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Linking Health Hazards and Environmental Justice: A Case Study in Houston, Texas

Marilyn Marie Williams

University of South Florida

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Linking Health Hazards and Environmental Justice: A Case Study in
Houston, Texas

by

Marilyn Marie Williams

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
Department of Geography
College of Arts and Sciences
University of South Florida

Major Professor: Jayajit Chakraborty, Ph.D.
M. Martin Bosman, Ph.D.
Thomas Mason, Ph.D.
Steven Reader, Ph.D.
Graham A. Tobin, Ph.D.

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LIST OF TERMS

Agency for Toxic Substances and Disease Registry (ATSDR)
Areal Locations of Hazardous Atmospheres (ALOHA)
Centers for Disease Control and Prevention (CDC)
Emergency Planning and Community Right to Know Act (EPCRA)
Federal Highway Administration (FHWA)
Hazardous Air Pollutants (HAPs)
Hazardous Materials Information System (HMIS)
Hazardous Substances Emergency Events Surveillance (HSEES)
Health Effects Assessment Summary Tables (HEAST)
Integrated Risk Information System (IRIS)
National Environmental Protect Act (NEPA)
National Health and Nutrition Examination Survey (NHANES)
National Oceanic and Atmospheric Administration (NOAA)
National Response Center (NRC)
National-Scale Air Toxics Assessment (NATA)
Pipeline and Hazardous Materials Safety Administration (PHMSA)
Resource Conservation and Recovery Act (RCRA)
Risk-Screening Environmental Indicators for Chronic Human Health Model (RSEI)
Toxic Release Inventory Site (TRI)
U.S. Coast Guard's National Response Center (NRC)
U.S. Department of Transportation (DOT)
U.S. Environmental Protection Agency (USEPA)
LINKING HEALTH HAZARDS AND ENVIRONMENTAL JUSTICE:
A CASE STUDY IN HOUSTON, TEXAS

Marilyn M. Williams

ABSTRACT

This dissertation seeks to extend quantitative research on environmental justice and address methodological limitations of previous studies by: (a) using new indicators of exposure to air pollution and contemporary risk modeling techniques; (b) assessing disparities in human health risks, instead of focusing only on potential exposure or proximity to pollution sources; and (c) using multivariate regression models that consider the effects of spatial dependence. The case study examines racial/ethnic and socioeconomic disparities in the geographic distribution of exposure to airborne toxic emissions from industrial point sources in the Houston-Galveston-Brazoria metropolitan statistical area. Industrial pollution sources for this study comprise facilities listed in the US EPA’s Toxic Release Inventory (TRI). The Risk-Screening Environmental Indicator (RSEI) model is used to estimate potential human health risks from air pollutants based on data on toxicity and dispersion of chemical releases from TRI facilities. The analyses utilize four indicators of potential exposure to industrial pollution: (a) presence or absence of air emissions, (b) total quantities (pounds) of air emissions, (c) toxicity-weighted quantities of emissions and (d) modeled risk scores based on the cumulative health risk posed by air emissions. Traditional linear regression and spatial autoregressive techniques based on several neighborhood configurations are used to model the occurrence and magnitude of these four indicators, using relevant explanatory
variables from the 2000 census, at the census tract and block groups levels of aggregation.

Results indicate a disproportionate pattern of health risks from TRI facilities in the HGB-MSA, with the Hispanic population facing the highest exposure. The locations and magnitude of toxic pollution are significantly statistical effected by the presence of minority residents and population density. Additionally, key differences in the significance of explanatory variables between the spatial and conventional regression models demonstrate the importance of correcting for spatial dependence in environmental justice analysis. The analytical results for several variables are also sensitive to the choice of data resolution (tract or block group). Overall, this study indicates that more flexible spatial analytic techniques are required to improve the identification of environmental injustice and past studies utilizing conventional statistical methods should be revisited to explicitly account for spatial effects.
1. INTRODUCTION

The use and production of industrial chemicals has increased significantly in the United States since the Industrial Revolution, resulting in an increase of potential exposure and health risks to the population. Racial and socioeconomic inequities associated with the distribution of pollution burdens and related health impacts sparked the environmental justice movement in the 1980s. The goal of environmental justice or environmental equity is to ensure that all people, regardless of race, national origin or income, are protected from disproportionate impacts of environmental hazards (Clinton 1994). Spatial inequities in the distribution of toxic pollution in the US was first reported by a study conducted by the General Accounting Office (GAO) in 1983, which found the location pattern of hazardous waste landfills to be inequitable with respect to race and income in eight southeastern states (US General Accounting Office 1983). This study followed on the heels of resident protests in Warren County, North Carolina, against the location of a proposed landfill for polychlorinated biphenyl (a known carcinogen) in a predominantly Black neighborhood. These protests attracted substantial media and congressional attention and became a pivotal event for the environmental justice movement. Following the Warren County protests, the United Church of Christ (UCC) conducted the first comprehensive national scale study on environmental justice (United Church of Christ Commission for Racial Justice 1987). The UCC report was significant because it found race to be the most potent variable in predicting where commercial hazardous waste facilities were located in the US. In addition to galvanizing
the attention of the government and the citizens to the occurrence of environmental injustice, the UCC report triggered a series of empirical case studies that investigated the association between environmental risks and potentially affected populations, based on race/ethnicity and economic status.

There is a growing literature which suggests that industries that store, use, manufacture, and release toxic chemicals are disproportionately located in greater densities in urban and minority spaces as compared to suburban and non-minority areas (Mohai and Bryant 1992; Liu 2001). This location pattern may result in greater exposure of industrial chemicals to surrounding residents and consequently imposes an uneven health risk upon the affected population. This increased exposure has created a new environmental health burden on society where communities are exposed to a multitude of toxic chemicals on a continuous basis. Studies have found that the impact of sustained atmospheric, water and land exposure may result in adverse health effects. These health effects can cause increased morbidity and mortality including cancers, renal and liver diseases (Gee and Payne-Sturges 2004) as well as low birth weight babies (Dolk and Vrijheid 2003).

1.1 Types of Exposure

There are two distinct types of chemical exposures identified in toxicological studies, namely, acute and chronic. Chronic exposures occur as a result of long-term exposures to toxic chemicals and routine emissions from facilities such as industrial manufacturing plants, toxic waste disposal sites, and landfills. Chronic exposures also can result in lifetime adverse health effects which have been known to increase the incidence of low birth weight, birth defects and asthma (Gilboa and Fixler 2005; Morello-
As the siting of industries has progressed in residential neighborhoods and as neighborhoods have encroached on the locations of some of the most toxic spaces in the US, an increase of chronic exposure and adverse health effects have occurred. Adverse health outcomes can be exacerbated by prolonged exposure to a single chemical and interaction with multiple chemical exposures potentially resulting in greater morbidity and mortality (Klassen 2001).

Acute pollution events are non-routine, accidental releases of hazardous substances that have immediate public health consequences for the affected population (Chakraborty 2001). Unlike chronic hazards, acute hazards are short-term, unintentional spills that frequently lead to injury, fatalities, and adverse health outcomes which are known to range from minor respiratory irritation to protracted and progressively debilitating diseases, such as cancers (Gee and Payne-Sturges 2004). Acute exposures can result from unexpected releases from railway cars, fuel truck, and fixed facilities. Increased morbidity and mortality rates have been known to result from these releases. These exposures can be additive and synergistic to chronic exposures and as such there is a difficulty collecting data and determining independent effects on the affected population.

Measurement of adverse health outcomes requires the implementation of longitudinal epidemiological studies. The lack of sufficient data collection supports the need of adequate databases that contain information collected for extended periods of time (Payne-Sturges and Gee 2006). Data gathering of acute health outcomes requires an established record keeping system which tracks the type of chemical exposure as well as demographics and resultant health outcomes. Collection of data on chronic health
outcomes differs from those on acute events in that it requires many years for the onset of
the disease or death to occur. Therefore the modeled risk to the population is used to
examine potential health impacts of chronic exposure while acute health outcomes data
are collected over a short period of time. These two types of health outcomes have been
observed to occur disproportionately in minority and low-income neighborhoods
resulting in environmental health disparities (Pastor Jr et al. 2005; Morello-Frosch and
Lopez 2006).

1.2 Environmental Justice and Health Disparities Research: Trends and Limitations

Environmental health disparities are defined as racial/ethnic and socioeconomic
inequities in illness, exposure and outcomes which are influenced by the biophysical,
social and built environments (Payne-Sturges and Gee 2006). Such disparities have
arisen as a result of racial/ethnic minorities and persons of lower socioeconomic status
living in spaces exposed to environmental pollution and related hazards (Morello-Frosch
and Lopez 2006). The study of the distribution and extent of environmental health
disparities has recently emerged as a discipline which extends environmental justice
research (Institute of Medicine 1999; Woodruff et al. 2003; Payne-Sturges and Gee
2006). Studies have begun to explore the association between the social construction of
health disparities and neighborhood locations, with respect to minority and/or low-
inecome residents in urban areas. Adverse health outcomes and patterns of population
locations are now being evaluated through geospatial tools that not only provide spatial
representations of affected populations, but also can be used to identify the social
dynamics which influence racial/ethnic and economic disparities.
Previous empirical research on environmental justice and health disparities has been plagued by several methodological limitations. First, a majority of studies have evaluated racial and economic inequities in the distribution of pollution sources such as hazardous waste facilities and industrial manufacturing plants based solely on their locations (United Church of Christ Commission for Racial Justice 1987; Mohai and Bryant 1992; Cutter and Clark 1996; Perlin and Wong 1999; Mohai and Saha 2006), thus ignoring the nature, quantity, or properties of the emitted pollutants and other factors that influence exposure. Second, although some studies have incorporated data on quantity and toxicity of released pollutants and local meteorological conditions to assess potential exposure to toxic emissions (Chakraborty and Armstrong 2004; Dolinoy and Miranda 2004), few studies have attempted to link disproportionate environmental exposure to their adverse health effects or risks (Maantay 2002). Third, most studies have used conventional statistical methods such as linear regression analysis to determine the effect of racial/ethnic and socioeconomic influences on response variables that represent exposure to toxic pollution. Previous research on environmental justice has thus failed to adequately account for spatial processes and effects that are an inherent feature of geographically referenced data sets.

In order to address these methodological limitations, this dissertation focuses on assessing chronic exposure to toxic atmospheric pollution sources within a single US metropolitan area, on the basis of newly emerging risk modeling and spatial statistical techniques. The study area is the Houston-Galveston-Brazoria (HGB) consolidated metropolitan statistical area, where several prominent studies on racial inequities...
associated with hazardous waste facility siting have been conducted (Bullard 1983; Bullard 1990).

1.3 Research Objectives

The broader aims of this dissertation are to extend quantitative research on environmental justice and address several methodological limitations of previous studies, by: 1) using new indicators of exposure to air pollution and contemporary risk modeling techniques; 2) assessing disparities in human health risks, instead of focusing only on potential exposure or proximity to pollution sources; and 3) implementing multivariate regression methods that consider the effect of spatial dependence and are thus more suitable for analyzing geographic data. The data sets used in the dissertation project for estimating exposure and health risks have not previously been applied in environmental justice analysis and required new methodological avenues to be explored. Fixed-facility point sources of industrial toxic emissions in the study area were used to estimate chronic or long-term exposure to outdoor air pollution in this dissertation.

