The term ‘environmental justice’ is used to describe the movement concerned with inequities in the distribution of environmental pollution and adverse health consequences of industrial activities and environmental policies. While the movement began in the 1980s as a grassroots effort to prevent potentially hazardous facilities from disproportionately impacting minority and low-income communities (United Church of Christ 2007), the current definition of environmental justice has expanded to include “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” (EPA 2008a).

Growing concerns regarding racial/ethnic and socioeconomic inequities in the distribution of environmental disamenities in the U.S. have instigated federal legislative actions and a substantial amount of scientific research. Presidential Executive Order 12898 (Clinton 1994), for example, requires all government agencies to identify and address the environmental justice implications of their programs, policies, and activities. Empirical research on this topic has focused mainly on the question of environmental equity—the extent to which environmental pollution burdens are distributed evenly across society. Numerous case studies have been conducted at national, regional, state, and metropolitan scales in the U.S. to determine if racial/ethnic minorities and economically disadvantaged individuals are disproportionately exposed to various environmental contaminants, including air pollution (see reviews by Cutter 1995; Liu 2001; Ringquist 2005; Zilney et al. 2006).

Although prior empirical studies have made important strides towards understanding the intricacies of the causes and outcomes of environmental inequity, they have been limited methodologically in two
critical ways. First, a large number of studies have used proximity to hazardous facilities or pollution sources as a proxy for potential human exposure, instead of assessing the nature and quantity of pollutants emitted, local meteorological conditions, and other factors that influence exposure (e.g., Anderton et al. 1994; Pollock and Vittas 1995; Cutter et al. 1996; Sheppard et al. 1999; Perlin et al. 2001; Pastor et al. 2004; Chakraborty and Zandbergen 2007). While specific studies focused on modeling exposure to toxic pollution (e.g., Chakraborty 2001; Bevc et al. 2007), few have attempted to examine whether unequal exposure patterns lead to disproportionate health risks among minority and low-income communities. Second, past empirical studies have focused primarily on inequities associated with major stationary sources of pollution, thus ignoring mobile emission sources and smaller emitters that also pollute the local environment. An exclusive focus on major point sources such as industrial manufacturing facilities is likely to distort the assessment of environmental risk burdens within a community, because it fails to consider emissions from automobiles, smaller industries, and various other sources that contribute to air pollution and ultimately to potential health risk. Neighborhood dry cleaning facilities and auto body paint shops, for example, represent less conspicuous sources of pollution that may not be as noticeable as a billowing smokestack, but are also likely to have adverse health impacts on residents (Fitos and Chakraborty, 2003). Several recent environmental justice studies have emphasized the need for going beyond locational inequities and a focus on stationary emission sources towards a more cumulative exposure approach that considers the health risks that a community may face from various types of pollutants and emissions sources (Brulle and Pellow 2006; Maantay 2007). A risk modeling approach that considers multiple sources of pollution is also consistent with the emerging policy focus on cumulative exposure assessment (Pastor et al. 2005).

Recent advances in outdoor air emission inventories, risk modeling, and knowledge on the health effects of pollutants provide a foundation for developing new measures that address some of the methodological limitations of previous studies. Accordingly, this paper seeks to examine the environmental justice implications of inhalation
exposure to hazardous air pollutants in Florida, based on a recently released data set compiled by the U.S. Environmental Protection Agency (EPA) and socio-demographic information from U.S. Census 2000. Our specific objective is to determine if there are racial/ethnic inequities in the spatial distribution of both cancer and non-cancer (respiratory) risk from outdoor exposure to point and mobile sources of such pollutants, after controlling for well-documented contextual factors and variables. The broader goal is to extend environmental justice research through: (a) an explicit focus on the adverse health effects of exposure to air pollution; and (b) a cumulative exposure assessment approach that considers both stationary and mobile sources of air pollution.

Florida provides an appropriate geographic setting for studying spatial inequalities in environmental pollution and risks. It is the fourth largest state in the U.S. in terms of total population and one of the fastest growing states in the nation. Since 1970, nine million people have moved to Florida and an average of 800 individuals relocate to the state daily (Chapin 2006). This implies that an increasing share of Florida’s population is potentially exposed to the environmental externalities of residential, commercial, and industrial growth. Florida is also a racially and ethnically diverse state with 35 percent of the population classified as either Hispanic or non-Hispanic Black (U.S. Census 2006). It is thus important to investigate if minorities and disadvantaged communities in Florida are disproportionately impacted by the growing environmental pollution problems and related health risks.

