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Intersectional environmental justice and population health inequalities: A novel approach

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ABSTRACT

Drawing on the traditions of environmental justice, intersectionality, and social determinants of health, and using data from the EPA's NATA 2014 estimates of cancer risk from air toxics, we demonstrate a novel quantitative approach to evaluate intersectional environmental health risks to communities: Eco-Intersectional Multilevel (EIM) modeling. Results from previous case studies were found to generalize to national-level patterns, with multiply marginalized tracts with a high percent of Black and Latinx residents, high percent female-headed households, lower educational attainment, and metro location experiencing the highest risk. Overall, environmental health inequalities in cancer risk from air toxics are: (1) experienced intersectionally at the community-level, (2) significant in magnitude, and (3) socially patterned across numerous intersecting axes of marginalization, including axes rarely evaluated such as gendered family structure. EIM provides an innovative approach that will enable explicit consideration of structural/institutional social processes in the social production of intersectional and geospatial inequalities.

1. Introduction

Poor and minority communities are often disproportionately exposed to numerous environmental health hazards (Brulle and Pellow 2006; Nixon 2011; Taylor 2014). Often labeled as "fenceline communities" or "sacrifice zones" (Lerner 2010), the health of residents in these neighborhoods is undervalued in pursuit of the production, resource extraction, and waste management demanded in the capitalist, modern world (Pellow 2018; Pulido 2017). This disproportionate exposure to hazards is recognized as a key mechanism in the social production of health inequalities along racial/ethnic and class lines (Berkman and Kawachi 2000; Krieger 1994, 2011), as well as of geospatial inequalities in health (Kawachi and Berkman 2003; Pearce et al., 2010). Historically, environmental justice (EJ) research has relied heavily on case studies of particular communities to document injustices (Cole and Foster 2001; Roberts and Toffolon-Weiss, 2001). While case studies are valuable for their specificity, as well as their ability to humanize abstract processes, determining the extent to which findings generalize to communities across the country requires alternative approaches. Recently, a growing literature argues that environmental injustices are perpetrated *intersectionally* (e.g., Ducre 2012; Ducre 2018; Olofsson et al., 2016). Quantitative intersectional EJ scholarship using an *intercategorical* approach have examined the differences between intersecting socio-economic and racial/ethnic categories at the individual and neighborhood levels (Mohai and Saha 2006; Crowder and Downey 2010; Ard 2015; Liévanos 2015). Key gaps in the EJ literature therefore center on two questions: To what extent are findings from case studies that multiply marginalized communities are disproportionately burdened by environmental health hazards *generalizable* to the entire United States? And, are these structural forms of environmental injustice *intersectional* across systems of power?

Intersectionality scholars have long implicated structural-level processes, such as racism and sexism, in the production of intersectional experiences and outcomes (e.g., Collins 1990/2009; Crenshaw, 1991; McCall 2005). Intersectionality's concordance with theories of the social determinants of health, including ecosocial theory (Krieger 1994, 2011), has contributed to its growing use in studies of population health inequalities (e.g., Bowleg 2012; Evans et al., 2018; Veenstra, 2013; Warner and Brown 2011). However, while the mechanisms producing environmental health risks operate at the neighborhood-level, much of the intersectionality literature focusing on health inequalities makes use of individual-level data and their effects on individual-level outcomes.

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In recognition of this, the field has increasingly called for greater attention to structural-level processes in order to explain the observed social and geospatial patterning of inequalities, as well as for methodological innovations that will enable this (e.g., Bauer 2014; Evans 2019b; McCall 2005; Nash 2008; Schulz and Mullings 2006).

In this study we address these key questions and advance a novel analytic approach: Eco-Intersectional Multilevel (EIM) Modeling. This approach explicitly draws on the traditions of EJ, intersectionality, and social determinants of health for its framing and interpretation. An EIM approach treats neighborhoods as the primary unit of analysis, with the intersectional nature of these places measured using multiple axes of demographic and urbanization characteristics. Using multilevel models that nest U.S. census tracts (level 1) within intersectional strata of neighborhoods (level 2) defined by neighborhood-level demographics, we demonstrate a novel approach for estimating the intersectional effects of environmental health hazards. Combining social demographic and environmental health risk data in over 72,000 census tracts, we demonstrate the EIM approach by quantifying tract-level intersectional inequalities in exposure and population health impact from carcinogenic air pollutants.

1.1. *Theoretical orientation*

We position our present work within intersectionality, EJ, and the social determinants of health because all three scholarly traditions have converged on the issue of inequalities in environmental health threats. Our use of these approaches orients us towards a critical perspective on the placement of environmental hazards. We now briefly review these traditions.

1.1.1. *Intersectionality*

Intersectionality is a theoretical framework originating in Black feminist scholarship that draws attention to the interlocking, mutually constituted nature of systems of oppression and privilege such as racism, sexism, and socioeconomic inequality (Cho et al., 2013; Choo and Marx Ferree, 2010; Collins, 1990/2009; Crenshaw 1991; Hancock 2007, 2013). Intersectionality examines these overlapping systems of oppression at a variety of levels, from the individual to the structural, emphasizing the interconnection between them. Intended originally as a mechanism for critiquing single-axis modes of thought that focused on race(ism) and gender/sex(ism) as separate axes of marginalization, thus rendering invisible the experiences of multiply marginalized populations such as Black women, intersectionality scholarship today has expanded to encompass a variety of approaches, all unified by this original critical perspective. In her oft-sighted work, McCall (2005) identifies three major approaches to intersectionality: the anti-categorical, the intracategorical, and the intercategorical. Anti-categorical approaches focus on the “deconstruct[ion] of analytical categories” while intracategorical approaches “focus on particular social groups at neglected points of intersection … in order to reveal the complexity of lived experience within such groups” (ibid:1773-4). Intercategorical approaches, on the other hand, are typically quantitative and involve “provisionally adopt[ing] existing analytical categories to document relationships of inequality” (ibid:1773).

Conventional approaches to quantitative, intercategorical analyses involve fitting regression models saturated with fixed additive and interaction effects in order to estimate outcomes across intersectional[1] social strata. This approach poses several methodological challenges, particularly because of the importance of broadening intersectionality’s focus beyond gender and race/ethnicity to additional axes of marginalization (McCall 2005; Nash 2008). As more axes are added to the analysis, methodological limitations emerge, including: (1) a limited sample size in many strata, and therefore unreliable stratum-specific estimates; (2) reductions in model parsimony, and therefore limitations to the scalability of the approach for evaluating high-dimensional interactions; (3) difficulties with the interpretability of results when the number of interactions increases. These issues have prompted calls for innovative approaches to intercategorical analysis (Bauer 2014; Bowleg 2012; McCall 2005; Nash 2008). One recent methodological advancement is intersectional Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (intersectional MAIHDA), which offers several advantages over conventional interaction models (Evans 2015; Evans et al., 2018; Merlo 2018).