Specific research questions posed to examine the geographic distribution of chronic industrial atmospheric pollution sources and health disparities in the study area are summarized as follows:

a. What is the association between locations of industrial atmospheric pollution sources and the racial/ethnic and socioeconomic status of the population?

b. What is the association between quantity (pounds) of pollutants released from industrial pollution sources and the racial/ethnic and socioeconomic status of the population?
c. What is the association between toxicity-weighted quantities (hazard scores) of emissions from industrial pollution sources and the racial/ethnic and socioeconomic status of the population?

d. What is the association between health risks (modeled risk scores) from chronic exposure to industrial pollutants and the racial/ethnic and socioeconomic status of the population?

This dissertation is organized into nine chapters. The Introduction is followed by a comprehensive review of the pertinent literature in chapter 2, which includes the theoretical foundations for the research questions and an overview of geospatial techniques and methodologies used in this study. Chapter 3 provides background information on the study area and chapter 4 describes the data sources, models, and statistical techniques used in this research. The empirical findings associated with each research question are presented in the following four chapters (chapters 5 to 8), while chapter 9 summarizes the conclusions and broader significance of this work.
2. LITERATURE REVIEW

This chapter provides a review of the environmental justice and health disparities research literature. It encompasses relevant theories as well as methodologies used in prior studies to explain, document, and analyze disparities on the spatial distribution and impact of toxic pollution. The first section of this chapter outlines a selection of common and contemporary theories used to examine the causes of environmental injustice and inequity. The second section describes analytical tools and methodologies that have been used in environmental justice research, while the third section explores the analysis and measurement of health disparities. The fourth section explains how disease clusters are defined and outlines several statistical tools that can be used to analyze the spatial distribution of disease health events to determine the presence of statistically significant disease clusters.

2.1 Theoretical Explanations for Spatial and Environmental Justice

A large variety of theories have been proposed to explain and substantiate the occurrence of injustices. Sections one and two outlines the common theories used to address social justice, as well as several alternative theories. Section three offers more contemporary theories and explanations of environmental justice. Section four defines how and why these theories and explanations were used in relation to geographical principles of environmental justice.
Theories developed to interpret the causes and consequences of environmental injustice and health disparities include social justice, economic residential and location theories, as well as theories of neighborhood change. Mainstream theories of justice and equity have been identified as utilitarianism, contractarianism, egalitarianism, and libertarianism. These theories can be expanded upon by the principles of Marxism and feminism in order to dispel the rigidity brought to the concept of justice through the mainstream theories. Additionally, specific environmental justice explanations such as the neighborhood life-cycle model, has brought to light new ideas that can be used to examine environmental justice issues.

2.1.1 Theories of Justice

The four mainstream theories of justice and equity have been identified as utilitarianism, contractarianism, egalitarianism and libertarianism. These theories are representative of distributive justice through use of goods and services. Egalitarianism is the equal distribution of justice and treatment for individuals (Smith 1994). This theory hypothesizes that people should receive equal inputs (e.g., education, resources) and have equal outputs (e.g., monies, social welfare), regardless of their geographical location. There are several problems with strict egalitarian principles in that: 1) although people may receive the same education they may not receive the same jobs or monies once they graduate; 2) geographical locations inherently have different resources available; and 3) redistribution of goods from the wealthiest group of people may not be feasible or practical.

Another theory of distributive justice is utilitarianism. Utilitarianism states that goods should be produced and distributed to maximize the total welfare or aggregate
social utility (Smith 1994; Rawls 1999; Liu 2001). Implementation of utilitarian policy ignores individual inequity and would distribute justice over the aggregate, thereby ignoring the effects on individuals. This theory is not concerned with equity and distributive justice since the goal is the aggregate effect and not individuals who are in greatest need. In essence, utilitarianism could increase the existing inequity which is the polar opposite of the goal of egalitarianism.

Contractarianism uses a “social contract where individuals would distribute goods equally unless an unequal distribution of any or all goods is to the advantage of the least favored” (Smith 1994; Rawls 1999). This theory of justice as represented by Rawls states that “1) each person is to have an equal right to the most extensive basic liberty compatible with a similar liberty for others; and 2) social and economic inequalities are to be arranged so that they are both: a) to the greatest benefit of the least advantaged, and b) attached to offices and positions open to all under conditions of fair equality of opportunity” (Rawls 1980, 1999). This theory, like the egalitarian theory, strives to make the least well off in society as well off as possible, but unlike the egalitarian approach it does not strive to eliminate the inequality. Therefore, Rawlsian theory is seen as the principle theory of “fairness” and not equality.

Libertarianism stresses the freedom of the individual to perform whatever task he/she desire as long as he/she respects the rights of others to do the same. The state, (i.e., government), is only allowed to interfere if there is aggression or fraud. Libertarianism emphasizes free choice, free market economy, and property rights of the individual, but it does not provide avenues of conflict resolution when dealing with pollution or other justice issues that involve large groups of people (Liu 2001).
Therefore, this theory would have limited ability to resolve environmental justice issues since these issues inherently involve large groups of people who experience varying levels of injustice.

2.1.2 Alternative Explanations

Common social justice theories are limited in their ability to help explain the intricacies of why environmental injustices may occur. Further explanations have been suggested and have become alternative pathways used to broaden justice theory. Two additional ideas to the more established theories are Marxism and feminism, which are summarized below.

**Marxism**: The Marxist view of justice is anti-capitalist, and as such it expresses opposite views of what influences justice in most developed countries. Karl Marx focused on two particular avenues of justice, namely alienation and exploitation. He used these ideals as explanations of how production in a capitalist economy (i.e., means and mode of production), contribute to injustices and inequalities among workers. Marx identifies alienation as the ability of the worker in a capitalist society to be alienated from their “most important capacity” thereby denying the worker the ability to realize his/her own potential. The alienation denies the worker any creativity and thus inhibits true fulfillment. Although fulfillment may be a goal of a worker as viewed by this theory, it is not necessarily unjust if a person does not feel that they are unfulfilled. Smith (1994) recognizes that a person can perform a job which is monotonous, but provides significant monetary compensation therefore allowing them to be fulfilled in other aspects of their lives outside of their job. Consequently, the evaluation of exploitation may be a better
choice as a representation in Marxism as it pertains to explanations of environmental justice.

Marxists view capitalist exploitation as the ability of the persons who possess ownership to receive a greater value from the production of the workers than is given to the workers. In essence, the product produced by the worker is of greater value than the worker is compensated and therefore the owner receives the surplus as profit. A more contemporary view of this Marxist principle is the “unfair advantage within broader distribution arrangements which include uneven access to resources in general and to the means of production in particular” (Smith 1994). This definition of exploitation as part of justice issues, particularly environmental justice, helps to explain the importance of equal access to resources and uneven distribution of externalities from toxic pollution. For example, by having locally unwanted land uses (LULUs) concentrated in impoverished or minority neighborhoods, the pollution caused by these LULUs denies the residents of these neighborhoods access to clean air as a resource and consequently denies them equal access to good health, thus representing this principle of Marxist theory.

**Feminism:** Feminism explores the use of gender identity as an influence on justice. It explores the inequalities experienced by women due to the paternalistic view that shapes society. Understanding the impact of how societal structure influences where people live, the jobs they receive and how much they earn are important in identifying the basic principles of justice. Young (1990) proposes that distributive justice, which includes distribution of benefits and burdens among society, limits social justice because it does not explore the institutional or social context where these burdens were created. The
contemporary framework of theories of justice, as represented by Rawls (contractarian), utilitarian, egalitarian and libertarian principles, as well as Marxism, are based on principles of distributive justice. These theories emphasize the importance of distribution of goods and worker related production, but not decision making processes or exploration of the social and institutional context which determines the distribution of these goods. Marxism, for example, views exploitation in the sense of the worker only but does not examine exploitation of women or individuals by race (Young 1990; Smith 1994).

In exploring siting of LULUs, Young (1983) argues that the prevailing approaches to reasoning about justice cannot treat justice used for decision making of where pollution sources should be sited. Justice does not only include the distribution of facilities but participation in the process of choosing where to place such facilities. Young states that the utilitarian argument for siting pollution sources, which consists of placing the facilities in one area, would provide the greatest benefit to most people, but does not take into account fairness as it effects distributive justice. Although Rawlsian theory of justice is viewed as representing fairness as justice and distributive justice, in particular, it does not outline the decision making processes. This theory neglects the rights of the potentially affected population to participate in the siting process, which denies them power, thereby denying them justice.

2.1.3 Contemporary Explanations of Environmental Justice

While mainstream social, moral, ethical and political theories were outlined in the previous section, more specific theories help to identify and explain the concentration of pollution sources in minority and low-income neighborhoods.
2.1.3.1 Theories of Economics and Location

Economics can play an important role in determining how justice is distributed. Pareto efficiency is a state where no one can be made better off without making someone worse off, and therefore to achieve efficiency there should be “no unexploited gains to trade, no unexploited way of increasing output with the same level of inputs and no mix of products that do not reflect the preferences of the consumer” (Liu 2001).

Environmental problems such as environmental inequity and environmental injustice are produced as externalities of processes of industrial pollution and therefore do not achieve efficiency. Industrial pollution can result in externalities that require a higher cost to be paid by communities which are in vicinity to the industries. These negative externalities resulting from air, land, and water pollution can lead to adverse and disproportionate health effects as referenced in EO 12898 (Clinton 1994).

2.1.3.1.1 Industrial Location

Location theory for industries in the US can be explored using a combination of frameworks. Least cost is identified as a theory where industrial location decisions are made based upon labor and transport costs and Hotelling (1990) outlined that location of industries was influenced by spatial competition and oligopolistic (small number of sellers of a single product, e.g., airlines, personal computers) (Liu 2001). In essence, industries locate near areas which minimize the cost of transport, whether the cost is from direct access to raw goods or waste disposal sites. These theories are represented by the agglomeration of a variety of industries and businesses in close proximity to each other and close proximity to transportation routes. The choice of industry locations has also been found to include land prices which are known to vary dependent upon the distance
from the city center. Additionally, researchers have stressed that industry locations follow the “path of least resistance” and are thus deliberately placed in areas where land prices are low, labor is inexpensive, and residents have little political influence to resist siting (Mohai and Bryant 1992).

2.1.3.1.2 Residential Location

Von Thunen developed the theory of agricultural landuse where land is distributed according to an individual’s willingness to bid. Initially house location theory proposed that locations were determined by accessibility and space. Later it was expanded to include environmental amenities to the residential population (Fujita 1989). Kanemoto (1987) found that land rent increases at the boundary between industrial and residential zones. In essence, if pollution zones expand or encroach on neighborhoods then the following items hold true:

1) The residential land and/or rent will decrease allowing for an increase in industrial purchasing of inexpensive land. This can result in an increase in negative impact on the population in the neighborhood and can force people to relocate.

2) More low-income individuals can afford to live in these areas increasing the exposure to a larger population.

3) If there are people of middle income it may drive them to other areas away from the industry.

4) Externalities among neighbors can occur when one group has racial and/or economic prejudice against another group (Fujita 1989). This can result in segregation in the neighborhood as well as “White flight” where certain
race/ethnic groups (e.g., Hispanics) move into a majority White neighborhoods resulting in the population relocating elsewhere (Pulido 2000).

5) Externalities resulting from transportation can be from high congestion of traffic alone, locations of freeways near neighborhoods and air pollution resulting from traffic. These externalities can result in property values declining and increased health concerns from exposure to car exhaust.

2.1.3.2 Explanations of Neighborhood Change

The theoretical models outlined below provide a temporal component to environmental justice explanations. They ask the question how and whether environmental risks change over time, by understanding the siting process of local unwanted land uses (LULUs), the spatial associations of potential exposures to the impacted populations, and the factors influencing the construction and degradation of neighborhoods.

