Air-Toxic Clusters Revisited: Intersectional Environmental Inequalities and Indigenous Deprivation in the U.S. Environmental Protection Agency Regions

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Abstract

The research on quantitative intersectional environmental inequality outcomes examines how the spatial concentration of individuals occupying multiply marginalized social identities is associated with unequal exposure to environmental hazards. One recent exemplar study analyzed racialized and "intercategorical" environmental inequality outcomes in cancer-causing air pollution exposures for Whites, Blacks, Latinxs, and Asian/Pacific Islanders (APIs) at the census tract level in the continental United States. That study found that—net of region, urban-industrial context, and other intercategorical variables—a variable representing elevated concentrations of economically deprived and foreign-born Latinxs, Latina single-mother families, and primarily Spanish-speaking households was the most consistent intercategorical predictor of tract exposure to spatial clusters of carcinogenic air pollution in 2005. The present study reproduces that nationwide analysis while being the first to include disadvantaged Indigenous peoples in the examination of intercategorical environmental inequality outcomes in the continental United States and for the ten U.S. Environmental Protection Agency (EPA) regions. Logistic regression analyses indicate that the spatial concentration of disadvantaged Indigenous peoples was not a significant nationwide predictor of tract exposure to the carcinogenic air pollution clusters. However, the regional analyses revealed eight new patterns of intercategorical environmental inequality outcomes across the U.S. EPA regions, and the spatial concentration of disadvantaged Indigenous peoples was a significant positive predictor of tract exposure to carcinogenic air pollution clusters in the Mid-Atlantic region. These findings have implications for future environmental justice research, policy, and activism.

Keywords Regional racial formation · Indigenous peoples · Intersectionality · Environmental inequality · Environmental justice · Carcinogenic air pollution · U.S. Environmental Protection Agency

Introduction

Intersectionality studies generally focus on how categories of social division "operate not as unitary, mutually exclusive entities, but as reciprocally constructing phenomena that in turn shape complex social inequalities" (Hill Collins 2015, p. 2). Dovetailing with recent developments in qualitative and historical environmental justice studies (Malin and Ryder 2018; Pellow 2016), the research on quantitative intersectional environmental inequality outcomes assesses the extent

to which the *spatial concentration* of individuals occupying multiply marginalized social identities is associated with the unequal exposure to environmental hazards. The present study approaches intersectional environmental inequalities by attending to their "intercategorical complexity," which is understood as "relationships of inequality among social groups and changing configurations of inequality along multiple and conflicting dimensions" (McCall 2005, p. 1773).

In a recent nationwide study (Liévanos 2015), I implicitly developed an intercategorical approach to racialized environmental inequality outcomes. It is the first and only study of the continental United States to test a number of intercategorical environmental inequality hypotheses that specified which spatially concentrated, multiply marginalized statuses for Whites, Blacks, Latinxs, and Asian/Pacific Islanders (APIs) are associated with heightened risk of census tract exposure to spatial clusters of cancer-causing air

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pollution, net of regional and urban-industrial contexts. Its primary finding was that a factor variable representing elevated concentrations of economically deprived and foreign-born Latinxs, Latina single-mother families, and primarily Spanish-speaking households was the predominant positive intercategorical predictor of tract exposure to carcinogenic air pollution clusters in 2005.

Despite its merits, my previous study is limited in two important respects. First, it did not include disadvantaged Indigenous peoples in its comparative analysis of multiply marginalized census tracts. This limitation is important as a majority of enumerated Indigenous peoples in the United States live in nonreservation residential settlements (Ogunwole 2010). These spaces include the diverse settings where Indigenous peoples experience environmental health disparities and multiple oppressions of capitalism, colonialism, and racism (Downey et al. 2008; Ducre 2018; Fenelon 2016; Nakano Glenn 2015; Golash-Boza 2016; Hoover 2018; Jacobs 2019; Malin and Ryder 2018; Mohai et al. 2009; Norgaard et al. 2018; Steinman 2012, 2016; Vickery and Hunter 2016; Waldron 2018). Second, my previous study found that spatial clusters of carcinogenic air pollution occurred extensively in two regional jurisdictions of the U.S. Environmental Protection Agency (EPA): Region 9 (the West/Southwest: Arizona, California, and Nevada) and Region 2 (the Northeast: New Jersey and New York) (Liévanos 2015). Accordingly, that study controlled for tract location in these regions in its multivariable analyses, but it did not attend to the relationship between the racialized and intercategorical statuses of census tracts and environmental health vulnerability *within* the U.S. EPA regions. Yet, research speaks to the importance of a regional view on racial formations and hierarchies (Cheng 2013; Pulido 2006), intercategorical complexity (McCall 2005; Nakano Glenn 2002), and the unequal distribution of environmental health hazards in the United States (Anderton et al. 1994; Ard 2015; Perlin et al. 1995; Zwickl et al. 2014).

The present study's objective is to overcome these limitations in my previous nationwide analysis (Liévanos 2015) and contribute more explicitly and broadly to research on racialized and intercategorical environmental inequality outcomes. In doing so, it seeks to answer the following research question: Net of other factors, to what extent do concentrations of multiply marginalized Indigenous peoples, Whites, Blacks, Latinxs, and APIs affect the probability of tract exposure to carcinogenic air pollution clusters across the continental U.S. and within the ten regions of the U.S. EPA?

In order to build on my previous study (Liévanos 2015), all data used in this study are from 1999 to 2005. This study includes demographic data from the 2000 U.S. Decennial Census and estimates of carcinogenic air pollution from the 2005 U.S. EPA National Air Toxics Assessment. More recent data are available, especially for various population

vulnerability measures from the American Community Survey and the 2010 U.S. Decennial Census. However, I elaborate at the close of this article how such demographic data are ill suited to examine the multidimensional intercategorical complexities in carcinogenic air pollution exposures that I accomplish in the present study with the 2000 census data. Thus, the present study uses older yet more reliable and comprehensive data *to develop a comparative framework* and *analytical techniques* upon which future research could draw for analyzing the spatial dimensions of environmental health vulnerability across different regional contexts and a narrower range of multiply marginalized social identities for Indigenous peoples and other racialized groups in the United States. In addition to outlining these future research implications, the article closes with a discussion of its practical import for environmental justice policy and activism.

Racialized Intercategorical Complexity of Air-Toxic Lifetime Cancer Risk Clusters

Spatial clusters of carcinogenic air pollution represent significantly high concentrations of toxic exposures for residents within a residential settlement and in neighboring settlements. In Liévanos (2015), I focused specifically on spatial clusters of estimated lifetime cancer risk (LCR) associated with cumulative toxic air pollution. I found that those clusters tend, on average, to have a post-industrial urban character (i.e., high population density, low manufacturing employment, relatively high median housing values, and older housing stock) and a concentration of industrialized air pollution sources (i.e., automobile traffic and industrial and commercial land uses) near major transportation corridors.

I analyzed the racialized intercategorical complexity of small- and regional-scale "air-toxic LCR clusters" by creating separate composite variables of "economic deprivation" for Whites, Blacks, Latinxs, and APIs with principal component analyses (Liévanos 2015). Those analyses included limited education (i.e., no high school diploma or equivalent), unemployment, poverty, and single-mother families for each racialized group. Two additional "isolated immigrant-economic deprivation" factor variables operationalized the "global" nature of many Latinx and API neighborhoods in the U.S. (Logan and Zhang 2010). Specifically, these factors added immigrant status and linguistically isolated households to the racialized economic deprivation variable set for Latinxs and APIs. Linguistically isolated households are those in "which all members 14 years old and over speak a non-English language and also speak English less than 'very well' (have difficulty with English)" (U.S. Census 2002, p. B-32).
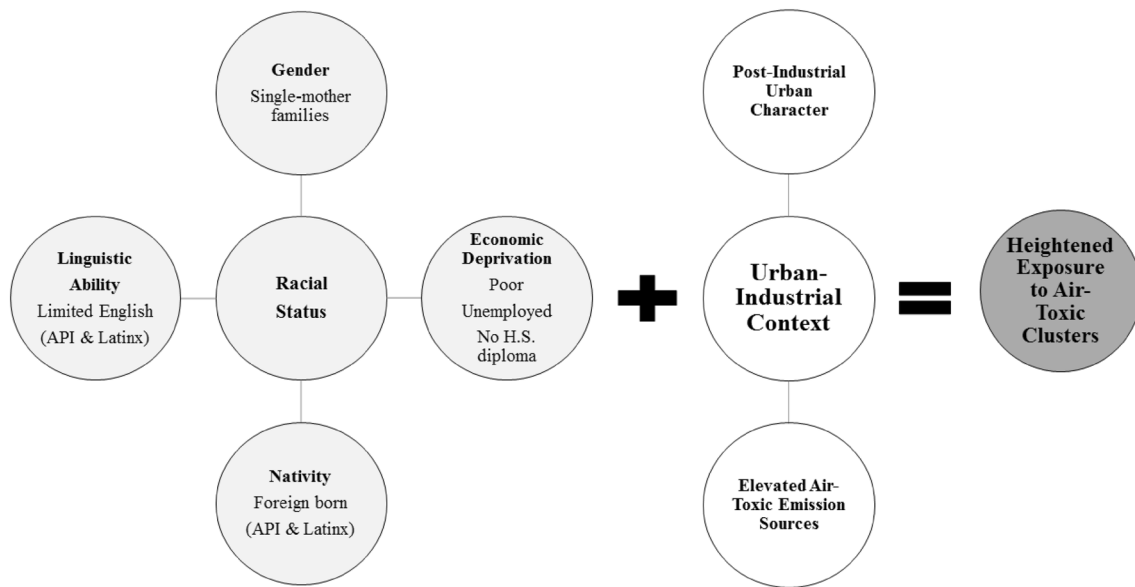
Fig. 1 National racialized intercategorical model of census tract exposure to air-toxic LCR clusters. Model adapted from Liévanos (2015)

The above-cited study demonstrated the consistently high vulnerability of multiply marginalized Latinx tracts (Liévanos 2015). It also found that the spatial concentrations of multiply marginalized APIs and Blacks were positive racialized intercategorical predictors of exposure to local and regional air-toxic LCR clusters. White economic deprivation was an inconsistent positive predictor of tract exposure to local air-toxic LCR clusters, but it was consistently a negative predictor of tract exposure to regional air-toxic LCR clusters.

Figure 1 presents a slight modification to the national model I developed in my previous study (Liévanos 2015). Initially, the model followed Wilson (1987, 1996), Mosher (2001), and Smith (2007) to conceptualize elevated levels of single-mother families as an economic deprivation indicator. However, U.S.-based environmental inequality outcome studies demonstrate that the concentration of single-mother families is an independent predictor of heightened risk of exposure to environmental toxins (Downey 2005; Downey and Hawkins 2008; Downey et al. 2017). Building on Black feminism's focus on the particular and systemic disadvantages of women of color (Hill Collins [2000] 2009; Hill Collins 2015; Crenshaw 1989, 1991; Ducre 2018; McCall 2005), further research shows that Black women disproportionately experience economic deprivation, and adverse human and environmental health conditions over their life course (Gee and Payne-Sturges 2004; Geronimus 1996; deFur et al. 2007).