Intersectional MAIHDA is a tool for intercategorical intersectional analysis that “apply[s] hierarchical, multilevel models to study large numbers of interactions and intersectional social identities, such as race, gender, and class, while partitioning the total variance between two levels——the between-strata (or between category) level and the within-strata (or within category) level” (Evans et al., 2018:64). This is aligned with scholars using multilevel modeling structures to assess interactions (Jones et al., 2016). Briefly, the approach hinges on nesting individuals (level 1) hierarchically within intersectional strata (level 2), defined according to combinations of relevant identities and axes of marginalization, in much the same way that individuals (level 1) are nested in physical contexts such as neighborhoods (level 2) in conventional multilevel models. Leveraging features of multilevel models such as parsimony and adjustment of stratum-specific estimates based on sample size, this approach addresses many of the abovementioned shortcomings of conventional intersectional approaches (Evans et al. 2018, 2020). Estimates of variance within strata provide recognition of the inherent heterogeneity of effects within social strata, while estimates of variation between strata provide convenient summary statistics quantifying the magnitude of inequalities. The EIM approach builds on these recent advancements in intersectional analysis, but centers exposures and outcomes at the community-level rather than the individual-level.

1.1.2. *Environmental justice*

EJ research arose alongside the EJ movement (Chavis, 1987; Mohai and Saha, 2006; Taylor, 2014) to address issues of public health, workplace safety, and environmental inequalities (Taylor 2014; Mohai et al., 2009). Central to the struggle against environmental injustices has been the demonstration of unequal exposure to environmental hazards in minority and low-income communities (e.g., Mohai and Saha 2006; Mohai and Saha 2007). Case studies of particular cities or communities are common in EJ scholarship, with particular attention to the ways in which local environmental hazards disproportionately impact marginalized communities (e.g., Ducre 2012; Grineski et al., 2007; Lerner 2010; Sicotte and Swanson 2007). The extent to which these findings are generalizable has usually been explored either through a single-axis/additive framework (e.g., Anderton et al., 1994; Mohai et al., 2009) or by using intracategorical intersectional approaches across race and ethnicity and socio-economic status (e.g., Collins et al., 2011; Grineski et al., 2013; Liévanos 2017; McKane et al., 2018). Scholars have increasingly called for explicit intersectional theorizing of systems of power in EJ scholarship (e.g., Ducre 2018; Malin and Ryder 2018; Mohai et al., 2009; Olofsson et al., 2016; Pellow 2018).

Intercategorical intersectional scholarship in EJ that examines national patterns has been limited to a small handful of studies, most of which have focused on the intersections of race/ethnicity and income at the neighborhood-level. For example, in their groundbreaking study Downey and Hawkins (2008a) explored census tract-level inequalities in exposure to air toxics intersectionally throughout the U.S. and found that Black, white, and Latinx households with similar income levels

[1] Intersectionality scholarship is a vast field examining intersectional experiences from health outcomes to policy analysis (Choo and Ferree 2010). Throughout this paper, we use the adjective *intersectional* to convey the multitude of intersectionality scholarship as well as to describe the various “intersectional experiences” including research focusing on health and environmental outcomes that manifest through overlapping systems of power.

tended to experience inequalities in environmental hazards, with low-income Blacks being the most likely to experience high levels of hazards. Zwickl et al. (2014) found similar results for exposure to industrial air toxics, with racial/ethnic disparities in pollution being stronger among neighborhoods with lower median household incomes. Furthermore, Ard (2015) examined trends in exposure to industrial air toxics by race/ethnicity and socioeconomic status (SES) at the census block group from 1995 to 2004 and found that while exposure to air toxics decreased for everyone during this period, African-Americans remained consistently more exposed than whites and Hispanics, and that SES was not as protective for African-Americans. Paralleling an increased interest in intersectionality beyond race and class, Liévanos (2015; 2019) expands the attention of national EJ scholarship to also consider immigrant isolation and concentration of single-mother families in predicting the intersectional spatial demography of air toxics exposure. He found Latinx-immigrant, Black, and Latinx economically deprived communities predicted tract exposure to spatial clusters of carcinogenic air pollution in 2005.

As in intercategorical intersectional analyses at the individual-level, adding numerous axes of marginalization to community-level models poses many of the same methodological challenges. Answering calls for consideration of interactions of axes of marginalization beyond the traditional focus on just race and class (Downey, 2005; Downey et al., 2017; Downey and Hawkins 2008b; Ducre 2018; Liévanos 2015), this study outlines an innovative approach that addresses many of these methodological limitations.

1.1.3. *Social determinants of population health inequalities*

Population health is an interdisciplinary field focused on addressing the social determinants of health inequalities. A key theory in population health is Krieger's ecosocial theory (Krieger 1994, 2011). As she argues: "we literally incorporate, biologically, in societal and ecological context, the material and social world in which we live" (Krieger 2011:214). Relevant social determinants of health have been identified across numerous ecological levels, but particularly concerning are those that operate at structural/institutional levels (Bauer 2014; Berkman and Kawachi 2000). This includes processes involved in determining the placement of environmental hazards in communities. Krieger identifies exposure to exogenous hazards, including toxic substances and hazardous conditions, as a key pathway through which embodiment occurs and health inequalities are generated.

Population health also focuses on the geospatial patterning of health risks and adverse outcomes, including a broad literature on neighborhoods and health (e.g., Kawachi and Berkman 2003). Multilevel (random effects) models and spatial approaches such as GIS are frequently used and adept at identifying inequalities across geographical spaces. However, analogous to the EJ literature, the linking of these spatial inequalities to social determinants such as residential segregation by race/ethnicity or SES have tended to inadequately address the extent to which these processes are interlocking and co-constituted (Williams and Collins 2001). Furthermore, these studies often examine the spatial patterning of health outcomes measured at the individual-level, and the role of mediating processes such as the presence of emissions sources is rarely evaluated (Arcaya et al., 2016).

Intercategorical intersectionality is rapidly becoming a popular framework in the study of population health (e.g., Bowleg 2012; Green et al., 2017; Merlo 2018; Schulz and Mullings 2006; Veenstra, 2013; Warner and Brown 2011). Ecosocial theory and intersectionality are highly compatible (Agénor et al., 2014; Evans et al., 2018), and their joint use helps to ensure that the critical edge of intersectional thought is not lost in translation when it is applied to population health. Increasingly, scholars have called for new approaches that will enable the modeling of social processes generating these inequalities (Bauer 2014; Evans 2019b). The intersectional MAIHDA approach has emerged within medical sociology and social epidemiology in response to these calls for methodological innovation (Evans 2015; Evans et al., 2018; Jones et al., 2016; Merlo 2018). This provides a new tool for examining the social determinants of health and represents a "gold standard for investigating health disparities in (social) epidemiology" (Merlo 2018: 74). This literature is rapidly developing, and holds considerable promise for integrating EJ, intersectionality, and population health scholarship in order to address the shared concerns of these fields.

1.2. *Toward an eco-intersectional multilevel perspective*

In introducing the term "eco-intersectionality" to describe the analytic approach we propose, we are aware that this may be deemed unnecessary by some intersectionality scholars. As noted previously, intersectionality has long focused on the structural, institutional and ecological-level processes involved in the production of intersectionally patterned discrimination, experiences, and outcomes. Why, then, the new term? We introduce this term in order to differentiate our *modeling approach* from analyses of individual-level data, such as the emerging intersectional MAIHDA approach. We acknowledge and stress, however, that we are merely applying intersectionality theory to an ecological and multilevel *analysis framework*, not proposing a new form of intersectionality *theorizing*.

