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Hispanic heterogeneity and environmental injustice: Intra-ethnic patterns of exposure to cancer risks from traffic-related air pollution in Miami

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1. Hispanic/Latino Ethnic Status and Environmental Injustice

> Environmental justice (EJ) is the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies. Fair treatment means that no group of people should bear a disproportionate share of the negative environmental consequences resulting from industrial, governmental and commercial operations or policies (Environmental Protection Agency, 2012, n.p.).

While EJ remains an important public policy goal, a majority of empirical studies indicate that racial minority and lower socioeconomic status groups experience disproportionate exposure to environmental health hazards, i.e., they experience environmental injustice (Brown, 1995; Brulle & Pellow, 2006; Chakraborty, Maantay, & Brender, 2011; Mohai, Pellow, & Roberts, 2009). Immigration-related variables, specifically proportion foreign-born and proportion lacking English proficiency, have also been associated with increased environmental risk factors, such as the presence of proposed Superfund sites in counties across the U.S. (Hunter, 2000). While the EJ field continues to expand in new directions, this paper seeks to address one critical limitation in the EJ literature: the use of broad racial and ethnic categorizations to analyze racial/ethnic disparities in hazard exposure (Collins, Grineski, Chakraborty, & McDonald, 2011). In relying on traditional categorizations of race and ethnicity (e.g., Hispanic), EJ researchers have tacitly assumed a significant degree of homogeneity within minority populations. They have thus failed to clarify how racial/ethnic status articulates with other social characteristics in contributing to unequal environmental risks. While a few recent EJ studies have highlighted situations of ‘triple jeopardy’ defined by the convergence of social, environmental, and health inequalities (Grineski, Collins, Chakraborty, & McDonald, 2012; Jerrett et al., 2001; Pearce, Richardson, Mitchell, & Shortt, 2010), health researchers have made more progress in disaggregating racial/ethnic categories and focusing on how class, gender, age and other dimensions of social inequality

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intersect to contribute to health disparities (Hankivsky et al., 2010; Schultz & Mullings, 2005).

In EJ research, the use of the aggregated Hispanic/Latino[1] category is becoming increasingly problematic because it lumps together people with differences in culture, country of origin, migration trajectories, social class, age and gender, among other characteristics. This assumption may be relatively valid in study sites with a homogeneous group of Hispanics but more troubling in study sites with diverse Hispanic populations, such as Miami, Florida. Given the growing diversity of Hispanics in the U.S., grouping them into a single category will become more problematic in EJ research, as it will conceal significant intra-group heterogeneity in the experience of environmental injustice; this was the case in El Paso County, Texas (Collins et al., 2011).

In one of the first studies to disaggregate the category of Hispanic (see also Gunier, Hertz, Von Behren, & Reynolds, 2003), Collins et al. (2011) found that racial/ethnic status combined with other dimensions of social inequality in complex ways to shape divergent intra-group relationships with cancer risks from hazardous air pollutants for Hispanics in El Paso County as compared to non-Hispanic Whites. Hispanics were prone to experience a multiple jeopardy in which their disadvantageous ethnic status interacted in significant ways with their class, gender, age, language, nativity and citizenship status to amplify experiences of disproportionate risk. In contrast, results for non-Hispanic Whites suggested that Anglo-whiteness tended to interact as a protective factor with class, gender and age status to attenuate potential cancer risk disparities. In other words, results indicated that disadvantages associated with class, age and gender status operated in a mutually reinforcing manner to compound cancer risks from exposure to air toxics for Hispanics in El Paso County, but not for non-Hispanic Whites (Collins et al., 2011). However, a limitation of this study was that in El Paso County, the vast majority of the population is of Mexican origin, with a shared culture and broadly similar migration experiences. Building off Collins et al.'s (2011) work in El Paso, we selected the Miami metropolitan area, with its complex history of Latin American and Caribbean migration, as the study site to provide new insights into the role of intra-ethnic heterogeneity in shaping patterns of environmental injustice. In doing so, we focus on the contextually relevant hazard variable of cancer risk from traffic pollution.

2. Rapid Latinization and Growth in Miami: The Relevance for Environmental Injustice

Despite Miami's large and ethnically diverse population, its dramatic socioeconomic inequalities and its serious air quality issues stemming from vehicular traffic, this metropolis has never been the subject of spatial-quantitative EJ analysis. As such, the Miami-Fort Lauderdale-Pompano Beach Metropolitan Statistical Area (MSA), henceforth called the Miami MSA or Miami (Figure 1), represents an ideal case study location. Miami is an urban area that has Latinized dramatically over the past 40 years; in these regards, it provides a climactic urban case of demographic processes occurring across the U.S. and the most appropriate choice for this study, since its racial/ethnic composition facilitates our examination of Hispanic diversity and its role in shaping patterns of environmental injustice.

2.1 Air Quality and Traffic Problems in Miami

With a total population of 5.4 million (2009), the Miami MSA is the largest MSA in Florida and the seventh largest in the U.S. The three counties of this MSA - Miami-Dade, Broward,

[1]We use the term Hispanic, as opposed to Latino, in this paper as it is more commonly used in Florida.

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and Palm Beach - represent those facing the greatest cumulative cancer risk from ambient exposure to hazardous air pollutants (HAPs) in Florida (Environmental Protection Agency, 2009). Given the relative lack of industrialization (e.g., the city of Miami ranks only 29th in terms of total pounds of on-site industrial toxic releases out of all cities in Florida [2010], according to RTK.net), the high HAP concentrations in Miami largely reflect the dense network of highly trafficked roadways throughout the study area.