Systematic quantitative research on the environmental justice implications of exposure to air pollution has been limited at the state level. A study conducted by Pollock and Vittas (1995) focused on analyzing distance to industrial manufacturing facilities that release toxic chemicals in Florida, based on demographic and socioeconomic characteristics of census block groups. Racial and ethnic minority sub-populations, particularly African American households, were found to reside closer to polluting sources. Stretesky and Hogan (1998) examined the spatial relationship between Superfund sites and socio-demographic characteristics of census tracts surrounding these sites, in a longitudinal study of Florida. They found that Blacks and Hispanics were more likely to live near these sites and this association increased with time. While
these previous studies have investigated inequities associated with major point sources, more research is necessary to analyze exposure to other types of pollution sources in Florida. By focusing on the health risks from cumulative exposure to multiple emission sources, our re-examination of environmental justice within the state of Florida addresses prior limitations and aims to advance the methodology of environmental justice analysis.

Data and Methodology

The 1990 Clean Air Act Amendments and subsequent policy initiatives focus on two classes of air pollutants: criteria air pollutants and hazardous air pollutants. While criteria air pollutants comprise common contaminants such as particulate matter, ground-level ozone, carbon monoxide, sulfur oxides, nitrogen oxides, and lead (EPA 2008b), air toxics include 177 air pollutants that are known to cause or are suspected of causing cancer or other serious health problems such as damage to the immune system, and neurological, reproductive, developmental, and respiratory problems (EPA 2008c). While the environmental justice implications of exposure to criteria air pollutants have been examined previously (Wernette and Nieves 1992; Jerrett et al. 2001; Kingham et al. 2007), only a handful of recent studies have focused specifically on air toxics (Morello-Frosch et al. 2001, Pastor et al. 2005).

In order to measure health risks from cumulative exposure to multiple sources of air toxics, this study uses data from the EPA’s National-Scale Air Toxics Assessment (NATA). The NATA was designed to help the EPA, state, local, and tribal governments identify and prioritize air toxics, emission source types, and locations that are of potential concern in terms of contributing to population risk (EPA 2008d). The EPA releases NATA estimates every three years with the latest NATA based on 1999 air emissions data. While data from the 1996 NATA have been used to evaluate the equity implications of air toxics in California (Pastor et al. 2005) and Maryland (Apelburg et al. 2005), health risk estimates from the 1999 NATA have not been analyzed with respect to Census 2000 variables in the state of Florida.
The assessment is the result of a four step process that integrates ambient air toxics data from local, state, and federal levels (EPA 2008e). First, the 1999 National Emissions Inventory (NEI) is used to obtain data on outdoor emissions for major stationary sources such as large factories, smaller stationary sources such as dry cleaning facilities, on-road mobile source such as cars and trucks, and off-road mobile sources such as all terrain vehicles and lawnmowers. The 1999 NEI data are then entered into ASPEN (Assessment System for Population Exposure Nationwide), a Gaussian dispersion model developed by the EPA, in order to estimate annual ambient concentrations of each air pollutant. These concentrations estimates from ASPEN are then used to determine population exposure based on Hazardous Air Pollutant Exposure Model version 5 (HAPEM5), an inhalation exposure model. This model utilizes census population data, human behavior such as breathing rates and activity patterns, indoor/outdoor concentration relationships, climate characteristics, and ambient air quality to estimate an expected range of inhalation exposure concentrations. Finally, for the 133 of these air toxics for which information on chronic risks exists, the exposure concentration estimates are used to quantify potential health effects (cancer and non-cancer) from inhalation of air toxics using EPA’s risk assessment and characterization guidelines. Non-cancer risks are further split into respiratory and neurological hazards. The census tract is the smallest analytical unit for which exposure and health risk estimates are provided in the 1999 NATA and represents the spatial resolution for this study.