My earlier empirical finding that the percent of Black and Latina single-mother families in a tract loaded particularly high in the Black- and Latinx-economic deprivation factors, respectively (Liévanos 2015), takes on an alternative "social explanation" in light of these considerations (Clarke and McCall 2013). That is, racialized single-mother families represent a racialized *and* gendered environmental inequality factor, and the broader "deprivation" term is more conceptually valid for each racialized intercategorical factor variable. The rest of the model remains intact and "anchored" (Nakano Glenn 2002) in the racial composition and statuses of census tracts due to the centrality of race in shaping U.S. residential segregation and environmental inequality outcomes (Gee and Payne-Sturges 2004; Mohai et al. 2009; Pellow 2016). When racialized intercategorical statuses combine with a tract's post-industrial urban character and elevated air pollution sources, then those tracts are likely to experience heightened risk of exposure to air-toxic LCR clusters. The present study tests the following two hypotheses that stem from the most consistent empirical findings in Liévanos (2015):

Hypothesis 1 (H1) The *dissimilar intercategorical environmental inequality hypothesis* posits that the spatial concentration of different multiply marginalized racial groups will be associated with dissimilar likelihood of tract presence in an air-toxic cancer risk cluster, net of other factors.

Hypothesis 2 (H2) The *isolated Latinx immigrant deprivation hypothesis* posits that the spatial concentration of linguistically isolated, economically deprived, foreign-born, and gender-marginalized Latinxs will be a positive predictor of tract presence in an air-toxic cancer risk cluster, net of other factors.

Multiple Social and Environmental Inequalities Among U.S. Indigenous Peoples

Previous research demonstrates the need to incorporate Indigenous peoples into the U.S. models of racialized intercategorical environmental inequalities. Indigenous peoples experience ongoing capitalist, settler colonial, and White supremacist forces of dispossession, assimilation, relocation, isolation, and erasure that contribute to Indigenous peoples' uniquely alienated, colonized, *and* racialized statuses in the United States (Fenelon 2016; Nakano Glenn 2015; Norgaard et al. 2018; Steinman 2012, 2016). Throughout these experiences, Indigenous peoples are formally and informally excluded from environmental policy-making at the same time their health and wellbeing are threatened by environmentally destructive activities associated with militarism, industrial manufacturing, and the production of energy resources (Hooks and Smith 2004; Hoover 2018; Norgaard et al. 2018; Vickery and Hunter 2016).

With regard to urban-industrial air pollution exposures, Indigenous environmental inequality outcomes are typically dependent on the type of pollutant considered, Indigenous settlement patterns, and spatial context. For example, Grineski et al. (2017) found that Indigenous peoples experienced the least population-weighted mean carcinogenic air pollution exposures in 2011 when compared to other racialized groups that are more concentrated in U.S. urban areas. Yet, Downey et al.'s (2008) study of hazardous industrial air pollution found that Indigenous people were the most burdened in 44 (13.4%) of 329 U.S. metropolitan areas in 2000. Zou et al. (2014) found that county-level concentrations of Indigenous peoples were significantly associated with the spatial clustering of benzene air pollution in 1999 in New England, the West Coast, and the Midwest. Shaikh and Loomis (1999) found a positive association between zip code-level concentrations of American Indians and the siting of hazardous air pollution sources in the Denver–Aurora–Broomfield, Colorado metropolitan area.

Quantitative, nationwide research has yet to incorporate an intersectional analysis of Indigenous environmental inequalities. However, research shows that class divisions are manifest within the Indigenous population. Socioeconomically marginalized American Indians, for example, experience concentrated poverty despite the recent growth in Native gaming establishments that have benefited some American Indians (Davis et al. 2016). In addition, Liévanos and Horne (2017) found that a U.S. power utility's organizational protocols for restoring power outages that tend to occur in hot summer months explain the slower outage restoration times in census block groups with elevated concentrations of American Indians with low-to-moderate income and education levels, as well as American Indians who are unemployed and renters.

Qualitative case studies demonstrate how destructive settler colonial environmental management practices have uneven and gendered impacts on Indigenous peoples (Norgaard et al. 2018). Indigenous women, in particular, consistently face significant "environmental reproductive injustices" through their intersecting and ongoing experiences of environmental health hazard exposure, colonization, racialization, and gender marginalization—all of which threaten their social, cultural, and biophysical reproductive health (Hoover 2018). The present study tests the following hypothesis given the literature on the multiplicity of spatialized inequalities experienced by Indigenous peoples in the United States:

Hypothesis 3 (H3) The *Indigenous deprivation hypothesis* posits that the spatial concentration of economically deprived and gender-marginalized Indigenous peoples will be a positive predictor of tract presence in an air-toxic cancer risk cluster, net of other factors.

The Salience of U.S. EPA Regions

Nationwide examinations of racialized intercategorical environmental inequalities could benefit by attending to how such inequalities vary by the regional jurisdictions of the U.S. EPA. The ten regions of the U.S. EPA (see Fig. 2) were established because they mapped onto the boundaries of the ten standard federal regions (SFRs) initiated by the Nixon administration in the 1960s under the apparent federalist premise of distributing the nation-state's power and administration regionally throughout the United States (Whitford 2007). The U.S. EPA regions outlived the SFRs, which were disbanded in 1995 (Federal Register 1995). The contemporary salience of U.S. EPA regions most typically hinges on the consistent finding of variation in environmental *enforcement* actions across the regional jurisdictions (Konisky 2015). Such findings are attributed to the complexity of environmental problems within the U.S. EPA's regional boundaries, the decentralized organizational structure and culture of the U.S. EPA, and the federalist environmental policy context that often gives "primacy" over federal environmental law implementation to the states (Hunter and Waterman 1992; Landy et al. [1990] 1994; List 1999; Mintz [1995] 2012; Ringquist 1993; Scheberle 2004; Sigman 2003; U.S. General Accounting Office 2000; Whitford 2007).

The salience of U.S. EPA regions also manifests in a handful of studies of environmental inequality outcomes. Studies in the mid-1990s documented the uneven distribution of environmental hazards and populations defined by
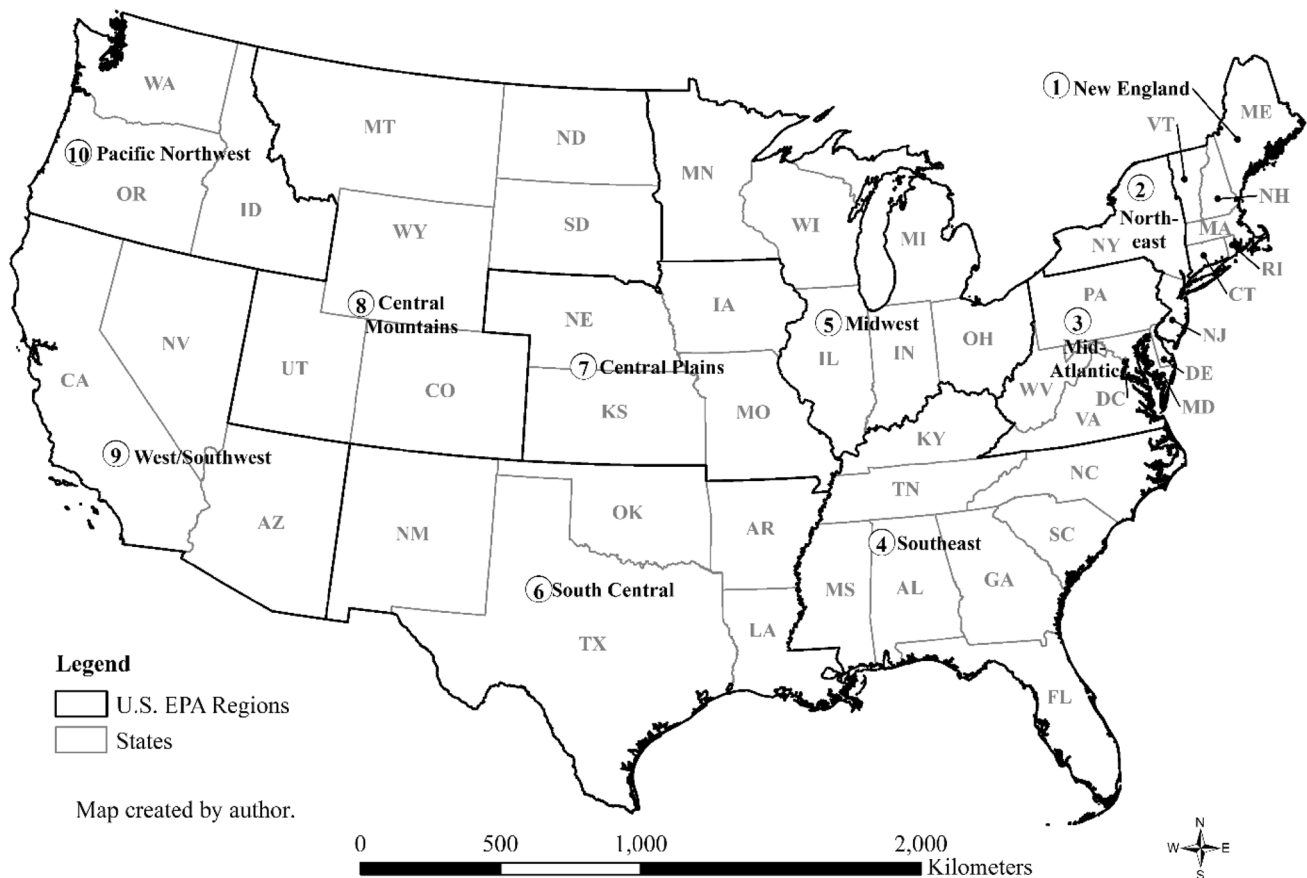
Fig. 2 U.S. Environmental Protection Agency (EPA) regions and states in the continental United States

different racial, ethnic, and income statuses across U.S. EPA regions (Anderton et al. 1994; Perlin et al. 1995). Zwickl et al.'s study (2014) is exemplar among the recent ones for its systematic examination of race and class variations in block group-level estimated exposure to toxic industrial air pollution nationwide and across the U.S. EPA regions (see also Ard 2015). Zwickl et al. (2014) produced a number of important findings. Noteworthy among them, the study demonstrated "that racial and ethnic disparities in pollution exposure [were] strongest among [block groups] with median incomes below $25,000, while income-based disparities [were] stronger among [block groups] with median incomes above that level" (Zwickl et al. 2014, p. 494).[1] The racial patterns of environmental inequalities below the $25,000-income threshold manifested in predominantly Black block groups experiencing the greatest toxic industrial air pollution exposures, followed by block groups

with higher concentrations of Whites, Latinxs, and other nonwhites.

Zwickl et al.'s (2014) regional analysis uncovered complexities obscured by their nationwide analysis. The association between the percentage of Black residents in low-income block groups and toxic exposures was significant and positive in all regions, except in the Central Mountains (Region 8). The percentage of Latinxs in low-income block groups was significantly and positively associated with toxic exposures in seven regions, excluding New England, the Mid-Atlantic, and the Pacific Northwest. The association between toxic exposures and the percentage of Whites living in low-income block groups was significant and positive in five regions (New England, Northeast, Midwest, Central Plains, and Central Mountains). Lastly, the association between toxic exposures and the percentage of other nonwhites living in low-income block groups was significant and positive in four of the regions (New England, Northeast, West/Southwest, and Pacific Northwest). Zwickl et al. (2014, p. 495) attributed their regional findings to the meaningful "[d]ifferences in demographic, political, economic, and environmental history, and geography [that] dictate the circumstances under which…[the U.S. EPA] regulate."

