and a greater proportion of Black residents were more likely to contain LIHTC properties, all else equal.

The point estimates of the relationship between present-day industrial air pollution and the odds of LIHTC development was relatively consistent across three periods in the history of the LIHTC program (exhibit 3). Similar to trends noted above for all LIHTC properties, tracts with higher industrial air pollution had higher odds of LIHTC development in the 2000–2007 and 2008–2018 periods. In addition, in models fully adjusted for neighborhood covariates, higher industrial air pollution was associated with lower odds of LIHTC development in the 1987–1999 and 2000–2007 periods.

Exhibit 3

Logistic Regression for Odds of LIHTC Built in One of Three Periods Associated with a 10-Point Increase in RSEI Industrial Air Pollution Percentile

	Unadjusted			Adjusted		
	1987–1999	2000–2007	2008–2018	1987–1999	2000–2007	2008–2018
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
RSEI Industrial Air Pollution Percentile (10-point increase)	1.05 (1.00, 1.10)	1.09*** (1.04, 1.14)	1.08*** (1.04, 1.13)	0.95* (0.92, 0.99)	0.96* (0.93, 1.00)	0.97 (0.94, 1.00)
Number of Tracts	56,138	56,206	56,138	55,505	55,572	55,505

CI = confidence interval. OR = odds ratio. RSEI = Risk-Screening Environmental Indicators.

** p < 0.05. ** p < 0.01. *** p < 0.001.*

Notes: Sample includes metropolitan tracts nationwide with >200 residents and multifamily housing. All models include MSA fixed effects. Adjusted models are controlled for population density, urbanicity, median rent, % renter, % vacant, % unemployment, % below poverty, % Black residents, and % Hispanic residents.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Similar trends were seen when analyzing by individual states (exhibit A1). In general, most states had higher odds of LIHTC among more polluted tracts, and this relationship tended to be attenuated or reversed in adjusted models. In two states (NV and WA), however, LIHTC properties were more likely to be found in more polluted tracts, even when adjusting for neighborhood covariates.

Industrial air pollution was also associated with the number of LIHTC units among those tracts that contain at least one LIHTC unit (exhibit A2). A 10-percentile-point increase in industrial air pollution was associated with an increase of nearly 10 LIHTC units within a given MSA (beta 9.7, 95 percent CI [7.0, 12.5]). That relationship was no longer significant when accounting for neighborhood covariates, however (beta -0.6, 95 percent CI [-3.1, 0.8]).

In sensitivity analyses, similar trends to the main findings described above were observed when using the 2012 12-state sample from Ellen, Horn, and Kuai (2018) (exhibit 4); that is, higher levels of air pollution—using either the HUD environmental health index or RSEI industrial air pollution percentile from 2012 or 2018—were associated with increased odds of LIHTC in unadjusted models. As above, the direction of those relationships was reversed in the fully adjusted models.

Results using the full national sample and the four measures of pollution were similar to those found using the 12-state sample. Correlations across all four indices were positive and significant; correlations were stronger between 2012 and 2018 versions of the same index than correlations between the HUD index and the RSEI percentile (exhibit A3).

Exhibit 4

Logistic Regression for Odds of LIHTC in a Tract Associated with a 10-Point Increase in Air Pollution Percentile

	12-State Sample, 2012		Full National Sample, 2018	
	Unadjusted	Adjusted	Unadjusted	Adjusted
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
RSEI Percentile 2012	1.06* (1.01, 1.12)	0.95* (0.92, 0.99)	1.08** (1.03, 1.13)	0.96* (0.93, 0.98)
RSEI Percentile 2018^	1.07** (1.03, 1.12)	0.94*** (0.90, 0.97)	1.08*** (1.04, 1.12)	0.95** (0.93, 0.98)
HUD Index 2012^^	1.16*** (1.10, 1.23)	0.93*** (0.89, 0.97)	1.15*** (1.11, 1.18)	0.92*** (0.89, 0.94)
HUD Index 2018	1.19*** (1.12, 1.26)	0.97 (0.93, 1.01)	1.18*** (1.14, 1.22)	0.95** (0.91, 0.98)
Number of Tracts	27,372	27,083	56,354	55,722

CI = confidence interval. OR = odds ratio. RSEI = Risk-Screening Environmental Indicators.

^ Index used in current analysis.

^^ Index used in Ellen, Horn, and Kuai (2018).

$* p < 0.05$. $** p < 0.01$. $*** p < 0.001$.

Notes: Sample includes metropolitan tracts with >200 residents and multifamily housing. Outcome is presence of LIHTC units built in 2012 or earlier (12-state sample) or presence of LIHTC units built in 2018 or earlier (full national sample). All models include MSA fixed effects. Adjusted models are controlled for population density, urbanicity, median rent, % renter, % vacant, % unemployment, % below poverty, % Black residents, and % Hispanic residents.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) Model

Analyses that categorized industrial air pollution in quartiles revealed similar results (exhibit A4). The odds of LIHTC increased monotonically with higher quartiles of industrial air pollution (OR 1.47, 95 percent CI [1.20, 1.80] for most polluted quartile, compared with least polluted quartile) in unadjusted models. In adjusted models, the effect size of the relationship with LIHTC also increased with increasing air pollution quartile. In other words, tracts with the highest burden of industrial air pollution had the lowest odds of LIHTC, when controlling for neighborhood characteristics. Finally, analyses that retained tracts without multifamily construction revealed similar results to the main findings that include only tracts with multifamily construction (exhibit A5).