**Dependent Variables**

Our analysis of environmental injustice in Florida focuses on two dependent variables: lifetime cancer risk and the respiratory hazard index. The NATA estimates cancer risk on the basis of the inhalation unit risk (IUR) factor, a measure of the cancer-causing potential of each air toxic. The concentration of each pollutant in a given census tract is multiplied by its IUR in order to estimate individual lifetime cancer risk. Cancer risks are assumed to be additive and lifetime cancer risk from all air toxics present in a tract are summed to obtain the total estimated lifetime cancer risk for the tract. Estimated lifetime cancer risks are
expressed by "N" people per million, where "N" is the likelihood of contracting cancer out of one million people exposed to a specific concentration of the air pollutant continuously (24 hours a day) over a lifetime (defined as seventy years). This number is only accurate for 1999, so longitudinal or temporal studies are not possible with the NATA.

Respiratory risks are estimated using the concentration of the pollutant in the air believed to have no adverse effect on the lungs and air passages with constant exposure, referred to as the inhalation reference concentration. To estimate respiratory risk for each census tract, a hazard quotient is calculated by dividing the ambient concentration of the pollutant in the tract by its inhalation reference concentration. An aggregate respiratory hazard index is then derived by summing the hazard quotients of all air toxics present within the tract. Index numbers below one are not expected to cause adverse effects to the lungs and air passages over a lifetime of exposure, while an index above one indicates the potential for respiratory problems.

**Explanatory Variables**

Estimated cancer and respiratory health risks are analyzed in this study using a set of census tract level explanatory variables from U.S. Census 2000 Summary File 3 for Florida. To examine the influence of race/ethnicity, the main focus of our environmental justice analysis, we included the two largest minority population groups in Florida: individuals identifying themselves as non-Hispanic Black and Hispanic/Latino (of any race). These variables are expressed as proportions of a tract's total population. Environmental justice theory leads us to anticipate increased health risks from air toxics for racial/ethnic minorities due to discrimination, white racism, and lack of representation in relevant decision-making processes (United Church of Christ 1987; Pulido 2000).

Socioeconomic variables for our analysis include the proportion of the population with an annual income below the federal poverty level and the proportion of occupied housing units that are owner-occupied. The proportion below poverty level functions as an indicator of overall financial means within the tract and represents a commonly used
variable in environmental justice research. The proportion of owner-occupied housing units, also known as home ownership rate, allows us to consider the wealth possessed by the community. The poverty rate reflects the yearly income of the community, while home ownership indicates financial security. Home ownership is a potential indicator of political involvement, assuming that a greater proportion of home ownership implies increased concern for the local environment due to invested capital (Pastor et al. 2005). Again, our hypothesis argues that with increased wealth and power, the risks from air pollution will be reduced. More specifically, we expect tracts with smaller poverty rates and greater home ownership rates to have lower health risks. It is important to consider, however, that association between income and pollution levels may not be linear. Previous studies have found evidence of a curvilinear or U-shaped relationship between income and degree of risk (e.g., Boer et al. 1997; Morello-Frosch et al. 2001; Pastor et al. 2005). These studies assert that at very high levels of income there is a decrease in risk due to an abundance of power and influence that allows affluent communities to resist pollution-generating facilities and activities. In contrast, severely impoverished areas have lower levels of risk due to a lack of economic or industrial activities that cause pollution. Additionally, we include the proportion of the population above the age of 65 years, a variable that gains particular importance in Florida, a state characterized by a large population of senior citizens. We expect older populations to be located in tracts with decreased health risks because of increased wealth among retirees and the propensity to live away from urban centers.

Population density is a commonly used control variable in pollution studies because densely populated areas are more likely to contain air polluting facilities and activities. While population density is commonly measured as the number of people per square mile, the natural logarithm of this value was taken in order to account for the diminishing effect of higher numbers, as suggested by Mennis (2002) and Pastor et al. (2005). In addition to population density, a categorical variable that classifies a census tract as either urban or rural is included as a rudimentary indicator of land use. An urban tract is defined as one with 50 percent or more of the tract's population residing within an
urban area or an urbanized cluster, as designated by the U.S. Census. Following the same logic as with population density, we expect ‘urban’ tracts to contain more point and mobile emission sources for air toxics, and therefore pose greater health risks than their rural counterparts.