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[1] Their analysis was quite rigorous, uncovering national and regional patterns of racialized environmental inequalities at and above the $25,000-income threshold (see Zwickl et al. 2014. pp. 497–502). Their results pertaining to racialized environmental inequalities at the lower-income ranges are most relevant to the present study.

The salience of the U.S. EPA regions could also rest in the general manner in which the nation-state apparatus is regionally structured by—and structuring of—state–society relations (Hooks 1994; Li 2002). These relations include the varied social forces that give rise to complex patterns of multiple marginalizations, and environmental health vulnerability among different racialized groups within each region (Goldberg 2002; Kurtz 2009). The importance of regions in structuring racialized and intersecting inequalities overlaps with scholarship on regional racial formations and hierarchies. Cheng (2013, p. 10) defines regional racial formation "as place-specific processes of racial formation, in which locally accepted racial orders and hierarchies complicate and sometimes challenge hegemonic ideologies and facile notions of race." Cheng (2013) builds on Omi and Winant (1994), Gilmore (2002), Molina (2006), and especially Pulido (2006, p. 29) whom argues that racial hierarchies constitute "an ever-changing landscape composed of distinct racial positions [that are]…shaped by local demographics, regional economies, local history, and national racial narratives." Furthermore, since "the United States is so large and diverse, it is primarily at the regional level that nuanced and meaningful comparison must take place" (Pulido 2006, p. 4). Pulido's (2006) own analysis of the regional racial hierarchy of Los Angeles, California links the differential racialization of African, Mexican, and Japanese Americans to their class positions and divergent leftist activisms over time.

The literature reviewed above on the variation in environmental inequality outcomes across U.S. EPA regions and on racial formations and hierarchies thus suggest researchers should attend to the "spatial non-stationarity" of intersecting environmental health vulnerabilities in the United States. Spatial non-stationarity refers to how relationships between variables examined at one spatial scale (e.g., the census tract) using the same method of assessing exposure can vary across different geographic extents (i.e., nationwide versus U.S. EPA regions) (Wang et al. 2018). Other instances of subnational patterns of spatial non-stationarity in unequal environmental health exposures are documented in the United States (Gilbert and Chakraborty 2011; Grineski et al. 2015; Liévanos 2018b; Mennis and Jordan 2005) and the United Kingdom (Jephcote and Chen 2012). In addition, geographers demonstrate how health conditions and inequalities vary regionally and locally throughout the world (Bambra et al. 2015; Castillo et al. 2017; Grady and Wadhwa 2015; Ruiz-Muñoz et al. 2012; Sun et al. 2011; White et al. 2011). The present study does not formally test for the presence of spatial non-stationarity in racialized intercategorical environmental inequality outcomes in the United States. However, using the literature reviewed above as a guide, it *explores how the relationship between* *the spatial concentration of multiply marginalized racial groups, urban-industrial context, and tract exposure to carcinogenic air pollution clusters varies by U.S. EPA region.*

Data and Methods

With a few exceptions, the present study replicates the data and methods described in Liévanos (2015, pp. 53–57) to analyze census tracts with year 2000 boundaries. First, binary logistic regression analyses featured below assess the likelihood of census tract exposure to "regional" air-toxic LCR clusters across the continental United States and in each U.S. EPA region. This study does not consider "local" air-toxic LCR clusters because they are rare events within each region, and alternative modeling strategies (e.g., King and Zeng 2001) are needed to assess the likelihood of tract exposure to such clusters. Following Lee et al. (2008, p. 775), I reclassify "regional" air-toxic LCR clusters as "macro-scale" air-toxic LCR clusters given the relatively large spatial extent such clusters represent. I also use "macro-scale" so I can reserve the "region" terminology for U.S. EPA regions. Second, this study's nationwide regression models differ from Liévanos (2015) by including a measure of disadvantaged Indigenous peoples to test the Indigenous deprivation hypothesis. Third, this study's regional analyses include the same variables featured in its nationwide analyses, except for the U.S. EPA regional controls. In addition, I present the best-fitting regional regression model results below, which was determined by identifying the smaller -2 log likelihood value for competing models for each region (DeMaris 1995).

Macro-Scale Air-Toxic Lifetime Cancer Risk Clusters and Dependent Variable

Macro-scale air-toxic LCR clusters derive from the U.S. EPA's 2005 National Air Toxics Assessment (NATA) of annual average ambient toxic air concentrations in the United States (U.S. EPA 2011). The NATA is the primary data source that enables researchers to examine across the entire nation the estimated cumulative health risk of toxic air pollution emissions from combined stationary (e.g., large manufacturing facilities) and a variety of other sources (e.g., small manufacturing facilities, vehicles, marine vessels and trains, and background and secondary sources) on residential settlements. The NATA LCR estimates are conservative ecological measures of excess "N" cancer cases per million (U.S. EPA 2011). This probability indicates "that as many as N out of one million equally exposed people would contract cancer if exposed to ambient air-toxic concentrations 24 [hours] per day over the assumed lifetime of 70 years" (Liévanos 2015, p. 54). In 2005, the mean LCR for 64,738

census tracts in the continental United States was 50.32 cases per million.

The 2005 NATA integrated available health data on 187 toxic air contaminants classified by the 1990 U.S. Clean Air Act Amendments as known or suspected to cause serious human health risks. That NATA also drew from the National Emission Inventory of federal, state, and local sources; the U.S. EPA's Toxic Release Inventory of stationary source estimates; and the U.S. EPA's Office of Transportation and Air Quality's mobile source emission estimates (U.S. EPA 2011). The U.S. EPA analyzed these data along with data on emission toxicity, transport, and fate due to atmospheric processes. In the process, it modeled toxic air pollution concentrations to the geographic center of census tracts with the AERMOD version of the Human Exposure Model-3, the Assessment System for Population Exposure Nationwide, and the Community Multiscale Air Quality model.

The dependent variable used in this study is a binary measure of the likelihood of tract presence in macro-scale air-toxic LCR clusters (1=yes, 0=no). I constructed macro-scale air-toxic LCR clusters using the procedures described in detail by Liévanos (2015, pp. 54–5). In summary, this first entailed conducting a local Moran's I_i (Anselin 1995) analysis of air-toxic LCR values across 64,738 continental U.S. census tracts with a 95,428.75-meter (i.e., 59.30-mile) distance threshold to ensure each tract had at least one distance-based neighbor. Macro-scale air-toxic clusters are "hot spots" of "high-high" cluster tracts from the resulting Moran's scatterplot (Liévanos 2015, p. 54). That is, they are tracts with high within-tract LCR values that were significantly correlated with other high LCR values in neighboring tracts within the 95-kilometer search radius. I used a Bonferroni-corrected $p = 0.000002715$ threshold—rather than the typical $p < 0.05$ threshold—to determine statistically significant spatial clustering. This corrected threshold mitigates against the problems of multiplicity, spatial dependence, and abnormally distributed $Z(I_i)$ values from the Moran's I_i analysis (Liévanos 2015, pp. 54–5; see also Anselin 1995; de Castro and Singer 2006; Getis and Ord 2000; Ord and Getis 1995).

The spatial cluster analysis detected 559 contiguous macro-scale air-toxic LCR clusters composed of 13,638 tracts (21% of the 64,738 tracts analyzed). These cluster tracts were located within and sometimes across 70 core-based statistical areas (CBSAs) and the ten U.S. EPA regions (see Liévanos 2015, pp. 60–63). Sixty-nine CBSAs that contained the cluster tracts were metropolitan statistical areas, which have an urbanized core of at least 50,000 people. One cluster-containing CBSA was a micropolitan statistical area, which includes urban cores composed of 10,000 to 50,000 people. Macro-scale air-toxic LCR cluster tracts tend to have greater than the national average air-toxic LCR of 50.32 cases per million, and they reside

Table 1 Tract-level mean estimated lifetime cancer risk (LCR; cases per million) by macro-scale air-toxic LCR cluster status for U.S. EPA Regions in the continental United States

U.S. EPA region	Mean LCR (cases per million)		
	Overall mean	Within macro-scale air-toxic LCR clusters	
		Yes	No
Region 1: New England	45.91	68.79	43.47
N	3203	309	2894
Region 2: Northeast[a]	67.63	90.27	40.76
N	6794	3687	3107
Region 3: Mid-Atlantic	47.65	73.85	41.9
N	6719	1211	5508
Region 4: Southeast	45.45	75.04	43.59
N	11,126	656	10,470
Region 5: Midwest	44.26	73.53	39.36
N	12,628	1811	10,817
Region 6: South Central	42.5	76.08	41.14
N	7551	296	7255
Region 7: Central Plains	39.04	77.61	37.38
N	3336	138	3198
Region 8: Central Mountains	33.84	79.14	28.51
N	2404	253	2151
Region 9: West/Southwest[a]	72.67	93.37	45.5
N	8625	4896	3729
Region 10: Pacific Northwest[a]	45.42	89.06	36.98
N	2352	381	1971
All Regions: Continental U.S.	50.32	85.81	40.85
N	64,738	13,638	51,100

[a]One of the top three regions in the continental United States for elevated mean LCR levels (above the national macro-scale air-toxic LCR cluster mean of 85.81 estimated cancer cases per million)

in close proximity to industrial land uses, major transportation corridors, and population centers that typically contribute to regional air quality problems (Liévanos 2015).

Table 1 shows the mean tract-level LCR in 2005 by macro-scale air-toxic LCR cluster status and regional and national context. The table reflects the existence of regional hotspots of macro-scale air-toxic LCR clusters and regions that are relatively buffered from such risk. Consistent with Liévanos (2015), most macro-scale cluster tracts and those tracts with the highest average air-toxic LCR concentrations reside in the West/Southwest and Northeast regions. The Pacific Northwest was the only other region in which the average air-toxic LCR values in macro-scale cluster tracts exceeded the national average in 2005. All other regions had air-toxic LCR values below the national average in their cluster tracts, and none of their shares of macro-scale air-toxic LCR cluster tracts exceeded the nationwide share of 21% in 2005.

Table 2 Results from seven principal component analyses of the racialized intercategorical complexity of continental U.S. census tracts, 2000

Variables	Factor loadings						
	Deprivation					Isolated immigrant deprivation	
	Indigenous	White[a]	Black[a]	API[a]	Latinx[a]	API[a]	Latinx[a]
Percent racial group and:							
Single-mother families	0.926	0.702	0.963	0.775	0.905	0.748	0.869
No H.S. diploma	0.931	0.794	0.960	0.857	0.945	0.874	0.968
Unemployed	0.933	0.729	0.934	0.797	0.922	0.751	0.894
Poor	0.962	0.857	0.970	0.849	0.963	0.822	0.946
Foreign-born						0.901	0.903
Percent linguistically isolated households and:							
API-language speaking						0.899	
Spanish speaking							0.947
Alpha	0.940	0.734	0.924	0.782	0.873	0.834	0.933
Eigene value	3.520	2.387	3.663	2.692	3.490	4.185	5.098
% of total variance explained	88.001	59.680	91.570	67.303	87.243	69.742	84.964
N	64,437	64,437	64,437	64,437	64,437	64,436	64,436

[a]Factors reproduced from Liévanos (2015)

Comparatively, low-risk areas were the contiguous South Central, Central Plains, and Southeast regions.