Interstate development across South Florida began in earnest in the 1950s as the region grew more dense and larger, riding the wave of the post-war boom and the advent of in-home air conditioning (Nijman, 2011). Miami's 1956 Expressway Plan, which served as a blueprint for freeway development in the city and was built out by 1968, called for a giant interchange over the heart of Black Miami (Mohl, 2004). This area, the Overtown neighborhood, was home to half of Miami-Dade's Black population during the 1960s (Nijman, 2011)). After completion, this four level interchange displaced 10,000 people (Mohl, 2004); it cut the neighborhood into quadrants and produced dead spaces underneath the highways that remain today (Nijman, 2011). Mohl (2004) has argued that the building of the freeway system in Miami was an opportunity for the civic elite to achieve their longstanding racial political goals while recapturing central city space for business purposes. Currently, the Overtown area is still predominantly African-American, and has a very high poverty rate and some of the worst housing conditions in South Florida (Nijman, 2011).

Today, five interstate highways and eight state expressways crisscross the Miami MSA. The Miami MSA experienced a staggering 300% increase in daily vehicle miles traveled (VMT) between 1992 and 2005, and ranked first among all U.S. metropolitan areas in daily VMT change (1992–2005). In terms of highest annual VMT, this MSA is currently ranked fourth in the U.S. with an annual VMT of about 48.5 million (FHWA, 2008). The racial history combined with high traffic volumes make an EJ study of disproportionate exposure to traffic pollution particularly relevant in this MSA.

2.2 Ethnic Diversity in Miami

A fifth of the Miami MSA's population is non-Hispanic Black, and nearly 40% of residents are Hispanic. This makes the urban area very different from others where the geographic distribution of air pollution has been studied from an EJ perspective. Miami has a larger proportion of its total population being Hispanic than even Los Angeles (where there are more Hispanic people) (Suro & Singer, 2002). Within the Miami MSA, Hispanic and non-Hispanic Black populations are more concentrated in Miami-Dade County than in Broward and Palm Beach Counties (Figure 2). Visual inspection of Figure 2 reveals that Hispanic and Black residents are concentrated in areas with higher levels of cancer-causing hazardous air pollutants associated with the transportation network.

A measure of the diversity of Miami's Hispanic community can be captured by considering the ancestry of these residents. Miami's four largest Hispanic country-of-origin subgroups, based on 2005–2009 American Community Survey estimates, are: Cuban (42% of the Hispanic population), Puerto Rican (10%), Colombian (9%), and Mexican (6%). These groups generally inhabit different parts of this city (see Figure 3). The spatial divergence between Mexican census tracts and other Hispanic census tracts is especially stark, with Mexican tracts being located on the fringes of the metro area, instead of in the central city.

In Miami, Cubans are the most numerous and socially powerful of the Hispanic origin groups. Miami continues to be the destination for the majority of Cuban immigrants into the U.S. and, when also considering American-born Cubans, has the largest population of Cubans outside of Cuba (Woltman & Newbold, 2009). The Cuban diaspora has generally

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been considered the most successful Hispanic migration in the U.S. as Cubans tend to have higher earnings than other Hispanic migrants (Woltman & Newbold, 2009).

The first wave of Cuban migrants (1959–1961) were of the professional class and White; they had the social capital to access business ventures (Haller & Landolt, 2005). This first wave was followed by subsequent middle- and working class migrants (e.g., Freedom Flights) (Nijman, 2011; Woltman & Newbold, 2009). Migrants in the next major wave (Mariel in 1980) did not have the human capital or resources that were more common in the first wave. These*marielitos* were primarily poor with low levels of education, and they had little in common with previous Cuban migrants (Nijman, 2011). But they provided the older arrivals with privileged access to low-wage laborers and a market for cultural goods (Haller & Landolt, 2005).

During the 1970s-1980s, Broward County (see Figure 1) became the destination of choice for Whites fleeing the Latin Americanization of Miami; few Broward county residents were Hispanic and those who were Hispanic were primarily U.S.-born of Puerto Rican ancestry (Nijman, 2011). Other Latin American and Caribbean migrants have arrived in a less dramatic fashion in relatively steady flows (Haller & Landolt, 2005). In the 1980s and 1990s, Colombians, Haitians, Dominicans, and Mexicans, among other groups, arrived in larger numbers (Nijman, 2011). The unique ethnic composition and history of Miami makes it an intriguing site for an EJ study. In sum, the primary aim of this study is to explore intra-ethnic diversity (in terms of Hispanic origin groups) as an influence on patterns of environmental injustice related to potential cancer risk from ambient exposure to traffic pollution in this MSA.

3. Data

To achieve this aim, we related 2005–2009 American Community Survey (ACS) tract-level estimates with measures of cancer risk from exposure to on-road pollutants from the 2005 National-scale Air Toxics Assessment (NATA); both data sets utilize 2000 census tract boundaries. ACS estimates were downloaded at the census tract level for 887 tracts in the Miami MSA with complete data for tracts with populations over 1,200 residents. Four tracts were removed from the analysis due to missing median income data and 9 tracts were removed due to low population counts and attendant concerns about the stability of the proportion variables.

3.1 Socio-demographic Indicators

We used the traditional environmental justice variables of Median Household Income, Proportion Hispanic, and Proportion Non-Hispanic Black. In addition, we explored four Hispanic Origin variables: the proportion of the each tract's total population that was Cuban, Puerto Rican, Colombian, and Mexican in origin. In the ACS, the country of origin variable is based on self-reported Hispanic origin. Specifically, respondents are asked if they are "Mexican/Mexican-American/Chicano", "Cuban", "Puerto Rican" or "Another Hispanic, Latino or Spanish Origin"; if the respondent selects "Another Origin," he/she is asked to write in their origin (e.g., Colombian). This variable is not the same as place of birth, nor does it indicate immigration status (Lopez & Dockterman, 2011). For example, a U.S. citizen born in Miami of Cuban immigrant parents or grandparents may or may not identify his or her country of origin as Cuba; therefore, this variable captures ethnic origin self-identification.

Independent variables were tested for skewness and kurtosis, and log transformed when either was present. This was the case for Median Household Income, Proportion Colombian,

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and Proportion Mexican. All independent variables were standardized before entering them in the statistical models (see Table 1 for descriptive statistics).

