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Intersectional inequalities in industrial air toxics exposure in the United States

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ABSTRACT

Environmental justice and health research demonstrate unequal exposure to environmental hazards at the neighborhood-level. We use an innovative method—eco-intersectional multilevel (EIM) modeling—to assess intersectional inequalities in industrial air toxics exposure across US census tracts in 2014. Results reveal stark inequalities in exposure across analytic strata, with a 45-fold difference in average exposure between most and least exposed. Low SES, multiply marginalized (high % Black, high % female-headed households) urban communities experienced highest risk. These inequalities were not described by additive effects alone, necessitating the use of interaction terms. We advance a critical intersectional approach to evaluating environmental injustices.

1. Introduction

Air pollution can cause acute and chronic health problems ranging from asthma to mortality, yet exposure to anthropogenic drivers of pollution, such as industrial facilities and major transport infrastructures, is unequally distributed. In the US, hazardous facilities are more likely to cluster in communities of color and poorer neighborhoods (Campbell et al., 2010; Mohai et al., 2009; Pastor et al., 2001). Neighborhood-level patterns of disparity in exposure to air pollution have been widely documented, with neighborhoods with more Black and Latinx residents (Ard, 2015; Downey and Hawkins 2008b; Liévanos 2015), lower socioeconomic status households, and more female-headed households (Downey et al., 2017; Downey and Hawkins 2008b) at greatest risk of exposure. These patterns align with a robust literature from social epidemiology that identifies social determinants as the fundamental drivers of health inequalities (Bauer, 2014; Kawachi and Subramanian, 2018; Krieger, 1994). These findings are bolstered by recent work which incorporates an intersectional framework (Ducre, 2012, 2018; Liévanos, 2015; Malin and Ryder, 2018), and draws attention to the multiplicative effects of environmental hazards across the United States.

Originating in Black feminist scholarship, intersectionality theory critically addresses the structural determinants of social experiences and illustrates how the interlocking nature of these systems of inequality erase the experiences of Black women from the status quo (Collins, 1990; Crenshaw, 1993). Intersectional frameworks move beyond additive approaches (e.g., race + class), and instead examine inequalities at the intersections of multiple social dimensions (e.g., race x class). Historically, most intersectional scholarship has made use of individual-level data; however, our work joins a growing movement of critical environmental justice scholarship (Ducre, 2012; Malin and Ryder, 2018; Pellow, 2017) that examines intersectionality at the level of neighborhoods. This level of analysis is appropriate for a study of this kind (Alvarez and Evans, 2021) because environmental injustices are perpetrated through complex social, economic, political, and historical processes that adversely expose entire communities to risk, rather than selectively targeting individuals or households, as is the case with some other forms of discrimination and violence. Our present work fits with recent calls for *structural intersectionality* research (Homan et al., 2021) and for consideration of intersectional geographical inequalities in health (Bambra, 2022).

A variety of analytic approaches to quantitatively evaluate intersectional inequalities have been developed and advanced (Bauer et al., 2021; Homan et al., 2021). The conventional, most commonly applied approach remains single-level regression models with fixed interaction parameters, which render visible multiplicative effects. However, this

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approach presents important challenges: geometric increases in interaction terms as more categories of analysis are added rapidly consumes degrees of freedom and decreases model parsimony in high-dimensional analyses (Bauer, 2014). Our recent work (Evans et al., 2018; Alvarez and Evans, 2021) addresses these concerns and improves conventional approaches by applying multilevel models to quantify structural inequalities across racialized, gendered, and classed neighborhoods.

Previous research (Ard, 2015; Collins et al., 2011; Downey and Hawkins, 2008a, 2008b; Liévanos, 2015) demonstrates relational effects across neighborhood demographics, including racial/ethnic composition, gendered family structure, socio-economic status, and urbanicity. Yet these dimensions are seldom evaluated simultaneously, especially using higher-level interactions. Moreover, the majority of intersectional environmental justice studies focus on single-case studies (see e.g., Chakraborty et al., 2017; Collins et al., 2011; Grineski et al., 2013). While these studies are crucial in that they establish that health hazards place intersectionally-marginalized communities at heightened risk, they also leave open the question of generalizability. In order to take the next step and establish whether environmental health inequalities are intersectionally patterned in communities across the US, we utilize an intercategorical intersectional approach. This allows us to evaluate the patterning of local industrial air pollution disparities at the neighborhood level along interacting dimensions of race and ethnicity, female-headed household, educational attainment, income, and urbanicity. We use an innovative intersectional method—Eco-Intersectional Multilevel (EIM) modeling—to examine these inequalities at the geographical level, combining social demographic and air pollution data for over 70,000 census tracts. We find considerable, systematic, and non-additive patterns of inequality in air pollution exposure. By examining multiple racial and socioeconomic dimensions (as theorized critically within intersectionality), we uncover extreme polarities of environmental inequalities. Our findings illustrate the importance of examining intersectional geographic inequalities in environmental and health disparities research. Moreover, these findings should serve as a call to action for remediating environmental injustices.

2. Background

2.1. Environmental justice

Environmental justice (EJ)—a movement focused on ensuring all communities have access to clean neighborhoods and workplaces—has sparked research on environmental inequalities, calling particular attention to the disproportionate exposure of low-income communities of color to hazardous conditions (Mohai et al., 2009; Pellow, 2000; Taylor, 2014). Air pollution from industrial facilities and major transport infrastructures causes acute and chronic health effects ranging from respiratory illnesses to mortality (Kampa and Castanas, 2008). A recent report by the American Lung Association reported 4 out of 10 residents live in counties with "monitored unhealthy ozone and/or particle pollution" (American Lung Association, 2019). Health research has found local environments, particularly neighborhoods, to be important determinants of health outcomes (Arcaya et al., 2016). Early EJ research focused on the relationship between racial/ethnic and socioeconomic disparities of hazardous pollution (Bullard, 1983; Downey et al., 2008). One of the first EJ reports, *Toxic Wastes and Race in the United States* (Chavis, 1987) evaluated the relationship between toxic landfill placement and the racial composition of zip codes and found racial environmental disparities to be significant even when controlling for SES and urbanicity. Though such work remains foundational, the EJ literature has expanded to demonstrate that exposure to pollution varies across multiple social dimensions, including race, ethnicity, socioeconomic status (SES), gendered family structures, immigrant status, and urbanity (Chakraborty et al., 2017; Collins et al., 2011; Crowder and Downey, 2010; Downey and Hawkins, 2008b; Heynen et al., 2006; Liévanos, 2019; Pais et al., 2014). These multiple social dimensions of marginalization *intersect and interact* to produce environmental health inequalities (Ducre, 2012; Liévanos, 2015; Malin and Ryder, 2018).

Some scholars have focused on the relationship between SES and racial and ethnic environmental inequalities. Downey and Hawkins (2008b) found that income level and pollution exposure vary based on neighborhood racial composition, with higher levels of income showing the strongest negative correlation with air pollution among census tracts with a higher percentage of Black residents as compared to percent of White residents.[1] Similarly, Zwickl, Ash, and Boyce (2014) found racial and ethnic disparities in industrial air toxics were higher among neighborhoods with low median household incomes. Previous work using interactions of race and ethnicity and SES, found an overall decline over time in industrial air pollution levels and exposure (Ard, 2015). Still, Black residents faced greater exposure than white and Latinx residents, even when comparing SES with measures of income and educational attainment. Research focusing on intracategorical intersectional disparities among Hispanic communities found neighborhoods with greater median household income and educational attainment reported less cancer risk from air toxics (Collins et al., 2011). These studies make clear that SES inequalities in exposure to environmental hazards differ across racial/ethnic lines.