Explanatory Variables

I test this study's first two hypotheses (H1 and H2) with the same intercategorical principal component factor variables for Whites, Blacks, Latinxs, and APIs that were used in Liévanos (2015). I test the new Indigenous deprivation hypothesis (H3) with a new factor variable for multiply marginalized Indigenous peoples—specifically, American Indians and Alaska Natives. I use all seven explanatory factor variables in my exploration of the variation in racialized intercategorical environmental inequality outcomes by U.S. EPA region. I created these factor variables using separate principal component analyses (PCAs) that reduce sets of highly correlated component variables into a multifaceted composite indicator of concentrated multiple marginalizations for each racial group in geographic space (Liévanos 2015; see also Liévanos 2017, 2018a, 2018b; Liévanos and Horne 2017). Accordingly, my approach differs from those who use a single PCA to extract multiple factors of vulnerability of exposure to environmental hazards from hundreds of component variables (e.g., Cutter et al. 2003).

I derived seven factor variables from their respective individual PCAs. The PCAs assessed the correlations between each component variable, using a maximum of 25 iterations, eigenvalues greater than 1.00, and a listwise deletion for missing values. Each PCA also featured a regression method to derive a standardized linear combination of factor loading weights for each component variable into separate unrotated factor solutions for each racial group. I assessed the validity

and reliability of the factors, respectively, by estimating the total variance explained by each factor component and calculating Cronbach's alpha scores from additional scale analyses of the factor components.

The component variables that I analyzed separately for each racial group come from summary files 1 and 3 in the 2000 U.S. Decennial Census. The factors include the race-specific gender marker of percent single-mother families, as well as economic deprivation measures of percent persons 25 years and over without a high school education, percent civilian population 16 years and over that were unemployed, and percent of individuals whose 1999 income was below the poverty level. Additional variables for APIs and Latinxs pertain to nativity (i.e., percent of the population that are foreign born and API or Latinx) and linguistic ability (i.e., percent of households that are linguistically isolated and speak non-English-languages associated with each group).

Table 2 displays the results for the seven PCAs of tract-level racialized intercategorical complexity throughout the continental United States. The factor variables used in the previous nationwide study (Liévanos 2015) had relatively high Cronbach's alpha scores ($\geq$ .734) and eigenvalues ($\geq$ 2.387). The new results presented here for Indigenous deprivation indicate it is on par with Black deprivation and the Latinx factor variables in regards to reliability and validity. Indigenous deprivation had a high Cronbach's alpha score (.940), eigenvalue (3.520), and percent of the variance explained in the factor components (88%). Further, the high factor loading for Indigenous single-mother families shown in Table 2 speaks to how tract-level concentrations of Indigenous deprivation in the continental United States in 2000 was highly gendered in ways that resemble the highly

Table 3 Descriptive statistics for the dependent and explanatory variables used in the nationwide logistic regression analyses ($N=64{,}162$)

	Min.	Max.	Mean	Std. Deviation
Dependent variable				
Tract presence in a macro-scale air-toxic LCR cluster	0.00	1.00	0.26	0.44
Explanatory variables				
Indigenous deprivation	−0.14	37.59	0.00	0.97
White deprivation	−1.77	10.46	0.00	0.99
Black deprivation	−0.47	8.92	0.00	0.99
API deprivation	−0.37	21.89	0.00	0.99
Latinx deprivation	−0.47	10.10	0.00	0.99
Isolated API immigrant deprivation	−0.39	23.85	0.00	0.99
Isolated Latinx immigrant deprivation	−0.48	9.14	0.00	1.00

gendered character of the Black and Latinx factor results (Liévanos 2015). Overall, these figures build on Davis et al. (2016), Liévanos and Horne (2017), and Hoover (2018) by demonstrating the significant spatial concentration of multiple marginalizations among Indigenous peoples in the United States.

Control Variables

I incorporate a number of controls variables that represent the urban-industrial predictors of tract presence in macro-scale air-toxic LCR clusters (Liévanos 2015). Five of these controls came from the 2000 census. Specifically, I control for population density (i.e., population per square kilometer in thousands), the percent employed in manufacturing, and the median year housing units were built. I also include a regionally varying measure of tract housing value (i.e., the ratio of tract median values to state median values of owner-occupied housing units), and the average travel time in minutes to work for the population who is at least 16 years old and employed outside the home. Two control variables came from the U.S. Geological Survey. The first of which is distance (kilometers) from each tract's geographic center to the nearest major transportation route (i.e., a toll road, ferry crossing, interstate or other limited access highway, or other state-numbered or U.S.-numbered highway (USGS 1999)). The second is the percent of tract area covered by "high intensity development" (i.e., dense commercial, residential, and industrial land use) from version 2.0 of the 2001 National Land Cover Database (Homer et al. 2004; USGS 2011; see also Liévanos 2015, p. 56).

Two additional control variables account for spatial effects not captured by other variables in the regression analyses. I use distance (kilometers) from each tract's geographic center to the geographic center of the nearest macro-scale air-toxic LCR cluster in the national and regional regression models. This control variable operationalizes the distance-decay principle in geography, which holds that proximate

spatial phenomena are more similar than distant ones (Tobler 1970). Lastly, the nationwide model incorporates the same U.S. EPA regional control used in the previous nationwide study (Liévanos 2015), which accounts for tract presence in carcinogenic air pollution hot-spot regions of the West/Southwest and Northeast (all other U.S. EPA regions are the omitted reference category). The regional models exclude this final spatial control.

The previous nationwide study (Liévanos 2015) suggests a number of expected effects of the control variables in the regression models. Average travel time to work, high intensity development, population density, and relative median housing value should be associated with greater likelihood of tract presence in a macro-scale air-toxic LCR cluster. In contrast, percent employed in manufacturing, median age of housing stock, and distances to nearest major transportation route and to the center of the nearest cluster should be negatively associated with the odds of tract presence in a macro-scale air-toxic LCR cluster.

Results

Descriptive Statistics

Table 3 displays the descriptive statistics for the dependent and explanatory variables used in this study's nationwide logistic regression analyses. Tables 4 and 5 display comparable descriptive statistics for the same variables for each U.S. EPA region. The tables exclude descriptive statistics for the control variables because of article space constraints and this study's primary interest in the dependent and explanatory variables.

Table 3 shows that tract presence in a macro-scale air-toxic LCR cluster had a mean of 0.26. This indicates that 26% of the tracts in this national sample of 64,162 tracts resided in a macro-scale air-toxic LCR cluster in 2005. The racialized intercategorical explanatory variables all

Table 4 Descriptive statistics for the dependent and explanatory variables used in the logistic regression analyses in U.S. EPA Regions 1 through 5

	Summary statistic	Region 1: New England	Region 2: Northeast	Region 3: Mid-Atlantic	Region 4: Southeast	Region 5: Midwest
Dependent variable						
Tract presence in a macro-scale air-toxic LCR cluster	Min.	0.00	0.00	0.00	0.00	0.00
	Max.	1.00	1.00	1.00	1.00	1.00
	Mean	0.17	0.55[a]	0.24	0.09	0.20
	Std. deviation	0.38	0.50	0.43	0.28	0.40
Explanatory variables						
Indigenous deprivation	Min.	−0.14	−0.14	−0.14	−0.14	−0.14
	Max.	10.14	16.51	1.04	17.06	20.61
	Mean	−0.09	−0.08	−0.11	−0.08	−0.07
	Std. deviation	0.24	0.39	0.08	0.35	0.36
White deprivation	Min.	−1.77	−1.77	−1.77	−1.77	−1.77
	Max.	7.53	9.64	10.46[b]	8.51	8.60
	Mean	0.09[a]	−0.11	−0.01	0.04[a]	−0.04
	Std. deviation	0.89	0.96	1.14	1.06	0.97
Black deprivation	Min.	−0.47	−0.47	−0.47	−0.47	−0.47
	Max.	4.19	5.69	7.69	8.13	8.87
	Mean	−0.30	0.08[a]	0.09[a]	0.32[a]	0.04[a]
	Std. deviation	0.45	1.00	1.09	1.19	1.18
API deprivation	Min.	−0.37	−0.37	−0.37	−0.37	−0.37
	Max.	19.86	21.89[b]	19.17	9.34	18.62
	Mean	−0.06	0.26[a]	−0.14	−0.23	−0.17
	Std. deviation	0.87	1.42	0.60	0.36	0.66
Latinx deprivation	Min.	−0.47	−0.47	−0.47	−0.47	−0.47
	Max.	8.39	10.10[b]	8.70	6.01	6.29
	Mean	−0.11	0.22[a]	−0.34	−0.26	−0.29
	Std. deviation	0.91	1.22	0.45	0.51	0.52
Isolated API immigrant deprivation	Min.	−0.39	−0.39	−0.39	−0.39	−0.39
	Max.	20.12	20.27	19.47	7.78	16.88
	Mean	−0.07	0.28[a]	−0.14	−0.25	−0.18
	Std. deviation	0.81	1.42	0.59	0.32	0.63
Isolated Latinx immigrant deprivation	Min.	−0.48	−0.48	−0.48	−0.48	−0.48
	Max.	6.61	7.24	6.70	7.48	5.68
	Mean	−0.15	0.19[a]	−0.34	−0.22	−0.29
	Std. deviation	0.79	1.16	0.41	0.66	0.55
N		3187	6655	6666	11,069	12,516

[a]Exceeds mean for this variable in the continental United States (shown in Table 3)

[b]Maximum value for this variable in the continental United States (shown in Table 3)

had means of zero and a standard deviation of approximately one because they are standardized PCA factors. Yet, their minimum and maximum values differed notably, with higher values indicating higher spatial concentration of multiple social disadvantages for a given racialized group. While White deprivation had a minimum of −1.77, the nonwhite racialized intercategorical variables had minimum values that ranged from −0.47 to −0.14. The maximum values for White deprivation and Black deprivation, as well as for the Latinx factor variables, differed by less than two points, ranging from 8.92 to 10.46. Indigenous deprivation had the highest maximum value of 37.59, followed by the API factor variables with similar maximum values of which ranged from 21.89 to 23.85. These descriptive statistics demonstrate the especially high degree of multiple marginalizations that were spatially concentrated among the U.S. Indigenous peoples in 2000.