Statistical Methodology

In order to identify the factors affecting both lifetime cancer risk and respiratory risk, we use a combination of bivariate correlation and multivariate regression methods. The first phase of our analysis uses bivariate parametric correlations to examine the relationship between each of our explanatory factors and health risk variables. Correlation analysis provides a preliminary picture of the strength and significance of the association between various tract-level characteristics and variation in the distribution of health risks from cumulative exposure to air toxics. The second phase of the analysis uses multivariate regression analysis, based on the ordinary least squares method, to estimate both cancer and respiratory risk (dependent variables) as a function of racial/ethnic, demographic, and socioeconomic characteristics (independent variables) in a single model. By examining the effects of all explanatory factors simultaneously we can identify the extent to which each variable exerts independent effects on the degree of cancer or respiratory risk even when the impacts of other relevant variables are considered. All statistical analyses were conducted using SPSS statistical software (version 16).

Results

Before analyzing the effect of tract-level characteristics on cancer and respiratory risks from air toxics, it is important to explore the spatial distribution of health risks and assess their general geographic trends within Florida. Our dependent variables are therefore displayed as classified choropleth maps in Figures 1 and 2. In Figure 1, census tracts in the state are grouped into four quartiles based on estimated values of lifetime cancer risk. The major metropolitan areas of Tampa Bay, Orlando, Miami/Ft. Lauderdale/West Palm Beach, and Jacksonville contain a majority of census tracts that are in the highest quartile (top 25 percent) for cancer risk. Tracts in the second and third quartiles (middle
Figure 1: Lifetime Estimated Cancer Risk (people per million) by Census Tract, Florida, 1999.

Source: Author.

50 percent) can be found mostly in the secondary urban centers such as Pensacola, Fort Myers, and Tallahassee. Tracts in the lowest quartile (bottom 25 percent) are typically in small towns or isolated areas located away from the state’s urban cores and their suburbs.

The tract level distribution of respiratory hazard index, classified into four quartiles, is depicted in Figure 2. The map suggests a very different geographic pattern compared to the distribution of estimated lifetime cancer risks in the state and appears to be more influenced by the presence of interstate highways and highway interchanges. Far from
grouping around urban centers, tracts in the highest quartile for respiratory hazards (top 25 percent) are distributed in the rural, suburban, and urban areas alike in the Panhandle stretching into the central part of the state. The majority of tracts in the lowest quartile are in the south central inland portion of the state, but we notice tracts in the highest quartile along the interstate that runs through the Everglades and southern Florida.

Summary statistics for all variables used in our study are provided in Table 1. The locations of the maximum and minimum values for the dependent variables provide clues regarding which factors may
Table 1: Descriptive Statistics for Variables Analyzed

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Std Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cancer Risk (person/million)</td>
<td>3,151</td>
<td>37.295</td>
<td>9.936</td>
<td>108.130</td>
<td>11.998</td>
</tr>
<tr>
<td>Respiratory Risk (Hazard Index)</td>
<td>3,151</td>
<td>8.024</td>
<td>0.679</td>
<td>25.440</td>
<td>3.429</td>
</tr>
<tr>
<td><strong>Independent Variables:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion non-Hispanic Black</td>
<td>3,151</td>
<td>0.154</td>
<td>0.000</td>
<td>0.989</td>
<td>0.227</td>
</tr>
<tr>
<td>Proportion Hispanic</td>
<td>3,151</td>
<td>0.146</td>
<td>0.000</td>
<td>0.954</td>
<td>0.196</td>
</tr>
<tr>
<td>Proportion Owner Occupied</td>
<td>3,145</td>
<td>0.629</td>
<td>0.000</td>
<td>1.000</td>
<td>0.234</td>
</tr>
<tr>
<td>Proportion Below Poverty</td>
<td>3,149</td>
<td>0.131</td>
<td>0.000</td>
<td>0.768</td>
<td>0.105</td>
</tr>
<tr>
<td>Proportion over 65 years</td>
<td>3,151</td>
<td>0.184</td>
<td>0.000</td>
<td>0.940</td>
<td>0.135</td>
</tr>
<tr>
<td>Population Density</td>
<td>3,151</td>
<td>3,227</td>
<td>0.000</td>
<td>34,289</td>
<td>3,497</td>
</tr>
<tr>
<td>Urban Tract (yes/no)</td>
<td>3,151</td>
<td>0.900</td>
<td>0.000</td>
<td>1.000</td>
<td>0.299</td>
</tr>
</tbody>
</table>

be more helpful in explaining areas of higher and lower risk. The maximum values of estimated lifetime cancer risk from ambient air toxics are located predominantly in densely populated urban areas. The highest values are located near the Interstate 4/Interstate 275 interchange near downtown Tampa, in the Central Business District of Tampa, and in Englewood, Sarasota County. The lowest levels of estimated cancer risk, in contrast, occur in tracts that are distant from metropolitan areas. The lowest values are in tracts in rural areas such Taylor County, Palmdale in Glades County, and Zolfo Springs in Hardee County.