3.2 Cancer Risk from Air Toxics

Potential cancer risks from ambient exposure to hazardous air pollutants (HAPs) were derived from the U.S. EPA's National-Scale Air Toxics Assessment (NATA), which has emerged an important and reliable database for estimating public health risks associated with the inhalation of HAPs from various emission sources (Chakraborty & Maantay, 2011). HAPs, also known as air toxics or non-criteria air pollutants, include 188 specific substances identified by the Clean Air Act Amendments of 1990 that are known to or suspected of causing cancer and other serious health problems, including respiratory, neurological, immune, or reproductive effects (Environmental Protection Agency, 2011a). The NATA is becoming a commonly used source of data in EJ studies (e.g., Apelberg, Buckley, & White., 2005; Chakraborty, 2009; Collins et al., 2011; Linder, Marko, & Sexton, 2008). Our study utilizes the 2005 NATA, which was released in 2011 (Environmental Protection Agency, 2011b). The census tract, our unit of analysis, is the smallest spatial unit for which health risk estimates are publicly available.

While the NATA generates potential lifetime cancer risk from inhalation exposure to four different types of HAP emission sources (i.e., point, nonpoint, on-road mobile and non-road mobile sources), we selected only on-road mobile sources for this study. On-road mobile sources include motorized vehicles operating on roads and highways (e.g., cars, trucks, busses); this emission category does not include airplanes, trains, lawnmowers, and construction vehicles. We focus on the on-road mobile category because it comprises the majority (54%) of local, known sources of cancer risk in the 2005 NATA for the Miami MSA. As points of reference, these other sources comprise the following shares: point (5%), non-point (19%), and non-road mobile (23%).

The methodology used to generate estimates of health risk for the 2005 NATA comprises several steps (Environmental Protection Agency, 2011c). Data on mobile source emissions for the NATA are based largely on the 2005 National Emissions Inventory. However, highway vehicle emissions of several air toxics such as diesel particulate matter and benzene are based on EPA's Motor Vehicle Emission Simulator. Emissions from on-road sources of air toxics are modeled using an air dispersion model, i.e., Human Exposure Model-3(HEM-3). Estimates of ambient concentrations from HEM-3 are utilized as input in a screening-level inhalation exposure model known as the Hazardous Air Pollution Exposure Model (HAPEM5). Through a series of calculation routines, the HAPEM5 model uses census population data, human activity patterns, ambient air quality levels, meteorological information, and indoor/outdoor concentration relationships to estimate an expected range of inhalation exposure concentrations for groups of individuals. From these exposure concentrations, the NATA estimates cancer and non-cancer health risks from inhalation of on-road HAPs following the EPA's risk characterization guidelines which assume a lifelong exposure to 2005 levels of outdoor air emissions.

Cancer risk estimates in the 2005 NATA, which we use here, are derived by combining exposure concentration estimates with available unit risk estimates. A unit risk estimate (URE) is calculated by using dose-response information for a pollutant and developing a factor in the appropriate units that can be combined directly with exposure concentrations in air to estimate individual cancer risks, given certain assumptions regarding the exposure conditions. Specifically, the URE represents the upper-bound of the excess lifetime cancer risk estimated to result from continuous exposure to a concentration of one microgram of a pollutant per cubic meter of air, over a 70-year lifetime. The interpretation of the URE is as follows: if the URE is 1.5 × 10-6 $\mu g/m^3$, no more than 1.5 excess tumors would develop per

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one million people, if they were exposed daily for a lifetime to a concentration of 1 μg/m^3 (EPA 2011c). Although the type of cancer (e.g., liver, blood, lung) and available evidence (e.g., known, suspected, or possible) varies by pollutant, cancer risks of different HAPs are assumed to be additive and are summed to estimate an aggregate lifetime cancer risk for each census tract.

For this study, estimates of lifetime potential cancer risk from inhalation exposure to on-road emission sources were obtained from the 2005 NATA for census tracts in the Miami MSA and used to represent the dependent variable for regression analysis. We used the natural logarithm of this variable due to skewness and kurtosis, and standardized it for entrance into the regression models (see Table 1 for descriptive statistics and Figure 4 for a map of its distribution).

4. Methods

To explore basic relationships, we began by examining bivariate correlations between all analysis variables. Then, we utilized two regression models in our analysis. The first (model 1) considered Median Household Income, Proportion Hispanic and Proportion non-Hispanic Black as predictor variables. The second (model 2) included the disaggregated Hispanic origin variables in place of the Proportion Hispanic variable used in model 1. Following Chakraborty (2009), we used the open source software, GeoDa (available at http://geodacenter.asu.edu/) to conduct the regression analysis. GeoDa software provides diagnostic statistics to aid model specification (Anselin, 2005). We initially ran both regression models using ordinary least squares (OLS) to test model residuals for spatial autocorrelation using the Univariate Moran's I test. Spatial autocorrelation is typically caused by geographic clustering when values at nearby locations are more similar or different than would be expected of a random distribution (Kissling & Carl, 2008). This phenomenon has the potential to cause spatial dependence of regression model residuals, thus violating the classical assumption of independence. Models 1 and 2 indicated positive spatial autocorrelation in the residuals (i.e., Moran's I values were significant at a p-value of 0.001; spatial weight: 1,000 m); this meant that our data did not meet the assumptions of OLS regression models.

We used the Lagrange Multiplier (LM) and the Robust LM diagnostic tests to determine if the spatial lag or spatial error model specification should be used (Anselin, 2005). Spatial lag models assume that spatial autocorrelation is present in the dependent variable (Chakraborty, 2009), while spatial error models assume that the independent variables exhibit spatial dependence (Pastor, Morello-Frosch, & Sadd, 2005). In this case, the LM tests suggested that the spatial lag specification was appropriate for both models. Another specification diagnostic offered by GeoDa in OLS regression is the multicollinearity condition index. The condition index measures the stability of the regression results due to multicollinearity (Anselin, 2005; Chakraborty, 2009). Anselin (2005) suggests that a condition index of 30 is indicative of serious collinearity problems. In our case, the condition indices were 2.2 for model 1 and 2.4 for model 2, which indicate the absence of multicollinearity issues.