Another line of EJ research has focused on gendered family structures. An early national study on neighborhood family composition by Downey and Hawkins (2008a) found single-mother households to be significantly correlated with industrial air toxics exposure even after controlling for racial/ethnic composition and SES. Collins et al. (2011) found significant elevated levels of air pollution as percent of female-headed households increases in Hispanic communities. A more recent study by Liévanos (2015) focused on intersectional environmental inequality hypotheses—including female-headed households—found census tracts with higher racial/ethnic and immigrant economic deprivation measures[2] had a greater likelihood of residing in clusters of lifetime cancer risk from air toxics. These results highlight the importance of further examining this understudied topic of gendered family structure within environmental inequality.

While EJ research has demonstrated important relationships between neighborhood demographic characteristics in the patterning of hazard exposure, important gaps remain. First, while measures of neighborhood-level income and education reflect different aspects of social status, power, and resources at the community level, the differences between these measures in producing inequalities in exposure have been inadequately explored. Second, possible interactions between other social dimensions such as gendered family structure and urbanicity with established intersectional inequalities by race/ethnicity and class remain underexamined. Third, a unique feature of environmental justice research is the focus on neighborhood-level outcomes, a geographical approach which can be compellingly applied to health research. While the use of individual-level data in previous health research has been productive, it has also shifted theoretical and analytic attention to individual experiences within interlocking systems of oppression, rather than structural, community-level experiences. This has left gaps in our understanding of how certain types of social problems impact the community as a whole, which are crucial to unpack when thinking about potential interventions, as they necessarily occur at the community level. Further, the limited availability of individual-level, geographically specific data that encompasses the entire US makes it difficult to approach generalizability with an individual-level focus. Fourth, there is room for innovative approaches to evaluate

[1] The authors interpret their findings to be a result of Black geographic mobility, wherein high-income Black residents move out of highly polluted neighborhoods.

[2] The economic deprivation measure consisted of a principal component factor analysis of educational attainment, unemployment, female-headed households, and poverty.

higher-level interaction effects within environmental inequalities, which might better answer calls for analysis of structural intersectionality (Homan et al., 2021). It is not required to use interaction terms to examine intersectional inequalities. Several analytic approaches have been proposed to examine the relational and intersectional nature of environmental inequalities between neighborhood demographics (such as racial/ethnic composition, SES, and gendered family structure), including interaction terms (Downey and Hawkins, 2008b), bivariate analysis (Collins et al., 2011), and principal component analysis factor analysis (Liévanos, 2015; Smith, 2009). Regardless of the specific quantitative approach used, applying intersectionality to quantitative methods poses challenges related to interpretability as the number of interactions in the model increases. This paper joins a recent movement to apply a critical intersectional lens to study structural and geographic patterns of environmental health disparities (Bambra, 2022; Homan et al., 2021; Malin and Ryder, 2018; Pellow, 2017). In summary, current EJ scholarship demonstrates clear evidence of environmental inequalities patterned intersectionally along racial/ethnic, socioeconomic, and gendered family structure categorizations, yet key gaps in our understanding remain. To address this, we employ an intersectional analytic framework to examine environmental disparities between multiple social dimensions.

2.2. Intersectionality

Originating in Black feminist thought, intersectionality brings focus to interlocking systems of power such as racism, sexism, and classism (Collins, 1990; Crenshaw, 1993). Intersectionality showcases how additive/singular approaches are incapable of adequately describing the unique experiences and burdens of communities with multiply marginalized populations, thus contributing to the erasure of the experiences of Black women (Crenshaw, 1989). To amend the multiplicative inequalities, intersectionality builds theory and methods from the standpoint of Black women (Crenshaw, 1989). Intersectional studies examine power dynamics ranging from the individual to the structural level, focusing on the relational inequalities of overlapping axes of marginalization (Cho et al., 2013; Collins, 1990). From this foundation, scholars have brought attention to other areas of marginalization such as age-based inequality (Calasanti and King, 2020), developed new methodological approaches for intersectional analysis (Evans et al., 2018), and identified pathways to create social change outside of the academy (Cho et al., 2013).

Acknowledging intersectionality's unique methodological challenges, McCall (2005) identifies three approaches in intersectional scholarship: the anti-categorical, the intracategorical, and the intercategorical. Anti-categorical approaches emphasize the fluidity of social categories and the "deconstruct[ion] of analytical categories" (McCall, 2005, p. 1773). Intracategorical approaches "focus on particular social groups at neglected points of intersection … to reveal the complexity of lived experience within such groups" (McCall, 2005, p. 1774). Finally, intercategorical approaches "provisionally adopt existing analytical categories to document relationships of inequality" (McCall, 2005, p. 1773) and are typically used in quantitative analyses. An intercategorical framework emphasizes the "process-centered" analysis which uncovers the relational interactions of multiple systems of power and discusses the subordinate groups as well as dominant groups (Choo and Ferree, 2010). The relational approach emphasizes the social constructionist perspective of the inequalities and the *process* of social positions such as "racialization rather than race, economic exploitation rather than classes, gendering and gender performance rather than gender" (Choo and Ferree, 2010, p. 134).

Intercategorical intersectional approaches using quantitative methods face specific challenges (Bauer, 2014). A recent review of quantitative methods within intersectionality work found researchers use a wide range of methods, from bivariate analyses to advanced multivariable regression analyses (Bauer et al., 2021). A common approach involves the use of higher-level interaction terms to capture the relationship between two variables (Bauer et al., 2021). Generally, several challenges occur in the application of higher-level interactions terms. As the number of interactions in the model increases (as demanded by theory to account for additional axes of marginalization) this rapidly consumes the limited degrees of freedom based on the sample size. This has the unfortunate consequence of limiting certain methods based on sample size alone. Moreover, the increase of interaction terms within the model decreases model parsimony and complicates interpretability of the results. Recent methodological advances, such as intersectional Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (intersectional MAIHDA) and Eco-Intersectional Multilevel (EIM) modeling, use the structure of multilevel modeling to quantify a large number of interaction effects without compromising model parsimony (Evans et al., 2018, 2020; Jones et al., 2016; Merlo, 2018). These models have numerous other methodological advantages over conventional single-level regression models and other approaches, including improved interpretability, scalability, and adjustment of intersectional stratum-specific estimates based on sample size (Alvarez and Evans, 2021; Bell et al., 2019; Evans et al., 2018, 2020; Mahendran et al., 2022; Merlo, 2018).

2.3. Intercategorical intersectional approach: Eco-intersectional multilevel modeling

A growing body of literature uses intersectionality theory to examine and explain health disparities at the intersection of multiple social identities, including race, gender, and class (Bauer, 2014; Bowleg, 2012). Recent work calls for intersectional approaches in health to be expanded from individual-level analyses to structural and place-based analyses (Bambra, 2022; Homan et al., 2021). Such macro-level approaches draw attention to the consequences of multiple systematic processes, such as the labor market, residential segregation, and manufacturing zones, all of which shape environmental health outcomes (Homan et al., 2021).

Our previous work introduces Eco-Intersectional Multilevel (EIM) modeling, an innovative approach that combines intersectionality, EJ, and social determinants of health theorizing to inform its methodology while expanding the intersectional MAIHDA approach from the individual to the neighborhood level (Alvarez and Evans, 2021; Evans et al., 2018). The EIM approach allows for the examination of environmental injustices above the individual level, which provides valuable insight into specific types of injustices. For example, environmental injustices occur at the neighborhood level, where the placement of "environmental harms" (e.g., industrial sites and other pollution sources) and "environmental benefits" (e.g., parks and other green spaces) have important consequences for the whole neighborhood. This does not conflate individual experiences with those at the community level; rather, it assesses systematic processes that determine the toxicity of environments, which are experienced at the community level. Black feminist scholarship has long argued that marginalization and discrimination operate intersectionally at the structural level, which Crenshaw (1993) notably describes as "structural intersectionality." *Structural intersectionality* operates through structural racism, structural classism, and gendered racism (Homan et al., 2021; Pirtle and Wright, 2021), and environmental injustices fit this pattern of structural intersectionality. Given this, while the majority of intersectional health inequalities scholarship employs individual-level data, we argue that the use of neighborhood-level data in the present study is a strength, not a limitation. Indeed, we are returning to the theoretical roots of intersectionality while answering calls for greater consideration of structural processes. We use the term "eco-intersectional" not to imply that we are reinventing intersectional theorizing, but instead to differentiate our approach from intersectional analyses of population health that focus on individual-level observations (which are often decontextualized, see Evans, 2019).