The three highest values of the respiratory hazard index all occur in tracts around the Miami International Airport, with values ranging from a hazard index of 22 to 25. The majority of the highest index levels occur in Miami-Dade County. The lowest levels of respiratory risks can
be found in Marathon and Key West in the Florida Keys, on the Northwest shore of Lake Okeechobee in Glades County, and in Monroe County.

As indicated in Table 1, most of our explanatory variables suggest substantial variability in their values across census tracts in Florida. The average proportion of non-Hispanic Blacks and Hispanics (0.154 and 0.146, respectively) and their corresponding standard deviations are very similar. Two other sub-populations of interest for this study, those below poverty and above 65 years of age, also indicate mean proportions that do not exceed 0.20 and exhibit similar standard deviations. The majority of housing units in an average census tract are owner-occupied, and 90 percent of tracts are classified as ‘urban’ according to our definition.

Bivariate Analysis

Bivariate parametric correlation is first used to investigate the nature of the relationship between the dependent variables and each independent variable at the tract level. Pearson’s correlation coefficients (r-values), presented in Table 2, indicate that all variables are

<table>
<thead>
<tr>
<th>Table 2: Pearson’s Correlation Coefficients for Dependent Variables</th>
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</thead>
<tbody>
<tr>
<td><strong>Cancer Risk</strong></td>
</tr>
<tr>
<td>-----------------</td>
</tr>
<tr>
<td>Proportion non-Hispanic Black</td>
</tr>
<tr>
<td>Proportion Hispanic</td>
</tr>
<tr>
<td>Proportion Owner Occupied</td>
</tr>
<tr>
<td>Proportion Below Poverty</td>
</tr>
<tr>
<td>Proportion over 65 years</td>
</tr>
<tr>
<td>Population Density (natural log)</td>
</tr>
<tr>
<td>Urban Tract (yes/no)</td>
</tr>
</tbody>
</table>

*p<.01
significantly associated \((p<.01)\) with both estimated lifetime cancer risk and the respiratory hazard index and yield signs that are consistent with our theoretical expectations regarding demographic and socioeconomic inequities in the distribution of health risks. Both our racial/ethnic variables are positive correlated with cancer and respiratory risk, with the Hispanic proportion showing a considerably stronger association than the non-Hispanic Black proportion. Socioeconomic disparities in the distribution of health risks in Florida are also evident from Table 2. Home ownership rates yields a significantly negative association with both cancer and respiratory risk, while proportion below poverty indicates a positive association. As expected, the proportion over 65 years was negatively associated with both dependent variables. Population density shows a very strong and positive correlation with both types of health risk, and cancer risk, in particular. While cancer risk is also significantly higher in urban tracts, the urban classification appears to have a smaller effect on respiratory risk values.

**Multivariate Analysis**

The next phase of our analysis uses multiple regression models to simultaneously consider the effects of all independent variables on cancer and respiratory health risk, respectively. Table 3 shows the standardized regression coefficients and corresponding t-values associated with each multivariate model. To detect multicollinearity problems in our regression models, we calculated the Variance Inflation Factor for each independent variable. None of these scores were high enough to suggest collinearity concerns for the variables used in our models.

For estimated lifetime cancer risk, the ANOVA F-test indicates significance for the overall model \((p<.001)\) and the value of the adjusted multiple \(R\)-squared exceeds 52 percent. All explanatory variables except the urban classification show a significant effect on cancer risk \((p<.01)\) and expected signs. Variables describing racial/ethnic characteristics of the population reveal a positive and highly significant association with the cancer risk estimates, with the proportion of Hispanics yielding larger standardized coefficients than the proportion of non-Hispanic Blacks. Home ownership rate shows a negative relationship with lifetime
Table 3: Multivariate Regression Results