2.1.3.2.1 Classical Invasion-Succession Model

This model originated through ecological theory and can be metaphorically represented by an example where an indigenous group (White population) living in a neighborhood is invaded by an outsider (Black person) resulting in the neighborhood initially having some resistance. As the Black person becomes more acclimated and begins to change their space others with their similar background and socioeconomic status begin to move into the neighborhood resulting in an increased resistance. If the indigenous group fails in its resistance then they withdraw resulting in a racial/ethnic change in the neighborhood.
This model shows the importance of understanding the construction of the neighborhood and the temporal aspects of its space. It is important to understand the history not only of the neighborhoods succession process but of the people (e.g., Black migration) who have inhabited the neighborhood in the past. This model stresses that once the succession has occurred it is expected for density of the new residents to increase thereby causing the boundary areas inhabited by Whites to decline in value and potentially selling to industries resulting in an increase in pollution. Industries could be sited before the succession began (pre-siting) or after the succession was complete (post-siting). Therefore, it is important to understand when industries were sited in order to determine if an environmental injustice has occurred.

2.1.3.2.2 Neighborhood Life-Cycle Model

The importance of recognizing the temporal element of neighborhoods can also be seen in the neighborhood life-cycle model which also originates from an ecological theory. This model states that a neighborhood has a natural life-cycle and as it ages and declines its residents become members of successively lower socioeconomic groups. The model has five cycles which are: residential development, transition, downgrading, thinning-out and renewal. The life-cycle model is exclusive of LULUs or other external forces. Therefore it is anticipated that each neighborhood “naturally” will physically age and decline as well as socially and economically decline. Additionally, post-siting of LULUs in this neighborhood may exacerbate the decline but is not the cause. This model seems intuitively misguided since it does recognize that pre-siting of industries influences the degradation of the neighborhood but it stresses that people can relocate to another neighborhood at a higher cycle of development thereby gaining a benefit. Additionally, it
ignores the factors which may influence why the neighborhood changes overtime but embraces that the change occurs.

2.1.3.2.3 Push-Pull Model

The last model to be addressed is the push-pull model. It is represented by many social, cultural, and economic impacts. This model relates why people move or remain in certain spaces. The push factors are represented as undesirable factors that influence people to move while pull factors are positive factors which attract people to an area (Been 1994). Push factors are identified in neighborhoods as LULUs, fear, violence, lack of employment, aging infrastructure, prejudice, traffic congestion etc. Some pull factors may include job opportunities, better housing, safety, and lack of pollution. These factors work independently but tend to have some interconnectivity.

2.1.4 Geographical Principles of Environmental Justice

The theoretical bases for environmental justice and inequity have been addressed in the previous section. The foundation of this topic has been laid in economic, political and social theories and has progressed into urban and location (i.e., residential and industry) theories. Additionally, a more practical component of environmental justice theories are the temporal theories and explanations as previously indicated. The challenge is to understand the interdisciplinary nature of environmental justice and to encourage a variety of thought be applied to solutions of inequities.

In blending of these theories with geographical principles, a broader perspective of the environment and of justice can be achieved. The basic tenets of geography are space, place, scale and time and they all have numerous and varied definitions (Castree 2005). The Explanations of Neighborhood Change as previously defined, stress the
importance of relating time to space (spatio-temporal relationships). Space can be perceived as “undergoing continual construction exactly through the agency of things encountering each other more or less organized circulations”; in essence this is a relational view of space (Thrift 2005). In environmental justice these spaces are created by the relationship of neighborhoods (not just a house but the demographics and socioeconomics of the neighborhood), industries, pollution and adverse health effects. In recognizing that space is recreated throughout time, it is also necessary to recognize that a definition for space is the creation of place.

Place once again has several definitions. It can be defined as: 1) a location on earth, 2) a sense of place- which can be a subjective feeling a person has about a place and 3) a setting and scale for people’s daily actions and interactions (Castree 2005). It is understood that places are interconnected and exert certain influences upon each other but it is also recognized that places exist independently. In relating environmental justice to neighborhoods, it is important to understand not only the history of the neighborhood, i.e., the period each group inhabited the space, but also the social issues of the time (e.g., segregation, desegregation, and migration patterns of populations into areas), the economic structure of the city, and different types and length of time of the industries inhabited by the space, as well as the size of their footprint on the landscape. A place has a distinct individuality. The idea of place is one of the most important aspects of understanding why environmental injustices occur. The nexus of certain conditions e.g., economic, social, pervasive institutional racism has lead to these injustices and health disparities occurring in specific and distinct locations.
As a geographic principle, the understanding of scale for environmental justice research must also be stressed. The spatial scale is determined by the resolution which indicates the level at which we focus on a particular item of interest (Herod 2005). Numerous environmental justice studies have been conducted at different spatial scales in order to assess different outcomes. Scales include national, state, county, and local, and can be represented by different units of analysis such as census unit boundaries or zip codes.

2.2 Methodology for Environmental Justice Assessment

This section describes geographic analytical units and approaches utilized to identify potentially exposed areas and populations in environmental justice research. It provides the evolution of how geographical analytical units have been previously selected and used in environmental justice research, their contemporary usage, and some of the pitfalls and problems of selecting geographical analytical units.

2.2.1 Geographical Unit of Analysis

The selection of the geographical unit of analysis for environmental justice research has been subject to an ongoing debate in determining the proper scale of selection and representation of neighborhoods (Williams 1999; Liu 2001). The spatial definition of a neighborhood has been routinely left to the researchers and their research agenda and thus these studies have varying results based on the choice of analytical unit. Several geographical units of analysis such as zip codes, census tracts, counties, and census blocks/block groups have been used in the research literature. Additionally, nonstandard geographical analytical units are used by the US census bureau namely
statistical areas e.g., consolidated metropolitan statistical areas for year 2000 census or
micropolitan statistical areas (Figure 1). Additionally, with the advent of grids a new
way of structuring census data has been established. Figure 1 depicts the variety of units
of analysis and their components as used by the US Census with the most commonly
used units in environmental justice studies explained in the following section.

Figure 1: Geographical Hierarchy for the Decennial Census, (US Census Bureau 2005).
2.2.1.1 Zip Codes

In the infancy of environmental justice research, zip codes were the primary geographic unit of analysis. The pioneering United Church of Christ (1987) study was the first on a national scale to use five-digit zip codes as units to conclude that race was the most influential variable in the location of hazardous waste facilities. Zip codes are arbitrary five digit numbers used by the US Postal Service for ease of distributing mail to neighborhoods not for analyzing populations. These numeric codes represent the aggregation of households and businesses into small areas and thus facilitate a configuration of neighborhoods throughout the US. One concern with using the zip code as an analytical unit is that not all businesses or industries receive mail at the site location, therefore certain important sources of pollution could be missed. Additionally, large neighborhoods can be comprised of several zip codes and as such these zip codes must be aggregated to obtain a true representation of the affected locations (Liu 2001). Furthermore, since zip codes are not units defined by the US Census, population data are not collected specifically for their configuration, and the sizes and shapes of the zip codes do not remain consistent from year to year. Therefore, zip codes are an unstable unit if performing inequity studies. Although the use of zip codes as analytical units have facilitated the discovery of environmental inequity in the past (Brooks and Sethi 1997), their limitations called for a more rigorous unit to be developed and used to improve robustness of equity studies.

2.2.1.2 Census Tracts

Census units including tracts (Downey 2006), block groups (Grineski et al. 2007) and blocks have emerged as the most commonly used geographical units of analyses used
in environmental justice research. Census tracts are subdivisions of counties that were established to provide a small statistical area unit with comparable boundaries between decennial censuses (US Census Bureau 1997). For the 2000 US Census, a census tract must 1) contain between 1,500 and 8,000 people (4000 person average) (Williams 1999), 2) meet boundary feature criteria, 3) be reasonably compact land area, 4) be accessible by roads, 5) have the same boundary as the county, and 4) cover the entire land and inland water area of each county.

Census tract data are routinely used in environmental justice studies because there is a wealth of data variables collected on a decennial basis by the US Census Bureau on various population and housing characteristics. A second reason to use census tract data is that on average they comprise a smaller area of land than zip codes and therefore are more representative of neighborhoods (Anderton et al. 1994). Additionally, because of the inherent criteria for establishing a census tract, i.e., the population size (Figure 1), there is reasonable comparison between census tracts versus zip codes where there is no population limit attributed to spatial size.

2.2.1.3 Census Blocks/Block Groups

Census block groups are statistical subdivisions of census tracts and are comprised of census blocks. For the 2000 US Census, a census block group must 1) contain between 600 and 3,000 people, 2) meet boundary feature criteria, be reasonably compact, contiguous land area, all parts must be accessible by roads, 3) be reasonably compact contiguous land area, 4) be accessible by roads and 5) have the same boundary as the census tract and cover the entire land and inland water area of each county. Additionally, each census tract must contain a minimum of one block group and a
maximum of nine block groups. A block group within a Native American reservation is allowed to extend across state lines.

The 1990 US Census allowed for the first time the land mass of the US to be numbered using census blocks as the unit. The census block is the smallest unit of analysis collected by the US Census (US Census Bureau 1997). The census block must fulfill the same boundary criteria as the census block group and unlike census block groups its delineation is not primarily based on the population. The census block can contain zero or thousands of people (up to the 3,000 person limit of the census block group as it is the larger of the two boundaries). The primary reason for using the census block and/or block groups is to allow for analysis of the population at a finer resolution. The census block group is more useful than the census block for environmental justice research because it contains detailed data on population, housing, income, poverty, education and other many other characteristics. In order to preserve the privacy of individuals and households, only a limited number of variables describing basic population and housing characteristics are published at the block level.

2.2.2 Geographic Problems and Spatial Effects

In environmental justice research, it is important to understand the strengths and weaknesses of each unit of analysis in order to limit the errors associated with geospatial analysis. This section introduces the major limitations of selection criteria for geographical units of analysis and stresses the importance of appropriate selection. Furthermore, it outlines the necessity for spatial analyses that help to mitigate the effects of spatial dependence in the data.
2.2.2.1 Modifiable Areal Unit Problem

There are several common problems related to the selection of proper geographical unit of analysis. The modifiable areal unit problem (MAUP) is comprised of the scale effect and the zoning effect (Fotheringham and Wong 1997). The scale effect occurs “when different statistical findings are obtained from the same data set when the information is grouped at different levels of resolution” e.g., census tracts, blocks and counties (Wrigley et al. 1996). The zoning effect occurs “when different statistical findings are obtained with a modifiable areal unit as a function of various ways these units can be grouped at a given scale, and not as a result of the variation in the size of those areas”, i.e., the difference in results which follows from merely altering the boundaries or configurations of the zones at a given scale of analysis. Results from both effects have been found to result in varying levels of goodness of fit for a model, different regression coefficient estimates and t-values, as well as an increase in correlations between variables in zoning alone.