Table 5 Descriptive statistics for the dependent and explanatory variables used in the logistic regression analyses in U.S. EPA Regions 6 through 10

	Summary statistic	Region 6: South Central	Region 7: Central Plains	Region 8: Central Mountains	Region 9: West/Southwest	Region 10: Pacific Northwest
Dependent variable						
Tract presence in a macro-scale air-toxic LCR cluster	Min.	0.00	0.00	0.00	0.00	0.00
	Max.	1.00	1.00	1.00	1.00	1.00
	Mean	0.08	0.10	0.13	0.63[a]	0.20
	Std. deviation	0.27	0.30	0.34	0.48	0.40
Explanatory variables						
Indigenous deprivation	Min.	−0.14	−0.14	−0.14	−0.14	−0.14
	Max.	37.59[b]	9.29	29.51	28.31	20.68
	Mean	0.13[a]	−0.07	0.53[a]	0.11[a]	0.09[a]
	Std. deviation	1.41	0.30	2.73	1.52	1.01
White deprivation	Min.	−1.77	−1.77	−1.77	−1.77	−1.77
	Max.	8.18	5.29	5.64	5.53	8.97
	Mean	0.16[a]	0.07[a]	−0.04	−0.14	0.18[a]
	Std. deviation	1.12	0.90	0.82	0.79	0.87
Black deprivation	Min.	−0.47	−0.47	−0.47	−0.47	−0.47
	Max.	8.92[b]	6.50	1.67	5.10	1.57
	Mean	0.06[a]	−0.19	−0.43	−0.29	−0.41
	Std. deviation	1.01	0.79	0.15	0.40	0.16
API deprivation	Min.	−0.37	−0.37	−0.37	−0.37	−0.37
	Max.	9.82	10.64	5.28	21.76	20.13
	Mean	−0.17	−0.22	−0.21	0.72[a]	0.11[a]
	Std. deviation	0.50	0.41	0.33	1.74	0.99
Latinx deprivation	Min.	−0.47	−0.47	−0.47	−0.47	−0.47
	Max.	9.62	3.24	5.70	7.38	5.12
	Mean	0.41[a]	−0.34	−0.13	0.73[a]	−0.20
	Std. deviation	1.38	0.30	0.65	1.43	0.51
Isolated API immigrant deprivation	Min.	−0.39	−0.39	−0.39	−0.39	−0.39
	Max.	8.49	9.41	4.93	23.85[b]	16.36
	Mean	−0.17	−0.24	−0.22	0.76[a]	0.10[a]
	Std. deviation	0.50	0.38	0.31	1.79	0.94
Isolated Latinx immigrant deprivation	Min.	−0.48	−0.48	−0.48	−0.48	−0.48
	Max.	9.14[b]	3.63	4.40	7.33	4.96
	Mean	0.38[a]	−0.35	−0.15	0.77[a]	−0.20
	Std. deviation	1.31	0.34	0.61	1.49	0.51
N		7495	3305	2381	8542	2346

[a]Exceeds mean for the continental United States (shown in Table 3)

[b]Maximum value for this variable in the continental United States (shown in Table 3)

Compared with Table 3, the descriptive statistics summarized in Tables 4 and 5 shed light on the regional dimensions of macro-scale air-toxic LCR cluster prevalence and exposure. Specifically, the tables highlight which regions have elevated levels of tracts located in macro-scale air-toxic LCR clusters. Again, the degree of tracts located in macro-scale air-toxic LCR clusters exceeded the nationwide mean of 0.26 in the West/Southwest and Northeast regions. The Mid-Atlantic, Midwest, and Pacific Northwest also approached that nationwide mean.

Comparing the mean and maximum values for each racialized intercategorical explanatory variable across Tables 3, 4, and 5 reveals the regional dimensions of racialized and intercategorical complexity among census tracts for the year 2000 in the continental United States (c.f., Cheng 2013; McCall 2005; Nakano Glenn 2002; Pulido 2006).

Table 6 Odds ratios from logistic regression predicting tract presence in macro-scale 2005 air-toxic LCR clusters in continental United States

	Model 1	Model 2
Explanatory variables		
Indigenous deprivation	1.024	1.016
White deprivation	0.821***	0.820***
Black deprivation	1.048**	1.063***
API deprivation	1.047**	
Latinx deprivation	1.185***	
Isolated API immigrant deprivation		1.098***
Isolated Latinx immigrant deprivation		1.254***
Control variables		
Average travel time to work (minutes)	1.009***	1.008**
Kilometers to nearest major transportation route	0.872***	0.877***
Percent high intensity development	1.027***	1.026***
Population per square kilometer (1000 s)	1.245***	1.229***
Percent employed in manufacturing	0.995*	0.993**
Relative median housing value	1.089***	1.098***
Median year housing units built	0.986***	0.985***
Kilometers to centroid of nearest macro-scale cluster	0.943***	0.943***
U.S. EPA region		
2: Northeast	3.734***	3.723***
9: West/Southwest	9.368***	8.813***
All other regions (reference)		
− 2 log likelihood	27,476.55	27,387.55
Pseudo R^2	.701	.702

$N = 64{,}162$. Odds ratios for the constant not shown in table

$*p < .05$; $**p < .01$; $***p < .001$ (two-tailed tests)

The mean value for one racialized and intercategorical variable exceeded the respective mean value for the continental United States in five regions: Indigenous deprivation in the Central Mountains, White deprivation in New England and the Central Plains, and Black Deprivation in the Mid-Atlantic and Midwest. The Mid-Atlantic also contained the maximum value of 10.46 for White deprivation. Mean levels of Black and White deprivation were elevated above the nationwide mean in the Southeast. The means for Indigenous and White deprivation, as well as for both API factors, exceeded their respective nationwide means in the Pacific Northwest.

The mean and maximum values for select racialized and intercategorical variables exceeded comparable nationwide values in the two most-risky regions. The Northeast contained elevated means for Black deprivation and for both API and Latinx factors, as well as the maximum values for API deprivation (21.89) and Latinx deprivation (10.10). The West/Southwest contained elevated means for Indigenous deprivation and for both API and Latinx factors. That region also held the maximum value for isolated API immigrant deprivation (23.85).

Lastly, the South Central is noteworthy for its broad extent of multiple marginalizations among its racialized census tracts in 2000. As shown in Table 5, this region contained elevated means for both Latinx factors, as well as for Indigenous, White, and Black deprivation. It also held the maximum values for Indigenous deprivation (37.59), isolated Latinx immigrant deprivation (9.14), and Black deprivation (8.92).

Nationwide Regression Analyses

Table 6 displays the results for the two full nationwide binary logistic regression models. These models include the same explanatory variables used in Liévanos (2015) to test the dissimilar intercategorical environmental inequality hypothesis (H1). They also include the new Indigenous deprivation factor in this study's novel test of the Indigenous deprivation hypothesis (H3). Following Liévanos (2015), Models 1 and 2 in Table 6 differ by the extent to which they integrate nativity and linguistic ability into the intercategorical factor variables for APIs and Latinxs. This modeling approach avoids multicollinearity issues between highly correlated variables for APIs and for Latinxs. It also facilitates an assessment of the interlocking dimensions of inequality for APIs and Latinxs that are most salient in isolation from, and in combination with, the other explanatory and control variables used in each model (Liévanos 2015). Model 2, in

particular, contains the isolated Latinx immigrant deprivation factor and tests the isolated Latinx immigrant deprivation hypothesis (H2).

Table 6 reports the odds ratios and significance levels of the associated regression coefficients for each independent variable. The results indicate that, on average, tract-level concentrations of Indigenous deprivation in 2000 had no significant effect on the probability of tract presence in macro-scale air-toxic LCR clusters in 2005, net of similarly marginalized Latinxs, Blacks, APIs, and Whites and the urban-industrial and regional controls. The nationwide results do not support the Indigenous deprivation hypothesis (H3) while demonstrating that inserting Indigenous deprivation into the national model for macro-scale air-toxic LCR clusters produces no substantive changes to the findings reported in previous research (Liévanos 2015, p. 64). As found in Liévanos (2015), Model 2 best fits the data with a smaller -2 log likelihood and has more explanatory power with a larger pseudo R^2. Net of controls and Indigenous deprivation, the odds of tract presence in a macro-scale air-toxic LCR cluster across the continental United States in 2005 was most consistently associated with elevated levels of isolated Latinx immigrant deprivation, followed by isolated API immigrant deprivation and Black deprivation. White deprivation was once again negatively associated with tract presence in a macro-scale air-toxic LCR cluster, net of other factors in Model 2. Accordingly, these findings support the dissimilar intercategorical environmental inequality hypothesis (H1) and the isolated Latinx immigrant deprivation hypothesis (H2).

Regional Regression Analyses

The odds ratios and significance levels of the associated regression coefficients for the best-fitting logistic regression model for each U.S. EPA region are shown in Tables 7 and 8. Table 1 indicated that the West/Southwest, Northeast, and Pacific Northwest were the most risky regions according to their elevated air-toxic LCR levels and percentages of macro-scale air-toxic LCR cluster tracts (c.f., Zwickl et al. 2014). As summarized in Table 9 and elaborated below, the regional results show that eight sets of significant positive predictors of racialized intercategorical environmental inequality outcomes manifest across the regions—at times cutting across the most risky regions and comparatively low-risk regions. In addition, Tables 3, 4, and 5 compared tract-level variations in each racialized intercategorical explanatory variable across the continental United States and the U.S. EPA regions. Contextualized in those descriptive statistics, the differential effects of the racialized intercategorical explanatory variables summarized in Tables 7, 8, and 9 indicate that heightened mean (and maximum) concentrations of racialized and multiply marginalized populations

did not always translate into racialized intercategorical *environmental* inequalities within each U.S. EPA region. Nonetheless, the regional regression results consistently support the dissimilar intercategorical environmental inequality hypothesis (H1). They further indicate that this dissimilarity in outcomes varies across the United States. That is, the relationship between the spatial concentration of multiply marginalized racial groups, urban-industrial context, and tract presence in a macro-scale air-toxic LCR cluster varies by U.S. EPA region.

New England had above average levels of White deprivation (see Table 4). Despite this, the first model shown in Table 7 indicates that the spatial concentration of White deprivation and other racialized and multiply marginalized groups were not significantly associated with the likelihood of tract presence in a macro-scale air-toxic LCR cluster in New England. Instead, it was the control variables—except for the median year that housing was built—which were significantly associated with tract presence in a macro-scale air-toxic LCR cluster in the region.

Significant positive racialized intercategorical predictors manifested across the remaining nine regions. In four regions, the spatial concentration of one racialized intercategorical group was the primary positive intercategorical predictor of tract presence in a macro-scale air-toxic LCR cluster. The Midwest had elevated levels of Black deprivation (see Table 4). Consistent with this, Black deprivation was the significant and positive racialized intercategorical predictor in the Midwest. In this region, a one-unit increase in Black deprivation was significantly associated with an increase of 29% in the odds of tract presence in a macro-scale air-toxic LCR cluster (see Table 7).

Average Latinx deprivation levels were particularly high in the South Central and West/Southwest regions (see Table 5). The regression results shown in Table 8 are consistent with that pattern, as Latinx deprivation was the positive intercategorical predictor in the relatively low-risk South Central and the most risky West/Southwest. In the South Central and West/Southwest, respectively, a one-unit increase in Latinx deprivation was significantly associated with increases of 30% and 17% in the odds of tract presence in a macro-scale air-toxic LCR cluster.

Isolated API immigrant deprivation was the most consistent positive predictor among the explanatory variables in the second-most risky Northeast region. In this region, average levels of isolated API immigrant deprivation were particularly high (see Table 4). In the Northeast region's better-performing model, a one-unit increase in isolated API immigrant deprivation was associated with an increase of 69% in the odds of tract presence in a macro-scale air-toxic LCR cluster (see Table 7).