EIM uses multilevel models to examine outcomes (and inequalities) across interacting categorizations, referred to as intersectional strata. While multilevel models typically use geographical or administrative groupings to hierarchically nest units—for example, nesting census tracts (level 1) within counties (level 2)—in EIM, census tracts (level 1) are nested in intersectional strata (level 2). EIM reflects the common usage of place analysis in quantitative environmental justice research (Ard, 2015; Downey and Hawkins, 2008a; Liévanos, 2015) and focuses on geographical levels, including census blocks and census tracts. One strength of EIM's multilevel structure, in which variables are combined linearly for the purposes of prediction rather than weighted inference, is that multicollinearity does not pose the same challenge here that it would in many conventional approaches. These intersectional strata are defined based on theoretically and empirically relevant categorizations of neighborhood-level sociodemographics, however they are understood to be provisionally-adopted analytic categories and are not intended as naturalistic, reified typologies (Choo and Ferree, 2010).

A natural follow-up question is: Does EIM commit ecological fallacy? No, because EIM analyzes neighborhoods and makes assessments of neighborhoods. A neighborhood-level focus is appropriate since environmental injustices operate at the neighborhood level and have consequences for all residents, as opposed to particular individuals or households within the same neighborhood.

Though many sociodemographic variables are expected to correlate with each other, multicollinearity does not affect how we structure the present model. Intersectionality demands inclusion of multiple axes of marginalization, even if they are correlated (e.g., race and poverty) because they are understood to represent interlocking systems of marginalization and oppression. Furthermore, the main use of the present model is to generate predictions of air pollution exposure for each stratum—linearly recombining fixed and residual parameters—and multicollinearity does not hamper this use. To the extent that multicollinearity affects parameter estimates, the EIM approach has a comparative advantage over conventional intersectional interaction models. Correlation between sociodemographic variables reduces the expected sample size of some strata (e.g., there are fewer communities with high SES and a high percentage of racial/ethnic minorities). In a conventional regression model, estimates for small strata are less reliable. In EIM, on the other hand, estimates for each stratum are automatically adjusted based on the sample size, providing more conservative but ultimately more reliable estimates.

An intercategorical intersectional approach to environmental inequalities at the neighborhood level is important when examining air toxics exposure because facilities that emit industrial air toxics have spatial, community-level effects. Moreover, risk of exposure varies across interactions of neighborhood demographic profiles, as defined by characteristics such as communities' racial/ethnic and socioeconomic composition. In the present study, census tracts are used as a proxy for neighborhoods. Intersectional strata are specified according to five neighborhood characteristics: race and ethnicity, gendered family structure, educational attainment, income, and urbanicity. Using EIM, we contribute to the growing interest in quantitative intersectional analysis by quantifying tract-level intersectional inequalities in industrial air pollution exposure and critiquing the underlying social processes that give rise to these environmental injustices.

2.4. *Dependent variable: Industrial air toxics*

The air pollution data is an annual estimate of industrial air toxics concentrations from the Environmental Protection Agency's Risk-Screening Environmental Indicators Geographic Microdata (RSEI-GM) (U.S. Environmental Protection Agency, 2015). RSEI-GM derives air pollution estimates from the Toxic Release Inventory (TRI) and uses geographical modeling techniques to estimate air toxic exposure at a 1-km square spatial resolution (see U.S. Environmental Protection Agency, 2015 for detailed methodology). The RSEI-GM's 1 km-grid map of the air toxics concentrations were aggregated up to the census tract level based on the area of tract within each grid cell (see Ard, 2015 for methodology). Here, we used the natural log transformation of the total amount of industrial air toxics concentration measured in micrograms per cubic meter ($\mu g/m^3$) for the year 2014. Three-hundred and sixty-four tracts have null values and were recorded as having zero estimated pollution exposure (about 0.51%). Because TRI air pollutants have varying levels of toxicity, we chose to use direct total air toxics concentration ($\mu g/m^3$) as a starting place to understand how the total amount of air toxics relates to neighborhood characteristics. Future research should endeavor to incorporate chemical toxicity and interactions.

2.5. *Neighborhood demographic data*

Demographic data is from the American Community Survey (ACS) 2010–2014 (U.S. Census, 2014), made available at the census tract level by the National Historical Geographic Information System (Manson et al., 2018). The ACS collects in-depth demographic and housing data. We follow precedent set by previous intersectionality research by utilizing census tracts as a proxy for neighborhoods (e.g., Liévanos 2015). While not always a perfect representation of how one might define their community, tracts offer several benefits. For example, census tracts fall neatly within county boundaries, therefore reflecting administrative and budgeting priorities within local governments. This is particularly important when trying to understand the structural mechanisms that perpetuate inequality, such as variation in welfare and social service funding (Kelly and Lobao, 2021). Metropolitan data is from the most current version of the Rural-Urban Continuum Codes (RUCC) (U.S. Department of Agriculture Economic Research Service, 2013). RUCC categorizes counties into a 1–9 scale with 1–3 classified as "metropolitan counties" and 4–9 classified as "nonmetropolitan counties." We converted the RUCC codes to a binary metro/nonmetro where 1–3 RUCC codes were classified as metro and 4–9 classified as nonmetro. The sample includes a total of 71,625 census tracts within the contiguous United States. Of the entire sample, 134 tracts have population of less than 500 residents (approximately 0.19%). Tables 1 and 2 report descriptive statistics.

2.6. *Intersectional strata*

In the present EIM models, analytic intersectional strata are identified using a five-digit stratum code based on race and ethnicity, gendered family structure, SES, and urbanicity status. The racial and ethnic dimension consists of four categories and represents the racial and ethnic composition: (1) census tracts *below* the median percent Black non-Latinx[3] and *below* the median percent Latinx residents; (2) census tracts *above* the median percent Black and *below* the median percent Latinx residents; (3) census tracts *below* the median percent Black and *above* the median percent Latinx residents; and (4) census tracts *above* the median percent Black and *above* the median percent Latinx residents. Gendered family structure represents the percent of female-headed households and consists of three categories: (1) lowest; (2) middle; and (3) highest tercile. Educational attainment is the percent of residents over the age of 25 with some college education or higher and has three categories: (1) lowest; (2) middle; and (3) highest tercile. Median household income consists of the following three categories: (1) lowest; (2) middle; and (3) highest tercile. Finally, urbanicity is represented by two categories: (0) non-metro and (1) metro.

Table 3 summarizes the categories of the stratum ID. For example, the intersectional stratum code 21320 indicates census tracts with a racial and ethnic composition of *above* the median percent Black and *below* the median percent Latinx residents (2), lowest tercile of female-

[3] Henceforth we refer to Black non-Latinx residents as Black for simplicity.

Table 1
Descriptive statistics.