Discussion

The findings indicate that, within a given metropolitan area, LIHTC properties are more likely to be found in tracts with poorer air quality. Although the specific health impact of this excess industrial air pollution burden is not known, a small difference between LIHTC and non-LIHTC neighborhoods could have important health implications when applied across millions of LIHTC residents nationwide. Indeed, small reductions in average PM2.5 levels have been associated with communitywide decreases in asthma exacerbation rates and cardiovascular mortality (Rajagopalan, Al-Kindi, and Brook, 2018; Simeonova et al., 2021). These findings add to the growing body of literature that describes the qualities of LIHTC neighborhoods and the complex relationships that exist among neighborhood features.

This finding aligns with previous work that suggested that LIHTC units are exposed to more air pollution than rental units overall within the same MSA (Ellen, Horn, and Kuai, 2018). Previous studies, however, presented associations that do not account for neighborhood-level covariates such as renter population, median rent, or neighborhood demographics, which may be associated with both air pollution burden and LIHTC development. The adjusted analysis in this study indicates that the direction of the relationship between air pollution and LIHTC location *reverses* when adjusting for those important covariates. This reversal of association between adjusted and unadjusted models was consistent even when applying the current model to the 12-state sample used in previous work and with different environmental health indices from multiple years.

In particular, housing market factors—including median rent, vacancy, and proportion of renters—may drive many LIHTC siting decisions, based on property values and rental demand, and those forces may have the undesired effect of locating LIHTC developments in more polluted neighborhoods overall. When local variations in housing markets are considered, LIHTC residents may experience somewhat *better* air quality when compared with residents of similar neighborhoods.

The findings from this study also show that, among neighborhoods with LIHTC, more polluted tracts were found to have higher numbers of LIHTC developments; however, that relationship was no longer significant when controlling for neighborhood covariates. Thus, LIHTC units may be more concentrated in polluted neighborhoods within a given MSA, but that circumstance may be due to other factors, such as neighborhood poverty level or housing market factors, which may promote larger or multiple developments within a given area. These findings suggest that, on balance, the burden of air pollution is disproportionate in areas in which LIHTC residents reside.

Consistent with previous research, this study found that LIHTC properties are more likely to be found in neighborhoods with a greater degree of poverty and unemployment (Ellen, Horn, and Kuai, 2018). LIHTC properties were in areas with lower median rents and higher concentrations of renters, which reflects the demand for low-cost rental properties in those areas. LIHTC properties were also more likely to be found in tracts with a higher proportion of Black residents, even after controlling for other neighborhood factors, such as socioeconomic status and housing market characteristics. The combination of higher exposure to industrial air pollution and higher proportion of Black residents in a neighborhood should motivate investigation into structural forces, such as housing segregation and environmental racism, which produce both poor quality housing and environmental harms in neighborhoods with low-income residents and people of color.

The spatial distribution of LIHTC should be considered in the context of complex funding priorities in Qualified Allocation Plans (QAPs). Although recent policy shifts are expanding the development of LIHTC properties in higher-income and suburban areas, multiple federal and state priorities over the program's history have concentrated properties in urban low-income neighborhoods. Other well-intentioned incentives within QAPs may also increase air pollution exposure, such as incentives awarded for locating LIHTC near employment or transit centers. The excess pollution risk experienced by workers of color living near industrial centers generally exceeds the excess employment benefit, however (Ash and Boyce, 2018), so developers should carefully evaluate those opposing forces when considering where to locate new properties. Developers must choose between maximizing the number of households that can be assisted by their properties and offering fewer units in areas where building is more expensive. When choosing between similar neighborhoods, developers likely prioritize areas that may be more appealing to potential tenants or that may face less resistance to development from local stakeholders. Many developers may choose to use LIHTC funds to modernize existing public housing developments. Because those properties are also more likely to be located in disadvantaged neighborhoods, developers may tend to concentrate LIHTC developments in areas with higher pollution exposure. Overall, many complex tradeoffs exist in deciding where LIHTC developments are built, and policy priorities that provide value in one area (transit access, proximity to community health centers, renovation of distressed housing) may bring about unintended or unavoidable consequences (neighborhood poverty, segregation, or air pollution exposure). Indeed, the definition of a "healthy neighborhood" is complex and may vary on the basis of the priorities and perceptions of its residents. In qualitative interviews with LIHTC tenants, residents recognize benefits (such as proximity to work, school, and cultural groups) and limitations (such as crime and pollution) of living in a neighborhood that may be considered impoverished or disadvantaged and often view their neighborhood more positively than objective measures of neighborhood quality might suggest (Reid, 2019). The current work suggests that developers and officials must consider air quality in relation to the range of factors when making decisions about where to prioritize housing credits.