In this study we advance an eco-intersectional multilevel (EIM) modeling approach to evaluate intersectional experiences of environmental injustice at the community-level. While most intercategorical intersectional analyses treat individuals as the unit of analysis, an EIM approach treats neighborhoods (or communities) as the unit of analysis. When addressing environmental threats this shift in unit of analysis is sensible, because it is frequently the community-level at which exposures are determined. While individuals who are multiply marginalized may be more likely to experience these hazards on average and may possess fewer resources to cope with the adverse consequences of exposure once it occurs, the mechanisms at work do not selectively target individuals. Instead, the mechanisms of environmental hazards placement work at a structural neighborhood-level with intersecting classed, racialized, gendered, and urbanized dimensions. If communities experiencing marginalization through multiple intersections of racism, classism, and patriarchy are discriminated against (or at least not the recipients of public or state concern), under-resourced, low in available time for mobilizing, and/or lacking in power/social capital, then this can result in the placement of harmful production and other environmental health hazards in those communities. Furthermore, it will be more difficult for communities with lower social and political capital to organize to remove or mitigate existing threats. The end result is residents in these communities being disproportionately exposed to externalities from production, waste treatment, or other hazardous processes. Simultaneously, social processes at work creating hazards for marginalized communities also operate by privileging other communities based on intersections of racialized, classed, and gendered systems of power (Pulido 2000).

Here, we use census tracts as a geographical proxy for the neighborhood/community-level. In this study, we examine racial/ethnic composition, percent female-headed households, educational attainment, median household income level, and metro/non-metro locale. Inequalities by neighborhood SES have been central to EJ literature, however SES is often operationalized as median household income. By expanding our analysis to also consider educational attainment of residents we acknowledge that while income and education are frequently correlated, they may operate through very different processes to shape environmental risk (Ard 2015). For instance, a community with a higher percentage of residents who have some college education may, regardless of median household income level, possess greater social capital and power to resist placement of hazards in their community or to organize to mitigate existing risks. Our inclusion of percent female-headed households is based on clear findings of its salience and under-recognized importance (Ducre 2012). Following others, we theorize percent female-headed households both as a marker of deprivation (Mosher 2001; Smith 2007; Wilson 1987, 1996) and as "an independent predictor of heightened risk of exposure to environmental toxins" (Liévanos 2019: 163; see also: Downey, 2005; Downey et al., 2017; Downey and Hawkins 2008b; Liévanos 2015). Similarly, the importance of metro versus non-metro environments in shaping environmental hazards has been well established, with urban areas having greater concentration of sources of air pollution including transportation and industrial uses (Liévanos 2019; Clark et al., 2014).

It is important to recognize that while we have selected these axes for our focus, future work could examine other aspects of marginalization and inequality. These choices are not based on *naturalistic* categorizations, but rather *analytic* ones. For example, while SES at the neighborhood-level is clearly an important determinant shaping environmental hazard exposure, choosing analytic thresholds is always a somewhat arbitrary process. Intercategorical intersectionality scholars have wrestled with this issue for some time, and it is for this reason that scholars speak of "provisionally adopt[ing] existing analytical categories" (McCall 2005:1773) while retaining an awareness of the inherent limitations of both thresholds and labels. As in all intersectionality scholarship that makes use of labels, care should be taken to avoid reification (Cho et al., 2013).

While conventional multilevel approaches typically model clustering by geographical boundaries or environments, intersectional MAIHDA and EIM examine clustering by analytic groupings. For example, a conventional multilevel model might nest census tracts (level 1) within counties (level 2) within states (level 3) (Fig. 1, Panel A). Intersectional MAIHDA is conducted using individual-level data, and involves nesting individuals (level 1) within intersectional social strata (level 2) (Fig. 1, Panel B). Intersectional social strata are identified based on every possible combination of categorizations being analyzed, such as categories of gender, race/ethnicity, SES, and sexual identification. We expand the MAIHDA approach from the individual-level to the census tract-level. EIM modeling nests census tracts (level 1) within intersectional *strata of census tracts* (level 2) (Fig. 1, Panel C), where intersectional strata of census tracts are defined using all examined combinations of analytic categories of neighborhood demographics such as racial and ethnic composition and socio-economic status. In EIM models neighborhoods are clustered according to analytic typologies, reflecting their similarity of intersectional experiences regardless of their precise physical location. Despite their similarities, EIM is distinct from MAIHDA both because of the difference in analytic units (communities versus individuals) and because of the change this shift in focus requires in order to theorize the underlying intersectional processes at work.

While neighborhoods are the focus in EIM, it is also essential to recognize that these are embedded within a multilevel framework of interacting ecological levels, and that consequently they are shaped by processes at other levels, including policies, economies, and social movements at the city-, state-, national-, and international-levels. The placement of environmental hazards in particular locales is shaped by a combination of decision-making processes within organizations, cost of land, zoning laws, and environmental regulations. The present analysis is concerned with documenting the environmental health inequalities that are the end result of processes operating across all ecological levels.

The EIM approach: (1) brings intersectionality methods into greater alignment with theory by re-emphasizing the role of the community/structural level; (2) provides a new perspective on geospatial and social patterns of health inequalities; (3) expands on current efforts in the EJ literature to more explicitly incorporate intersectionality theorizing; and (4) generalizes questions examined previously in EJ case studies to test whether multiply marginalized communities are systematically exposed to excess environmental threats across the United States. We used a complete case sample of 72,103 census tracts from the United States.

1.3. Dependent variable: estimated cancer risk from air toxics

The National Air Toxics Assessment (NATA) is a "state of the science screening" for national air quality by the EPA (Office of Air Quality Planning and Standards 2018) and has been employed in previous EJ research (e.g., Depro et al., 2015; Liévanos 2015; Alvarez and Norton-Smith 2018). NATA evaluates exposure to carcinogenic air pollutants at the tract-level from a variety of sources, and estimates the potential cumulative risk to population health. Estimates are produced in a multi-stage process. First, a National Emissions Inventory is compiled of 180 air toxics that are known or suspected causes of cancer and other serious health issues. A wide variety of pollution sources are included, ranging from manufacturing and transportation to secondary sources such as air toxics that form in the atmosphere due to photochemical reactions.

The second step involves estimating ambient air concentrations through atmospheric dispersion and photochemical models. Finally, the EPA estimates the risks to human health associated with exposure to these concentrations, including lifetime cancer risk, and models human outdoor activity for exposure at the tract-level. Prior EJ scholars who have used NATA estimates have interpreted them as estimates of *relative cancer risk* attributable to outdoor residential hazardous air pollutant exposures (e.g., Grineski et al., 2017). NATA provides estimates of cancer risk from air toxics for each tract, defined as the predicted number of cases of cancer attributable to air toxics exposure per million people, assuming lifelong (70 years) exposure to those levels of emissions. We use the most current 2014 NATA estimates, which were released in August of 2018.