Spatial econometric models are supported by means of the maximum likelihood method and they require sparse spatial weights (Anselin, Syabri, & Kho, 2006; Chakraborty, 2009), which are calculated based on a set of neighbor relationships (Pastor et al., 2005). Defining neighbors is a critical but exploratory part of spatial econometric modeling in environmental justice research. We used the distance method of defining weights, following Chakraborty (2009). This method is more appropriate for irregularly-shaped census geography than the rook or queen method (Pastor et al., 2005). The process of selecting a bandwidth distance

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for neighbors is iterative. We began the process using 1,000 m as our distance band. In both models, the Moran's I test was significant at the p>.001 level, indicating that the autocorrelation had not been accounted for. We then proceeded to re-run the models adding 500 m to the band each time, until the spatial autocorrelation (examined using the Moran's I test) was accounted for at the p>.001 level, which it was at 2,500 m for both models (see Table 3). At this distance, all but 61 tracts had at least one neighbor; this means that only 7% were without neighbors, which is a lower percentage than in comparable studies (Chakraborty, 2009).

5. Results

In terms of bivariate linear correlations, we found traditional EJ relationships between On-road Cancer Risk and Median Household Income, Proportion Hispanic, and Proportion non-Hispanic Black. Pearson's correlation coefficients (r-values), presented in Table 2, indicated mixed results for the country-of-origin groups. Proportion Cuban was significantly positively correlated with cancer risk and Proportion Mexican was significantly negatively correlated with cancer risk. While Proportion Puerto Rican and Proportion Colombian were positively related to risk, neither approached statistical significance.

In terms of the predictor variables, correlations with income tended to be statistically significant and increasing proportions of the racial/ethnic minority groups being negatively correlated with income, with the exception of Proportion Colombian. In terms of the race and ethnicity variables, the correlations reveal that non-Hispanic Blacks and Hispanics by in large do not live in the same census tracts: Proportion non-Hispanic Black was negatively correlated with all Hispanic subgroups except for Proportion Mexican.

In the regression analysis, the first spatial lag model explained 53% of the variation in On-road Cancer Risk. Neighborhoods with lower incomes and higher proportions of Hispanic residents had significantly higher on-road cancer risk estimates. In the second spatial lag model, which also had a R-Squared value of 53%, we found continued significance for lower median income and divergent patterns of risk for Hispanic neighborhoods based on country of origin. Cuban and Colombian neighborhoods faced significantly (p<.001 and p<.10 respectively) increased cancer risk while Mexican neighborhoods faced significantly (p<.001) decreased risk. Findings for proportion Puerto Rican did not approach statistical significance.

6. Discussion

This paper contributes to the nascent project of clarifying important elements of Hispanic heterogeneity that shape patterns of environmental injustice in the U.S. Our study specifically identifies *origin groups* and therefore *migration history* as two key features of Hispanic heterogeneity that shape patterns of environmental injustice in Miami. Previous work in the predominately Mexican-origin city of El Paso focused on *socio-economics, socio-demographics* and *acculturation* as critical features of Hispanic heterogeneity that influenced patterns of environmental injustice in that U.S.-Mexican border city (Collins et al., 2011). *Race* may also be a significant element of Hispanic heterogeneity, although it has yet to be investigated.

The importance of *origin groups* was clearly illustrated through this Miami case study. Social marginality was not uniformly associated with Hispanic status in Miami. Mexicans are arguably the most socially marginalized Hispanic group, given their presence in agricultural work. Ironically, this marginality "protects" them from central city residence and the adverse health risks from traffic pollution faced by Cubans and Colombians.

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Mexican residents are likely to be disproportionately exposed to other environmental risks, such as those associated with exposure to pesticides used in farming. *Migration history* has played an important role in shaping this spatial pattern in Miami. The arrival of the early waves of socially advantaged Cubans to a small, but rapidly growing urban area, shapes the exposure of Cubans to traffic pollution today. As the city grew, freeways came to surround the historically Cuban neighborhoods near downtown Miami. Colombians were drawn to the areas near Cuban ethnic enclaves when they migrated to Miami in subsequent decades. More recently arriving Mexicans have settled in the fringes of the MSA, close to agricultural labor opportunities. The negative correlation (albeit not significant) between traffic pollution cancer risk and the Puerto Rican population reflects their longstanding presence in Broward County, a destination for "White flight" migration out of the central city (Nijman, 2011).

While not the focus of this analysis, *socio-economics* (i.e., income)*, socio-demographics* (i.e., age and gender) and *acculturation* (i.e., Spanish-speaking, foreign-born and non-U.S. citizen) were particularly salient dimensions of Hispanic ethnic status related to cancer risks from air toxics in El Paso, where 82% of residents are Hispanic (Collins et al., 2011). Researchers found substantial differences in cancer risk within the Hispanic population in El Paso, Texas. Another potentially relevant factor associated with Hispanic status which has not yet been investigated (to our knowledge) is *race*. According to the 2010 Census 53.0% of Hispanics classified themselves as "White" and 36.7% as "some other race" (Humes, Jones, & Ramirez, 2011). Research on whether this racial identification has material consequences is limited (see Bonilla-Silva, Fortman, Lewis, & Embrick, 2003; Padin, 2005) and it is currently unknown whether Hispanics' racial identification is connected to societal rewards, such as decreased residential risk from air toxics. However, we hypothesize that disparities may exist. In Miami, there is clear racialization within the Hispanic population. For example, White Cubans (native born and migrant) have higher levels of economic success as compared to their non-White counterparts. Non-White Cubans are less likely to speak English well and less likely to own homes than are White Cubans (Woltman & Newbold, 2009). The tract-level ACS data do not permit the disaggregation of Hispanic by Origin and by Race, making this analysis impossible using this data source. Future investigations will need to rely on primary survey data or other secondary datasets focused on immigrant populations that contain local geographic identifiers (e.g., census tract or home address).