	Mean	SD	Median	Min	Max
Industrial Air Toxics Concentration (μg/m^3)	0.31	1.10	0.11	0.00	128.22
Race and Ethnicity by Tract					
% Black	13.45	21.98	3.78	0.00	100.00
% Latinx	15.70	21.22	6.61	0.00	100.00
% Female-Headed Household	13.65	8.72	11.53	0.00	87.28
% Residents with Some College or More	57.10	17.84	56.19	4.74	100.00
Median household income ($)	57,179.34	28,489.62	50,906.00	2,499.00	250,001.00
Metro (binary)	0.83	0.37	1.00	0.00	1.00
Median age	38.75	7.62	38.80	11.50	84.30
% Housing units built in 1970 and after	55.39	28.78	57.08	0.00	100.00
Median housing value ($) [N = 70,921]	217,803.40	172,690.90	161,900.00	9,999.00	1,000,001.00
% Manufacturing Workers [N = 71,624]	10.50	6.90	9.17	0.00	61.39
% Renters	36.26	22.70	31.10	0.00	100.00
% Unemployment	9.78	6.01	8.45	0.00	100.00

Note: N = 71,625 unless otherwise stated. Median housing value is of owner-occupied housing units in tens of thousands of dollars. Percent of workers in manufacturing is the number of civilians (aged 16 years and older) employed in manufacturing divided by the total number of civilians (aged 16 years and older) who are employed. Percent renters was calculated as the number of rental housing units divided by the total number of housing units. Percent unemployed was calculated as the number of civilians (aged 16 years and older) in the labor force who reported being unemployed divided by the total population in the tract (aged 16 years and older) who are in the labor force.

Table 2
Descriptive Statistics of EPA region.

EPA Region	Frequency	%	Average Industrial Air Toxins Concentration Amount (μg/m^3)
1	3346	4.67	0.06
2	6789	9.48	0.09
3	7311	10.21	0.15
4	13,759	19.21	0.13
5	13,005	18.16	0.20
6	8554	11.94	0.10
7	3497	4.88	0.13
8	2645	3.69	0.05
9	10,153	14.18	0.08
10	2566	3.58	0.13

headed household (1), highest tercile of residents with some college or more (3), middle tercile of median household income (2), and not within a metro area (0). Fig. 1 displays maps of these categories as well as pollution estimates.

2.7. Control variables

We include several control variables to examine whether the observed inequalities could be explained by other factors, including some which may be correlated with variables in our analysis, and are often included in EJ research. First, we control for median age as previous research indicates older age is a disadvantaged status which may affect residential mobility (Calasanti, 2020; Crystal et al., 2017). Second, we follow earlier work and control for the percentage of rental units, as homeownership has been found to be an indicator of neighborhood wealth and social capital (Chakraborty et al., 2014; Morello-Frosch et al., 2002; Pastor et al., 2005). Third, we control for the percent of residents working in manufacturing industries, as prior scholarship notes manufacturing workers tend to reside in closer proximity to manufacturing industries (Anderton et al., 1994; Boer et al., 1997; Downey and Hawkins, 2008b; Pastor et al., 2005). Fourth, previous scholarship controls for the median year houses were built to gauge the age of the residences and other infrastructural components within a neighborhood (Downey and Hawkins, 2008a; Liévanos, 2015); we use the percent of housing units built during or after the 1970s to demarcate neighborhood age. Fifth, we follow previous research and include unemployment percentage as a measure of economic deprivation (Liévanos, 2015; Smith, 2009). Sixth, we follow earlier research and control for median housing value as an indicator of neighborhood wealth (Downey and Hawkins, 2008b; Morello-Frosch et al., 2002). Seventh, we echo researchers who examine differences within policy-implementing boundaries, such as EPA regions, which account for regional environmental enforcement differences as well as broader regional demographic profiles (Ard, 2015; Zwickl et al., 2014). In summary, we controlled for median resident age; the percentage of rented housing units; residents working in manufacturing; neighborhood age; and unemployment. We also included the median housing value of owner-occupied housing of the census tract and controlled for the ten EPA regions.

Table 3
Stratum ID reference table.

Stratum ID	1st digit		2nd digit		3rd digit		4th digit		5th digit	
	Racial and ethnic composition		Female-Headed Household		Educational Attainment		Median Household Income		Estimated Industrial Pollution Exposure	
	1	*Below* the median % Black and *below* the median % Latinx residents	1	Lowest tercile of % female-headed household	1	Lowest tercile of % some college or more	1	Lowest tercile of median household income	0	Non-metro
	2	*Above* the median % Black and *below* the median % Latinx residents	2	Middle tercile of % female-headed household	2	Middle tercile of % some college or more	2	Middle tercile of median household income	1	Metro
	3	*Below* the median % Black and *above* the median % Latinx residents	3	Highest tercile of % female-headed household	3	Highest tercile of % some college or more	3	Highest tercile of median household income		
	4	*Above* the median % Black and *above* the median % Latinx residents								

Notes: The digits combine to represent the stratum IDs. For example, stratum 32310 indicates census tracts with low % Black and high % Latinx residents, middle tercile of female-headed household, highest tercile of some college or more, lowest tercile of median household income, and within a non-metro area.

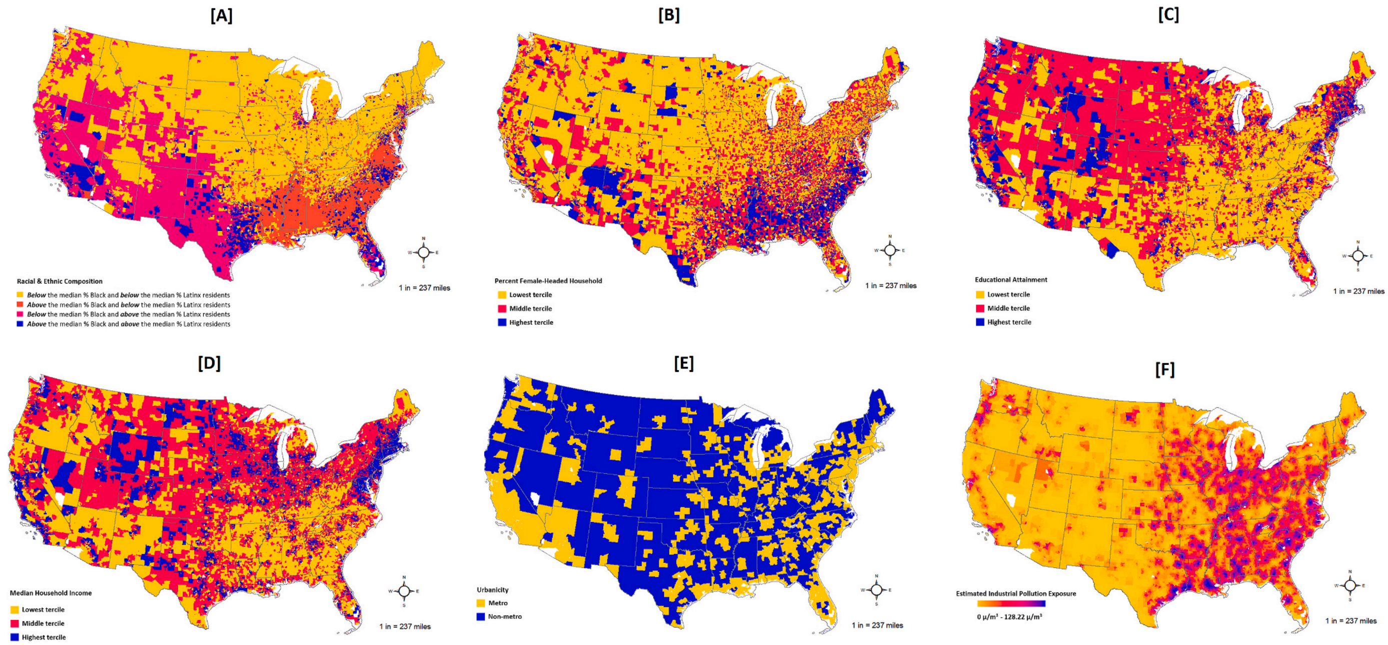

Fig. 1. Maps of stratum for 2010 census tracts and pollution exposure.
Notes: Each map shows the category breakdown for each dimension of the intersectional social strata: Map A shows racial and ethnic composition, Map B shows terciles of female-headed household, Map C shows terciles of educational attainment, Map D shows terciles of median household income, Map E shows metro/nonmetro, and Map F shows the estimated concentration of industrial pollution.