<table>
<thead>
<tr>
<th></th>
<th>Cancer Risk</th>
<th>Respiratory Risk</th>
<th></th>
<th>t-statistic</th>
<th></th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion non-Hispanic Black</td>
<td>0.194</td>
<td>11.884*</td>
<td>0.210</td>
<td>10.770*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion Hispanic</td>
<td>0.323</td>
<td>22.613*</td>
<td>0.487</td>
<td>28.459*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion Owner Occupied</td>
<td>-0.056</td>
<td>-3.779*</td>
<td>0.027</td>
<td>1.525</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion Below Poverty</td>
<td>-0.257</td>
<td>-6.777*</td>
<td>-0.232</td>
<td>-5.117*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion Below Poverty squared</td>
<td>0.228</td>
<td>6.611*</td>
<td>0.198</td>
<td>4.814*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion over 65 years</td>
<td>-0.104</td>
<td>-7.846*</td>
<td>-0.117</td>
<td>-7.364*</td>
<td></td>
<td></td>
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<tr>
<td>Population Density (natural log)</td>
<td>0.461</td>
<td>24.848*</td>
<td>0.119</td>
<td>5.365*</td>
<td></td>
<td></td>
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<tr>
<td>Urban Tract (yes/no)</td>
<td>0.008</td>
<td>0.488</td>
<td>-0.079</td>
<td>-3.860*</td>
<td></td>
<td></td>
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<tr>
<td>Adjusted R-squared</td>
<td></td>
<td>0.523</td>
<td></td>
<td>0.316</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td></td>
<td>430.473*</td>
<td></td>
<td>181.934*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td></td>
<td>3,145</td>
<td></td>
<td>3,145</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*p < .01

cancer risk, while the proportion below poverty level indicates a significant effect that confirms our U-shaped assumption regarding poverty rate and the magnitude of health risk. The positive sign for the quadratic or squared term suggests an upward concave relationship; lifetime cancer risk is relatively higher in census tracts with low and high poverty rates and smaller in tracts with moderate values of poverty rates. The proportion over 65 years of age shows a significantly negative relationship with estimated cancer risk, as we had expected. Although population density reveals the strongest positive association with cancer risk after controlling for the effects of all other independent variables,
the ‘urban’ categorical variable does not remain significant \((p>.10)\) in the regression model. This can be explained, in part, by the collinearity of the urban classification with population density and also may point to the need for a more detailed and precise classification system for measuring land use differences.

The ANOVA \(F\)-statistic of the regression model for respiratory risk indicates significance for the model \((p<.001)\) and has an adjusted \(R^2\) value of over 31 percent. The results observed for our cancer risk model are repeated for respiratory risk, with a few notable exceptions. The racial/ethnic variables are again positively associated and highly significant \((p<.01)\) in the respiratory risk model, with proportion Hispanic proving to be the more influential of the two. Compared to estimated lifetime cancer risk, the proportion of non-Hispanic Blacks and Hispanics have a greater positive association with the respiratory hazard index, based on their standardized coefficients. While home ownership rate does not indicate a significant effect \((p>.10)\) on respiratory risk when all other variables are accounted for, the coefficient for the proportion below poverty squared is again positive and supportive of our assertions regarding poverty’s U-shaped behavior in relation to risk. Proportion over 65 years again shows considerable negative association with respiratory risk. Population density retains its significant positive association in this model, yet has a relative smaller effect on respiratory risk than on lifetime cancer risk. The urban categorical variable exhibits a significant negative relationship with respiratory risk, in contrast to its positive effect on lifetime cancer risk. While cancer risks are higher in densely populated tracts located in the metropolitan areas, sparsely populated tracts intersected by interstate highways are more likely to be exposed to respiratory risk. It appears that while cancer risk follows the predicted pattern of displaying increased levels in high density urban areas, respiratory risk demonstrates a propensity to increase in lower density suburban areas in Florida.

**Concluding Discussion**

This paper addresses the growing need for environmental justice research to move beyond locational and chemical-by-chemical analyses
to a more cumulative approach that: (a) makes a systematic connection between exposure to noxious substances and public health risks (Maantay 2007); and (b) encompasses multiple pollutants and emission source types (Pastor et al. 2005). Our re-examination of environmental justice in Florida thus evaluates inequities in the spatial distribution of both lifetime cancer and respiratory risk from outdoor exposure to air toxics from point and mobile sources. Our bivariate and multivariate statistical analyses indicate that race and ethnicity play an undeniably pervasive role in explaining the distribution of adverse health risks from ambient air pollution in Florida, even when controlling for factors such as the degree of urbanization and socioeconomic characteristics such as poverty and home ownership that have been commonly used in the environmental justice literature. Although the tract level geography of lifetime cancer risk differs substantially from the geography of respiratory risk, the proportion of non-Hispanic Black and Hispanic residents remain consistent predictors of both categories of health risks from exposure to air toxics. Similar racial and ethnic inequities have been reported in previous state level studies on locational inequities in the distribution of stationary facilities such as industrial toxic plants and Superfund sites found (Pollack and Vittas 1995; Stretesky and Hogan 1998).