A more direct issue stemming from scale effect is described as the ecological fallacy. Anderton (1994) writes that an ecological fallacy is the reaching of conclusions from a larger unit of analysis that does not hold true in the analyses of smaller, more refined units. This reflects a sensitivity of results to the aggregation of data. This was observed in the Glickman et al., (1995) study, where racial inequities were not observed at the census block group and census tract levels, but detected only when the impacted area was defined by a circular buffer of radius 0.5 mile or 1 mile.
2.2.2.2 Edge Effect

A common problem identified as a result of geographic analytical unit selection and/or analytical technique selection is edge effect. Edge effect (or border effect) occurs as a result of pollution sources under study being located near the edge of two or more census units where pollution is counted as belonging solely to the host census unit of the facility. Methods suggested to mitigate the edge effect (Liu 2001) include: 1) aggregating the census units that are along the edge into one by determining the distance of impact (exposure) on the affected neighborhood; and 2) not aggregating the units but treating all units as potentially exposed. Both of these methods have been used to rectify the problem, but they work with varying degrees of results (Downey 2006; Mohai and Saha 2006). Since pollution from a facility is not limited by the boundaries of the analytical unit hosting the facility, if the pollution is not allocated to all areas where it travels then there can be an overestimation in the host analytical unit and an underestimation in adjacent non-host analytical units that are also likely to be impacted.

2.2.2.3 Spatial Autocorrelation

The first law of geography, as explained by Waldo Tobler (1970), states that “everything is related to everything else, but near things are more related to each other”. A variable is considered to be spatially autocorrelated if the geographic distribution of a variable indicates a systematic pattern and spatially independent if no pattern can be discerned. Positive spatial autocorrelation is often caused by geographic clustering when values at neighboring locations are more similar than would be expected of a random distribution (Kissling and Carl 2008). Most conventional statistical tests, however, are based on the assumption that the values of observations in each sample are independent.
of one another. Although the ordinary least squares (OLS) method for multivariate regression has been used extensively in quantitative studies on environmental justice and health disparities, spatial autocorrelation potentially leads to spatial dependence of regression model residuals, thus violating the OLS assumption of independent observations (uncorrelated errors) and biasing the regression coefficients associated with the explanatory variables. When analyzing spatial data, therefore, appropriate statistical modeling techniques must be used to account for the effects of spatial dependence.

Spatial regression, or the spatial autoregressive (SAR) models, address the spatial autocorrelation problem by augmenting the standard OLS regression model \( Y = X\beta + \epsilon \) to include the effects of spatial dependence (Anselin and Bera 1998). The SAR model is, in effect, a combination of the OLS model that includes the response variable \( Y \) and the term for predictors and errors \( X\beta + \epsilon \) along with an additional term which accounts for the spatial autocorrelation structure \( \rho W \) of a given data set. This additional term is implemented with a spatial weights matrix \( W \) where the neighborhood of location and the weight of each neighbor need to be defined (Kissling and Carl 2008). The SAR model requires the development of an appropriate set of neighbor relationships, or spatial weights matrix. The spatial weights matrix accounts for variation in the dependent variable explained by values at nearby locations instead of the explanatory variables.

The spatial weights matrix is constructed by identifying the neighborhood structure of each location or areal unit, based on a contiguity-based or distance-based technique. The queen contiguity includes all common points (boundaries and vertices) of the areal unit to determine the neighbors, while the rook continuity uses the common boundaries alone to determine the neighbors. Additionally, the distance band selects all
areal units whose centroids fall within a specified distance from the centroid of the areal unit under consideration. Since any chosen distance can be used to define the spatial extent of neighborhood effects, it is important to select the minimal distance from the boundary as the distance band which also negates spatial autocorrelation.

The open-source spatial statistics application GeoDA™ (Anselin 2004) can be used to develop OLS and SAR models, detect spatial autocorrelation, and generate weight matrices for this study. The SAR models operationalized by GeoDA™ utilize both contiguity-based spatial weights and distance-based spatial weights for a specified spatial analytical unit to identify the neighborhood configuration (Anselin 2006). Spatial weight matrices based on queen contiguity, rook contiguity, or distance bands can be calculated to represent neighbor relationships between areal units. Two types of SAR models can be used to improve the OLS model and account for spatial dependence in the data: spatial error and spatial lag. The spatial error regression model is implemented when the assumption of uncorrelated error terms is violated. This model assumes that the autoregressive process occurs only in the error term, and not in the predictor or explanatory variables (Dormann et al. 2007; Kissling and Carl 2008). The spatial error model is specified as:

\[ Y = X\beta + \lambda W\mu + \varepsilon \]  

(1)

where \((\lambda W\mu)\) represents the spatial structure \((\lambda W)\) in the spatially dependent error term \((\mu)\).

The spatial lag model, on the other hand, assumes that spatial autocorrelation occurs only in the response variable. This model thus includes a term for the spatial autocorrelation in

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the dependent variable and also the standard error term that is used in the OLS regression model. It is specified as:

$$Y = \rho W Y + X \beta + \epsilon$$  (Dormann et al. 2007; Kissling and Carl 2008),

(2)

where \((\rho W)\) is the term for spatial autocorrelation in the response variable \((Y)\).

The presence of spatial autocorrelation for regression residuals (error terms) is determined by the global Moran’s I, in this study. The Moran’s I is a global test that has an associated z-score which indicates that the point pattern could be a result of random chance if the z-score is near 0 and non-significant. The Moran’s I measures the spatial autocorrelation by

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{s^2 \sum_{i=1}^{n} \sum_{j=1}^{m} w_{ij}}$$  (Chang 2006; Torrens 2008),

(3)

where \(x_i\) is the value at point \(i\), \(x_j\) is the value at point \(i\)’s neighbor \(j\), \(w_{ij}\) is the coefficient for measuring adjacency between two points, \(n\) is the number of points, and \(s^2\) is the variance of \(x\) values with a mean of \(\bar{x}\). A positive I indicates that points tend to be located to similar high or low values, while a negative I suggests that high values tend to locate near low values in the study area.

Although multivariate regression has been used extensively in environmental justice research (Bowen and Cyran 1995; Pollock and Vittas 1995; Daniels and Friedman 1999; Bouwes et al. 2001; Morello-Frosch et al. 2001; Ash and Fetter 2004; Sicotte and Swanson 2007), spatial autoregressive (SAR) models have rarely been implemented as a
means to account for spatial dependence in the data. Utilizing SAR for multiple regression with spatially referenced data could potentially lead to more statistically valid conclusions about the significance of explanatory variables such as race/ethnicity or poverty, in quantitative analyses of environmental justice.

2.2.3 Spatial Analytical Approaches to Identifying Impacted Areas

Environmental justice studies have used several approaches used to determine the geographic boundaries of areas exposed to environmental pollution and related health risks and to estimate the population characteristics of these potentially impacted areas. These are described in detail below.

2.2.3.1 Common Analytical Techniques

Downey (2003) and Mohai and Saha (2006) outlined the “unit-hazard coincidence” method, which assumes that ambient pollution is confined to and evenly distributed within the host unit of analysis. This method sums the number of hazards located in the study area, sums the pounds of pollution emitted in the analysis unit or creates a dummy variable that indicates whether or not an analysis unit contains a hazard. This method does not account for edge effects, ambient pollution spreading outside the pre-set boundaries, or the lack of even distribution of pollution which can occur within the host unit. A large number of environmental justice studies have used this approach to compare the population characteristics of host areas with areas that do not host polluting facilities (e.g., United Church of Christ Commission for Racial Justice 1987; Anderton et al. 1994).
Circular buffer analysis is an alternative method used to establish impacted areas and populations from pollution exposure, typically on the basis of GIS software. The idea of buffering or uniform buffering is to identify a pollution source and then choose circular areas of a specified radius (e.g., 0.5, 1, 2, 5 miles from the center) with the pollution source representing the center of the circle. While circular areas address some of the limitations of the unit-hazard coincidence method, there are a few problems associated with its application. The first problem is the arbitrary choice of radius to define circular areas which is not generally based on the quantity or toxicity of emitted pollutants (Chakraborty and Armstrong 1997). Secondly, uniform buffering does not account for varying toxicity levels of exposure and assumes that all areas within the buffer are exposed to equal risks. The third problem is that it assumes that a population is only exposed to the one source instead of multiple sources. These issues can be mitigated by several more rigorous methods of buffering and modeling techniques.

The circular buffer approach has been utilized in many prior studies of environmental injustice. Glickman (1994), for example, used buffer analysis in Allegany County, Pennsylvania to determine the proximity of non-White residents to industrial manufacturing facilities reporting toxic emissions. He found that non-Whites bear less of a burden than Whites and populations above the poverty line. This finding was due to the aggregate effect of combining all hazard sites and based on the large size (2 mile radius) of the buffers. At a smaller scale (0.5 mile and 1 mile radius) the residents closer to the sites were predominantly non-White and impoverished but as the radius of the buffer expanded it encompassed the White and wealthier population. The updated version of the national scale *Toxic Waste and Race* study (United Church of Christ Commission for
Racial Justice 2007) used 1.8 mile radius buffers to examine populations in proximity to hazardous waste facilities. This study found that minorities were the predominant population who lived within the analyzed distance of hazardous waste sites in the US. Although studies relying on the circular buffer approach have reported disproportionate risk burdens imposed on the population, uniform buffers lack the ability to analyze dispersion patterns of emitted chemicals based on their physiochemical properties and related meteorological factors. Additionally, the buffers fail to determine the impact of individual and cumulative effects of toxicity related to the point sources of pollution and thus limits the discovery of health outcomes and the resultant health disparities on the affected populations.

2.2.3.2 Contemporary Analytical Techniques

New methods are being developed to address exposure, risks and outcomes as a result of hazardous pollutant emissions. In the past, limitations have been placed on environmental justice studies because of the lack of data pertaining to exposures from chemicals. Currently, methods are being constructed to take into account the influence of varying levels of toxicity and multiple chemical exposures on a population.

Dispersion Models Atmospheric dispersion modeling is a “predictive method used to estimate concentrations of pollutants in the atmosphere resulting from point or non-point atmospheric emissions” (Dent and Henriques 2000). Advances in fate and transport techniques have introduced dispersion models, allowing them to be interwoven with census derived socioeconomic parameters and demographics using GIS to go beyond basic identification of the location of industries and the populations. The models can
now provide assistance in exploring the potential health impacts as a result of the pollution.

Several dispersion models are available for modeling of fate and transport of industrial releases into the atmosphere (e.g., DEGADIS and ISCLT). These models are routinely used by the US EPA, NOAA and other private and governmental bodies as methods of discerning fate and transport of chemicals through the atmosphere. Specifically, DEGADIS and ISCLT are routinely used in conjunction with other models to identify different types of industrial releases (short and long-term releases).

**Short-Term Release Model** DEGADIS is a mathematical dispersion model that can be used as a refined modeling approach to estimate short-term ambient concentrations and the expected area of exposure to concentrations above specified threshold values for toxic chemical releases.

Chemicals with an atmospheric density greater than air, i.e., a heavy gas, is modeled using DEGADIS which accounts for the sinking of the gas cloud to the ground and as it dissipates with distance from the source then the chemicals behavior imitates a chemical with physiochemical properties more similar to air which is signified when the concentration drops below 1% or 10,000 parts per million (ppm) of air (Figure 2).
Figure 2: Heavy gas dispersion from gravity (US Environmental Protection Agency and National Oceanic and Atmospheric Administration 2007)

Limitations of the DEGADIS model include the fact that they cannot be used in complex terrain (e.g., valleys) and during high sea breeze. In spite of these limitations, this non-Gaussian model is particularly important for analyzing chemicals which are heavier than air and do not easily disperse in the environment. Scenna and Santa Cruz (2005) used DEGADIS to explore the risk of chlorine gas dispersion from mobile sources in Argentina. They found that the model was able to interpret that there was an increased risk to persons in cars and the resident population if a release were to occur.