Identification of these important elements of Hispanic ethnic status - *origin, migration history, socio-demographics, socio-economics, acculturation* and possibly *race* – does not negate the fact that local context remains very important when considering Hispanic heterogeneity variables in environmental justice research. For instance, origin variables would not be applicable to the U.S.-Mexico border context (e.g., in the El Paso study) as nearly all Hispanic residents are of Mexican origin, but it was highly relevant in the immigrant gateway of Miami studied here. A grounded understanding of the sociospatial context and meaning of *Hispanidad* in one's study area is essential to future EJ work considering Hispanic ethnic status.

7. Limitations

This analysis suffers from several limitations. Our focus only on traffic-related pollution neglects other sources of pollution. For example, we do not consider the risks associated with the Port of Miami, the busiest cruise ship terminal in the world (Nijman 2011), which is a "non-road mobile" source of air toxics. There are also limitations associated with the NATA data set. The NATA includes cancer risks from only direct inhalation of the emitted air toxics and ignores human exposure from other potential pathways such as ingestion or skin contact. The assessment does not include exposure to air toxics produced indoors, such

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as from evaporative benzene emissions from cars in attached garages (Office of Air Quality Planning and Standards, 2011). For some pollutants such as formaldehyde, indoor sources can contribute substantially to the total exposure for an individual, even if only inhalation exposures are considered. The NATA risk estimates only include individual and additive health effects. Synergistic interactions among air pollutants from multiple sources may pose additional cancer risks that are not analyzed in this study (Office of Air Quality Planning and Standards, 2011).

Some of the limitations of the ACS data used in this study are as follows. The 2005–2009 ACS data were collected continuously over the five year period from a sample of people, and are not a complete census of population for one point in time (like the decennial census) (U.S. Census Bureau, 2008). Estimates generated from samples have uncertainty associated with them because they are based on a sample of the population and not the full population. While there may be sampling error as well as nonsampling error associated with ACS data (U.S. Census Bureau, 2008, see Appendix 6), they are the best available for this work.

8. Conclusion

In the case of Miami, federal transportation funding was initially harnessed by Anglo Whites to build freeways and strategically destroy a longstanding Black community downtown. Since that time, the development of an extensive freeway network has facilitated sprawling development and White flight northward while simultaneously generating the primary regional source of air toxics, the impacts of which have been disproportionately experienced by generally lower socioeconomic status residents within the traditionally Black and rapidly Latinizing urban core. In other words, the freeway transportation infrastructure has been central to creating both the sociospatial inequalities and toxic exposures that underpin contemporary patterns of environmental injustice.

Specifically, we found that Miami neighborhoods with lower household incomes and higher proportions of Hispanic residents faced higher cancer risks from exposure to traffic-related air toxics in the spatial lag model. While the association between non-Hispanic Black and potential cancer risks was positive but non-significant in the spatial lag model, the Pearson's correlation coefficient was positive and significant. These findings are important because to our knowledge, since this is the first quantitative study of environmental injustice in the 7th largest MSA in the U.S. Interestingly, these analyses revealed divergent patterns of environmental injustice based on Hispanic country-of-origin, which connects to the differing migration and settlement patterns of Hispanic subgroups in Miami. While Cuban and Colombian neighborhoods were significantly more at-risk, Mexican neighborhoods were significantly less at-risk.

The Hispanic population is growing rapidly in the U.S. As of the 2010 Census, there were 50.5 million Hispanics in the United States, which represents 16 percent of the total population. Over the last decade, the Hispanic population grew by 43 percent—up from 35.3 million in 2000, when this group made up only 13 percent of the total population (Humes et al., 2011). By 2050, population projections indicate that 29% of the U.S. population will be Hispanic. In contrast, the Black population is expected to remain constant at 13% of the U.S. population. In order to formulate appropriate policy solutions that seek to address disproportionate exposure to environmental pollution for the growing and diversifying Hispanic population, EJ research must respond by targeting studies that seek to unpack Hispanic ethnic status.

In terms of policy implications, the case of environmental injustices in the Miami MSA reveals the need for integrated assessment of the social and environmental justice impacts of

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urban transportation infrastructures prior to their development and the implementation of measures to counteract injustices already created. While the EJ movement in the U.S. originally arose in response to the injustices that attended exposure to point sources of toxic pollution (e.g., hazardous waste or industrial sites), less resistance has been toward mobile sources associated with transportation systems, perhaps because roads and freeways tend to be viewed in apolitical terms, i.e., as basic elements of public infrastructures in U.S. cities. In order for transportation-based environmental injustices of the sort documented here to be addressed, transportation infrastructures must come to be contested as political constructions that embody social interests rather than as the technical domains of urban planners and engineers. For those cities like Miami which are already freeway-dependent, residents must demand policy solutions to incentivize smart growth and reduce air toxics exposures, such as by adopting more stringent vehicular emissions standards and creating viable public transportation alternatives for commuters (Chakraborty 2009). Switching to alternative and nonpetroleum fuel sources that are cleaner than gasoline and diesel has been proposed as long-term strategy for reducing mobile source air toxics by the U.S. EPA (Chakraborty 2009).