2.8. Analytic approach: EIM modeling

Here, we explain in detail the EIM approach, where census tracts (level 1) are nested hierarchically within intersectional strata (level 2). The general equation for the models is:

$$y_{ij} = \beta\delta_j + \mu_{0j} + e_{0ij} \tag{1}$$

$$\mu_{0j} \sim N(0, \sigma_\mu^2)$$

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

where in Eq. (1). y_{ij} represents the total amount of industrial air toxics concentration (log transformed) of a census tract i in intersectional stratum j, δ_j is the vector of the intercept and fixed effects for stratum j, and β represents the corresponding parameters. The tract-level residual is e_{0ij} for census tract i within stratum j, which is normally distributed with a mean of 0 and between-tract/within-stratum variance of σ_e^2. The stratum-level residual is μ_{0j} for stratum j, which is normally distributed with a mean of 0 and between-stratum variance of σ_μ^2.

Equation (2) is the variance partition coefficient (VPC) and estimates the proportion of the total variance of the dependent variable that resides at the between-stratum level, thus making it an excellent measure of inequalities between strata:

$$VPC = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2} \tag{2}$$

For the analyses, several models were estimated. The first model (Model A) is the null random-intercept model which includes no fixed effects. In this model, the VPC provides a measure of the total between-stratum inequalities in air toxics exposure, unadjusted for other factors. The null model also serves as the reference point for later models to compare variances.

The second model (Model B) adds fixed effect parameters to adjust for the additive neighborhood-level "main effects." In EIM models where the additive effects are controlled for, but no interactions are added as fixed effects, the stratum-level residuals (μ_{0j}) estimate the interaction effect unique to each stratum. Also of interest in this model is an assessment of how much variation (or inequality) remains between strata overall after adjustment for additive components. In cases where σ_μ^2 has decreased to zero, this indicates that overall, there is little interaction between the axes of marginalization evaluated. Where variation remains, this indicates that additive effects are inadequate to account for the existing inequalities. Helpful when examining this is the Proportional Change in Variance (PCV), which estimates what proportion of the total between-stratum variance (from Model A) is accounted for by the additive main effects. Equation (3) is the PCV as:

$$PCV = \frac{\sigma^2_{\mu,\ Model\ A} - \sigma^2_{\mu,\ Model\ B}}{\sigma^2_{\mu,\ Model\ A}} \tag{3}$$

Models C and D build on Model B by adding control variables to examine the extent to which these residual inequalities attributable to interaction effects can be explained by specific factors. Model C adds the neighborhood-level demographic controls and Model D adds the EPA regions.

In the results and discussion sections, we frequently discuss "additive effects" versus "interaction effects." To be clear, the additive effects refer to the singular main effects of the stratum such as "the middle tercile of percent female-headed household." As discussed above, the EIM modeling approach quantifies the "interaction effects" with the intersectional social strata by using the multilevel modeling structure. Thus, the interaction effects refer to the evaluation of the intersectional social strata including the VPC and PCV as well as the ranking of predicted values of each stratum and the significance of the stratum residuals.

All models were run in MLwiN 3.02 (Rasbash et al., 2017) called from Stata 14.1 using the *runmlwin* command (Leckie and Charlton, 2013). We use Bayesian Markov Chain Monte Carlo (MCMC) estimation procedures (Browne, 2017) with diffuse priors. The MCMC procedure with initialization values were provided with quasilikelihood methods. Models have a burn-in of 5000 iterations with a total length of 50,000 iterations (with thinning every 50 iterations). Credible intervals at 95% were calculated for all estimates.

3. Results

Table 1 reports descriptive statistics, while Table 2 reports the average industrial air toxics concentration by EPA region. The average level of industrial air toxics[4] was 0.31 μg per cubic meter (μg/m^3), however this varied widely, ranging from 0 to over 128 μg/m^3. While these numbers help to paint a picture of how crowded air is with estimated air toxics, what we are most interested in understanding is how the amount of estimated air pollution compares across community types. Neighborhood demographic characteristics also varied widely across census tracts in the sample. Percentage of Black or Latinx residents ranged from 0 to 100. Female-headed households averaged at 13.65% with a range of 0%–87.28%. Residents reporting some college education or higher averaged at 57.10% with a range of 4.74%–100%. Median household income ranged from $2,499 to $250,001 with an average of $57,179.34. We use EPA region 5, which had the highest average air pollution concentration (0.20 μg/m^3), as the reference category in our analyses.

Table 4 reports the results from the EIM models. The intercepts are negative due to the natural log transformation of the air toxics outcome variable, and negative values indicate extremely small numbers (e.g., exp(-2.550) ≈ 0.078 μg/m^3). We begin with the null model without main effects and add fixed effects to models thereafter. The VPC of the null model (Model A) is 23.49%, meaning nearly a quarter of the variation in industrial air toxics across census tracts is attributable to inequalities between intersectional strata, supporting a narrative of extreme environmental injustices.

The additive fixed effects model (Model B) demonstrates how much of the between-stratum variance can be explained when controlling for the additive main effects. The VPC of Model B decreased to 2.86%, indicating inequalities between strata are not explained by additive effects alone. This is confirmed by the PCV of 90.4% between the Models A and B, which suggests that approximately ten percent of the between-stratum variance may be attributed to interaction effects. The addition of the neighborhood-level demographic controls (Model C) decreases the VPC to 1.28%, and the further addition of EPA regions (Model D) resulted in a VPC of 1.27%. This indicates that despite inclusion of a variety of controls, considerable inequalities and residual interaction effects remained unexplained between strata.

Fig. 2 plots the expected value (and 95% CI) for each stratum and illustrates the wide inequalities summarized by statistics such as the VPC in Model A. Supplementary Table 1 reports these expected values numerically for each stratum. Fig. 3 contains a close-up of the ten highest and ten lowest ranking strata by total amount of air pollution. The stratum with the highest expected value of air toxics was stratum 23111 (high percentage Black and low percentage Latinx residents, high percentage female-headed households, lowest terciles of educational attainment and median household income, metro) with expected value = 0.361 μg/m^3. The predicted air pollution level for stratum 23111 was approximately 45-times higher than pollution levels predicted for the stratum with the least exposure, stratum 31330 (low percentage Black and high percentage Latinx residents, low percentage female headed-households, highest terciles of educational attainment and median household income, non-metro; expected value = 0.008 μg/m^3).

When examining strata with highest and lowest total amount of air pollution, several important findings stand out. The three strata reporting the highest exposure to air pollution share many characteristics (a high percentage of Black and low percentage of Latinx residents, high percentage of female-headed households, lowest tercile of median household income, metro area) and differ only in educational attainment. Generally, strata predicted to have the highest exposure levels are census tracts with a higher percentage of Black residents within a metro area, with all ten highest-exposed strata sharing these characteristics. On the other hand, census tracts exposed to lower levels of air pollution tended to be in non-metro areas and have fewer Black residents. The census tracts exposed to lower levels of air pollution tended to have fewer Black residents and more Latinx residents, fewer female-headed households, higher educational attainment, and classified as non-metro areas.