1.4. Intersectional strata of census tracts

All demographic variables used to classify census tracts according to

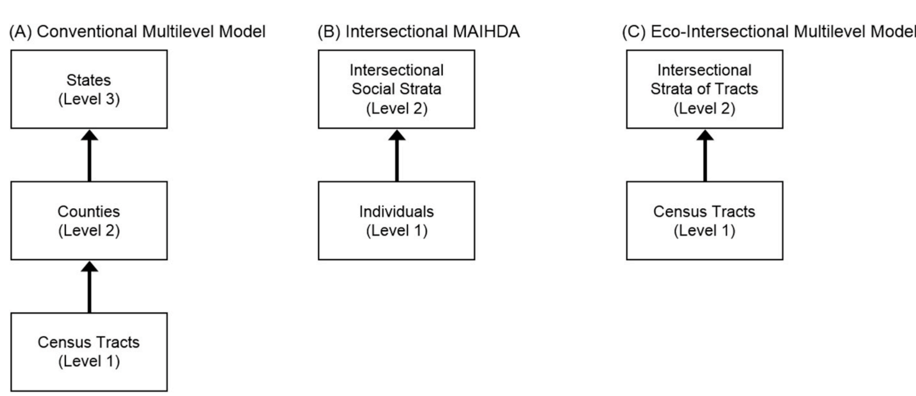

Fig. 1. Comparison of multilevel model structures. *Notes*: Arrows indicate hierarchical, nested structure of data. For instance, in conventional multilevel models, multiple census tracts (level 1) are nested within each county, and counties (level 2) are nested within each state (level 3).

intersectional strata were obtained from the 2010–2014 American Community Survey, available from the National Historical Geographic Information System (Manson et al., 2018). The metropolitan status is from the latest 2013 Rural-Urban Continuum Codes released by the U.S. Department of Agriculture Economic Research Service (USDA ERS 2013).

1.4.1. Racial/ethnic composition

To construct the racialized dimension, we derived four categories by first classifying all tracts as either above or below the median percentage of Black, non-Latinx residents and either above or below the median percentage of Latinx residents. For brevity, we henceforth refer to percent of Black non-Latinx residents as percent Black. A cross-tabulation of these values was used to construct the four categories: (1) tracts *below* the median percent Black and *below* the median percent Latinx residents; (2) tracts *above* the median percent Black and *below* the median percent Latinx residents; (3) tracts *below* the median percent Black and *above* the median percent Latinx residents; (4) tracts *above* the median percent Black and *above* the median percent Latinx residents.

1.4.2. Female-headed households

To construct the gendered family structure dimension of the stratum categories, we classified tracts according to terciles of percent female-headed household: (1) lowest tercile; (2) middle tercile; (3) highest tercile.

1.4.3. Educational attainment

The first classed dimension of the strata categories is educational attainment of residents who are 25 years or older. Tracts were classified according to terciles of percent residents with some college education or more: (1) lowest tercile; (2) middle tercile; (3) highest tercile.

1.4.4. Median household income

The second classed dimension of the stratum is median household income. Tracts were classified according to terciles of median household income: (1) lowest tercile; (2) middle tercile; (3) highest tercile.

1.4.5. Metro/non-metro

To measure urbanicity, we classified tracts based on the county-level metro/non-metro classifications using population and commuting data (USDA ERS 2013). We classified categories 1 through 3 (coded "1") as metro and 4 through 9 as non-metro (coded "0"). For this initial EIM analysis, we did not evaluate suburban classification, both because defining suburbanicity is notoriously difficult and because doing so substantially reduced sample sizes within many strata.

1.4.6. Stratum ID codes

Each stratum was given a unique five-digit code: racial/ethnic composition (digit 1), female-headed households (digit 2), educational attainment (digit 3), median household income (digit 4), and metro/non-metro (digit 5). The value in each digit corresponds with the codes above. For example, stratum 23310 refers to census tracts that are: *above* the median percent Black and *below* the median percent Latinx residents (2), highest tercile of percent female-headed household (3), highest tercile educational attainment (3), lowest tercile median household income (1), and non-metro (0).

1.5. Controls

We included a variety of control variables frequently adjusted for in similar analyses (Downey and Hawkins 2008a; Alvarez and Norton-Smith 2018; Liévanos 2019), including some that are potential intermediary effects. All control variables were mean-centered. We specifically control for median age, percent unemployment, percent of housing units built after 1970, median housing value, percent manufacturing workers, and percent of renters.

1.6. Analytical approach

Analytically EIM is similar to intersectional MAIHDA (Evans 2015; Evans et al., 2018), except that the EIM model treats area units (e.g., census tracts) as the level 1 unit of analysis, whereas MAIHDA utilizes individual-level data at level 1. Thus, many of the advantages of MAIHDA over conventional fixed effect interaction models are also advantages of the EIM approach. We therefore briefly review these advantages (and differences) from conventional models.

The conventional single-level approach to quantitative intercategorical analysis involves fitting a regression model that includes fixed parameters for all additive main effects and all permutations of interactions (first-order, second-order, and higher-order). For example, the linear model might take the form:

$$y_i = \beta_0 + \beta_1(woman_i) + \beta_2(Black_i) + \beta_3(woman_i)(Black_i) + e_{i0} \quad (1)$$

where y_i is the observed outcome for individual i, β values are the fixed additive and interaction parameters, and e_{i0} is the residual difference for individual i between the predicted value and the observed value y_i. In addition to the methodological limitations as the number of categories and axes of marginalization increases (e.g., low scalability, low model parsimony, small sample size in some intersectional strata, and issues with the interpretability of results), Evans et al. (2018) note two additional theoretical issues with this setup. First, while between-group comparisons are, to some extent, inherent to the task of identifying inequalities, this setup has the unfortunate side-effect of reinforcing the social primacy of the multiply privileged (in this case, white men), who when consistently used as the reference category can sometimes come to be seen as a "default" type of human. Second, this setup enables the detection of "interaction effects" only for some social strata—in this case, Black women—unless the model is re-run with different reference levels. Some theorists have called for attention to intersections that mix privilege and marginalization (Bauer 2014; Choo and Ferree 2010; Hancock 2007; Nash 2008). Ideally, we want to estimate an "interaction effect" for all social strata, with this interaction effect capturing the difference between what is *observed* for that stratum and what we might have *predicted* for it based on the additive contributions of the main effects.

Using individual-level data, a linear intersectional MAIHDA model would resemble:

$$y_{ij} = \beta\delta_j + u_{0j} + e_{0ij} \; u_{0j} \sim N(0, \sigma_u^2) \; e_{0ij} \sim N(0, \sigma_e^2) \quad (2)$$

where y_{ij} is the value of the outcome for individual i in social stratum j, δ_j is a vector of the intercept and additive effects for stratum j and β is a vector of the associated parameter values, u_{0j} is the stratum-level residual for stratum j, and e_{0ij} is the individual-level residual for individual i in social stratum j. Both residuals are normally distributed with mean 0. The between-stratum residual variance is σ_u^2 while the within-stratum (between-individual) residual variance is σ_e^2. In a null model, which includes no additive main effects, the σ_u^2 would provide a measure of the total variation (or inequality) between strata. In a model inclusive of additive main effects that *does not include any fixed interaction parameters*, u_{0j} represents the residual interaction term for stratum j, and a unique residual is estimated for all strata. In the additive main effects model, σ_u^2 would describe the variation between strata that is not explained by additive effects alone. Two additional statistics frequently calculated for intersectional MAIHDA (Axelsson et al., 2018; Evans 2019a; Evans et al., 2018; Evans and Erickson 2019; Hernández-Yumar et al., 2018) are the Variance Partition Coefficient (VPC) and the Proportional Change in Variance (PCV). The VPC is calculated as:

$$\text{VPC} = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2} \times 100\% \quad (3)$$

while the PCV is calculated as:

$$\mathrm{PCV} = \frac{\sigma^2_{u,\ Null\ model} - \sigma^2_{u,\ Non\ null\ model}}{\sigma^2_{u,\ Null\ model}} \times 100\% \tag{4}$$

The VPC from the null model provides a measure of the proportion of total variation in the sample that exists at the between-stratum level. In the case where a non-null model is the model inclusive of additive effects, the PCV provides a measure of the extent to which the observed between-stratum variation from the null model is explained by the additive effects, and the value of $1 - \mathrm{PCV}$ is the percent of residual between-stratum variation that is not explained by additive effects (and therefore might be attributable to interactions, under the assumption of no omitted variable bias).