The spatial concentration of two sets of racialized intercategorical groups was significantly associated with

Table 7 Odds ratios from logistic regression predicting tract presence in macro-scale 2005 air-toxic LCR clusters in U.S. EPA Regions 1 through 5

	Region 1: New England	Region 2: Northeast	Region 3: Mid-Atlantic	Region 4: Southeast	Region 5: Midwest
Explanatory variables					
Indigenous deprivation	1.071	0.363	6.897***	0.310	1.106
White deprivation	0.938	0.758**	0.859*	0.780**	0.963
Black deprivation	1.313	0.591***	1.228***	1.122	1.288***
API deprivation					0.873**
Latinx deprivation					0.970
Isolated API immigrant deprivation	1.012	1.693***	1.372***	2.635***	
Isolated Latinx immigrant deprivation	1.097	0.884	1.504***	3.137***	
Control variables					
Average travel time to work (minutes)	1.052*	1.082***	0.951***	1.190***	0.932***
Kilometers to nearest major transportation route	0.335***	1.108	0.601***	0.754*	0.674***
Percent high intensity development	1.034***	1.078***	0.989***	1.058***	1.068***
Population per square kilometer (1000 s)	1.139**	2.194***	0.985	1.239*	1.454***
Percent employed in manufacturing	0.922***	1.024	0.850***	0.865***	1.078***
Relative median housing value	1.616**	1.971***	0.644***	1.691***	1.395***
Median year housing units built	0.997	0.974***	0.997	0.971***	0.972***
Kilometers to centroid of nearest macro-scale cluster	0.666***	0.890***	0.913***	0.937***	0.907***
−2 log likelihood	666.800	2072.019	3341.319	1833.490	4081.656
Difference in log likelihood from other U.S. EPA regional model (% difference)	−0.485 (−0.07%)	−6.367 (−0.31%)	−33.239 (−0.98%)	−23.041 (−1.24%)	−0.823 (−0.02%)
Pseudo R^2	.736	.877	.583	.680	.694
N	3187	6655	6666	11,069	12,516

Results shown for regression models that best fit the data. Odds ratios for the constant not shown in table

*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests)

tract presence in a macro-scale air-toxic LCR cluster in two regions. Isolated Latinx and API immigrant deprivation were significant positive predictors in the Southeast and the Central Mountains despite both of these regions having particularly low average levels of both racialized intercategorical variables (see Tables 4 and 5). The results for the isolated Latinx immigrant deprivation factor in these two regions support the isolated Latinx immigrant deprivation hypothesis (H2). The odds of tract presence in a macro-scale air-toxic LCR cluster increased by 164% and 214%, respectively, for one-unit increases in isolated API immigrant deprivation and isolated Latinx

immigrant deprivation in the Southeast (see Table 7). One-unit increases in isolated API immigrant deprivation and isolated Latinx immigrant deprivation in the Central Mountains were associated, respectively, with increases of 203% and 459% in the odds of tract presence in a macro-scale air-toxic LCR cluster (see Table 8). These effects are particularly noteworthy, given the effects of the racialized intercategorical factor variables in most of the other regions, and they suggest that linguistically isolated and deprived Latinx and API immigrant tracts faced exceptionally high risk of exposure to cancer-causing air pollution in the Southeast and Central Mountain regions in 2005.

Table 8 Odds ratios from logistic regression predicting tract presence in macro-scale 2005 air-toxic LCR clusters in U.S. EPA Regions 6 through 10

	Region 6: South Central	Region 7: Central Plains	Region 8: Central Mountains	Region 9: West/South-west	Region 10: Pacific Northwest
Explanatory variables					
Indigenous deprivation	0.576	0.171	3.957	0.871	0.919
White deprivation	0.645**	1.859**	0.514*	0.614***	1.833**
Black deprivation	1.050	1.621**	2.174	1.299	8.887**
API deprivation	0.747*			0.888***	
Latinx deprivation	1.302**			1.167***	
Isolated API immigrant deprivation		1.361	3.025*		0.682***
Isolated Latinx immigrant deprivation		1.251	5.590***		1.371
Control variables					
Average travel time to work (minutes)	1.036*	0.981	0.943	0.998	0.709***
Kilometers to nearest major transportation route	0.820	0.116**	0.265***	1.007	0.841
Percent high intensity development	1.071***	1.085***	1.099***	1.044***	1.006
Population per square kilometer (1000 s)	0.899*	1.591**	1.638**	1.522***	1.307**
Percent employed in manufacturing	1.096***	0.955	0.892*	1.038***	1.099***
Relative median housing value	1.148	1.819**	0.777	0.782***	0.359***
Median year housing units built	0.963***	0.969**	0.957***	0.973***	1.022**
Kilometers to centroid of nearest macro-scale cluster	0.865***	0.835***	0.895***	0.972***	0.860***
−2 log likelihood	1187.695	408.498	370.669	6960.367	769.042
Difference in log likelihood from other U.S. EPA regional model (% difference)	−0.498 (−0.04%)	−0.679 (−0.17%)	−2.129 (−0.57%)	−5.774 (−0.08%)	−5.640 (−0.73%)
Pseudo R^2	.558	.674	.825	.570	.727
N	7495	3305	2381	8542	2346

Results shown for regression models that best fit the data. Odds ratios for the constant not shown in table

*$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests)

In the Central Plains and the Pacific Northwest, Black deprivation and and White deprivation were the significant predictors of racialized intercategorical environmental inequality outcomes. However, of these two factors, only average levels of White deprivation exceeded the national average in both regions (see Table 5). Consistent with this, White deprivation was the strongest racialized intercategorical predictor in the Central Plains: a one-point increase in that factor variable was associated with an increase of 86% in the odds of tract presence in a macro-scale air-toxic LCR cluster (see Table 8). Despite

the low average levels of Black deprivation (see Table 5), a one-point increase in Black deprivation was associated with an increase of 62% in the odds of tract presence in a macro-scale air-toxic LCR cluster in the Central Plains. This White–Black racial hierarchy was reversed in the third-most risky, Pacific Northwest, where the odds of tract presence in a macro-scale air-toxic LCR cluster increased by 789% and 83%, respectively, with one-unit increases in Black deprivation and White deprivation (see Table 8). The magnitude of the effect for tract-levels of Black deprivation in the Pacific Northwest was the highest

Table 9 Significant positive predictors of racialized intercategorical environmental inequality outcomes by the U.S. EPA Region in the continental United States

Significant positive racialized intercategorical predictors	U.S. EPA Region(s)
No significant positive predictors	1: New England
Black deprivation[b]	5: Midwest
Latinx deprivation[b]	6: South Central; 9: West/Southwest[a]
Isolated API immigrant deprivation[b]	2: Northeast[a]
Isolated Latinx and API immigrant deprivation	4: Southeast, 8: Central Mountains
White[b] and Black deprivation	7: Central Plains
Black and White[b] deprivation	10: Pacific Northwest[a]
Indigenous deprivation, Isolated Latinx and API immigrant deprivation, Black[b] deprivation	3: Mid-Atlantic

[a]One of the top three regions in the continental United States for elevated mean LCR levels (above the national macro-scale air-toxic LCR cluster mean of 85.81 estimated cancer cases per million)

[b]Positive effect for the racialized intercategorical predictor accords with elevated mean levels (above the national mean of zero) of that racialized intercategorical factor in the region

among all other effects witnessed for the racialized inter-categorical factor variables across the regions. This finding is especially noteworthy since the Pacific Northwest had low mean concentrations of Black deprivation (see Table 5), and it suggests that economically deprived and gender-marginalized Black census tracts in the Pacific Northwest experienced the *highest* risk of tract exposure to cancer-causing air pollution compared to other U.S. EPA regions in 2005.

The remaining results for the Mid-Atlantic region center on the spatial concentration of all nonwhite racialized and multiply marginalized groups. Furthermore, it is in this region where the regional results support the Indigenous deprivation hypothesis (H3): the concentration of Indigenous deprivation emerges as a significant (and primary) racialized intercategorical predictor of environmental inequality outcomes, net of other variables included in the model. In this region, the odds of tract presence in macro-scale air-toxic LCR clusters increased by 590%, 50%, 37%, and 23%, respectively, with one-unit increases in Indigenous deprivation, isolated Latinx immigrant deprivation, isolated API immigrant deprivation, and Black deprivation (see Table 7). The results for isolated Latinx immigrant deprivation in this region support the isolated Latinx immigrant deprivation hypothesis (H2). The findings for Black deprivation accord with the elevated average concentration of Black deprivation in the Mid-Atlantic (see Table 4). However, despite Indigenous deprivation reaching the lowest average and maximum levels in the Mid-Atlantic (compare Tables 3, 4, and 5), the concentration of multiply marginalized Indigenous peoples in that region was associated with some of the highest risk of tract exposure to cancer-causing air pollution in the United States in 2005.

Discussion

The nationwide results reported above are consistent with those reported in Liévanos (2015, p. 64) and thus support the dissimilar intercategorical environmental inequality (H1) and isolated Latinx immigrant deprivation (H2) hypotheses. Further, those results do not support the Indigenous deprivation hypothesis (H3). However, this study's regional regression results compare and contrast with the nationwide results summarized above and in Liévanos (2015) in several notable ways. The regional results in the present study generally support the dissimilar intercategorical environmental inequality hypothesis, showing how racialized intercategorical environmental inequality outcomes vary by region. In so doing, however, they indicate that immigrant status and limited English-speaking ability may be less relevant for explaining the interlocking axes of inequality that contribute to gender-marginalized and economically deprived Latinx neighborhoods' heightened risk of exposure to macro-scale air-toxic LCR clusters in the South Central and West/Southwest regions. Accordingly, those results do not support the isolated Latinx immigrant deprivation hypothesis. In contrast, the Mid-Atlantic, Southeast, and Central Mountains results support the isolated Latinx immigrant deprivation hypothesis. In these regions, we see that immigrant status and limited English-speaking ability appear to combine with the spatial concentrations of single-mother families and economic deprivation to increase Latinx neighborhoods' vulnerability of exposure to macro-scale air-toxic LCR clusters. Despite this regional variation in support for the isolated Latinx immigrant deprivation hypothesis, it is noteworthy that *none* of the Latinx factor variables were negative *and* significant predictors of tract exposure to the carcinogenic air pollution clusters in any of the regions. These findings

complement the nationwide results presented above and in Liévanos ([2015](#)) regarding the importance of the concentration of multiply marginalized Latinxs in predicting tract presence in macro-scale air-toxic LCR clusters in the continental United States in 2005.

Additional nationwide patterns varied across all regions. White deprivation was the only significant *and* negative racialized intercategorical predictor of tract presence in macro-scale air-toxic LCR clusters across the continental United States. In the Central Plains and the Pacific Northwest, however, White deprivation was a significant and positive racialized intercategorical predictor of tract exposure to macro-scale air-toxic LCR clusters, net of other factors included in those regional models. Likewise, the API factor variables were negative and significant racialized intercategorical predictors in the Midwest, South Central, the West/Southwest, and the Pacific Northwest models. In addition, Black deprivation was a significant and negative predictor only in the Northeast region. Further, the racialized intercategorical variables exhibited nonsignificant effects in the New England model.