In Model B, a purely additive take on the results suggests that strata will tend to have higher air pollution levels if they are metro neighborhoods with a higher percentage of Black residents, in the highest tercile of female-headed household, and lowest tercile of educational attainment. Overall, strata with a high percentage of Black and high percentage of Latinx residents tended to have elevated pollution levels, but it was the "high % Black and low % Latinx" strata that had the highest levels. While additive fixed effects for median household income did not show clear evidence of inequalities in Model B, adjustment for demographic controls in Model C *did* reveal inequalities, with higher income levels correlating (on average) with higher pollution levels. Furthermore, even when additive fixed effects are not statistically significant, income remained important to predicting pollution inequalities for some strata, which is reflected in the stratum-level residuals. In Model C, all other additive fixed effects maintain the direction and significance found in Model B except for educational attainment. Model D includes EPA regions, and all additive fixed effects maintain their direction significance except for educational attainment, which is no longer significant.

While additive results are worth examining, it is essential to understand that these additive patterns can obscure intersectional patterns of inequalities. As noted previously, the VPC suggests that substantial variation (or inequality) between strata is accounted for by interaction effects. For instance, although additive parameters for educational attainment and median household income are inconsistent in their statistical significance, education and household income do appear to combine with other demographic factors to place certain strata at heightened (or reduced) risk of high industrial air pollution exposure. For instance, strata 31330, 31320 and 31310 were three of the four strata with lowest overall predicted air pollution levels. These strata have substantially similar profiles, consisting of communities with a low percentage of Black and high percentage Latinx residents, low percentage female headed households, high average educational attainment, in metro areas. The three strata differ only with respect to median household income. This indicates that the educational attainment of residents is a salient component of the intersectional advantage experienced by these communities with respect to air toxics exposure.

Fig. 4 plots the 56 (out of 216) strata with significant residual interaction effects in Model B. We focus here on the "total interaction effects" in Model B because subsequent models' adjustment for controls may be identifying and attenuating for underlying explanations of inequalities. Strata with significant residual interaction effects appear to experience predicted air pollution levels that substantially differ from what might be expected based on a purely "additive story" about results. The magnitude of these residuals and the frequency of significant residuals among strata support our conclusion that it is essential to examine interactions in order to adequately describe patterns of inequality in air toxics exposure.

We ran robustness checks on Models A-D and Figs. 2–4 by dropping census tracts with less than 500 residents, removing 134 tract observations. Estimates were consistent with findings from all the models. For the caterpillar plot (Model B), there was a slight change in the order of the strata within the top ten highest and the top ten lowest, but there was no evidence of substantive changes. This indicates the original findings were robust.

4. Discussion

In an EIM analysis of United States census tracts, we find evidence of significant, intersectional inequalities in industrial air toxic exposure

[4] The reported values are the unlogged estimates of industrial air toxics.

Table 4
Multilevel regression results.

	Model A (Null)				Model B (Main Effects)				Model C (Demographic Controls)			
	Est.	95% CI		P	Est.	95% CI		P	Est.	95% CI		P
FIXED EFFECTS												
Intercept	−2.550	−2.654	−2.438	0.000	−3.266	−3.373	−3.153	0.000	−3.045	−3.140	−2.957	0.000
Racialization												
Low % Black, Low % Latinx (ref)												
High % Black, Low % Latinx					0.604	0.506	0.702	0.000	0.663	0.599	0.728	0.000
Low % Black, High % Latinx					−0.292	−0.389	−0.192	0.000	−0.172	−0.236	−0.108	0.000
High % Black, High % Latinx					0.098	−0.006	0.194	0.031	0.190	0.124	0.258	0.000
Female Headed Household												
Low Tercile (ref)												
Middle Tercile					0.215	0.130	0.291	0.000	0.079	0.022	0.136	0.005
High Tercile					0.345	0.246	0.429	0.000	0.141	0.077	0.204	0.000
Educational Attainment												
Low Tercile (ref)												
Middle Tercile					−0.128	−0.214	−0.046	0.003	0.059	0.004	0.118	0.015
High Tercile					−0.216	−0.311	−0.127	0.000	0.149	0.086	0.214	0.000
Median Household Income												
Low Tercile (ref)												
Middle Tercile					0.012	−0.072	0.092	0.405	0.123	0.066	0.178	0.000
High Tercile					−0.031	−0.122	0.056	0.243	0.264	0.193	0.334	0.000
Metro					1.039	0.967	1.116	0.000	1.029	0.979	1.081	0.000
CONTROLS												
Median Age*									−0.015	−0.016	−0.013	0.000
Housing built in and after 1970s (%)*									−0.010	−0.010	−0.010	0.000
Median Housing Value**									−0.160	−0.179	−0.141	0.000
Manufacturing (%)*									0.054	0.052	0.055	0.000
Renters (%)*									0.006	0.005	0.007	0.000
Unemployment (%)*									−0.004	−0.005	−0.002	0.000
RANDOM EFFECTS	Est.	95% CI			Est.	95% CI			Est.	95% CI		
Stratum Variance (σ^2_{u0})	0.470	0.384	0.583		0.045	0.034	0.059		0.017	0.012	0.023	
Individual Variance (σ^2_{e0})	1.532	1.516	1.548		1.532	1.515	1.548		1.314	1.299	1.326	
VPC	23.49%				2.86%				1.28%			
PCV (from null model)					90.40%				90.40%†			
N	71,625				71,625				70,920			

	Model D (EPA Regions)			
	Est.	**95% CI**		**P**
FIXED EFFECTS				
Intercept	−3.443	−3.529	−3.357	0.000
Racialization				
Low % Black, Low % Latinx (ref)				
High % Black, Low % Latinx	0.502	0.438	0.567	0.000
Low % Black, High % Latinx	−0.130	−0.194	−0.067	0.000
High % Black, High % Latinx	0.161	0.095	0.228	0.000
Female Headed Household				
Low Tercile (ref)				
Middle Tercile	0.118	0.064	0.172	0.000
High Tercile	0.204	0.145	0.263	0.000
Educational Attainment				
Low Tercile (ref)				
Middle Tercile	0.030	−0.025	0.084	0.286
High Tercile	0.037	−0.024	0.099	0.237
Median Household Income				
Low Tercile (ref)				
Middle Tercile	0.154	0.100	0.208	0.000
High Tercile	0.383	0.317	0.448	0.000
Metro	0.998	0.947	1.049	0.000
CONTROLS				
Median Age*	−0.014	−0.015	−0.013	0.000
Housing built in and after 1970s (%)*	−0.012	−0.012	−0.012	0.000
Median Housing Value**	0.084	0.063	0.107	0.000
Manufacturing (%)*	0.047	0.046	0.049	0.000
Renters (%)*	0.008	0.007	0.008	0.000
Unemployment (%)*	0.002	0.000	0.004	0.026
EPA Regions				
1	−1.047	−1.089	−1.003	0.000
2	−0.887	−0.923	−0.847	0.000
3	−0.092	−0.125	−0.058	0.000
4	0.031	0.000	0.061	0.023
5 (ref)				
6	−0.126	−0.161	−0.091	0.000
7	0.079	0.035	0.119	0.000

(*continued on next page*)

Table 4 (*continued*)

	Model D (EPA Regions)			
	Est.	**95% CI**		**P**
8	−0.635	−0.688	−0.579	0.000
9	−0.691	−0.729	−0.656	0.000
10	0.060	0.011	0.112	0.006
RANDOM EFFECTS	Est.	95% CI		
Stratum Variance (σ^2_{u0})	0.016	0.011	0.022	
Individual Variance (σ^2_{e0})	1.221	1.208	1.234	
VPC	1.27%			
PCV (from null model)	96.67%†			
N	70,920			

Notes: * Variable is mean-centered. ** Variable is natural log transformation. † The PCV of Model C and D should be interpreted carefully because of the change in the sample size due to missing values of control variables.