Intersectional MAIHDA and EIM models thus avoid at least two important theoretical limitations of conventional modeling approaches, and address many of the methodological limitations of conventional approaches as well. For instance, as categories/axes of marginalization are added to intersectional analyses, the number of fixed parameters in conventional models grows *geometrically*, while MAIHDA and EIM grow *linearly*, improving model parsimony and scalability. The issue of interpretability is also largely resolved because of model parsimony, and because an estimate of a residual/interaction is obtained for each stratum. Useful summary statistics such as the VPC and PCV are also obtained, which enable a consideration of variation within and between strata as well as differences in average effects.

In this study we focus almost exclusively on the total predicted values for each stratum, which combine additive fixed effects and the stratum-specific residuals, rather than on the residual interaction effects themselves. What, then, is the purpose of fitting this "intersectionality-plus" (Weldon 2008) multilevel model, when it might be simpler to just estimate the mean cancer risk in each stratum? The answer to this relates to the final advantage of MAIHDA and EIM over conventional approaches, which is in how these models address strata with small sample sizes. While there is no ultimate way to avoid the issue of small sample size in many strata if the data is parsed too finely, simulation analyses have shown that the intersectional multilevel approaches are more robust to adverse consequences of this than their conventional counterparts (Evans 2015; Evans et al., 2018; Bell et al., 2019). The main issue is that as sample size decreases in a given stratum, any estimates for that stratum will become unreliable. However, multilevel models automatically adjust estimates based on reliability and sample size, whereas conventional approaches would simply estimate the predicted value with no adjustment for reliability (Evans et al., 2020).

The EIM model structure used in this study is the same as in Equation (2), however the model describes the outcome y_{ij} for census tract i in intersectional social stratum j (Fig. 1). A total of 72,103 census tracts were nested in 216 unique social strata. Seventy-five percent of the intersectional strata of neighborhoods contained 30 or more census tracts and all strata contained some census tracts (Supplemental Table 1).

Our model building progressed as follows. Model 1A is a null model, which provides information about overall levels of inequality in air toxics-related cancer risk between strata. Model 1B is the additive main effects model, and Model 1C further includes control variables. In order to ensure that any notable effects were not simply driven by a few "outlier" census tracts, where perhaps something unique is occurring that is not part of a larger story of intersectionality, we conducted a set of robustness checks. For this we dropped from the data set all census tracts with extremely high predicted cancer risk values ($\geq$ 250 cases per million) and re-fit the above models. Models 2A (null), 2B (main effects) and 2C (main effects + controls) are therefore fitted to the data where 22 census tracts were dropped from the analysis. We identified each of these 22 cases individually, determined their precise geographic location (particularly relative to other census tracts also considered outliers), and conducted searches for information about why the cancer risk in these communities was estimated to be particularly high.

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). Estimations were performed using Bayesian Markov Chain Monte Carlo (MCMC) estimation procedures (Browne 2017) with diffuse priors. Quasilikelihood methods were used to provide the MCMC procedure with initialization values. For all models a burn-in of 5000 iterations and total length of 50,000 iterations (with thinning every 50 iterations) was used, and 95% credible intervals were obtained for all estimates.

2. Results

The median value of predicted cancer risk in the sample was 31.7, with a substantial range of 6.2 to 1505.1 cases per million (see Table 1). Parameter results for Models 1A-C are provided in Table 2. The VPC in Model 1A was 18.33%, indicating a high degree of clustering at the intersectional strata level, as well as meaningful between-stratum inequalities. This can be best visualized in Fig. 2A, which provides a caterpillar plot of the predicted values and 95% CI by stratum (see Supplemental Table 1 for exact predicted values). The "top ten" highest and lowest predicted values are identified in Fig. 3. As can be seen here, the predicted values ranged from 19.41 (stratum 11330: low % Black and low % Latinx, low % female-headed households, high educational attainment, high median household income, non-metro) to 51.04 cases per million (stratum 23131: high % Black and low % Latinx, high % female-headed households, low educational attainment, high median household income, metro). All three strata that were high % Black and low % Latinx, high % female-headed households, low educational attainment, and metro (at varying levels of median household income) were in the highest four predicted values for any strata. This indicates that, regardless of median household income, this intersection was especially likely to experience exposures to carcinogenic air toxics.

Considered from a purely additive perspective, the results obtained in Models 1B and 1C match what we might expect in general for how marginalization relates to exposure likelihood (Table 2). Higher percentages of Black and Latinx residents, higher percentages of female-

Table 1
Descriptive statistics of census tracts.

	Mean	SD	Min	Max	Median
Estimated Air Toxics Cancer Risk	31.65	12.92	6.17	1505.12	31.00
Race/Ethnicity by Tract					
% White, not Latinx	63.22	30.16	0	100.00	72.69
% Latinx	15.65	21.16	0	100.00	6.61
% Black, not Latinx	13.38	21.93	0	100.00	3.74
% Female-Headed Households	13.64	8.71	0	87.28	11.53
% Residents with Some College or More	57.26	17.82	4.74	100.00	56.26
Median Household Income (in $1,000s)	57.23	28.49	2.50	250.00	51.00
Metro (binary)	.8338	.3723	0	1	1
% Renters	36.30	22.70	0	100	31.15
% Unemployed	9.76	6.01	0	100	8.44
% Housing units built after 1970	55.49	28.77	0	100.00	57.21
Median Housing Value (in $1,000s) (n = 71,375)	219.10	173.75	10.000	100.00	162.50
% Workers in Manufacturing (n = 72,102)	10.45	6.91	0	71.77	9.13
Median Age	38.75	7.62	11.50	84.30	38.80

Note: n = 72,103 unless otherwise stated. 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. 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.

Table 2
Results from multilevel linear regression models.