These findings should be interpreted in the context of several limitations. Although this dataset is the most accurate source of LIHTC property data available, the data are reported to HUD by the programs and thus may be inaccurate or incomplete. This analysis describes average trends within MSAs; given that certain states have more expressly focused on building LIHTC in low-poverty areas, important variation likely exists between states or MSAs in the characteristics of LIHTC neighborhoods. State and local policymakers should consider how LIHTC and air pollution may be related in their specific jurisdiction. This analysis is not able to describe the timing of the placement of LIHTC developments compared with the timing of industrial development, although it attempts to demonstrate the relationship between phases of LIHTC development and present-day industrial air pollution. Industrial development may come before or after LIHTC construction, so this analysis shows the present results of decades of LIHTC siting decisions. For example, a new LIHTC property could be built near an existing industrial site, or a new industrial site could be built near an existing LIHTC property. In both situations, LIHTC residents are exposed to pollution, but the two scenarios would require different sets of policy solutions. For example, QAP disincentives could discourage building in areas with a high burden of pollution, whereas community organization and empowerment of LIHTC residents could prevent the construction of new pollution facilities in vulnerable neighborhoods. This analysis is unable to describe specific health consequences using these percentile-based environmental health indices, as it does not contain an inherent cutoff over which an area is considered "unsafe." The analyses do not account for spatial autocorrelation in the distribution of air pollution, LIHTC siting, or other neighborhood covariates, which are likely to be spatially dependent. Finally, this analysis does not include other important sources of pollution, such as traffic; the impact of industrial versus vehicular air pollution on LIHTC may be different given explicit priorities in some QAPs to locate LIHTC properties either away from highways or near transportation hubs. However, there were similar results when using the HUD AFFH environmental health index (based on the NATA index), which includes mobile sources of pollution, such as cars and trucks, in addition to stationary industrial sources.

Conclusions and Policy Recommendations

Overall, the findings of this study emphasize the importance of considering place when developing affordable housing. Local policymakers should consider how to use QAPs to prioritize building LIHTC properties in neighborhoods that promote the well-being of their residents. Recent initiatives to shift LIHTC development to high-opportunity neighborhoods show promise in locating LIHTC properties in lower poverty areas, which may carry an added benefit of decreasing air pollution exposure. Given the findings of this study, there are several suggested avenues for minimizing air pollution exposure while balancing the complex tradeoffs inherent in decision-making around LIHTC siting.

State QAPs can incentivize (or mandate) developers to provide a comprehensive summary of neighborhood conditions in areas where new properties are proposed. Notably, developments funded by HUD must comply with certain environmental justice standards and produce environmental assessments before receiving funding (Haberle, 2017). Those requirements do not necessarily apply to LIHTC properties, however, which are administered through the Department of the Treasury (Joint Center for Housing Studies of Harvard University, 2009). Although state LIHTC funding authorities often require such assessments, those environmental assessments or remediation efforts could be strengthened by mandatory enforcement, as in HUD programs.

Harmful exposures to pollution, however, should be considered alongside neighborhood assets, including access to schools, jobs, green space, healthy food, social support, and other opportunities. Some states, such as California, have expanded their emphasis on describing and incentivizing developments in high-opportunity neighborhoods (Reid, 2019). Beyond describing neighborhood conditions, states can also commission Health Impact Assessments to characterize the health benefits or risks of developing in a particular area. QAPs can use these data to explicitly prioritize development in health-promoting neighborhoods, recognizing that tradeoffs and balances among different factors may exist (for example, locating close to transportation hubs versus less dense neighborhoods). Finally, given that households living in LIHTC properties may experience less industrial air pollution compared with other, similar neighborhoods, more research is needed to understand the specific mechanisms within QAPs that produce this benefit. Much of that analysis will be most meaningful if conducted at a state or local level to understand how the national findings apply to the housing markets and policy landscapes in each jurisdiction.

In addition to housing agencies, other stakeholders can take steps to reduce pollution exposure among LIHTC residents. Although the implications of those findings for the siting of new industrial facilities is beyond the scope of this current study, policies can be considered which limit the development of polluting facilities in close proximity to existing LIHTC properties or other federally assisted housing. Enhanced coordination between HUD, LIHTC, and EPA can ensure that local housing agencies (and their tenants) are informed about environmental concerns (Coffey et al., 2020). Overall, governmental agencies, advocacy organizations, and community members should work in concert to limit the disproportionate burden of air pollution and other environmental harms on federally assisted households.

Appendix

Exhibit A1

Logistic Regression for Odds of LIHTC in a Tract Associated with a 10-Point Increase in RSEI Industrial Air Pollution Percentile (1 of 2)

State	Unadjusted	Adjusted	Number of Tracts
	OR	OR	
AK	1.41***	0.99	92
AL	0.97	0.99	734
AR	1.06	0.84*	365
AZ	1.11**	0.98	1,163
CA	1.02	0.88***	7,236
CO	1.13	1.09	938
CT	1.16	0.87	738
DC	0.79	1.11	175
DE	1.20	0.84***	190
FL	1.12**	0.96	3,721
GA	0.99	1.01	1,326
HI	1.28***	0.93	258
IA	1.07	0.89	433
ID	0.98	0.94	190
IL	1.05	0.92	2,562
IN	1.15***	1.04	1,057
KS	0.90*	0.90	437
KY	1.03	0.93	578
LA	0.91**	0.88	841
MA	1.01	0.90*	1,400
MD	1.14**	0.91*	1,190
ME	1.30***	1.08	183
MI	1.04	0.92	1,991
MN	1.03	0.93	920

Exhibit A1

Logistic Regression for Odds of LIHTC in a Tract Associated with a 10-Point Increase in RSEI Industrial Air Pollution Percentile (2 of 2)

State	Unadjusted	Adjusted	Number of Tracts
MO	1.10***	0.86	942
MS	1.01	0.97	261
MT	1.26	1.03	81
NC	1.13*	1.00	1,493
ND	1.81***	1.40	74
NE	1.24	0.93	289
NH	1.91***	1.33	165
NJ	1.07**	0.93**	1,864
NM	1.20	0.77***	272
NV	1.22*	1.10*	549
NY	1.26	0.97	4,270
OH	1.12	0.99	2,277
OK	0.88***	1.02	592
OR	1.05	0.94	627
PA	1.13*	1.00	2,700
RI	1.08	1.12	237
SC	0.96	1.00	785
SD	1.59**	1.13	82
TN	1.14**	1.04	1,027
TX	1.06	0.98	4,017
UT	0.91*	0.93	476
VA	1.20***	0.95	1,377
VT	0.19	0.028	37
WA	1.23***	1.17*	1,181
WI	1.04	0.85*	993
WV	0.96	1.01	286
WY	2.37*	1.20	33

CI = confidence interval. OR = odds ratio.