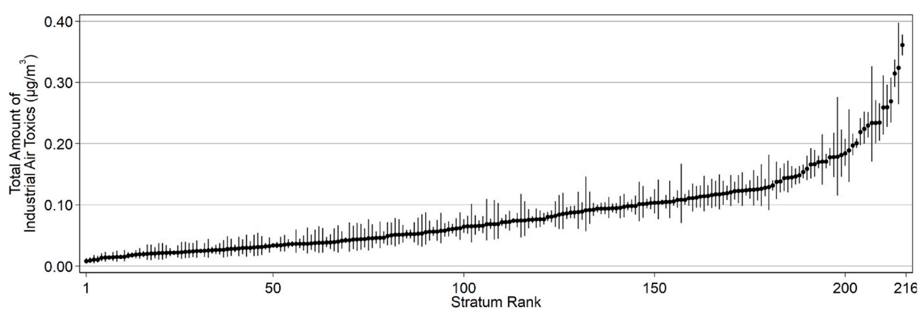

Fig. 2. Expected values of total air pollution by stratum, ranked from lowest to highest exposure levels.
Notes: Markers indicate expected values of air pollution and lines indicate 95% credible intervals for each stratum from Model 1B.

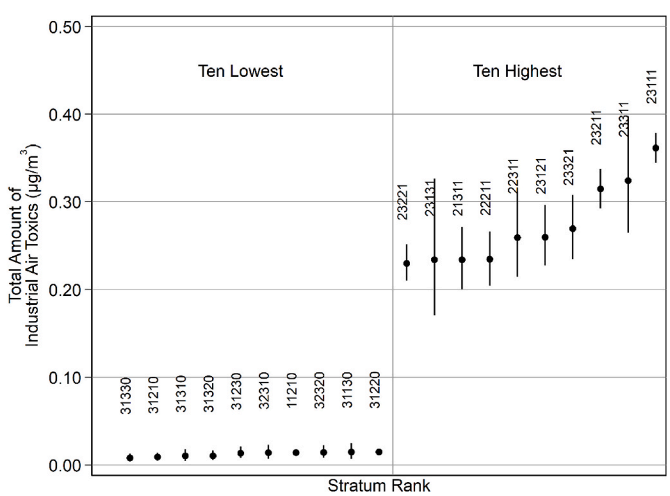

Fig. 3. Up-close of high- and low-risk air pollution exposure by stratum ranking.
Notes: Markers indicate expected values of air pollution and lines indicate 95% credible intervals for each stratum from Model 1B. The numeric value for Stratum IDs is a five-digit code: Digit 1: racial/ethnic composition (1 = low% Black low% Latinx, 2 = high% Black low% Latinx, 3 = low% Black high% Latinx, 4 = high% Black high% Latinx); Digit 2: percent female-headed households tercile (1 = low, 2 = middle, 3 = high); Digit 3: educational attainment tercile (1 = low, 2 = middle, 3 = high); Digit 4: median household income tercile (1 = low, 2 = middle, 3 = high); Digit 5: metro/non-metro (1 = metro, 0 = non-metro).

between strata of census tracts, patterned according to racial/ethnic composition, percent female-headed households, educational attainment, household income, and urbanicity. The magnitude of these inequalities was *considerable*, with tracts from the highest-exposed stratum (stratum 23111: high percentage Black, low percentage Latinx residents, high percentage female-headed households, lowest terciles of educational attainment and median household income, metro) experiencing 45 times more exposure on average than tracts from the least-exposed stratum (stratum 31330: low percentage Black, high percentage Latinx residents, low percentage female headed-households, highest terciles of educational attainment and median household income, non-metro). Of the total variation in industrial air pollution in the sample, 23.5% was at the between-stratum level, again indicating significant inequalities. Phrased differently, while there was substantial variation in exposure level across census tracts, with some experiencing very high or very low pollution levels, exposure was also meaningfully patterned such that *certain multiply marginalized strata were significantly more likely to experience high exposure levels*. Fig. 2 shows a pronounced spike in exposure in the right-hand tail, indicating that not only were inequalities pronounced overall, but a subset of strata experienced dramatically heightened toxic exposures. Importantly, these inequalities are not adequately represented by the additive contributions of these axes of marginalization alone. Nearly 10% of this between-stratum variation remained unexplained after adjusting for additive main effects, indicating interaction effects contribute meaningfully to the inequalities as well.

We find evidence of interaction effects impacting air quality for *both* marginalized and privileged strata. In other words, this is not a simple story of additivity explaining inequality for most strata, with a few multiply marginalized strata experiencing an additional burden (captured by interaction effects) above and beyond the additive. Strata at various intersections of privilege and marginalization experience positive (higher exposure) and negative (lower exposure) interaction effects than would be expected for them based on additive effects alone. For example, stratum 11331 (low percentage Black and low percentage Latinx residents, low percentage female-headed household, highest tercile of educational attainment and median household income, metro) reported significant positive interaction residuals and ranked 152nd (out of 216) for best air quality. On the other hand, stratum 41120 (high percentage Black and high percentage Latinx residents, low percentage

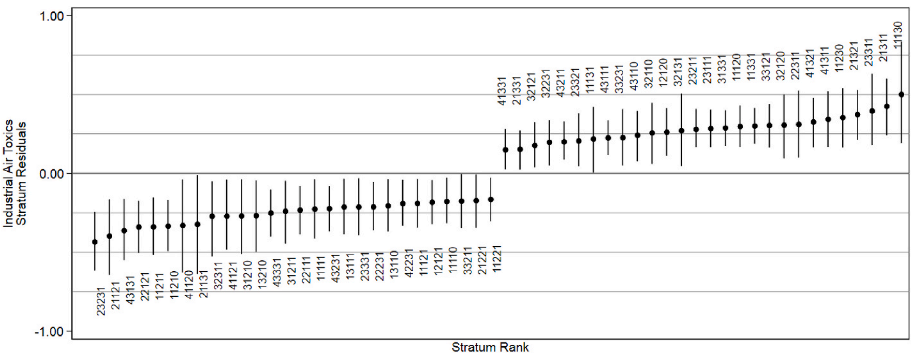

Fig. 4. Ranked stratum-level of statistically significant residuals for industrial air toxics.
Notes: Markers indicate stratum residuals and lines indicate 95% credible intervals for strata with statistically significant residuals in Model 1B. The numeric value for Stratum IDs is a five-digit code:
Digit 1: racial/ethnic composition (1 = low% Black low% Latinx, 2 = high% Black low% Latinx, 3 = low % Black high% Latinx, 4 = high% Black high% Latinx).
Digit 2: percent female-headed households tercile (1 = low, 2 = middle, 3 = high)
Digit 3: educational attainment tercile (1 = low, 2 = middle, 3 = high)Digit 4: median household income tercile (1 = low, 2 = middle, 3 = high); Digit 5: metro/non-metro (1 = metro, 0 = non-metro).

female-headed household, low tercile of educational attainment, middle tercile of median household income, non-metro) reported significant negative interaction residuals and ranked 19th (out of 216) for best air quality. In other words, despite the differences in neighborhood demographics categories and air quality, both strata showed evidence of significant interaction effects—which work to either increase the health risk for the most marginalized or decrease the health risk for the most privileged.