FIXED EFFECTS	Model 1A (Null)				Model 1B (Main Effects)				Model 1C (Main Effects + Controls)			
	Est	95% CI		P	Est	95% CI		P	Est	95% CI		P
Intercept	29.70	28.86	30.51	<0.001	21.99	20.88	23.04	<0.001	23.41	22.29	24.52	<0.001
Racialization												
Low% Black, Low% Latinx (ref)	–	–	–	–	–	–	–	–	–	–	–	–
High% Black, Low% Latinx					8.29	7.34	9.25	<0.001	7.95	6.88	9.00	<0.001
Low% Black, High% Latinx					3.30	2.33	4.22	<0.001	2.41	1.37	3.38	<0.001
High% Black, High% Latinx					6.85	5.87	7.89	<0.001	5.76	4.75	6.84	<0.001
Female Headed Household												
Low Tercile (ref)	–	–	–	–	–	–	–	–	–	–	–	–
Middle Tercile					1.02	0.10	1.85	0.014	1.13	0.25	2.03	0.006
High Tercile					2.73	1.92	3.60	<0.001	2.66	1.75	3.61	<0.001
Educational Attainment												
Low Tercile (ref)	–	–	–	–	–	–	–	–	–	–	–	–
Middle Tercile					−1.95	−2.79	−1.09	<0.001	−2.39	−3.20	−1.58	<0.001
High Tercile					−1.67	−2.59	−0.77	0.002	−3.21	−4.12	−2.27	<0.001
Median Household Income												
Low Tercile (ref)	–	–	–	–	–	–	–	–	–	–	–	–
Middle Tercile					−0.46	−1.26	0.41	0.145	−0.10	−0.88	0.77	0.401
High Tercile					−0.74	−1.60	0.16	0.069	−0.64	−1.57	0.32	0.095
Metro					6.45	5.72	7.16	<0.001	6.04	5.25	6.76	<0.001
CONTROLS												
Median Age*									−0.03	−0.05	−0.02	<0.001
Housing built after 1970 (%)*									0.03	0.02	0.03	<0.001
Median Housing Value*‡									0.06	0.05	0.07	<0.001
Manufacturing (%)*									−0.05	−0.06	−0.03	<0.001
Renters (%)*									0.04	0.03	0.04	<0.001
Unemployment (%)*									0.01	−0.01	0.03	0.186
RANDOM EFFECTS	Est	95% CI			Est	95% CI			Est	95% CI		
Stratum Var (σ^2_{u0})	32.61	26.36	39.92		4.76	3.48	6.41		4.61	3.28	6.30	
Census Tract Var (σ^2_{e0})	145.25	143.74	146.74		145.30	143.84	146.81		144.31	142.77	145.81	
VPC (%)	18.33	15.50	21.39		3.17	2.36	4.19		3.10	2.25	4.14	
PCV (%) **					85.40				85.86			
N	72,103				72,103				71,374			

Notes: * Variable is mean-centered. ** Proportional Change in Stratum-Level Variance relative to model 1A (null model). ‡In tens of thousands. Due to missing data in ACS on median housing value (n = 728) and percent manufacturing (n = 1), the total number of census tracts in Model 1C was reduced to 71,374.

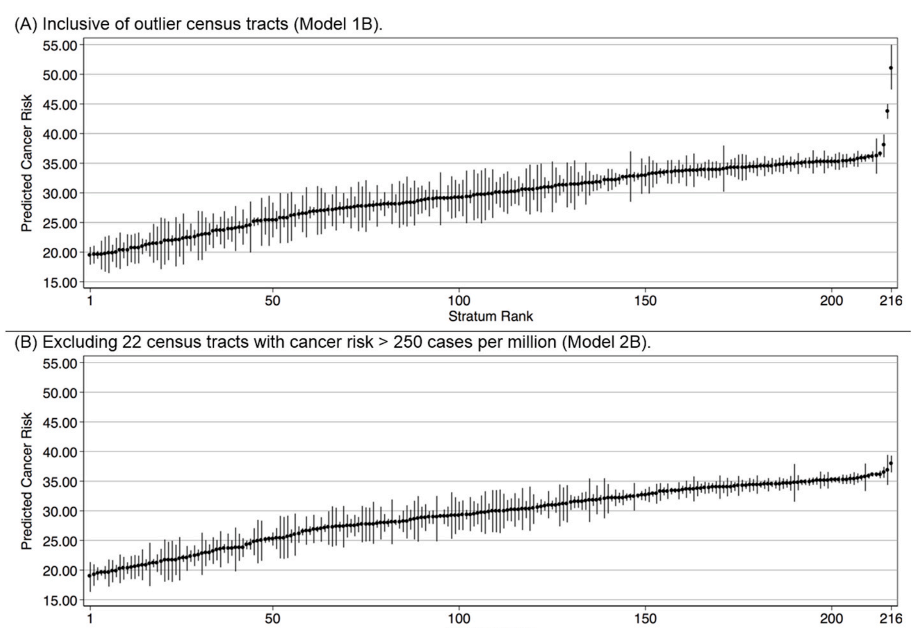

Fig. 2. Predicted Cancer Risk By Stratum, ranked from low to high. Notes: Estimates (indicated by markers) and 95% CI (indicated by spikes) were obtained by combining fixed additive main effects and random (residual) effects for each stratum in Model 1B. Predicted values for strata were ranked from low (rank 1) to high (rank 2016).

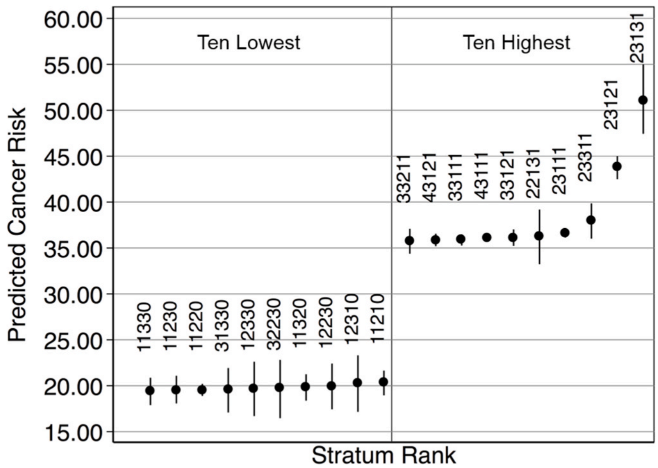

Fig. 3. Strata with highest and lowest predicted cancer risk.

headed households, and metro location were significant predictors of elevated cancer risk, while higher average education attainment was correlated with reductions in cancer risk. Higher median household income was associated with reductions in cancer risk, however this was not statistically significant. Relative to strata with low percent Black and low percent Latinx residents, increasing the concentration of either Black or Latinx residents increased the predicted cancer risk, however the risk increases were particularly large for strata with a high percent Black residents. These results were robust to inclusion of controls.

Comparing Models 1B and 1A, the VPC was reduced from 18.33% in the null model to 3.17% in the main effects model, with a PCV between models of 85.4%. This value was largely unchanged after adjustment for controls (VPC = 3.10% in Model 1C, PCV = 85.86%). *This indicates that while additive main effects were capable of explaining a large proportion of the between-stratum inequalities, they were by no means sufficient to explain all of these inequalities.* Furthermore, 54 of 216 intersectional strata have residuals that differ statistically from the null (Supplement Figures 1 and 2). In other words, considerable interactions exist between these axes of marginalization and an intersectionality story is appropriate.