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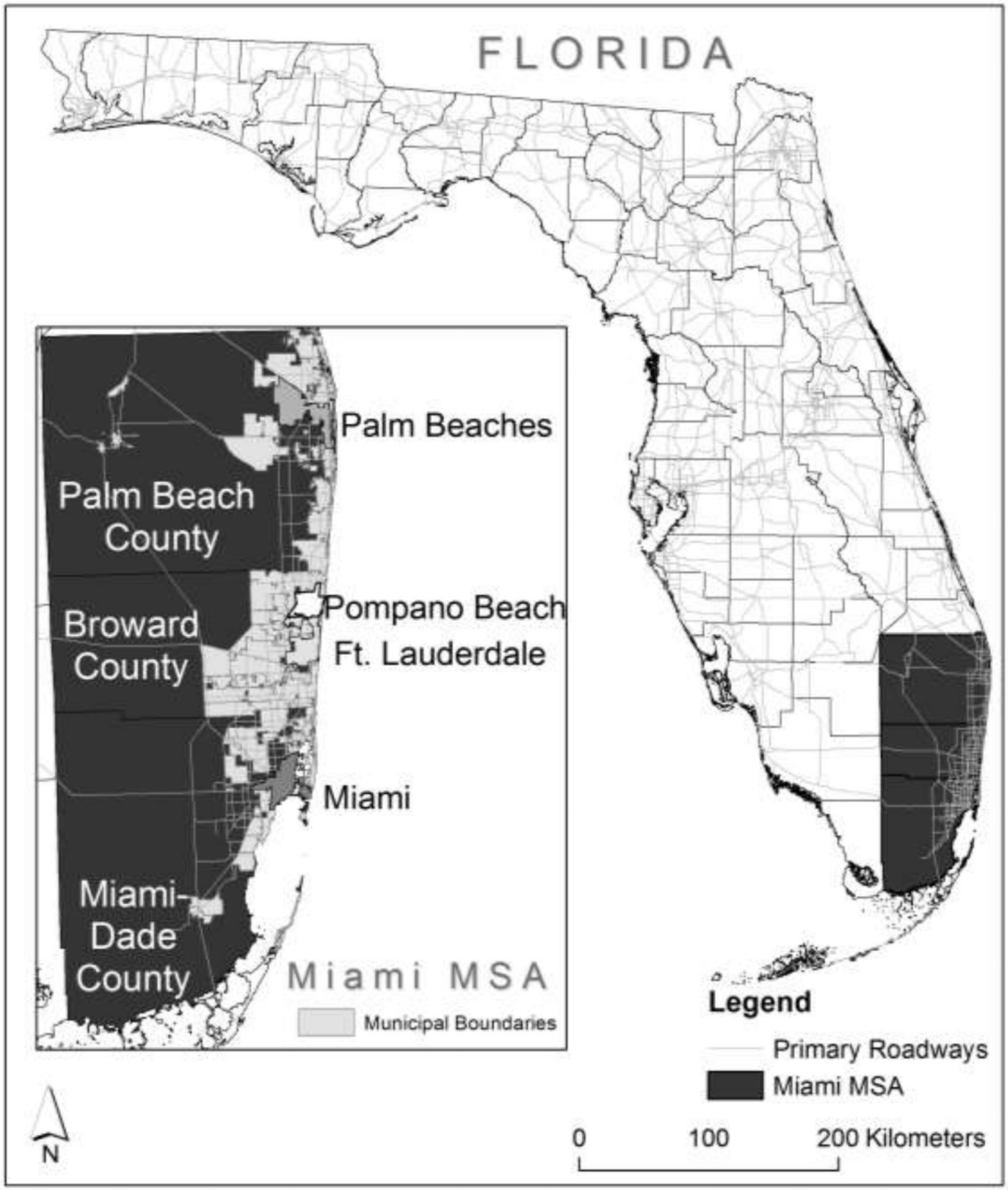

Figure 1.
The Miami MSA Study Area

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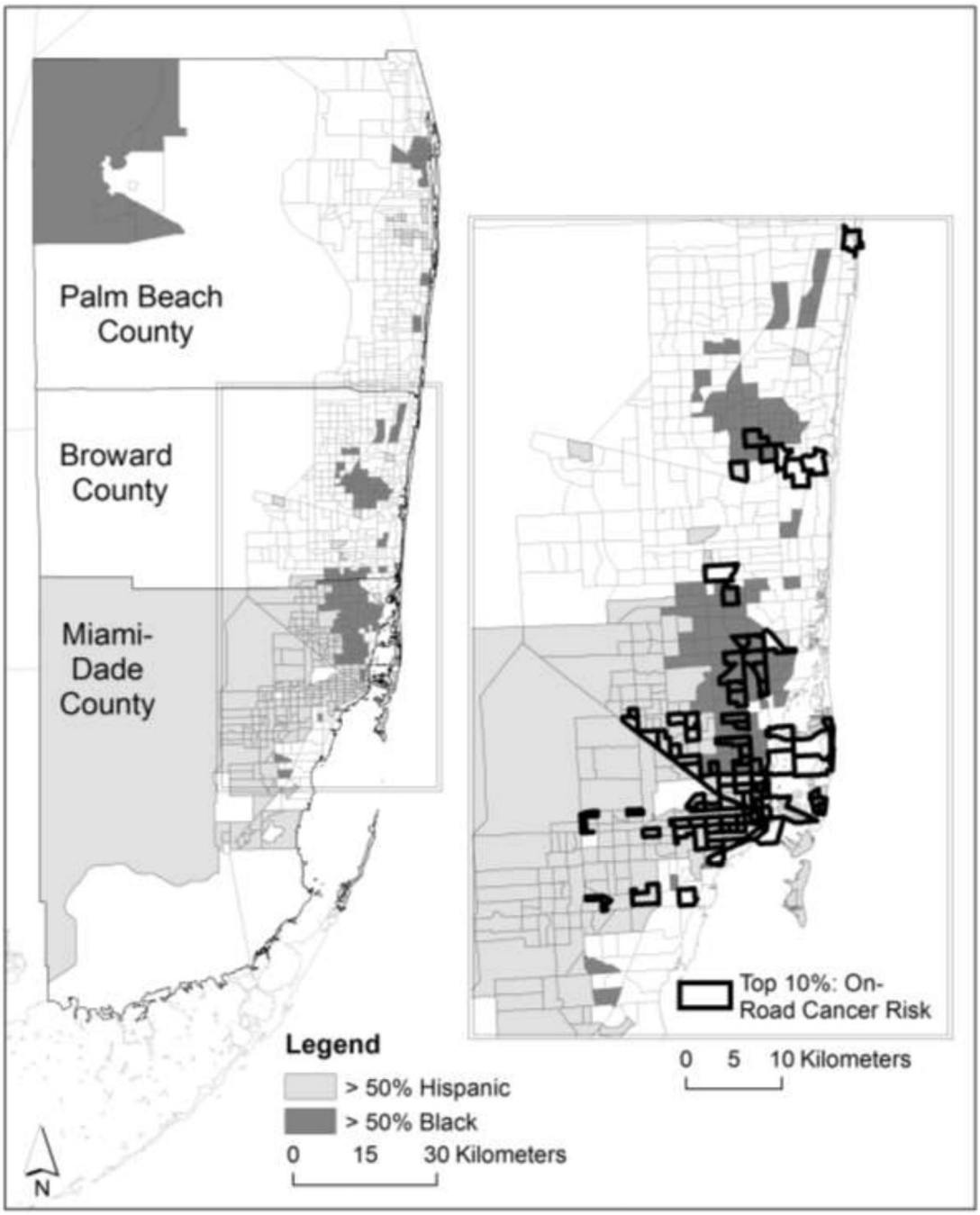