** $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.*

Notes: Sample includes metropolitan tracts with >200 residents and multifamily housing. All models include MSA fixed effects. Adjusted models are controlled for population density, urbanicity, median rent, % renter, % vacant, % unemployment, % below poverty, % Black residents, % Hispanic residents.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Exhibit A2

Linear Regression for Number of LIHTC Units in a Tract Associated with a 10-Point Increase in RSEI Industrial Air Pollution Percentile

	Unadjusted	Full Model
	Beta (95% CI)	Beta (95% CI)
RSEI Industrial Air Pollution Percentile (10-point increase)	9.7*** (7.0, 12.5)	-0.6 (-3.1, 1.8)
Population Density, in 100 Persons/mi²	---	-0.02 (-0.07, 0.03)
Urbanicity (ref: Urban)	---	Ref.
- Suburban	---	-22.2*** (-31.1, -13.3)
- Large Rural	---	-10.8 (-23.3, 1.64)
- Small Rural	---	-23.3*** (-36.0, -10.5)
Median Rent, in $100	---	-2.2 (-4.7, 0.3)
% Renters^	---	2.2*** (1.9, 2.5)
% Vacant^	---	-2.9*** (-3.5, -2.3)
% Unemployment^	---	-0.9* (-1.6, -0.2)
% Below Poverty^	---	0.4 (-0.1, 0.8)
% Black^	---	0.5*** (0.3, 0.8)
% Hispanic^	---	-0.5** (-0.9, -0.2)
Number of Tracts	16,406	16,357

CI = confidence interval. RSEI = Risk-Screening Environmental Indicators.

^ signifies change in odds ratio, ceteris paribus, associated with a 1-point increase in the independent variable from its mean.

** $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.*

Notes: Sample includes metropolitan tracts nationwide with >200 residents and multifamily housing that contains at least one LIHTC property. All models include MSA fixed effects. Betas correspond to the change in number of LIHTC units in a tract per change in independent variable.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Exhibit A3

Correlation Coefficients Between Air Pollution Percentile Indices

	RSEI Percentile 2012	RSEI Percentile 2018	HUD Index 2012	HUD Index 2018
RSEI Percentile 2012	--	--	--	--
RSEI Percentile 2018	0.85***	--	--	--
HUD Index 2012	0.25***	0.20***	--	
HUD Index 2018	0.36***	0.32***	0.66***	--

RSEI = Risk-Screening Environmental Indicators.

*** $p < 0.001$.

Notes: Higher scores on each air pollution index indicates higher burden of air pollution. HUD index used here is inverted from original form, so that higher values correspond to higher pollution. Sample includes metropolitan tracts with >200 residents and multifamily housing.

Sources: HUD, Affirmatively Furthering Fair Housing (AFFH) Opportunity Indices; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Exhibit A4

Logistic Regression for Odds of LIHTC in a Tract Associated with Increasing Quartiles of Risk-Screening Environmental Indicators (RSEI) Industrial Air Pollution Percentile

	Unadjusted	Full Model
RSEI Industrial Air Pollution Percentile	OR (95% CI)	OR (95% CI)
Quartile 1 (0–25%)	Ref.	Ref.
Quartile 2 (25–50%)	1.19* (1.01, 1.40)	0.96 (0.83, 1.10)
Quartile 3 (50–75%)	1.20 (0.97, 1.48)	0.84* (0.71, 0.99)
Quartile 4 (75–100%)	1.47*** (1.20, 1.80)	0.77** (0.63, 0.93)
p-Value for Trend	<0.001	-0.007
Number of Tracts	56,361	55,726

CI = confidence interval. RSEI = Risk-Screening Environmental Indicators. OR = odds ratio.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Notes: Sample includes metropolitan tracts nationwide with >200 residents and multifamily housing. All models include MSA fixed effects. Adjusted models are controlled for population density, urbanicity, median rent, % renter, % vacant, % unemployment, % below poverty, % Black residents, % Hispanic residents.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Exhibit A5

Logistic Regression for Odds of LIHTC in a Tract, Given a 10-Point Increase in RSEI Industrial Air Pollution Percentile