Twenty-two census tracts had a predicted cancer risk higher than 250 cases per million. To examine the robustness of our results, these cases were excluded from Models 2A-C (Supplemental Table 2). Fig. 2B is a caterpillar plot of predicted cancer risk by stratum without the outliers. Notably, the exclusion of the outliers particularly affected the upper tail of predicted values, with predictions for the "highest risk" strata being reduced. To further examine whether the exclusion of the

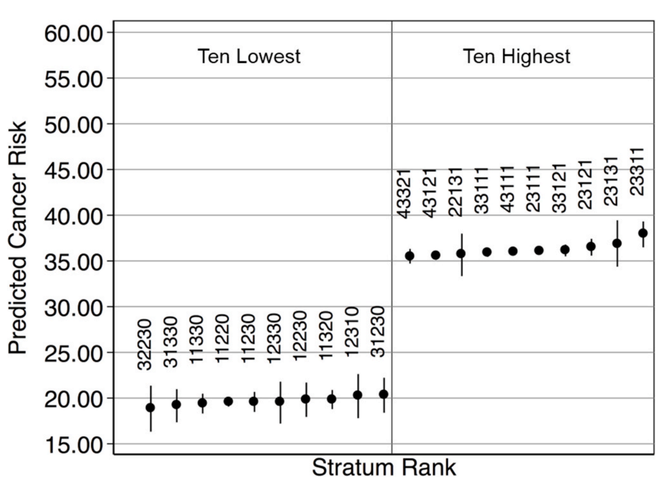

Fig. 4. Strata with highest and Lowest Predicted Cancer Risk, excluding 22 census tracts with cancer risk >250 cases per million.

outliers changes the overall intersectionality story, Fig. 4 provides details on the "top ten" strata at the higher and lower predicted values. Nine out of ten strata of the "top ten" high risk strata from Fig. 4 were present in Fig. 3, suggesting that the exclusion of the outliers did not substantially reshuffle which strata were identified as being high or low risk. While the actual predicted values for strata which had tracts removed were naturally affected, the overall patterns of inequality were robust to exclusion of extreme cases.

Each of the outlier tracts was examined individually in the NATA data files to determine the particular toxic(s) responsible for the elevated cancer risk estimate. Once these toxics were identified, we conducted a search to identify news reports, official communications from the EPA, and/or websites for State Departments of Health that identified particular polluters as the sources of the toxics of concern to the EPA. The results of this are provided in Table 3.

In several cases, these outlier tracts were in contiguous clusters with other outlier tracts, forming geographic clusters of particularly high risk, including a large cluster in the infamous "Cancer Alley" along the Mississippi River in Louisiana (Roberts and Toffolon-Weiss, 2001). All twenty-two tracts experienced elevated risk at least in part due to exposure to ethylene oxide emissions from local facilities. While ten of the twenty-two tracts belonged to strata ranked in the "top ten" highest for predicted cancer risk, twelve were from strata at a variety of ranks. One of these tracts was even in an intersectional social stratum reporting less environmental health risk (in stratum 11331: low % Black and Latinx, low % female-headed households, high educational attainment, high median household income, and metro) in Willowbrook, IL, though this tract was contiguous with another intersectional social stratum reporting worse environmental health risk. In our examination of these cases, there was nothing to suggest that these "outliers" were in any way systematically different than other tracts in how they came to be exposed, except that they happen to play host to producers of particularly carcinogenic air toxics. In other words, these tracts are simply part of the larger pattern of systematic marginalization experienced by other tracts that share the same intersectional characteristics across neighborhood demographics. We therefore argue that it is most appropriate to include these tracts in our final estimates for strata and to focus on results from Model 1.

3. Discussion

In this study we propose a novel eco-intersectional multilevel modeling approach that addresses many limitations of conventional approaches and explicitly integrates critical theory from EJ, population health, and intersectionality for its framing and interpretation. We have demonstrated the utility of the EIM approach by modeling carcinogenic air toxics risk of census tract-level burden among various intersectional neighborhood demographics across the U.S. Our finding that marginalized communities—namely those with higher concentrations of racial/ethnic minorities and single-mother families, and lower average income and educational attainment residing in metro areas—experience drastically elevated levels of exposure to carcinogenic air toxics will surprise few who have a passing familiarity with these issues. However, with rare exceptions (e.g., Ard 2015; Downey and Hawkins 2008a; Zwickl et al., 2014; Liévanos 2015) what has been largely missing from the literature are national-level, explicitly intersectional accounts that seek to generalize findings from earlier case studies to communities across the country. This could lead, unintentionally, to a sense that communities enduring worse environmental health risk through an intersection of systems of power are somehow the exception, rather than the rule. Our intention is not to replace case study research, but to generalize findings from case studies to a national-level story.

Our findings confirm the generalizability of the conclusions that environmental injustices are: (1) experienced intersectionally at the community-level, (2) significant in magnitude, and (3) socially patterned across numerous intersecting axes of marginalization,

Table 3
Details for twenty-two "outlier" census tracts with estimated cancer risk≥ 250 cases per million.

State	County	EPA Region	Tract #	Stratum ID	Population Size	Est Cancer Risk	Explanation for Elevated Risk[a]
CO	Jefferson	8	8059010902	33211	2310	525.56	Elevated estimated risk due to ethylene oxide emissions from Terumo BCT Sterilization Services in Lakewood, CO.
IL	DuPage	5	17043845811	42321	3838	263.44	These two census tracts are contiguous. Elevated estimated risk due to ethylene oxide emissions from the Sterigenics facility, located in Willowbrook, IL.
IL	DuPage	5	17043845902	11331	3411	281.81	
LA	St. Charles	6	22089060100	23131	1937	808.72	This cluster of twelve contiguous census tracts spans a section of the Mississippi River in two counties in Louisiana: St. Charles and St. John the Baptist. The area is part of the notorious "Cancer Alley." Elevated estimated risk due to chloroprene and ethylene oxide emissions. The La Place Chemical Plant operated by Denke Performance Elastomer (located in tract #22095070800) has been identified as the major source of chloroprene emissions. The Union Carbide facility and the Evonik Materials facility have been identified as the major sources of ethylene oxide emissions.
LA	St. Charles	6	22089062500	23121	2988	273.27	
LA	St. Charles	6	22089062700	23111	4753	284.51	
LA	St. John the Baptist	6	22095070100	22231	2685	303.01	
LA	St. John the Baptist	6	22095070300	22221	6258	296.31	
LA	St. John the Baptist	6	22095070400	22231	4381	286.54	
LA	St. John the Baptist	6	22095070500	43121	6229	329.27	
LA	St. John the Baptist	6	22095070700	23121	4348	511.32	
LA	St. John the Baptist	6	22095070800	23121	2537	1505.12	
LA	St. John the Baptist	6	22095070900	23111	3115	616.62	
LA	St. John the Baptist	6	22095071000	23111	2840	490.28	
LA	St. John the Baptist	6	22095071100	23121	3398	363.19	
PA	Lehigh	3	42077000101	43221	3661	346.52	These three census tracts are contiguous. Elevated estimated risk due to ethylene oxide emissions from the B Braun Medical Inc facility, located in Allentown, PA.
PA	Lehigh	3	42077005902	42221	1571	596.46	
PA	Lehigh	3	42077009200	31221	3768	256.05	
TX	Harris	6	48201343100	42231	4629	348.20	These two census tracts are contiguous and located in Houston, TX. Elevated estimated risk due to ethylene oxide emissions. East Houston is well known as the location of a variety of polluters in close proximity to fenceline neighborhoods.
TX	Harris	6	48201343200	41331	4944	296.18	
TX	Jefferson	6	48245010902	31331	4592	274.52	Elevated estimated risk due to ethylene oxide emissions from the Huntsman Corporation's Port Neches facility.
WV	Kanawha	3	54039013400	22211	2222	366.66	Elevated estimated risk due to ethylene oxide emissions from the Union Carbide facility.