**Long-Term Release Model** The Industrial Source Complex (ISCLT versions 1, 2 or 3) is a Gaussian model used for long-term releases into the atmosphere. It provides good spatial resolution near sources but cannot predict fate and transport greater than 50km from the source (US Environmental Protection Agency 1996b). Chemicals with an atmospheric density similar to air (1.1 kg m\(^{-3}\)) are processed in the Gaussian model which is represented by a bell curve that becomes flat as the concentration of the chemical declines as it diffuses from the source of the release (Figure 3).

![Figure 3](image)

Figure 3. Gaussian distribution and spread of chemical from source. (US Environmental Protection Agency and National Oceanic and Atmospheric Administration 2007).
Both these models provide significant contributions to interpreting the complexity of how toxic chemicals are dispersed throughout the environment. They lend important guidance to modelers and risk assessors to the identification of areas potentially exposure to chemical emissions and adverse health effects. Furthermore, they provide necessary information in pinpointing where environmental inequities can occur as a means of outlining the potential exposure to the population.

2.3 Environmental Health Disparities

Numerous definitions have been provided to explain a health disparity (Table 1). Keppel (2005) writes that health disparities are not simply about differences in health. The term “difference” in itself has many meanings including inequity, inequality and injustice (Krieger 2005). The first definition developed by the US government was prepared by the National Institutes of Health in 1999 as part of a development plan on reducing health disparities (Table 1). A year later this definition was improved with a broader definition provided by the National Center for Minority Health Disparities. This new definition included a proportional comparison to the general public not just “among population groups”(US Congress 2000; Institute of Medicine 2006).
Table 1: Government definitions of health disparities.

<table>
<thead>
<tr>
<th>Government Source</th>
<th>Definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>National Institutes of Health (1999)</td>
<td>“Health disparities are differences in the incidence, prevalence, mortality, and burden of diseases and other adverse health conditions that exist among specific population groups in the United States.”</td>
</tr>
<tr>
<td>Minority Health and Health Disparities Research and Education Act (2000)</td>
<td>“A population is a health disparity population if there is a significant disparity in the overall rate of disease incidence, prevalence, morbidity, mortality or survival rates in the population as compared to the health status of the general population.”</td>
</tr>
<tr>
<td>National Cancer Institute date unknown</td>
<td>“Differences in the incidence, prevalence, mortality, and burden of cancer and related adverse health conditions that exist among specific populations groups in the United States.”</td>
</tr>
<tr>
<td>Healthy People 2010 (2000)</td>
<td>The second goal of Healthy People 2010 is to “eliminate health disparities among different segments of the population, including differences that occur by gender, race or ethnicity, education or income, disability, geographic location, or sexual orientation.”</td>
</tr>
</tbody>
</table>

The National Cancer Institute (NCI) and Healthy People 2010 goals provide more topically focused definitions. The NCI specifically focused on cancer disparities while Healthy People 2010 goals are geared independently on all affected demographic groups (US Department of Health and Human Services 2000; National Cancer Institute 2007). Healthy People 2010 is a set of goals established by the US Department of Health and Human Services and includes this definition (Table 1) as part of its mission not only to decrease but eliminate health disparities in the US (US Department of Health and Human Services 2000).
This far-reaching definition encompasses all demographics of the population thereby extending the goal to all residents. The following section outlines the causes of health disparities, how they are measured, and their health outcomes.

2.3.1 Influential Variables on Health Disparities

There is not a single cause of a health disparity. Health disparities result from the interaction of social, cultural, racial and economic factors, as well as geographical locations. Socioeconomic status (SES) as measured by education attained, income levels, and occupation along with race/ethnicity are listed as the most common influences for health disparities (National Research Council 2004). Additional factors, including personal behaviors, culture (language and acculturation), genetics, gender, and physical environment (where you live, work, types of exposures), can also contribute to health disparities.

2.3.1.1 Race/Ethnicity

Numerous studies have determined that race/ethnicity is an influential factor of health disparities. Studies have found that minorities have higher risk to exposures because Whites and minorities do not “work, live or play” in the same places (Lee 2002). This idea is promoted through the persistent role of residential segregation still in effect post-desegregation and the related policies (Williams and Jackson 2005; Morello-Frosch and Lopez 2006). Acevedo-Garcia (2000) stressed that segregation concentrates poverty, overcrowded and dilapidated housing, and social disintegration in minority neighborhoods. Maantay (2005) identified that in the Bronx, New York, 13 percent of the population living near the hazardous facilities hospitalized for asthma were more likely to be minorities. At a different scale, Bai et al. (2007) found that Black children in
Pennsylvania were twice as likely to have more severe asthma symptoms after controlling for SES. Although anti-discrimination policies have been in effect in the US for over 40 years (US Department of Justice 1964), institutionalized racism is pervasive in society and has a powerful impact on where people live and work and their economic status. According to a study on infant mortality rates (IMR) conducted by Laveist (2002), the US White (IMR=11) population closely resembles more developed countries while the US Black population (IMR=20) reflects mortality rates in less developed countries, when viewed separately on an international scale.

2.3.1.2 Socioeconomic Status

Socioeconomic status (SES), independent of other factors, has been found to influence health disparities. When looking at the impact of SES on health disparities Maantay (2005) found that 30 percent of the population living near hazardous facilities in Bronx were hospitalized for asthma were more likely to be below the poverty level. Several other studies have observed that wealth is a contributing factor to health outcomes. Chen (2006) found that persons living in census tracts with high poverty levels have an increased incidence of premature death. Low-income areas are fraught with environmental pollution and poor infrastructure. Additionally, persons of low income tend to have limited access to health care and proper nutrition further contributing to the process of health disparities in this group (O'neill et al. 2003).

2.3.1.3 Other Factors and Susceptible Populations

Gender and genetics play a distinct role in health disparities. Health disparities have a link to genetics as they have been found to increase the susceptibility of certain
diseases on individuals carrying the gene (e.g. breast cancer, BRCA1,2 genes or Colon
cancer, MSH2 gene)(Edlin and Golanty 2004). Furthermore, gender (as a biological role
and a social role) can influence whether a health disparity occurs (Coreil and Henderson
2001). Human males and females not only have genetic variability, but also have a
physiologically different metabolism thereby allowing certain people to be susceptible to
various exposures. For example, men and women have different breathing patterns on
average and thus their inhalation of chemicals would be different (Hinds 1999).

The social role of gender can be expressed through cigarette smoking. Smoking
is known to be highly correlated with lung cancer. In the US, men smoke at a higher
percentage (23.4 percent) than women (18.5 percent) (Centers for Disease Control and
Prevention 2004). This lifestyle behavior provides evidence that if it was adapted then
the prevalence of lung cancer in the US populations would decrease. Additionally, other
lifestyle behaviors like nutrition, alcohol, and occupation could contribute to health
disparities and should be evaluated for causation.

Additional susceptible populations such as persons with compromised immune
systems, young children, elderly and fetuses (maternal exposure) can play a role in
outcomes of health disparities. Young children are susceptible to lead poisoning and
other neurologic damage as they grow into adulthood. The elderly population may have
compromised immune system from slower metabolisms and difficulty recovering from
injury. Lastly, fetuses are a susceptible population because exposure in the womb may
result in the increased opportunity for preterm deliveries, deformities, neurotoxicity,
decreased mental acuity and death (Carpenter et al. 2002; Woodruff et al. 2003).
2.3.2 Measures of Health Disparities

The choice of subpopulations as a method of measurement for environmental inequity studies is a critical issue for researchers. Several subpopulations are customarily studied as variables used to represent environmental inequities namely, race/ethnicity, and income. Additionally, there are specific susceptible subpopulations identified through evidence obtained from environmental health disparity and adverse health effect studies e.g., the elderly, children, fetuses (prenatal exposures) and persons with depressed immune systems (HIV and chronic illnesses (kidney, liver diseases).

2.3.2.1 Race/Ethnicity

Many studies use race/ethnicity as variables of choice for assessing health disparities but there are a multitude of challenges and potential inaccuracies that can, will, and do result from the use of race/ethnicity variables. In the US, race/ethnicity is primarily self-reported on the US Census and health care documents and thus it carries an inherent bias (positive or negative). The limitations of the US Census surveys as well as the multitude of mixed race individuals confound analyses in social and geographic research. Furthermore, the change in the racial/ethnic categories between decennial surveys results in a lack of consistency between the collection years. For example, over the last 30 years on the US Census, the category of Black “race” has been altered three times from Black in the 1900’s, to Negro in the 1950’s, to Black/African American in the year 2000 (National Research Council 2004). Additionally, race/ethnicity when not self-reported is assumed by the perception of individuals, entering more bias into the data stream. For example, persons from many Latin American countries may have African ancestry but tend to identify themselves as being Latino or Hispanic. These individuals
could be perceived as Black if visually surveyed, but if verbally questioned they would identify themselves as being of Hispanic origin. This is further exacerbated by the introduction of self-reported multiple race categories on the 2000 census.

Environmental justice studies typically use variables describing racial/ethnic and economic characteristics of the populations for studying the disproportionate impacts of toxic exposures. Most studies examine Black and White populations as the primary variables for assessing environmental injustice, but neglect the myriad of diverse races/ethnicities that exist in the US (Bullard 1990; Perlin and Wong 1999). This dichotomous relationship is slowly being expanded by the inclusion of Hispanic and Asian populations but other races/ethnicities such as Native Americans that potentially experience environmental injustice and environmental health disparities are neglected (Ash and Fetter 2004).

2.3.2.2 Socioeconomic Status and Income

Socioeconomic status encompasses income, occupation and education. Income itself can be parsed into current income, wealth, and lifetime wealth (National Research Council 2004). Current income variables provide data for annual cash flows and are presented by the most common used measures of income namely, median household, poverty levels and percent poverty. When using current income as a variable it is important to realize that, like race/ethnicity data, income is also self reported. Additionally, many individuals are unwilling to disclose their income level and will therefore leave the item blank or report false data.

Annual household income levels have been used to measure economic status in many environmental justice analyses. Studies use the income distribution of each
individual race/ethnicity, household income (median or mean), poverty thresholds and/or poverty guidelines. Median household income (MHI) is used in a particular area and can account for income status over space and time (US Census Bureau 2000; Liu 2001). The MHI reports the income of all residents of the household over 15 years of age. There are several problems with the median household income variable. First, it is not available at finer geographical scales. Second, the decennial US census reports MHI to the block group level while in outside of the decennial census year the county level is reported. Third, it is not possible to count low-income individuals.

Poverty thresholds are also used as tools for measuring income. The federal poverty threshold is based on the definition of poverty established by the US Social Security Administration (SSA) in 1964. The poverty measure is based on the recognition that families of three or more people across all income levels spend 1/3 of their income on food; therefore the SSA multiplied the Economy Food Plan established by the US Department of Agriculture by a factor of three to obtain the poverty threshold (US Census Bureau 2000; Liu 2001). The poverty threshold is revised annually to reflect the cost of living of United States in totem, but does not account for variation in regional cost of living. Additionally, household poverty levels only measure blood-related family members in households where a family member is the head. This measurement can result in an underestimation of the number of people in poverty since people who are unrelated may live together to pool their economic resources.

2.3.2.3 Wealth, Education, and Occupation

Wealth which is comprised of the accumulation of assets (e.g., stock and home ownership) and lifetime wealth are used in longitudinal studies as a measure of lifetime
income. Wealth and lifetime wealth can be difficult to measure, but are useful in that they can provide observations into how persons with high wealth can have access to healthcare thereby preventing a disparity and persons with low wealth could be mired in the welfare health care system resulting in higher morbidity and mortality rates.