The effects of urban-industrial context varied across the regions but were nonetheless highly influential. The results presented above indicate the Southeast is the only region where the effects of the urban-industrial control variables match that of the national model. Greater than or equal to 75% of those control variables for New England, the Northeast, the Midwest, the Central Plains, and the Central Mountains match the direction and significance of the urban-industrial controls in the national model. Overall, the regional models indicate proximity to major transportation routes is a major predictor of tract vulnerability of exposure to macro-scale air-toxic LCR clusters across the regions. The regional analyses also challenge the extent to which a post-industrial occupational structure predicts vulnerable tract status. In contrast to Liévanos ([2015](#)) and the new nationwide results shown above—but partially supportive of Anderton et al. ([1994](#))—percent employed in manufacturing was a significant and positive predictor of tract presence in macro-scale air-toxic LCR clusters in the Midwest, South Central, West/Southwest, and Pacific Northwest regions.

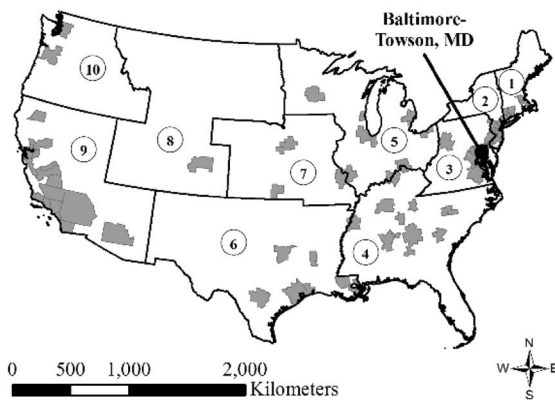## Indigenous Deprivation and Environmental Inequalities in the Mid-Atlantic Region

Results presented in Table [7](#) suggest the existence of a strong White-nonwhite color line of intercategorical environmental inequality in the Mid-Atlantic. The results for Indigenous deprivation in this region support the Indigenous deprivation hypothesis (H3). Further, the Mid-Atlantic results suggest that the small share of Indigenous people in the region were at particularly heightened risk of exposure to cancer-causing air pollution in 2005. These patterns must be understood in the context of the significant effects that three urban-industrial controls—low manufacturing employment and proximity to the nearest major transportation route and to the center of the nearest cluster—had on the odds of tract presence in a macro-scale air-toxic LCR cluster in that region.

It is important to note further that the Mid-Atlantic findings compare and contrast with previous studies, which focus almost exclusively on *industrial* air-toxic health hazards and contain no explicit indicators of Indigenous deprivation let alone presence in the region. Specifically, Ard ([2015](#)) found in this region that block group-level concentrations of Blacks were not significantly associated with more industrial air-toxic exposure than the spatial concentration of Whites, and Zwickl et al. ([2014](#)) found that poor White block groups generally had higher industrial toxic exposure rates than poor nonwhite block groups in the Mid-Atlantic. Ard ([2015](#)) suggests that such findings might be explained through historical case studies of the Mid-Atlantic city of Baltimore, Maryland. In particular, Boone ([2002](#)) found that the extent to which White neighborhoods were more likely near industrial facilities, as reflected in the Toxic Release Inventory (TRI) data analyzed by Ard ([2015](#)) and Zwickl et al. ([2014](#)), varied by unit of analysis and proximity measure. However, industrial zoning and racial settlement patterns have contributed to lower-income, White neighborhoods being more likely proximate to industrial air-toxic hazards in Baltimore (Boone [2002](#)).

Yet, at the state-level of Maryland, Apelberg et al. ([2005](#)) revealed the limitations of environmental inequality analyses that rely strictly on the TRI data. Similar to the present study, Apelberg et al. ([2005](#)) examined the association between race, socioeconomic status, and air-toxic LCR from industrial, vehicular, and other emission sources using the 1996 U.S. EPA NATA. That study found greater exposure disparities at the lower socioeconomic levels for different racial groups, especially Blacks. Importantly, though, the majority of the exposure disparities were attributable to vehicular sources from roads and highways. The present study builds on Apelberg et al. ([2005](#)) by illustrating that environmental inequality studies of air pollution must attend to industrial *and* other sources of air-toxic emissions as captured in the NATA data. The present study also demonstrates that the spatial concentration of multiply marginalized Indigenous peoples is a major predictor of environmental inequality outcomes in the Mid-Atlantic. Accordingly, failure to use more comprehensive data on air-toxic health risk and include deprived Indigenous peoples in the comparative analysis of racialized intercategorical environmental inequalities may lead to the underestimation of the spatial, racial, and intersectional dimensions of environmental inequalities, in general, and as they pertain to air pollution, in particular, within the Mid-Atlantic region.

Map A: U.S. EPA Regions and CBSAs with Macro-Scale
Air-Toxic LCR Clusters in the Continental United States

Map B: Macro-Scale Clusters and Indigenous Deprivation
in the Baltimore-Towson, MD Metropolitan Area
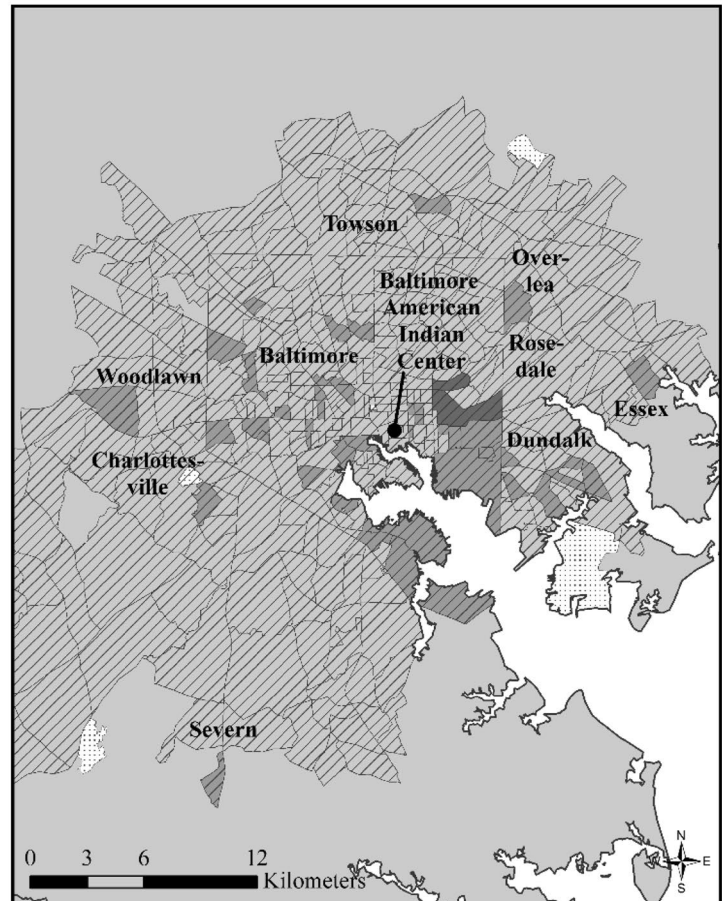
Fig. 3 U.S. EPA Regions, macro-scale air-toxic LCR clusters, and Indigenous deprivation in the Baltimore-Towson, MD metropolitan area, 2005

Still, one important question remains regarding the extent to which the racialized intercategorical predictors of tract presence in macro-scale air-toxic LCR clusters across the U.S. EPA regions is constant for the 70 CBSAs containing the clusters in those regions (see Liévanos 2015, pp. 62, 63). Further scrutiny of the Mid-Atlantic region's Baltimore–Towson metropolitan area (Baltimore metro) with data used in this study suggests Baltimore metro may be an important case study to begin addressing this question with an eye toward further locating Indigenous peoples in racialized intercategorical environmental inequalities in the United States. Of the 625 tracts in Baltimore metro, 399 (63.8%) were found in that region's macro-scale air-toxic LCR cluster. Macro-scale air-toxic LCR cluster tracts had, on average, 0.03 points higher levels of Indigenous deprivation than noncluster tracts in Baltimore metro. Figure 3 overlays macro-scale air-toxic LCR cluster tracts on national standard deviation ranges of Indigenous deprivation in Baltimore metro. It shows that above average levels of Indigenous deprivation concentrate near the center of the Baltimore

metro macro-scale air-toxic LCR cluster. Further, *almost all* (i.e., 46 of 50; 92%) of the Baltimore metro tracts that had above average levels of Indigenous deprivation in 2000 were also contained in the metro area's macro-scale air-toxic LCR cluster.

Figure 3 also highlights the spatial location of one important local Indigenous institution: the Baltimore American Indian Center (BAIC). The BAIC was established in 1968 to honor and commemorate the Lumbee people (BAIC 2018). The Lumbee in Baltimore were descendants of uprooted and dispossessed North Carolina farmers whom never lived on a reservation and sought to resist the adverse and intersecting effects of racism, colonialism, and capitalism on their health and wellbeing in Baltimore City (Makofsky and Makofsky 1973; Makofsky 1982). As of 2000, the Lumbee were prominent members of the "underserved and largely unrecognized" urban Indigenous youth in Baltimore, who were "[p]lagued by low academic performance, soaring dropout rates, and challenging domestic situations" (Oberdalhoff 2000, p. 16). The Indigenous deprivation factor and

macro-scale air-toxic LCR cluster displayed in Fig. 3 represents the spatial dimensions of this multiple marginalization, and environmental inequality for the Lumbee and other Indigenous peoples in Baltimore metro.[2]

Conclusions

Extant quantitative research has yet to include Indigenous peoples in assessments of intersectional environmental inequalities throughout the continental United States. This study addresses this limitation and uncovers a significant association between Indigenous deprivation and tract-level exposures to macro-scale air-toxic LCR clusters for the Mid-Atlantic region, which was not evident in the nationwide analysis. This study also identified eight new patterns of racialized intercategorical environmental inequality outcomes across the U.S. EPA regions that have yet to be identified in previous research. In addition, it focuses on spatial clusters of carcinogenic air pollution from multiple sources and a broad set of urban-industrial contextual indicators. In so doing, this study overcomes the tendency of earlier scholarship to focus exclusively on (1) industrial hazards, (2) manufacturing employment and/or central city or urban location as measures of urban-industrial context, and (3) neighborhood racial and/or class compositions in shaping environmental inequality outcomes (c.f., Anderton et al. 1994; Ard 2015; Zwickl et al. 2014).

Nonetheless, important questions remain for future research given this study's limitations. One limitation of the present study is its use of data from 1999 to 2005. However, the conceptual framework and analytic techniques used in this study could guide future research with more recent data on the racialized intercategorical complexity of air-toxic LCR clusters in the United States and the U.S. EPA regions. For example, environmental inequality researchers have paired the 2010 Decennial Census, the 2008–2012 American Community Survey (ACS) and the 2011 U.S. EPA NATA estimates of air-toxic LCR (released in 2015). Drawing on these data, they have uncovered tract-level environmental inequality outcomes for Asian subgroups and other racial groups (controlling for income and other factors) across the United States (Grineski et al. 2017) and in four prominent Asian-American U.S. metropolitan areas (Grineski et al. 2018). This line of inquiry with the ACS and census data illuminates intraracial environmental inequalities for Asian ancestry, and it can be applied to other manifestations of

"intracategorical complexity" (McCall 2005; Grineski et al. 2018) in environmental health hazard exposures within different racialized subgroups.