Notes: Estimated cancer risk is reported as cases per million persons, and assumes a lifetime (70 year) of exposure to concentrations of air toxics equivalent to those in the tract in that year.
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).
[a] Each tract was examined individually in the NATA data files to determine the particular toxic(s) responsible for the elevated cancer risk estimate. Once these toxics were identified, we conducted a search to identify news reports, official communications from the EPA, and/or websites for State Departments of Health that identified particular polluters as the sources of the toxics of concern to the EPA.

including axes rarely evaluated such as gendered family structure. The EIM approach provides several useful summary statistics that demonstrate the extent of interaction between axes of marginalization, such as the VPC and PCV. According to our primary models (Models 1A-C), there was considerable clustering of risk at the intersectional stratum-level (VPC = 18.3% in model 1A), indicating substantial inequalities between strata of census tracts. Furthermore, while controlling for additive effects did reduce the unexplained variation between strata (PCV = 85.4% in Model 1B), considerable inequality remained (VPC = 3.2%), indicating a meaningful contribution from interactions. A purely additive story is therefore insufficient to explaining the social and geographic patterning of risk from air toxics in the U.S. Our results tell a national intersectionality story where census tracts with a higher percent of Black and Latinx residents, a higher percent of single mothers, a lower percent of residents with higher education, and tracts that are located within metro areas have the highest rates of estimated cancer risk from air toxics. EIM analyses enable us to quantify the excess risk experienced by these multiply marginalized strata, whereas additive-only approaches might underestimate the risk these strata experience due to omission of interaction effects.

The magnitude of these inequalities is noteworthy. This EIM analysis reveals that a tract from the stratum with the highest predicted value (stratum 23131: high % Black and low % Latinx residents, high % female-headed household, lowest tercile of educational attainment, high household income, metro, risk est = 51.04) will on average be expected to have risk that is 2.6 times higher than a tract from the stratum with the lowest predicted value (stratum 11330: low % Black and low % Latinx residents, low % female-headed household, highest tercile of educational attainment, high household income, non-metro, risk est = 19.41). Through EIM, we can examine the relational intercategorical comparison between interaction groups to reveal the stark environmental health risk between them. Furthermore, this demonstrates a substantial inequality that is more universally experienced than a focus on individual tracts would imply. So-called "outlier" tracts with exceptionally high health burdens from environmental injustices, such as clusters in the notorious "Cancer Alley" Louisiana, are in fact part of a larger, national story of marginalization. The same social processes that systematically undervalue the health of residents in those communities also undervalue the health of similar communities across the country.

Our results confirm the salience of under-studied axes of marginalization to the experience of environmental injustice, particularly the concentration of female-headed households (Ducre 2012; Downey, 2005; Downey and Hawkins 2008b; Downey et al., 2017; Liévanos 2015). Additionally, as these results clearly show, future research may benefit from consideration of multiple dimensions of SES inequality, such as aggregate measures of educational attainment and household income.

Situating EIM within the broader history of EJ social movements, this study introduces a flexible novel tool for telling large-scale, intersectional stories of environmental injustice. Future work could address similar patterns of risk from other sources of pollution, including water or soil-based hazards. Rather than using a dependent variable that represents health burden attributable to a particular type of hazard, future work could also examine concentration of particular industries or pollutants or examine health outcomes other than cancer. EIM could be coupled with EJ screening tools such as the CalEnviroScreen or other exposure indicators to identify neighborhoods with greater vulnerability. We encourage academics, activists, community members, and practitioners to use EIM to further understanding of inequalities across communities and to eradicate social, health, and environmental injustices.

3.1. Limitations

This study and the EIM approach in general are not without limitations. First, we have not attempted to identify (nor argue for the existence of) naturalistic categories of census tracts. Rather, the categorizations we have used are analytic, and to some extent arbitrary. For example, would the degree of stratum-level clustering be maximized by categorizing percent female-headed households according to quartiles rather than terciles? Such a question, though intellectually interesting, is also somewhat beside the point of this exercise, which is broadly to demonstrate the unequal burden experienced systematically by some communities. Nevertheless, how census tracts are categorized is a topic worthy of future consideration, though we urge caution in order to avoid (unintentionally) reifying categorical labels. The successes of community-based participatory research (CBPR) in improving scientific rigor is noteworthy. By working with community members, future CBPR research could shed light on what social dimensions to focus analyses on and how best to operationalize them in EIM (Balazs and Morello-Frosch 2013).

Second, these analyses do not examine causal or life-course questions of how existing environmental inequalities came to be (Grace et al., 2020). For instance, were facilities producing known carcinogens systematically placed in certain communities because their residents were viewed as "expendable" (Pellow 2018)? Or because residents were viewed as less likely to offer (effective) resistance? Or because the land was cheaper? Or were poor and marginalized individuals more likely to choose (for a certain value of "choose") to live near polluters? Or some combination of these explanations? These causal questions are vital to address, and have been extensively examined by others (e.g., Pais, et al., 2014; Taylor 2014; Elliott 2015; Howell and Elliot, 2018). In this study we view the estimation of inequalities, the examination of their magnitude and direction, and their correspondence with axes of marginalization and social power, as a critical starting point for the conversation of how to proceed in pursuit of environmental and health justice. One line of future research could integrate the EIM approach with life-course approaches at residential levels such as length of residency to further advance intersectionality, environmental justice, and age (Brown 2018).

4. Conclusion

Three distinct scholarly traditions—environmental justice, population health, and intersectionality—have converged on a critical view of the treatment of residents of "fenceline communities" across the United States. EIM provides an innovative approach for all three fields that will explicitly frame EJ work through an intersectional lens, address known limitations of conventional approaches to modeling high-dimensional interactions, and focus attention on the intersectional, structural-level determinants of health inequalities. EIM and intersectional MAIHDA are useful tools for scholars, practitioners, and community members to assess intersectional inequalities across various systems of power from different vantage points (i.e., intersectional MAIHDA at the individual-level and EIM at the neighborhood-level).

Our results demonstrate that there are considerable inequalities in cancer risk attributable to environmental hazards, and that these inequalities likely explain, at least in part, observed inequalities along racial/ethnic, socioeconomic, and geospatial lines. Yet the existence of environmental hazards in neighborhoods is governed by social processes operating at higher levels than the neighborhood or community. Regulatory environments and enforcement mechanisms determine what types of emissions are allowed near places of residence, what concentrations of emissions are allowable, and the minimum distance required between places of residence and emission sources. Finding the political will to address these inequalities and enact more stringent regulations is, of course, the remaining challenge. For too long privileged communities have been silent bystanders to unfolding environmental injustices. While sometimes openly lamenting the human costs, they have nevertheless been inadequately involved in demanding accountability and change. It is our hope that this new tool will be used to generate the necessary will to act in pursuit of social and environmental justice.

Author credit statement

CH Alvarez conceived the study design and early analysis as well as wrote the first draft of the manuscript. **CH Alvarez and CR Evans** designed the final analysis, interpreted the results, and reviewed and edited the final manuscript.

Acknowledges

None

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2020.113559.

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