Educational levels are also used to determine SES. This variable typically is based on level of school completed; it gives a representation of intellectual, behavioral and financial ability. It can also be used as a proxy for the ability of a person to obtain and comprehend health information and diagnoses (National Research Council 2004). This measure is relatively stable over a life-time and correlates well with occupation, income and social status. The inadequacy in the measure is that it is not tracked geographically on an individual level; therefore the quality of education cannot be determined. Ash and Fetter (2004) and Sicotte and Swanson (2007) included residents with less than high school education as a variable in their studies and found that block groups with a larger amount of adults without diplomas tend to live in more polluted areas. Anderton et al. (1994) used the mean value of housing stock as a proxy for neighborhood wealth and found significantly lower values in tracts containing hazardous waste facilities. More recently, Pastor et al. (2005) have argued that home ownership is not only a measure of the wealth possessed by a community, but also a potential indicator of political involvement based on the assumption that home ownership implies leads to higher concern for the local environment due to invested capital. Their study indicated that the census tracts with higher levels of home ownership are less likely to be exposed to the adverse health risks from air pollution in California.
Occupation is used in exposure studies and can be an indicator of outcomes. Although the occupation variable may be less difficult to collect than the income variable and is a proxy for income, it suffers from a lack of economic information.

2.3.3 Effects of Environmental Health Disparities

Routes of exposure can be dermal, respiratory and oral pathways (Figure 4). These exposures can result from moderate to terminal adverse health outcomes (effects). Outcomes are defined as the affect of exposures on a given population. Some outcomes of environmental health have been identified as increased incidence of asthma in children in the inner city, cancer clusters and congenital birth defects (Oleckno 2002). Chemical exposures to populations can either be acute or chronic and can result in numerous outcomes to the exposed population.
2.3.3.1 Acute Exposure and Health Effects

According to the US Environmental Protection Agency (US Environmental Protection Agency 2006a) acute exposures are defined as single, non-repetitive exposures between 10 minutes and 8 hours. These exposures can cause adverse health outcomes ranging from mild eye and respiratory discomfort, irritation, prolonged multi-organ systemic effects to death. The effects of acute exposure are based on the interactions of susceptible populations the toxicity levels and the route of exposure. An acute exposure of mercury has been found to cause coughing, burning in the lungs, gastrointestinal
problems, increased blood pressure, eye irritation and in high doses kidney problems and
development issues with fetuses and death (Zeitz and Kaye 2002). Although mercury can
enter the body via dermal absorption or ingestion its most effective route of entry is by
inhalation therefore atmospheric exposure during spills can result in significant exposure
and concentrations to the general population.

2.3.3.2 Chronic Exposure and Health Effects

Vulnerable populations, namely the elderly, the chronic ill, people with
compromised immune systems and children, have been recognized as special populations
when evaluating health outcomes. These populations tend to have a greater risk from
environmental exposures for several reasons. The elderly as they age may suffer
debilitating diseases (decreased liver and kidney functions) and have increased poverty
rates resulting in poor health care and subsequently resulting in poor health. The chronic
ill with compromised immune systems (e.g., people with AIDS, cancers, liver and kidney
disease) tend to have depressed immune systems which make them highly susceptible to
environmental exposures. Children are listed as a special group because environmental
exposures to the young could negatively impact them for a lifetime. Lead (Pb) exposure
during the mental development phase of young children has been found to cause
neurological damage and result in slow mental cognition and brain damage (Lanphear
and Roberts 2005; Jain and Hu 2006). Additionally, numerous cohort studies have
identified the increased prevalence of asthma in the US of 75 percent between 1980 and
1994 (Brown and McCormick 2004). Although a single cause of asthma has not been
identified most studies agree that air pollution specifically PM$_{2.5}$ is the primary outdoor
pollutant that influence asthma attacks.
Additionally, fertility issues concerning exposure and disparities have arisen in the general population. Studies have found that air pollution during pregnancy increased the risk of poor birth outcomes in minorities and low-income populations (Bobak and Leon 1999; Woodruff et al. 2003). Specifically, low birth weight, premature births, and infant mortality have been found to be greater in areas where the mothers are of low socioeconomic status (as measured by education level attained) and minority status. Berry and Bove, (1997) found that full-term births of parents living closest to landfills in Gloucester County, New Jersey were 5 times more likely (OR=5.1) than the general population to have a low birth weight baby. Wilhelm and Ritz, (2003) also found that in addition to air pollution negatively impacting the birth outcomes, residential proximity to traffic could also affect birth outcomes in the exposed populations. Specifically, they found that women who were exposed to traffic pollution during the winter months (more stagnant air) received greater exposure and therefore negative birth outcomes could be increased.
3. STUDY AREA

The study area for the proposed dissertation research is the Houston Galveston Brazoria-Consolidated Metropolitan Statistical Area (HGB-CMSA) which is comprised of eight counties (Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, and Waller counties) as defined by the 2000 US Census (Figure 5). Over the last 50 years, this area has experienced substantial growth in population and land area. In 1950, the incorporated city of Houston comprised 167 square miles which increased to 617 square miles by the year 2000 (Melosi and Pratt 2007). In the same time-period (1950-2000), the population in the metropolitan statistical area more than quadrupled from 908, 822 to 4,715,407, and the land area of the MSA increased to approximately 2,000 square miles. This increase of land area was driven in part by annexation, uncontrolled urban sprawl and lack of zoning laws (Melosi and Pratt 2007).
Figure 5: Counties of the Houston Galveston Brazoria-Consolidated Metropolitan Statistical Area.
3.1 Racial, Economic, and Industrial Context

Table 2 outlines the racial/ethnic and poverty characteristics of the population in this metropolitan area. Over 90 percent of the population in 2000 lived in the urban areas of the MSA. According to the 2000 census, total population of the HGB-CMSA was about 4.7 million with nearly 15 percent below the federal poverty level. In the year 2000, racial/ethnic minorities comprised approximately half of the total population with the Hispanic population being the largest group.

Table 2: Census Year 2000 Houston--Galveston--Brazoria, TX CMSA Sociodemographic and Socioeconomic Status (Green Media Toolshed 2005)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Population</td>
<td>4,669,571</td>
</tr>
<tr>
<td>Urban:</td>
<td>4,294,571</td>
</tr>
<tr>
<td>Rural:</td>
<td>375,000</td>
</tr>
<tr>
<td>Percent Hispanic or Latino</td>
<td>28.9</td>
</tr>
<tr>
<td>Percent White alone</td>
<td>47.9</td>
</tr>
<tr>
<td>Percent Black or African American alone</td>
<td>16.6</td>
</tr>
<tr>
<td>Percent American Indian and Alaska Native alone</td>
<td>0.3</td>
</tr>
<tr>
<td>Percent Asian alone</td>
<td>4.8</td>
</tr>
<tr>
<td>Percent Native Hawaiian and Other Pacific Islander alone</td>
<td>0.0</td>
</tr>
<tr>
<td>Percent Some other race alone</td>
<td>0.1</td>
</tr>
<tr>
<td>Percent Two or more races</td>
<td>1.4</td>
</tr>
<tr>
<td>Percent Below Poverty Level</td>
<td>13.5</td>
</tr>
<tr>
<td>Median household income in 1999 ($)</td>
<td>44,761</td>
</tr>
</tbody>
</table>

The increase of the population from about 120,000 in 1900 to today’s count of 5.2 million (ca 2007) along with an increase in automobile usage has lead to the area becoming a nexus for widespread toxic pollution where oil production, oil refineries and automobile transportation coincide. Historically, this area has morphed from primarily farming to manufacturing industry. The discovery of crude oil at Spindletop (Beaumont, Texas) in 1901 provided ample employment and migration of populations into the Texas
Gulf Coast (US Census Bureau 2002). As the extraction of crude oil increased, related facilities (i.e., refineries, polymerization plants and facilities) were established to synthesize chemicals with the majority of industries related to oil processing. As a result, an increase in the population surrounding these facilities occurred along with an increase in ground transportation (e.g., trucking routes and railways), in addition to the existing shipping corridors via the Gulf of Mexico. Table 3 classifies polluting industrial facilities located in the study area listed in the USEPA’s Toxic Release Inventory database, based on their manufacturing activities as defined by Standard Industrial Classification (SIC) codes. As indicated in the table, a large majority of these polluting industries are involved in the production of organic chemicals and paint related chemicals as well as industries related to oil and gas refineries. The locations of the TRI facilities are provided in Figure 6.

Table 3: Industries in the HGB in 2000 (US Environmental Protection Agency 1996a)

<table>
<thead>
<tr>
<th>SIC Code Long Names</th>
<th>Number of Facilities</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industrial organic chemicals, n.e.c.</td>
<td>87</td>
<td>13.0</td>
</tr>
<tr>
<td>Plastics materials, synthetic resins, and non-vulcanizable elastomers</td>
<td>29</td>
<td>4.3</td>
</tr>
<tr>
<td>Oil and gas field machinery and equipment</td>
<td>27</td>
<td>4.0</td>
</tr>
<tr>
<td>Coating, engraving and allied services, n.e.c.</td>
<td>26</td>
<td>3.9</td>
</tr>
<tr>
<td>Chemicals and allied products, n.e.c. (wholesale trade)</td>
<td>22</td>
<td>3.3</td>
</tr>
<tr>
<td>Industrial inorganic chemicals, n.e.c.</td>
<td>22</td>
<td>3.3</td>
</tr>
<tr>
<td>Chemicals and chemical preparations, n.e.c.</td>
<td>21</td>
<td>3.1</td>
</tr>
<tr>
<td>Paints, varnishes, lacquers, enamels, and allied products</td>
<td>21</td>
<td>3.1</td>
</tr>
<tr>
<td>Industrial gases</td>
<td>19</td>
<td>2.8</td>
</tr>
<tr>
<td>Petroleum bulk stations and terminals</td>
<td>19</td>
<td>2.8</td>
</tr>
<tr>
<td>Plastics products, n.e.c.</td>
<td>18</td>
<td>2.7</td>
</tr>
<tr>
<td>Ship building and repairing</td>
<td>13</td>
<td>1.9</td>
</tr>
<tr>
<td>Petroleum refining</td>
<td>12</td>
<td>1.8</td>
</tr>
<tr>
<td>Other Industries</td>
<td>332</td>
<td>49.7</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>668</strong></td>
<td><strong>100.0</strong></td>
</tr>
</tbody>
</table>
Figure 6: Locations of Toxic Release Inventory Facilities in the HGB-MSA, 2000
3.2 Previous Environmental Justice Studies in the Houston Area

Several prior studies have examined environmental justice issues in the Houston metropolitan area. Table 4 provides a summary of empirical studies conducted in the Houston area, including the type of hazard examined, analytical unit used, and their research findings. Bullard’s seminal study, initially conducted in 1983 and published in his book *Dumping in Dixie* (1990), found solid waste facilities in Houston to be disproportionately located in Black “neighborhoods.” Been (1994) and Liu (1997) used longitudinal analyses to extend Bullard’s study, in order to assess pre-siting and post-siting changes in neighborhoods hosting these waste facilities. The objective of these studies was to determine whether polluting facilities were disproportionately sited in minority neighborhoods, or if minority residents moved to host neighborhoods subsequent to siting. Although Been’s (1994) choice of analytical unit was different from those used in the Bullard’s study (census tracts versus neighborhoods), Been’s study did not provide rigorous statistical comparisons. However, Been found that the percentage of African Americans and low-income individuals in census tracts containing landfills had increased over time. Liu (1994), on the other hand, used quantitative statistical techniques and did not find any evidence of solid waste facilities playing an important role in the locations of Black or impoverished populations in Houston. Additionally, an updated version of the pioneering *Toxics Wastes and Race* study conducted by the United Church of Christ (2007) found that Houston had the second largest percentage of minorities living in neighborhoods that contain hazardous waste facilities. Although these studies played an important role in exploring inequities in the siting process of waste facilities, they used simplistic methods to identify populations at risk and did not
assess disproportionate exposure to atmospheric pollution or related health effects associated with polluting facilities.