However, previous research suggests such data constrain one's ability to reliably examine the type of racialized intercategorical environmental inequalities as analyzed in the present study for a couple reasons. First, ACS estimates, such as that for median household income, have limited reliability in the U.S. South, at finer geographic scales (e.g., tracts), and for marginalized subpopulations (e.g., low-income racial minorities) compared with the 2000 census (Folch et al. 2016). This perhaps explains why environmental inequality researchers consistently use ACS tract-level estimates for overall median household income rather than for median household income by race (Grineski et al. 2017, 2018; Liévanos 2018a). Further, the 2008–2012 ACS contains five of the six racialized and intercategorical variables used in the present study: poverty, educational attainment, unemployment, and immigrant status by race, as well as linguistic isolation for Spanish- and API-language-speaking households. The 2008–2012 ACS tract-level estimates of poverty and poverty by race in the continental United States illustrate the problems of relying on the ACS to analyze racialized intercategorical environmental inequality outcomes (see Table 10 in the Appendix). Using a medium reliability threshold for ACS estimates (i.e., a coefficient of variation < .50) (Liévanos 2018a) leads to an estimated range of tracts from 64,615 to 64,770 with reliable estimates of the degree to which the tract residents whose poverty status was determined had an income in the past 12 years that was below the federal poverty level. In contrast, thousands of tracts contain far less-reliable estimates of the racialized share of the population living in poverty.

Given these data-quality issues with the ACS, future research could use the ACS for control measures of tract economic conditions, linguistic isolation, and immigrant status. The 2010 U.S. Decennial Census contains 100% counts of the population and can serve as the main data source for racialized intercategorical variables. Specifically, the Decennial Census contains the remaining racialized and intercategorical variables used in this study: tract-level single-mother family composition for different racialized groups. My preliminary tabulations indicate that, in contrast to the 2008–2012 ACS poverty by race estimates, 71,863 tracts had nonzero 2010 Decennial Census counts of families. This count of tracts with nonmissing data better matches the number of tracts (N=72,018) with nonmissing air-toxic LCR estimates from the 2011 U.S. EPA NATA in the continental United States. Accordingly, future research could build on the present study utilizing the 2010 U.S. Census data to focus more explicitly on intercategorical environmental inequalities in carcinogenic air pollution exposures (and other toxic exposures) for racialized single-mother families (and other gendered family structures), and advance our understanding of the intersecting racialized and gendered dimensions of environmental health vulnerability in the United

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[2] I analyzed the 2000 U.S. Census-based detailed data on racial and tribal identification. I found that the largest share of specified tribal identities was Lumbee (N=154 of 788 American Indians or Alaska Natives; 19.54 percent) in 40 of the 46 Baltimore metro tracts that had above average levels of Indigenous deprivation in 2000 and were contained in Baltimore metro's 2005 macro-scale air-toxic LCR cluster.

States. Further, the present study suggests that deprived Black, Indigenous, and Latinx tracts have a significant gendered character through their elevated prevalence of single-mother families. To what extent do Black, Indigenous, and Latina single-mother families experience disproportionate environmental health hazard exposure in contrast to other racialized single-mother families and gendered family structures?

In addition, future research could compare racialized intercategorical environmental inequalities in exposures to clusters of carcinogenic air pollution (and other environmental health hazards) across various regional contexts. For example, previous research that does not include an intersectional lens demonstrates that environmental inequality outcomes vary along the regions and subdivisions of the U.S. Census Bureau (Downey 2006, 2007; Morello-Frosch and Jesdale 2006). Such work builds upon Farley and Frey's (1994) articulation of how the census regions are characterized by different histories of restrictive residential settlement, segregation, and land use, which have continuing significance for shaping contemporary racial segregation patterns in the United States (see also Lee et al. 2008). To what extent might racialized intercategorical environmental inequality outcomes vary by census region and subdivision in the United States?

Another question stemming from the present study pertains to the finer-scale spatial dynamics of racialized intercategorical environmental inequalities that manifest throughout the regional boundaries of the U.S. EPA and/or the U.S. Census Bureau, especially for Indigenous peoples. Geographically weighted regression techniques are well suited for such questions because they can formally test for spatial non-stationarity in how the determinants of racialized intercategorical inequalities vary locally throughout a study area (Liévanos 2018b; see also Fotheringham et al. 2002; Gilbert and Chakraborty 2011; Grineski et al. 2015; Jephcote and Chen 2012; Mennis and Jordan 2005; Wang et al. 2018). Researchers could map the results from such analyses onto the regional boundaries of the U.S. EPA and/or the U.S. Census Bureau to assess the extent to which those administrative regional boundaries match empirically derived estimates of spatial non-stationarity in racialized intercategorical inequalities throughout the United States.

The present study suggests the Mid-Atlantic region and Baltimore metro may be important case studies to pursue this line of questions about local context and Indigenous intercategorical environmental inequalities further—perhaps through comparative examinations with other regions and metro areas. The Central Mountains and Denver, Colorado may be relevant comparators given this study's findings regarding the exceptionally high mean concentrations of Indigenous deprivation in the Central Mountains and previous research on Indigenous environmental inequalities in Denver metro (Shaikh and Loomis 1999). What processes and events contribute to the relatively low number of deprived Indigenous peoples in the

Mid-Atlantic and Baltimore, who experience heightened vulnerability of exposure to carcinogenic air pollution? Why are such environmental inequalities apparently not evident in the Central Mountains and Denver where there are comparatively higher concentrations of Indigenous deprivation?

Indeed, important broader questions remain regarding the collective processes and events that give rise to racialized intersectional environmental inequalities (e.g., Choo and Ferree 2010; Malin and Ryder 2018; Pellow 2016). Future research could address such questions while building on the present study through examinations of how and under what conditions organizations and institutions operating at multiple geographic scales contribute to the formation of racialized intercategorical environmental inequality within each of the U.S. EPA regions and their macro-scale air-toxic LCR cluster-containing urbanized areas.

This study raises a related set of questions that have implications for U.S. environmental justice policy-making and activism. Research indicates that environmental justice initiatives within and beyond the U.S. EPA represent marginal reforms rather than meaningful challenges to the organizational and institutional constraints on regulatory environmental justice programs (Harrison 2016, 2017; Konisky 2015) or to the systemic, state-sanctioned racialized problems of multiple marginalizations, and unequal cumulative environmental burdens throughout the nation (Pellow 2016). One key problem here rests in the devolved regulatory power of environmental protection to the state and local levels wherein coalitions of powerful political and economic elites drive land-use patterns and often have little concern over the regional and equity implications of their actions (Logan and Molotch [1987] 2007).

The federalist strategy of devolved environmental protection is intensified in neoliberal regimes represented well in the current Trump administration (Mann 2017), which has sought to limit the authority, budget, and staff of the U.S. EPA and its scientific and environmental justice initiatives elevated during previous administrations. Such rollbacks are guided by unprecedented aggression toward the agency (Sellers et al. 2017) and a philosophy of focusing on "core legal requirements," "limiting federal government," and "devolving authority to states, localities and, in some cases, corporations" (Eilperin et al. 2017). For example, despite some congressional pushback with the 2017 federal omnibus budget, the budget priorities of the Trump administration resulted in the resignation of key environmental justice personnel (Dennis 2017) and decreased funding for the science and technology programs within the U.S. EPA (Mervis and the Science News Staff 2017). It remains to be seen how these changes may impact the U.S. EPA regional offices' willingness and ability to intervene in the type of complex racialized intercategorical environmental inequalities that this study detected within their jurisdictions.

It is perhaps even more important for sociologists and other social scientists to conduct the sorts of analyses as in

the present study in light of these political-economic conditions. Doing so may fill important gaps in the U.S. EPA's regulatory scientific work in the Trump administration while informing community members, advocates, and policy-makers about the particular racialized patterns of intercategorical environmental inequalities and their urban-industrial sources manifest within and across each U.S. EPA region. Indeed, this study identifies various place-based "communities of fate" (Stinchcombe 1965; Logan and Molotch [1987] 2007), linked by common intercategorical positionalities and environmental health vulnerabilities. The interests and livelihoods of such communities may be well served by learning from previous coalition building efforts that successfully bridged differences across diverse social and geographic locations in the name of peace, environmental justice, and Indigenous "environmental reproductive rights" (Beamish and Luebbers 2009; Ducre 2018; Hoover 2018). Pressing questions then emerge regarding what factors enable and constrain their coalition efforts that seek to address neighborhood vulnerability of exposure to life-threatening air-toxic pollution throughout the regional jurisdictions of a federal agency "under siege" (Sellers et al. 2017) in the current political-economic context.

Appendix

See Table 10.

Table 10 Number (N) and percent (%) of tracts in the continental United States with nonmissing data for poverty and racialized poverty estimates drawn from the 2008–2012 American Community Survey (ACS), conditional on meeting medium reliability coefficient of variation (CV) criteria

Variable criteria	N	%
Greater than zero population with poverty status determined, 2008–2012 ACS	71,802	–
CV less than .50	71,168	99.12
Income in the past 12 months below poverty level		
CV less than .50, inclusive of 0 estimates	64,770	90.21
CV less than .50, exclusive of 0 estimates	64,615	89.99
Income in the past 12 months below poverty level: White		
CV less than .50, inclusive of 0 estimates	57,235	79.71
CV less than .50, exclusive of 0 estimates	56,172	78.23
Income in the past 12 months below poverty level: Black		
CV less than .50, inclusive of 0 estimates	39,936	55.62
CV less than .50, exclusive of 0 estimates	14,673	20.44
Income in the past 12 months below poverty level: Indigenous[a]		
CV less than .50, inclusive of 0 estimates	59,332	82.63
CV less than .50, exclusive of 0 estimates	827	1.15
Income in the past 12 months below poverty level: API[b]		
CV less than .50, inclusive of 0 estimates	49,726	69.25
CV less than .50, exclusive of 0 estimates	2370	3.30
Income in the past 12 months below poverty level: Latinx[c]		
CV less than .50, inclusive of 0 estimates	36,476	50.80
CV less than .50, exclusive of 0 estimates	14,152	19.71

The CV measures the standardized degree of uncertainty in an ACS estimate. It is calculated by first dividing the published margin of error with a 90% confidence interval for the ACS estimate by 1.645 to derive the standard error of the estimate. The CV results from dividing the standard error of the estimate by the estimate (Spielman and Folch 2015, p. 3). The < .50 CV threshold accords with a medium reliability level for ACS estimates that are typically used in the environmental health disparities literature (Liévanos 2018a). Zero estimates result from a number of factors, and their CVs cannot technically be calculated. However, for illustrative purposes, the zero estimates were assigned a CV of −1, so that they could be included and excluded in the tabulation of tracts whose CVs were less than .50

[a]Indigenous: "American Indian/Alaska Native" in the ACS

[b]API: Asian and Native Hawaiian/Pacific Islander. The coefficients of variation for this variable were calculated using official guidelines for combining ACS estimates and assessing their CV (Fuller 2018). In this case, it first involved summing the poverty estimates for Asians and Native Hawaiian/Pacific Islanders. Second, the 90% margin of error was approximated by taking the square root of the summed squared margin of errors for both estimates. Third, the approximated margin of error was divided by 1.645 to derive the standard error of the combined estimate. Lastly, the standard error was divided by the estimate to obtain the CV for the combined estimate

[c]Latinx: "Hispanic or Latino" in the ACS

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