	Unadjusted (all metro tracts)	Unadjusted (multifamily only)	Full Model (all metro tracts)	Full Model (multifamily only)
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
RSEI Industrial Air Pollution Percentile (10-point increase)	1.10*** (1.06, 1.14)	1.08*** (1.04, 1.12)	0.96** (0.93, 0.98)	0.95** (0.93, 0.98)
Population Density, in 100 Persons/Mi^2	---	---	1.00 (1.00, 1.00)	1.000 (0.999, 1.001)
Urbanicity (ref: Urban)	---	---	Ref.	Ref.
- Suburban	---	---	1.08 (0.94, 1.25)	1.22** (1.05, 1.41)
- Large Rural	---	---	1.96*** (1.67, 2.30)	2.01*** (1.71, 2.37)
- Small Rural	---	---	1.99*** (1.66, 2.39)	2.15*** (1.78, 2.50)
Median Rent, in $100	---	---	0.88*** (0.85, 0.92)	0.89*** (0.86, 0.92)
% Renters^	---	---	1.03*** (1.02, 1.03)	1.03*** (1.02, 1.03)
% Vacant^	---	---	0.98*** (0.98, 0.99)	0.98*** (0.98, 0.99)
% Unemployment^	---	---	1.01 (1.00, 1.01)	1.01 (1.00, 1.02)
% Below Poverty^	---	---	1.01** (1.00, 1.01)	1.01*** (1.00, 1.01)
% Black^	---	---	1.01*** (1.01, 1.02)	1.01*** (1.01, 1.02)
% Hispanic^	---	---	1.00 (1.00, 1.01)	1.00 (1.00, 1.01)
Number of Tracts	60,220	56,361	59,157	55,726

CI = confidence interval. RSEI = Risk-Screening Environmental Indicators. OR = odds ratio.

** p < 0.05. ** p < 0.01. *** p < 0.001.*

^ signifies change in odds ratio, ceteris paribus, associated with a 1-point increase in the independent variable from its mean.

Notes: Sample includes metropolitan tracts with >200 residents and multifamily housing. All models include MSA fixed effects.

Sources: 2014–2018 American Community Survey 5-year estimates; LIHTC HUD User database; U.S. Department of Agriculture Economic Research Service Rural-Urban Community Area Codes; U.S. Environmental Protection Agency, Risk-Screening Environmental Indicators (RSEI) 2018 Model

Acknowledgments

The authors gratefully acknowledge Max Goplerud and Kyle Aune for their technical assistance, as well as our anonymous reviewers.

Disclosure Statement

Dr. Pollack works part time on a temporary assignment with the U.S. Department of Housing and Urban Development (HUD), assisting the department on housing and health issues. All other authors have no disclosures to report. The findings and conclusions in this article are those of the authors and do not necessarily represent those of HUD or other government agencies.

Funding

This work was supported by NICHD Grant 1R03HD098411. This work was also supported by Grant TL1 TR003100 from the National Center for Advancing Translational Sciences (NCATS), a component of the National Institutes of Health.

Authors

Dana Goplerud is a resident physician in the Departments of Medicine and Pediatrics at the Johns Hopkins School of Medicine. She can be reached at dgopler1@jhmi.edu. Sarah Gensheimer is an MD/PhD candidate at the Johns Hopkins School of Medicine and the Department of Health Policy and Management at the Johns Hopkins Bloomberg School of Public Health. Benjamin Schneider is a research assistant in the Department of Health Policy and Management at the Johns Hopkins Bloomberg School of Public Health. Matthew Eisenberg is an associate professor in the Department of Health Policy and Management at the Johns Hopkins Bloomberg School of Public Health. Genee Smith is an assistant professor in the Department of Environmental Health and Engineering at the Johns Hopkins Bloomberg School of Public Health. Craig Pollack is the Katey Ayers Endowed Professor in the Departments of Epidemiology and Health Policy and Management at the Johns Hopkins Bloomberg School of Public Health and the Johns Hopkins Schools of Medicine and Nursing.

References

Adamkiewicz, Gary, Jahred Liddie, and Jonathan M. Gaffin. 2020. "The Respiratory Risks of Ambient/Outdoor Air Pollution," *Clinics in Chest Medicine* 41 (4): 809. https://doi.org/10.1016/J.CCM.2020.08.013.

Allen, Shauntice, Michelle V. Fanucchi, Lisa C. McCormick, and Kristina M. Zierold. 2019. "The Search for Environmental Justice: The Story of North Birmingham," *International Journal of Environmental Research and Public Health* 16 (12): 2117. https://doi.org/10.3390/IJERPH16122117.

Anastasiou, Elle, Alexis Feinberg, Albert Tovar, Emily Gill, M.J. Ruzmyn Vilcassim, Katarzyna Wyka, Terry Gordon, Ana M. Rule, Sue Kaplan, Brian Elbel, Donna Shelley, and Lorna E. Thorpe. 2020. "Secondhand Smoke Exposure in Public and Private High-Rise Multiunit Housing Serving Low-Income Residents in New York City Prior to Federal Smoking Ban in Public Housing, 2018," *Science of the Total Environment* 704: 135322. https://doi.org/10.1016/J.SCITOTENV.2019.135322.

Ard, Kerry. 2016. "By All Measures: An Examination of the Relationship Between Segregation and Health Risk from Air Pollution," *Population and Environment* 38 (1): 1–20. https://doi.org/10.1007/s11111-015-0251-6.

Ash, Michael, and James K. Boyce. 2018. "Racial Disparities in Pollution Exposure and Employment at US Industrial Facilities," *Proceedings of the National Academy of Sciences* 115 (42):10636–10641. https://doi.org/10.1073/PNAS.1721640115.

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. https://doi.org/10.1111/j.0038-4941.2004.08502011.x.

Bratspies, Rebecca M. 2020. "Public Housing, Private Owners: Sustainable Development Lessons from the Fight to Shut the Poletti Power Plant," *SSRN*, May 6. https://doi.org/10.2139/SSRN.3593946.

Brown, Phylicia Xin Yi Lee. 2022. "Industrial Pollution, Social Trust, and Civic Engagement: A Nationwide Study of the Socioenvironmental Nature of Social Capital," *Sociological Perspectives*, January 13. https://doi.org/10.1177/07311214211067755.