Consistent with previous research (Ard, 2015), we found that neighborhoods with the *most* air pollution tend to have a higher percentage of Black residents and Latinx residents. On the other hand, neighborhoods with a lower percentage of Black residents and a higher percentage of Latinx residents reported the *least* air pollution, as seen in Fig. 3. We hypothesize several potential explanations for this finding. First, Fig. 2 demonstrates there are a fair number of strata at the lower end; in other words, the lower end of the caterpillar is fairly flat, indicating those strata have similar exposure levels. Second, this finding may be explained by the overlapping dimensions of a high percentage of Latinx residents and non-metro strata living in more rural or agricultural communities with fewer industrial air pollution sources, as suggested by the macro regional patterns in Fig. 1. Our dependent variable does not capture agricultural sources of air pollution, so there may be additional pollutants in non-metro strata that we cannot assess. Third, while some research has suggested that Latinx residents may live in less polluted areas as compared to Black and White residents (Ash and Fetter, 2004; Downey and Hawkins, 2008a), this finding could be attributable to the census definition of Latinx, which collapses many ethnic groups, such as Puerto Ricans, Mexicans, and Cubans, as well as racial groups including white Latinxs, Afro-Latinxs, and Indigenous-Latinxs into a single category (Chakraborty et al., 2017; Collins et al., 2011; Grineski et al., 2013; Rubio et al., 2020). We use the "Hispanic or Latino Origin by Race" variable to capture the overlap between ethnicity and race, however this approach is limited in its understanding of all intracategorical groups of ethnicity and race within the Latinx community. These populations might have distinct spatial patterning and notable inequalities in exposure to pollution, yet these results may obscure inequalities that here would be captured as within-stratum variation. Also important to this summary, which thus far is distinctly additive, is the intersectional perspective. While strata with a high percentage of Latinx and low percentage of Black residents may tend to have lower levels of air pollution exposure, this is not universally true. For example, stratum 32131 (low percentage Black and high percentage Latinx residents, middle tercile of female-headed households, low educational attainment, high tercile of income, metro) has a relatively high level of air pollution: 0.156 mcg/m^3 (ranking 167th out of 216 strata for best air pollution). This stratum leans toward more disadvantage and marginalization on other axes, which is reflected by its higher-than-average exposure score and rank. Accurately estimating exposure levels for strata such as this necessitates an intersectional model capable of capturing residual interaction effects.

We also found strong evidence of the importance of an understudied neighborhood demographic—female-headed households—in the patterning of industrial air toxics. In both additive and intersectional effects, female-headed household is one of the most consistent predictors (after urbanicity and racial/ethnic composition) of total air pollution. Previous quantitative EJ literature has used female-headed household as an indicator of socioeconomic status within a measure of "economic deprivation index" along with unemployment and educational attainment (Smith, 2009; Liévanos 2015). It is important to note that there are unique ways in which gendered family structure is marginalized and locales are gendered (Ducre 2012); our findings clearly highlight its salience in air toxics exposure.

Viewed in purely additive terms, educational attainment and median household income appeared to have inconsistent correlation with air pollution levels. However, when viewed intersectionally, education and income were clearly important, placing neighborhoods either at heightened or reduced risk of exposure. For instance, higher average educational attainment was an important dimension in shaping the low-risk status of three of the four lowest-exposure strata (31330, 31320 and 31310), all communities with low percentage Black and high percentage of Latinx residents, and low percentage female headed households in non-metro areas. At the same time, the three strata reporting the highest exposure to air pollution (23111, 23311 and 23211) share many characteristics (high percent Black, low percent Latinx, high female-headed household, lowest income tercile, metro) and differ only in education level. For these strata, low median household income clearly contributed to a heightened risk of exposure as one of multiple axes of marginalization. This reflects the importance of an intersectional approach because whether income or education matters more for reducing risk of exposure will depend on other axes of marginalization. Higher levels of either income or educational attainment will vary across the strata and without the intersectional approach the effects can get washed out.

We also found clear and significant additive effects for urbanicity, wherein strata within metro areas generally had higher exposure to air pollution when compared to non-metro strata. The intersectional effects of urbanicity are more complicated to parse out. For example, stratum 31330 (low percent Black, high percent Latinx, low female-headed household, high educational attainment, high income, non-metro) is 1st for best air quality, while its metro analog 31331 (low percent Black, high percent Latinx residents, low female-headed household, high educational attainment, high income, metro) is 113rd for best air quality (a nearly 100 place difference in ranking for best air quality). Is this effect simply additive? Or is there a multiplicative effect wherein a multiply privileged stratum is able to move away from pollution or "vote with their feet" (Banzhaf and Walsh, 2008)? If the latter is the case, how do those mechanisms play out for multiply disadvantaged communities (Ard and Fairbrother, 2017)? These findings stress the importance of place and direction in the application of intersectionality theory. Altogether, our findings highlight the importance of an intersectional approach when analyzing industrial air toxic exposure.

No study is without limitations and ours is no exception. First is our inability to examine how the timing of residential mobility relates to the observed inequality in exposure. In other words, while we can observe the inequality, we are unable to make concluding statements about how these inequalities were generated. For instance, did industry predate the current sociodemographic profile, while marginalized populations moved there over time? Or were new industrial production sites disproportionately placed in marginalized communities because of their marginalized status? Residential mobility has been addressed in previous research (Crowder and Downey, 2010; Downey et al., 2017; e.g., Pais et al., 2014) and findings suggest that residents of color and single-mother households are more likely to reside in neighborhoods with higher air toxics, *and* are more likely to move into said neighborhoods. This happens in part because of policy or land-use decisions, such as redlining, restrictive covenants, or zoning (Ard, 2016; Maantay, 2001; Taylor, 2014). Regardless of how present patterns of unequal exposure came to be, the existence demands future action in order to shield vulnerable populations from the health inequities generated from air toxic exposure.

A second limitation relates to problems inherent to defining analytic categories for the purposes of comparison. Such categorizations may not be optimized to detect the full magnitude of inequalities. We focused on Black and Latinx residents because they are at present the largest racial and ethnic minority populations in the U.S. and this focus is consistent with prior research (Downey and Hawkins, 2008b). However, one oversight of this categorization is the grouping of white residents with Asian and Pacific Islander and Indigenous residents, who have also been found to experience heightened risk of hazards exposure (Grineski et al., 2017, 2019; Liévanos, 2019). Future research can expand on these categorizations and may include other axes of marginalization such as nationality and citizenship. These categories are not naturalist categories and are intended to describe larger inequalities across society. Moreover, our findings reflect ongoing segregation patterns of the US and so future research can investigate other measures such as segregation indices (Ard, 2016).

Future work bridging the EIM approach with a spatial analysis would be fruitful. Such efforts could provide an opportunity to determine what policies configurations, across administrative levels, are most impactful on social outcomes. Moreover, we can use the intersectionality framework to re-operationalize community, determining which boundaries align with health and well-being. Future research could develop a multiscalar framework linking EIM and intersectional MAIHDA to evaluate the individual- and neighborhood-levels as well as their interactions. Additional avenues for future research might include an examination of the mediating effects of socio-economic status such as income or educational attainment on various neighborhood demographics, as well as inequalities in other sources of environmental health hazards, such as drinking water contaminants (Uche et al., 2021) and land waste.

5. Conclusion

Scholarship in EJ and public health demonstrate environmental inequalities at the neighborhood-level, but the interaction between axes of marginalization in generating hazard exposure inequalities remains understudied. To incorporate intersectionality into our understanding of environmental inequalities, explore the generalizability of previous EJ research, and move toward greater consideration of structural intersectionality, we use EIM, an innovative statistical model, to examine the patterning of industrial air toxics. This intercategorical intersectional approach finds stark patterns of inequality in industrial air toxics exposure between strata of census tracts, which are of significant magnitude and inadequately explained by additive narratives of inequality. Future research should incorporate additional aspects of marginalization and environmental indicators into the EIM approach.

Air pollution has serious repercussions for public health and EJ. Estimates of chemical exposure used here have been deemed hazardous to health and therefore any amount represents a risk. Future work should examine how different chemicals and specific health hazards vary across these axes of marginalization. A large, unequal distribution of risk resides in historically marginalized communities. It is important to understand these disparities are based not on singular factors but rather on multiple, overlapping systems of oppressions. By taking a holistic approach to air pollution disparities we aim to shed light on this issue and seek to motivate social and political measures to address these inequalities.

Declaration of competing interest

Not applicable.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2022.102886.

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