Table 4: Selected Studies Examining Aspects of Environmental Justice in Houston, Texas

<table>
<thead>
<tr>
<th>Author/Year</th>
<th>Hazard</th>
<th>Unit of Analysis</th>
<th>Analytic Method</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bullard (1983)</td>
<td>solid waste facilities</td>
<td>City of Houston neighborhoods</td>
<td>Descriptive and historical analysis</td>
<td>Sites were more likely to be found near Black neighborhoods and Black schools a)LULUs had a disproportionate affect on Blacks and poor b)areas where LULUs were located drove down housing prices c)neighborhoods became increasing populated with Blacks</td>
</tr>
<tr>
<td>Been (1994)</td>
<td>solid waste facilities</td>
<td>City of Houston census tracts</td>
<td>Descriptive and historical analysis</td>
<td>a)LULUs had a disproportionate affect on Blacks and poor b)areas where LULUs were located drove down housing prices c)neighborhoods became increasing populated with Blacks</td>
</tr>
<tr>
<td>Liu (1997)</td>
<td>solid waste facilities</td>
<td>City of Houston census tracts</td>
<td>Difference of means parametric and nonparametric tests</td>
<td>No evidence provided to support the hypothesis that the presence of LULUs made the neighborhoods home to more Blacks and poor people</td>
</tr>
<tr>
<td>UCC (2007)</td>
<td>hazardous waste facilities</td>
<td>City of Houston neighborhoods</td>
<td>Descriptive and historical analysis</td>
<td>Second largest % of people of color living in host neighborhoods</td>
</tr>
</tbody>
</table>

3.3 Suitability of the Study Area for Proposed Research

The Houston Galveston Brazoria-Consolidated Metropolitan Statistical Area (HGB-CMSA) area is particularly well-suited for studying environmental justice and health disparities in the distribution of toxic pollution for several reasons. First, its location along the mid-Texas Gulf Coast has historically included a variety of industrial, petrochemical, and manufacturing companies. This agglomeration of industries was situated in proximity to shipping routes for ease of transporting crude oil throughout the global oil economy and as such the area is prone to exposure from toxic pollutants associated with petrochemical related emissions and runoff. Second, the area has a racially and ethnically diverse population as outlined in Table 3, with the White
population comprising less than 50 percent of the total population. Third, several national environmental databases suggest that counties in the Houston metropolitan area are among the most polluted in the US. In 2002, four of the eight counties in the CMSA (Brazoria, Fort Bend, Galveston, and Harris) were ranked in the top 10 percent of all US counties in terms of total chemical releases and waste generation (Green Media Toolshed 2005). Furthermore, three out of eight counties (Harris, Brazoria and Galveston) were ranked in the top five of counties in Texas with the greatest reported releases of recognized carcinogens to air, with Harris County being number one. These pollution-based rankings further support the selection of this area as appropriate for this dissertation research. The rankings underscore the severity of exposure on the population and how these exposures can potentially result in adverse health outcomes.
4. DATA SOURCES, MODELS, AND METHODS

A variety of methodologies and information sources have been used for environmental justice and environmental health disparities research, over the last two decades. Data sources are typically provided by government entities such as the US Environmental Protection Agency (USEPA), Centers for Disease Control and Prevention (CDC) and the National Cancer Institute (NCI). These organizations provide information on sources of toxic pollution and their health effects including morbidity, mortality and disease incidence and prevalence in a given population at the national, state and county levels. Recent advances in computer databases, surveillance systems, environmental monitoring and pollution modeling allow an improved and more rigorous analysis of environmental health risks and associated disparities. This chapter explores the use of data sources and risk models for assessing chronic exposure that were utilized in this research and provides an overview of the statistical techniques used to analyze racial/ethnic and socioeconomic inequities in the distribution of exposure. Demographic and socioeconomic data that were used to identify the population at risk and measure health disparities are also described.

4.1 Data Sources for Pollution Exposure and Health Risk Assessment

Chronic exposures were analyzed using the USEPA’s Toxic Release Inventory (TRI) database in conjunction with the Risk Screening Environmental Indicator (RSEI)
model. These data sources and models are thoroughly examined in the following sections to provide guidance on their usage in this research.

4.1.1 Chronic Exposure

4.1.1.1 The Toxic Release Inventory

The USEPA’s Toxic Release Inventory (TRI) database is the most widely used resource for assessing toxic pollution in research on environmental justice and health disparities since the early 1990s. The TRI provides information on the annual amounts of toxic chemicals released into the environment from industrial manufacturing activities, metals and coal mining, electric utilities, commercial hazardous waste treatment and government facilities. The TRI began in 1988 as a response to the Emergency Planning and Community Right to Know Act (EPCRA) and currently reports releases of nearly 650 different hazardous chemicals annually (US Environmental Protection Agency 2006b). For each facility, the TRI database includes its name and address, locational coordinates (degrees of latitude and longitude), the type of industry or manufacturing activity, federal information processing standards (FIPS) codes, and the annual quantity of each toxic pollutant released. A facility must report to the database if it meets the following conditions:

1) is involved in manufacturing, metal mining, coal mining, electrical utilities that combust coal and/or oil for the purpose of generating power for distribution in commerce;

2) is part of the Resource Conservation and Recovery Act (RCRA) Subtitle C hazardous waste treatment and disposal facilities, chemical wholesaler, petroleum
terminals and bulk stations, solvent recovery services with certain Standard Industrial Classification Codes (SIC), a federal facility in any SIC code;  
3) employs 10 or more full-time-equivalent employees; and  
4) manufactures or processes more than 25,000 pounds or otherwise uses more than 10,000 pounds of any listed toxic chemical during the calendar year (US Environmental Protection Agency 2004c).

In spite of providing a comprehensive inventory of annual releases, there are several limitations of the TRI for measuring adverse health effects. First, it reports only releases of chemicals and not exposure or toxicity data. Second, TRI data are self-reported and not monitored by the USEPA, which can lead to under-and/or overestimation of actual chemical releases. Finally, not all chemical releases are reported and only those which reach the established thresholds are collected. Additionally, it is important to note that small quantities of highly toxic chemicals may persist longer in the environment and be more toxic to the exposed population than certain chemicals that are in larger quantities and less toxic. Therefore, it is important to include fate and transport data, exposure and toxicity levels in order to have an effective tool for assessing risks to a given population.

4.1.1.2 Risk-Screening Environmental Indicators for Chronic Human Health Model

The Risk-Screening Environmental Indicators (RSEI) for Chronic Human Health Model is a screening tool that evaluates the exposure of toxic chemicals released to the environment from industrial sources. It was developed by the USEPA for assessing potential risk to human health based on physiochemical properties of ambient pollutants and related fate and transport in the environment, as opposed to using only the quantity
(pounds) of annual releases that are reported by the Toxic Release Inventory (TRI) database. The RSEI is capable of extending environmental health disparities and justice research by adding a much needed health risk assessment component to the TRI database.

The RSEI combines fate and transport, toxicity, exposure, population (US Census) with TRI data on a 1 km by 1 km tessellated grid system and models the risk from individual facilities at local, state and national levels (US Environmental Protection Agency 2004a). It combines the amount of chemicals released, the facility location, the toxicity of the chemical, fate and transport through the environment, the route and extent of human exposure, and the number of people affected for up to 44 miles from each industrial release source (US Environmental Protection Agency 2004b). The model itself can be adapted for use on other chemicals not included in the TRI, thereby expanding the number of substances that can be explored for human health and environment impacts.

The RSEI model begins with an “Indicator Element” which is the combination of the chemical release from the TRI facility and exposure pathway (e.g., emissions from powerplants). Each Indicator Element is associated with a set of results, which consist of three types of scores: (a) pounds-based, (b) hazard-based, and (c) risk-based, as summarized in Table 5.

Table 5: RSEI Indicator Element mode

<table>
<thead>
<tr>
<th>Results</th>
<th>Model Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk-based results</td>
<td>Surrogate Dose * Toxicity Weight * Population</td>
</tr>
<tr>
<td>Hazard-based results</td>
<td>Pounds * Toxicity Weight</td>
</tr>
<tr>
<td>Pounds-based results</td>
<td>TRI Pounds released</td>
</tr>
</tbody>
</table>

Source: (US Environmental Protection Agency 2004d)
Pounds-based results are provided for Indicator Elements as the number of pounds associated with each toxic chemical released annually from each facility reported by TRI. The model also calculates the pounds along with the chemical-specific toxicity weights. All of these Indicator Elements can be numerically combined to assess modeled risk of pollution to chemicals, facilities and by exposure pathways on local, state and national levels. Hazard-based results are calculated by multiplying pounds released by the chemical specific toxicity weight for the given exposure route (oral or inhalation). It also calculates ‘Modeled Hazard’ which is the chemical-specific toxicity weighted multiplied by the ‘Modeled Pounds’ without fate and transport modeling (Table 5).

The risk-based results score is a unitless value proportional to the potential risk-related impact of each element. Risk-based results are obtained by modeling the surrogate dose by using fate and transport and population exposure factors (exposure pathway). The model calculates Indicator Elements for the entire population, children under 10, children 10 to 17, males and females age 18 to 44 and adults over 65. It also calculates ‘Modeled Pounds’ which is the number of pounds that can be modeled before fate and transport and exposure assumptions are applied (Table 5). The scores for each hazard (i.e., pounds, hazard and risk-related results) are based on the aggregation of all chemicals released from each facility and their related toxicity. For each type of pollution indicator (pounds, hazard and modeled risk), a single number is computed for each released chemical and aggregated to represent the total atmospheric emissions from that source (TRI facility). Specifically, for hazard and modeled risk scores, the scores are calculated by determining the toxicity of each chemical and aggregating the resultant score to the TRI facility thereby creating a single score per pollution source.
The limitations for the RSEI are that the modeled scores are arbitrary in nature meaning that they are related to each other and toxicity weights may not directly correlate with criteria used for listing chemicals in the TRI. Therefore, the RSEI must be used as a screening tool only. Additionally, the Chronic Human Health model is for chronic effects associated with long-term exposure and not acute toxicity to humans or environment. Other limitations are that the toxicity weights used reflect the single most sensitive chronic human health effect dependent upon inhalation and oral pathways (fish consumption only), and not the most severe health effect or the additive or synergistic effects of exposure to multiple chemicals. These issues can contribute to biases in toxicity calculations by positively or negatively skewing the results and by not accounting for the additive effects of multiple chemicals.

For this dissertation research, a detailed dataset requested from the developers of the RSEI was used to allocate levels of modeled risk to each grid cell (1 km by 1 km). The model calculates concentrations of a 101 km by 101 km grid around the TRI facilities which is then separated into 1 km by 1 km grids. The USEPA provides crosswalk data which contains coordinates of each grid and the proportion of each census block which is contained in each grid. These data allow for ease of transfer of population data from the census block to the grid level.