Bu, Xiang, Zhonglei Xie, Jing Liu, Linyan Wei, Xiqiang Wang, Mingwei Chen, and Hui Ren. 2021. "Global PM2.5-Attributable Health Burden from 1990 to 2017: Estimates from the Global Burden of Disease Study 2017," *Environmental Research* 197: Article 111123. https://doi.org/10.1016/J.ENVRES.2021.111123.

Bullock, Claire, Kerry Ard, and Grace Saalman. 2018. "Measuring the Relationship between State Environmental Justice Action and Air Pollution Inequality, 1990–2009," *Review of Policy Research* 35 (3): 466–490. https://doi.org/10.1111/ROPR.12292.

Chakraborty, Jayajit, Timothy W. Collins, Sarah E. Grineski, and Alejandra Maldonado. 2017. "Racial Differences in Perceptions of Air Pollution Health Risk: Does Environmental Exposure Matter?" *International Journal of Environmental Research and Public Health* 14 (2): 116. https://doi.org/10.3390/IJERPH14020116.

Chakraborty, Jayajit, Juliana A. Maantay, and Jean D. Brender. 2011. "Disproportionate Proximity to Environmental Health Hazards: Methods, Models, and Measurement," *American Journal of Public Health* 101 (S1): S27–S36. https://doi.org/10.2105/AJPH.2010.300109.

Cicalese, Luca, Guiseppe Curcuru, Mauro Montalbano, Ali Shirafkan, Jeremias Georgiadis, and Cristiana Rastellini. 2017. “Hazardous Air Pollutants and Primary Liver Cancer in Texas,” *PLoS ONE* 12 (10): e0185610. https://doi.org/10.1371/journal.pone.0185610.

Coffey, Emily, Kate Walz, Debbie Chizewer, Emily Benfer, Mark Templeton, and Robert Weinstock. 2020. *Poisonous Homes: The Fight for Environmental Justice in Federally Assisted Housing*. Chicago, IL: Shriver Center on Poverty Law. https://www.povertylaw.org/report/poisonoushomes/.

Diez Roux, Ana V., and Christina Mair. 2010. “Neighborhoods and Health,” *Annals of the New York Academy of Sciences* 1186 (1): 125–145. https://doi.org/10.1111/j.1749-6632.2009.05333.x.

Ellen, Ingrid Gould, and Keren Horn. 2018a. *Housing and Educational Opportunity: Characteristics of Local Schools Near Families with Federal Housing Assistance*. https://www.prrac.org/pdf/HousingLocationSchools2018.pdf.

———. 2018b. “Points for Place: Can State Governments Shape Siting Patterns of Low-Income Housing Tax Credit Developments?” *Housing Policy Debate* 28 (5): 1–19. https://doi.org/10.1080/10511482.2018.1443487.

Ellen, Ingrid Gould, Keren Mertens Horn, and Yiwen Kuai. 2018. “Gateway to Opportunity? Disparities in Neighborhood Conditions Among Low-Income Housing Tax Credit Residents,” *Housing Policy Debate* 28 (4): 572–591. https://doi.org/10.1080/10511482.2017.1413584.

Freudenburg, William R., and Timothy R. Jones. 1991. “Attitudes and Stress in the Presence of Technological Risk: A Test of the Supreme Court Hypothesis,” *Social Forces* 69 (4): 1143–1168. https://doi.org/10.1093/SF/69.4.1143.

Galiatsatos, Panagis, Rachelle Koehl, Christine Caufield-Noll, Emily Brigham, Frank T. Leone, Michelle Eakin, Nadia N. Hansel, Cynthia Rand, and Meredith McCormack. 2020. “Proposal for Smoke-Free Public Housing: A Systematic Review of Attitudes and Preferences from Residents of Multi-Unit Housing,” *Journal of Public Health Policy* 41 (4): 496–514. https://doi.org/10.1057/S41271-020-00236-Z.

Gatzke-Kopp, Lisa M., Siri Warkentien, Michael Willoughby, Chris Fowler, David C. Folch, and Clancy Blair. 2021. “Proximity to Sources of Airborne Lead Is Associated with Reductions in Children’s Executive Function in the First Four Years of Life,” *Health and Place* 68 (March): Article 102517. https://doi.org/10.1016/j.healthplace.2021.102517.

Grineski, Sara E., Timothy W. Collins, and Daniel E. Adkins. 2020. “Hazardous Air Pollutants Are Associated with Worse Performance in Reading, Math, and Science Among US Primary Schoolchildren.” *Environmental Research* 181 (February): Article 108925. https://doi.org/10.1016/j.envres.2019.108925.

Haberle, Megan. 2017. “Fair Housing and Environmental Justice: New Strategies and Challenges,” *Journal of Affordable Housing and Community Development Law* 26 (2): 271–280. https://prrac.org/pdf/AH_26-2_06Haberle.pdf.

Hill, Dustin T., Michael Petroni, David A. Larsen, Kestutis Bendinskas, Kevin Heffernan, Nader Atallah-Yunes, Patrick J. Parsons, Christopher D. Palmer, James A. MacKenzie, Mary B. Collins, M. B., and Brooks B. Gump. 2021. "Linking Metal (Pb, Hg, Cd) Industrial Air Pollution Risk to Blood Metal Levels and Cardiovascular Functioning and Structure Among Children in Syracuse, NY," *Environmental Research* 193 (February): Article 110557. https://doi.org/10.1016/j.envres.2020.110557.