Figure 2.
Hispanic and Non-Hispanic Black Census Tracts (2005–2009) and Census Tracts in the Top 10% for On-Road Mobile Cancer Risk (2005) in the Miami MSA

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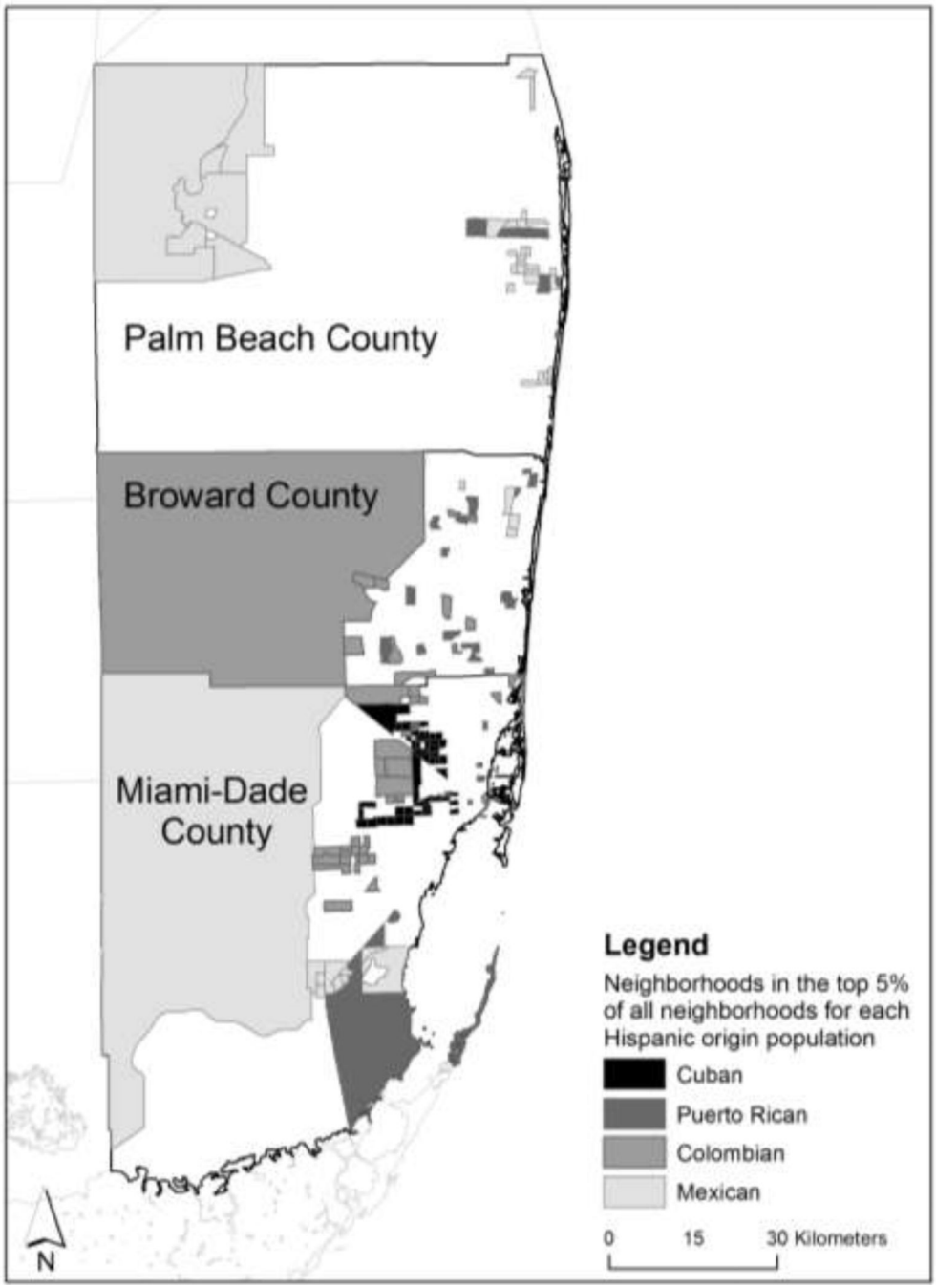

Figure 3.

Hispanic Ethnic Origin Census Tracts based on Country of Origin in the Miami MSA, 2005–2009

Note: While it is technically possible for a tract to be in the top 5% for more than one Hispanic origin group, this did not occur with these data.