There are, however, several limitations associated with EPA’s NATA data set used for this research. The NATA focuses only on inhalation exposure from air toxics and ignores exposure from other pathways (e.g., ingestion and skin contact). The NATA is also not a substitute for actual health outcomes data and diagnosis of causation. The numbers presented are modeled estimations and their accuracy is limited by the information available to the EPA. Despite these problems, our study demonstrates that the NATA is an effective data source for assessing the spatial distribution of health risks from air toxics at the census tract level of resolution.

It is important to consider some of the caveats of our methodology that can be addressed by future research. This study is a cross-sectional analysis of adverse health risks at a specific point in time (1999), and should not be used to elucidate causal relationships between race/ethnicity and pollution or deduce the chronological order of events.
leading to the current disparities. The inequitable outcomes reported in this study could be caused by various underlying factors such as discriminatory zoning and planning practices, the dynamics of the residential housing market, and other socioeconomic and political forces (Been 1994; Pulido 2000). The determination of causality for environmental injustice is a complex task and detailed longitudinal analyses based on historical data is necessary to understand the processes that underlie our findings (Chakraborty 2001). Given the consistently strong and significant effect of race and ethnicity after controlling for economic factors, however, our results suggest that voluntary in-migration to polluted census tracts spurred only by low income is less likely to be a plausible explanation for the observed disparities.

In addition to issues of temporality, there are problems associated with the use of conventional multivariate regression for spatial data. One concern might be that our regression analysis does not take into full account the effect of geographic clustering or relations of spatial dependence in the variables (Haynes et al. 2003; Pastor et al. 2005). Spatial autocorrelation in the regression residuals could overstate the significance of multivariate relationships (Getis 2006). Future research will explore the use of more sophisticated regression techniques that control for spatial dependence to address this issue. Likewise, it is important to consider that the use of traditional multivariate regression or a single ‘global’ model for the entire state can hide key local variations in the relationships between the dependent and independent variables in environmental equity analysis (Mennis and Jordan 2005). Geographically weighted regression, a technique that examines geographic variation in model parameter estimates (Fotheringham et al. 2002), can be utilized in future studies to investigate the spatial nonstationarity of model parameters within Florida and understand local and regional geographic differences.

While our explanatory variables are well-documented contextual factors, opportunities exist for further exploration. The urban land use designation serves as an indicator of increased economic activity in certain areas of the state, but future studies many need to go further in order to classify what type of activities are being engaged. More
sophisticated and precise land use classifications may reveal a more consistent pattern of the influence of urbanization on health risks caused by air toxics in Florida.

The results of this study have important implications for public policy. While specific recommendations are difficult to make, attention must be paid to the problem of unequal distribution of the negative by-products of economic growth in the state of Florida. It has become imperative to take preventive measures such as reconsidering the placement of future industrial facilities, service industries, or roadways, and utilize remediation techniques such as ensuring the compliance of facilities with pollution standards and educating the residents of measures they can take to reduce the negative health effects of the various sources of air toxics. The environmental justice framework indicates that fair treatment during, and inclusion in, the decision-making process is essential to equity. Our results suggest that environmental regulations, zoning decisions, and land-use plans must include the voices of Florida’s underrepresented and disadvantaged communities, and racial/ethnic minorities, in particular.

In conclusion, this article provides strong evidence of racial/ethnic and economic disparities in the adverse health effects of cumulative exposure to outdoor air toxics from point and mobile air pollution sources in Florida. Further research is needed to characterize the various socioeconomic, political, and spatial processes that are causing these environmental health disparities and identify areas or counties where estimated health risks and disparities are of greatest concern. Meanwhile, our results raise new challenges for both policy makers and environmental justice advocates in terms of developing regulatory and pollution prevention strategies that address stationary and mobile emission sources.
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