Horn, Keren M., and Katherine M. O'Regan. 2011. "The Low Income Housing Tax Credit and Racial Segregation," *Housing Policy Debate* 21 (3): 443–473. https://doi.org/10.1080/10511482.2011.591536.

Houston, Douglas, Victoria Basolo, and Dongwoo Yang. 2013. "Walkability, Transit Access, and Traffic Exposure for Low-Income Residents With Subsidized Housing," *American Journal of Public Health* 103 (4): 673–678.

Joint Center for Housing Studies of Harvard University. 2009. The Disruption of the Low-Income Housing Tax Credit Program: Causes, Consequences, Responses, and Proposed Correctives. https://www.jchs.harvard.edu/sites/default/files/media/imp/disruption_of_the_lihtc_program_2009_0.pdf.

Jones, Miranda R., Ana V. Diez-Roux, Anjum Hajat, Kiarri N. Kershaw, Marie S. O'Neill, Eliseo Guallar, Wendy S. Post, Joel D. Kaufman, and Ana Navas-Acien. 2014. "Race/Ethnicity, Residential Segregation, and Exposure to Ambient Air Pollution: The Multi-Ethnic Study of Atherosclerosis (MESA)," *American Journal of Public Health* 104 (11): 2130–2137. https://doi.org/10.2105/AJPH.2014.302135.

Kampa, Marilena, and Elias Castanas. 2008. "Human Health Effects of Air Pollution," *Environmental Pollution* 151 (2): 362–367. https://doi.org/10.1016/J.ENVPOL.2007.06.012.

Knezevich, Alison, and Christine Condon. 2020. "Baltimore Extends Trash Incinerator Contract Despite Protests," *Baltimore Sun*, November 5. https://www.baltimoresun.com/politics/bs-md-ci-bresco-contract-20201104-z5rqrc6qmbgg7jloa565p2fo2y-story.html.

Krisko, Perrin. 2021. "Using Environmental Protection Agency Data Tools to Map Particulate Matter 2.5 Near Public Housing Buildings and Major Roads in New York," *Cityscape* 23 (2): 417–424. https://www.jstor.org/stable/27039970.

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 U.S. Cities," *Environmental Science & Technology Letters*, March 9, acs.estlett.1c01012. https://doi.org/10.1021/ACS.ESTLETT.1C01012.

Lett, Elle, Jeanette A. Stingone, and Luz Claudio. 2017. "The Combined Influence of Air Pollution and Home Learning Environment on Early Cognitive Skills in Children," *International Journal of Environmental Research and Public Health* 14 (11): 1295. https://doi.org/10.3390/ijerph14111295.

Malek, Angela M., Aaron Barchowsky, Robert Bowser, Terry Heiman-Patterson, David Lacomis, Sandeep Rana, Ada Youk, and Evelyn O. Talbott. 2015. "Exposure to Hazardous Air Pollutants and the Risk of Amyotrophic Lateral Sclerosis," *Environmental Pollution*, 197: 181–186. https://doi.org/10.1016/j.envpol.2014.12.010.

Manson, Steven, Jonathan Schroeder, David Van Ripler, Tracy Kugler, and Steven Ruggles. 2020. IPUMS National Historical Geographic Information System: Version 15.0. https://www.ipums.org/projects/ipums-nhgis/d050.v15.0.

McClure, Kirk. 2006. "The Low-Income Housing Tax Credit Program Goes Mainstream and Moves to the Suburbs," *Housing Policy Debate* 17 (3): 419–446. https://doi.org/10.1080/10511482.2006.9521576.

McClure, Kirk, and Bonnie Johnson. 2015. "Housing Programs Fail to Deliver on Neighborhood Quality, Reexamined," *Housing Policy Debate* 25 (3): 463–496. https://doi.org/10.1080/10511482.2014.944201.

McClure, Kirk, and Alex F. Schwartz. 2021. "Neighbourhood Opportunity, Racial Segregation, and the Low-Income Housing Tax Credit Program in the United States," *Housing Studies* (July 20): 1–23. https://doi.org/10.1080/02673037.2021.1950646.

Moore, Roberta J. H., and Julie L. Hotchkiss. 2016. "The Importance of Toxicity in Determining the Impact of Hazardous Air Pollutants on the Respiratory Health of Children in Tennessee," *Environmental Pollution* 216: 616–623. https://doi.org/10.1016/j.envpol.2016.06.022.

Morello-Frosch, Rachel, and Russ Lopez. 2006. "The Riskscape and the Color Line: Examining the Role of Segregation in Environmental Health Disparities," *Environmental Research* 102 (2): 181–196. https://doi.org/10.1016/j.envres.2006.05.007.

O'Regan, Katherine M., and Keren M. Horn. 2013. "What Can We Learn About the Low-Income Housing Tax Credit Program by Looking at the Tenants?" *Housing Policy Debate* 23 (3): 597–613. https://doi.org/10.1080/10511482.2013.772909.

Persico, Claudia, David Figlio, and Jeffrey Roth. 2016. Inequality Before Birth: The Developmental Consequences of Environmental Toxicants. NBER Working Paper No. 22263. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/W22263.

Persico, Claudia L., and Joanna Venator. 2021. "The Effects of Local Industrial Pollution on Students and Schools," *Journal of Human Resources* 56 (2): 406–445. https://doi.org/10.3368/JHR.56.2.0518-9511R2.

Pietila, Antero. 2010. *Not in My Neighborhood: How Bigotry Shaped a Great American City*. Chicago: Ivan R. Dee.