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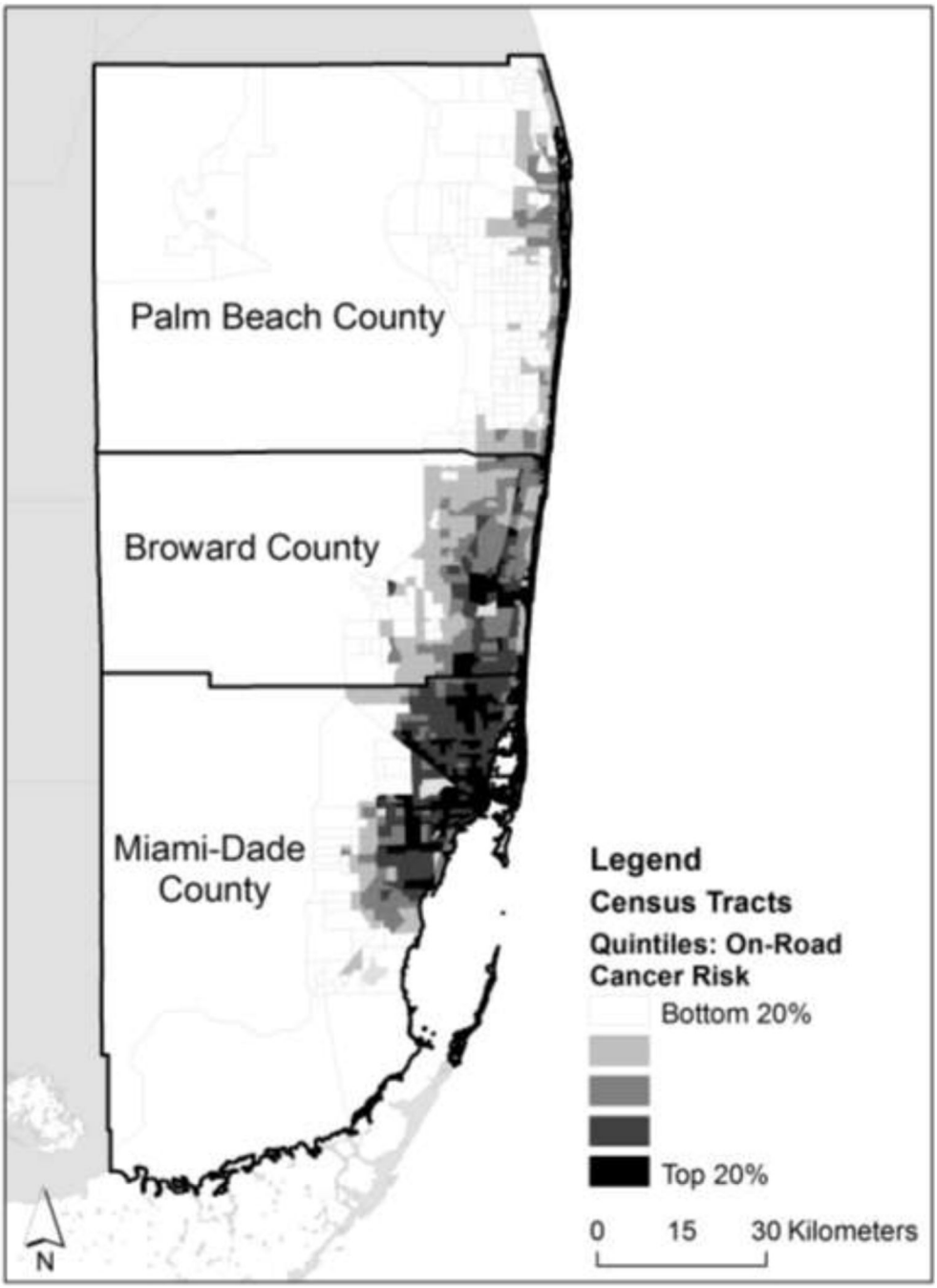

Figure 4.
Distribution of On-Road Mobile Cancer Risk in the Miami MSA by Census Tract, 2005

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Table 1

Descriptive Statistics of All Analysis Variables

	N	Min.	Max.	Mean	Std. Dev.
On-road Cancer Risk[1]	878	.000	0.051	.010	.005
Median Household Income	878	$11,563	$169,837	$53,751	$24,699
Proportion Hispanic	878	.000	.985	.346	.288
Proportion Non-Hispanic Black	878	.000	.979	.202	.268
Proportion Cuban	878	.000	.835	.140	.203
Proportion Puerto Rican	878	.000	.187	.034	.028
Proportion Colombian	878	.000	.216	.028	.032
Proportion Mexican	878	.000	.366	.023	.038

[1]Excess cancer cases per 1 million people * 1,000

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Table 2

Pearson Correlation Coefficients for All Analysis Variables (n=887)

		On-Road Cancer Risk	Med. HH Inc. (ln)	Hisp.	Non-Hisp. Black	Cuban	Prto. Rican	Mex. (ln)	Colo. (ln)
On-Road Cancer Risk	Correlation	1							
	Sig. (2-tail)								
Median HH Income (ln)	Correlation	−.378	1						
	Sig. (2-tail)	.000							
Hispanic	Correlation	.288	−.193	1					
	Sig. (2-tail)	.000	.000						
Non-Hispanic Black	Correlation	.175	−.449	−.373	1				
	Sig. (2-tail)	.000	.000	.000					
Cuban	Correlation	.293	−.134	.890	−.338	1			
	Sig. (2-tail)	.000	.000	.000	.000				
Puerto Rican	Correlation	.025	−.081	.274	−.053	.045	1		
	Sig. (2-tail)	.457	.016	.000	.114	.185			
Colombian (ln)	Correlation	.015	.198	.451	−.445	.293	.233	1	
	Sig. (2-tail)	.663	.000	.000	.000	.000	.000		
Mexican (ln)	Correlation	−.126	−.002	.245	.168	.044	.247	.243	
	Sig. (2-tail)	.000	.961	.000	.000	.193	.000	.000	

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Table 3

Spatial Lag Regression Results Predicting On-Road Cancer Risk (ln)

	Model 1		**Model 2**	
Neighbor Bandwidth	2500 m		2500 m	
Moran's I –OLS (p)	0.691 (p = .001)		I = .633 (p = .001)	
Moran's -Spatial Lag I (p)	0.078 (p = .002)		I = .062 (p = .002)	
R Square Spatial Lag Model	0.525		0.532	
	Parameter	**P**	**Parameter**	**P**
Rho	0.659	0.001	0.649	0.001
Constant	−0.065	0.001	−0.061	0.002
Median Household Income (ln)	−0.307	0.001	−0.342	0.001
Non-Hispanic Black	0.021	0.414	0.014	0.591
Hispanic	0.085	0.001	N/A	N/A
Cuban	N/A	N/A	0.076	0.001
Puerto Rican	N/A	N/A	0.024	0.243
Colombian (ln)	N/A	N/A	0.039	0.092
Mexican (ln)	N/A	N/A	−0.078	0.001

All variables are Z scores.