Rajagopalan, Sanjay, Sajeer G. Al-Kindi, and Robert D. Brook. 2018. "Air Pollution and Cardiovascular Disease: JACC State-of-the-Art Review," *Journal of the American College of Cardiology* 72 (17): 2054–2070. https://doi.org/10.1016/J.JACC.2018.07.099.

Reid, Carolina K. 2019. "Rethinking 'Opportunity' in the Siting of Affordable Housing in California: Resident Perspectives on the Low-Income Housing Tax Credit," *Housing Policy Debate* 29 (4): 645–669. https://doi.org/10.1080/10511482.2019.1582549.

Salazar, Debra J., Stacy Clauson, Troy D. Abel, and Aran Clauson. 2019. "Race, Income, and Environmental Inequality in the U.S. States, 1990–2014," *Social Science Quarterly* 100 (3): 592–603. https://doi.org/10.1111/ssqu.12608.

Schraufnagel, Dean E., John R. Balmes, Clayton T. Cowl, Sara de Matteis, Soon-Hee Jung, Kevin Mortimer, Rogelio Perez-Padilla, Mary B. Rice, Horacio Riojas-Rodriguez, Akshay Sood, George D. Thurston, Teresa To, Anessa Vanker, and Donald J. Wuebbles. 2019. "Air Pollution and Noncommunicable Diseases: A Review by the Forum of International Respiratory Societies' Environmental Committee, Part 2: Air Pollution and Organ Systems," *Chest* 155 (2): 417–426. https://doi.org/10.1016/J.CHEST.2018.10.041.

Shi, Marc, Abigail Baum, and Craig E. Pollack. 2020. "Perspectives on Integrating Health into the Low-Income Housing Tax Credit: A Qualitative Study," *Health Affairs* 39 (4): 622–630. https://doi.org/10.1377/hlthaff.2019.00853.

Shi, Marc, Barbara A. Samuels, and Craig Evan Pollack. 2017. "Low-Income Housing Tax Credit: Optimizing Its Impact on Health," *American Journal of Public Health* 107 (10): 1586–1588. https://doi.org/10.2105/AJPH.2017.303988.

Simeonova, Emilia, Janet Currie, Peter Nilsson, and Reed Walker. 2021. "Congestion Pricing, Air Pollution, and Children's Health," *Journal of Human Resources* 56 (4): 971–996. https://doi.org/10.3368/JHR.56.4.0218-9363R2.

Sun, Zhuanlan, and Demi Zhu. 2019. "Exposure to Outdoor Air Pollution and Its Human Health Outcomes: A Scoping Review," *PLoS ONE* 14 (5): Article e0216550. https://doi.org/10.1371/journal.pone.0216550.

Taylor, Lauren. 2018. "Housing And Health: An Overview of the Literature," *Health Affairs*, June 7. https://doi.org/10.1377/hpb20180313.396577.

U.S. Census Bureau. 2021. *Delineation Files*, October 8. https://www.census.gov/geographies/reference-files/time-series/demo/metro-micro/delineation-files.html.

U.S. Department of Agriculture, Economic Research Service. 2020. *Rural-Urban Commuting Area Codes*. https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/.

U.S. Department of Housing and Urban Development (HUD) Office of Policy Development and Research (PD&R). 2020. *Affirmatively Furthering Fair Housing Data and Mapping Tool (AFFH-T) Data Documentation*. https://www.hud.gov/sites/dfiles/FHEO/documents/AFFH-T-Data-Documentation-AFFHT0006-July-2020.pdf.

———. n.d. *Low-Income Housing Tax Credit (LIHTC)*. huduser.gov/portal/datasets/lihtc.html.

U.S. Environmental Protection Agency (EPA). 2021a. *Criteria Air Pollutants*. https://www.epa.gov/criteria-air-pollutants.

———. 2021b. *Hazardous Air Pollutants*. https://www.epa.gov/haps.

———. 2021c. *2014 National Air Toxics Assessment (NATA): Fact Sheet*. https://www.epa.gov/national-air-toxics-assessment/2014-nata-fact-sheet.

———. 2021d. *National Emissions Inventory (NEI)*. https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei.

———. 2021e. *Risk-Screening Environmental Indicators (RSEI) Model*. https://www.epa.gov/rsei.

———. 2021f. *Toxics Release Inventory (TRI) Program*. https://www.epa.gov/toxics-release-inventory-tri-program/what-toxics-release-inventory.

———. 2020. *EasyRSEI [Risk-Screening Environmental Indicators] Dashboard*. https://edap.epa.gov/public/extensions/EasyRSEI/EasyRSEI.html.

Washington State Department of Health. 2016. *Guidelines for Using Rural-Urban Classification Systems for Community Health Assessment*. https://www.doh.wa.gov/Portals/1/Documents/1500/RUCAGuide.pdf.

Woo, Ayoung, Chia-Yuan Yu, and Sugie Lee. 2019. "Neighborhood Walkability for Subsidized Households: Revisiting Neighborhood Environments of Housing Choice Voucher and Low-Income Housing Tax Credit Households," *Cities* 89: 243–251. https://doi.org/10.1016/J.CITIES.2019.03.002.

Zwickl, Klara, Michael Ash, and James K. Boyce. 2014. "Regional Variation in Environmental Inequality: Industrial Air Toxics Exposure in U.S. Cities," *Ecological Economics* 107: 494–509. https://doi.org/10.1016/j.ecolecon.2014.09.013.