4.2 Populations at Risk

The census topologically integrated geographic encoding and referencing (TIGER) database was developed by the US Census to establish official cartographic boundaries for the decennial censuses. This data source contains street centerlines, census unit boundaries, and landmarks in digital form. Additionally, data from the 2000
US Census from the summary file 3 (SF3) on the racial/ethnic and economic characteristics of the population was linked with the TIGER/Line files, at both the census tract and block group levels of aggregation. These data can be used with GIS tools, specifically ArcGIS, to spatially relate socioeconomic data to the cartographic boundary files.

Presidential Executive Order (EO) 12898 (Clinton 1994) states that “each Federal agency shall make achieving environmental justice part of its mission by identifying and addressing, as appropriate, disproportionately high and adverse human health or environmental effects of its programs, policies, and activities on minority populations and low-income populations.” The literature on environmental justice and health disparities research has used a large variety of variables to represent “minority” and “low-income” populations as outlined in EO 12898 and reviewed by (Liu 2001) and (McMaster et al. 1997). Minority variables in previous studies have included individuals of Hispanic origin, American Indian/Alaska Natives, Asian, and Blacks or African-Americans. Variables used to measure “low-income populations” and economic status have included the population with a family income below the federal poverty level, median household income, median housing values, home ownership rate, and level of education.

This dissertation research includes all racial and ethnic subgroups outlined in the year 2000 US census namely, White-alone, Hispanic-alone, American Indian or Alaska Native-alone, Asian-alone, Black or African American-alone, Native Hawaiian or Other Pacific Islander-alone, and Other race-alone. Racial subcategories under the non-Hispanic ethnic classification were used in this research to avoid double counting or overlap of racial and ethnic categories defined by the US Census. Additionally, the
overall minority percent was included as a general indicator of the racial/ethnic status of the population; this variable was computed by subtracting the percentage of the Non-Hispanic White population from the total population.

Explanatory variables describing the socioeconomic characteristics of the population included the percentage of the population below the poverty line, labor force, owner occupied houses, and median household income. Population density was used as a control variable based on the assumption that 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 (LN) of this value was included to account for the skewed distribution of the variable as suggested by Mennis and Jordan (2005) and Pastor et al. (2005). The percentage of individuals with an annual family income below the federal poverty line (poverty rate) and median household income were included to measure economic status, following numerous prior studies on environmental justice. The percentage of occupied housing units that are owner-occupied, also known as home ownership rate, was also included as an explanatory variable in an attempt to distinguish between wealth and income. Wealth measures family assets which can be used in case of economic hardship while income is a measurement of disposable cash (Pastor Jr et al. 2004). Previous studies suggest that an increase in the percentage of owner occupied housing is associated with lower levels of toxic pollution and facility occurrence (Pastor Jr et al. 2004; Pastor Jr et al. 2005). The civilian labor force was also included in this study as an explanatory variable. Pulido (1996) found that census tracts with industrial facilities tend to have a higher percent of their population that are in the labor force.
4.3 Methodology for Statistical Analyses

This section focuses on the implementation of methodological and statistical techniques utilized in this study. The initial phase of this research encompasses analytical methods utilized in previous studies of environmental justice, such as host/non-host techniques (bivariate analysis) and ordinary least squares (OLS) regression (multivariate analysis), to examine the effects of variables that influence the distribution of pollution sources and their adverse impacts. The subsequent phases of this study aim to enhance statistical analysis of environmental justice through the use of spatial regression models that control for the effects of spatial dependence in the data.

Each of the four research questions in this study emphasize an unique quantitative indicator of exposure to air pollution from facilities listed in the USEPA’s Toxic Release Inventory (TRI) for 2001:

1) presence/absence of TRI facilities reporting toxic emissions;
2) the total quantity (in pounds) of toxic chemicals released into the environment;
3) the toxicity-weighted hazard score associated with released chemicals; and
4) the modeled risk score, based on the quantity and physiochemical properties of released chemicals, in conjunction with fate and transport modeling.

The four research questions thus focus on determining if each of these variables are related to relevant explanatory factors that describe the race/ethnicity and socioeconomic characteristics of the population in the Houston MSA. Linear regression, specifically ordinary least squares (OLS) regression, was used as the statistical technique for exploring the associations between each dependent variable (i.e., facility presence/absence, pounds emitted, hazard scores, and modeled risk scores) and the set of
explanatory variables. To measure each dependent variable, three different search radii were implemented for each analytical unit (census tract and block group) to assess exposure to the adverse health impacts of toxic chemical emissions and consider releases from facilities that are situated at or near the boundary of the unit (edge effect). These search radii included: 0 mile (at the boundary of the analytical unit), 0.5 mile (0.8 km), and 1 mile (1.6 km). These distances are derived from buffer sizes used in previous studies (Anderton et al. 1994; Glickman 1994; Chakraborty and Armstrong 1997; United Church of Christ Commission for Racial Justice 1987) and recent research which suggests that atmospheric pollution rarely extends beyond two miles from its source (United Church of Christ Commission for Racial Justice 2007).

Racial/ethnic and socioeconomic explanatory variables for multivariate regression were finalized after an initial univariate analysis. Based on the univariate analysis and literature, White alone was removed based on high multicollinearity with Black alone, and median household income was removed based on its high multicollinearity with the other socioeconomic variables such as the percent below poverty and owner occupied housing. The percentage of Native Americans was removed because of its extremely low values across all census units in this study area. Furthermore, each dependent outcome variable and the explanatory variables were assessed for the common statistical assumptions of uncorrelated errors, normality, and constant variance. Following this assessment, the quantity or pounds of released chemicals, toxicity-weighted hazard scores, and the modeled risk scores were transformed to their natural logarithm (LN), while percentages of relevant racial/ethnic categories, individuals below the poverty line, and owner occupied housing units were determined.
Four final multiple regression models were formulated using various combinations of the individual explanatory variables, to explore the statistical effects of different configurations of race/ethnicity and socioeconomic status on the dependent variables (Figure 7). All four models contain population density (natural log of the number of people per square mile), one of the strongest predictors of economic activity and industrial pollution (Ash and Fetter 2004; Pastor Jr et al. 2005). Model 1 and 3 comprise only the race/ethnicity variables, with model 1 containing the overall percentage of minorities and model 3 containing separate variables that represent the percentage of Blacks, Asians, and Hispanics, respectively. Models 2 and 4 combine the race/ethnicity variables along with the socioeconomic variables and population density. These variables provide a more complete picture in order to help differentiate between whether race/ethnicity is the most influential variable on environmental justice or health disparity issues or if economic variables have a contribution.

Given that the first wave of environmental justice studies focused primarily on location inequity in the distribution of pollution sources (United Church of Christ Commission for Racial Justice 1987, 2007), the first research question in this dissertation attempts to determine if the presence or absence of TRI facilities are influenced by different racial/ethnic and socioeconomic variables. Binary logistic regression analysis was used to answer this question, with the dependent variable coded as 1 if the analytical unit (census tract or block group) contained at least one TRI facility and as 0 if it did not contain such a facility, based on the three distance definitions around each unit (0, 0.5, and 1 mile) as mentioned previously. For the remaining research questions that focus on pounds emitted, hazard scores, and modeled risk scores, respectively, ordinary least
squares (OLS) regression was initially used to determine the statistical associations between aggregated density of these dependent variables (based on the three distance definitions) and race/ethnicity and socioeconomic status. Since the assumptions of OLS regression may not be valid if the residuals (error terms) are spatially autocorrelated, further analysis is necessary to assess the effects of spatial dependence in the data.

It should be noted that the use of buffers (0.5 mile and 1.0 mile) around census units to compute these quantities (pounds emitted, hazard scores, and modeled risk scores) can be expected to introduce an additional amount of spatial clustering or autocorrelation in the dependent variable that potentially increases the extent of spatial autocorrelation in the regression residuals. While it is not possible to separate these effects or sources of autocorrelation, the results associated with spatial regression when the dependent variable is based on values obtained from neighboring census units must be interpreted with caution.

For this study, the SAR models use a spatial weights matrix which is specified by three configurations of neighbors: queen-based contiguity, rook-based contiguity, and distance-based bands. The spatial weights matrix for queen contiguity was created by selecting neighboring areal units that touch the boundary and the vertices of the analytical unit being examined. The rook contiguity identifies areal units that only touch the boundary of a given unit. The identification of neighbors in the distance-based spatial weights matrix is based on the inclusion of areal units whose centroids lie within a minimum distance from the centroid of the analytical unit in question, as computed in GeoDA. In order to create spatial weights matrices using distance bands, several different distance values (3 to 5) were examined to define the set of neighboring areal
units for assessing and minimizing spatial autocorrelation. Because census tracts and block groups vary widely in shape and size within a single urban area, a fixed distance band is more likely to ensure a consistent spatial definition of neighbors for detecting and addressing the effect of spatial dependence.

After specifying the spatial weight matrix on the basis of three neighborhood configurations (rook-based, queen-based, and distance-based), the initial diagnoses for spatial autocorrelation were conducted for the OLS regression models. First, Moran’s I was used to determine if spatial autocorrelation existed in the residuals. The residuals were found to be spatially dependent if they yielded a high coefficient for Moran’s I that was significantly different from 0 (p<0.05). To incorporate the effect of spatial autocorrelation, an appropriate spatial autoregressive model (spatial lag or spatial error) was utilized. Four statistical tests were used to determine if the spatial lag approach or spatial error approach would provide the most appropriate correction for each OLS regression model (Anselin 2006). The Lagrange Multiplier (error) was used to assess error dependence and the Lagrange Multiplier (lag) was used to determine if there was a missing spatially lagged variable. Additionally, a robust form of the Lagrange Multiplier (error) was used to test for error dependence in the possible presence of a missing lagged dependent variable and the Robust Lagrange Multiplier (lag) was used to test for a lagged variable in the presence of a missing error dependent variable.

Following the selection of the spatial autoregressive term (lag or error), the residuals from the spatial regression model were estimated and Moran’s I was again calculated. The residuals were found to be spatially dependent if they still indicated a high coefficient for Moran’s I that was significantly different from 0, based on an
inferential test that uses 999 permutations. Once the term was corrected for spatial lag or error, minimization of spatial dependence was confirmed by a lower value of Moran’s I that was not significantly different from zero.

The best fitted spatial autoregressive (SAR) model was first chosen based on the non-significant Moran’s I with a p-value closest to 0. A SAR model with a non-significant Moran’s I improves the OLS model by negating spatial dependence exhibited by the residuals obtained from conventional regression analysis of census data. The maximum likelihood method was used to fit the SAR models as represented by the Akaike Information Criterion (AIC). The AIC as outlined in (Allison 1999; Grove et al. 2006) helps to select the order of the likelihood of a set of nested or non-nested models.

The AIC as represented by

\[
AIC = -2 \log L(M) + 2k, 
\]

accounts for the fit of the model by using the maximized log-likelihood term (\( \log L(M) \)) as well as the number of parameters in the model (\( k \)). The benefit of this test is that it accounts for the model fit as well as the complexity of the model, thereby providing an effective tool in determining the best fitted model. This test has not previously been used in environmental justice research and can potentially contribute to an improved selection of explanatory variables. The AIC tests for the fit of the regression model with an enhancement of complexity of the model (number of variables). The AIC alone cannot be used for likelihood examination, but each measure must be compared to other AICs. The model yielding the smallest AIC is considered to be the best fitted model.
Lastly, the modifiable areal unit problem (MAUP) was examined for this study by running all regression models at both the census tract and block group levels, which allow us to assess the sensitivity of analytical results to the geographic resolution of the data. This issue is critically important in a large metropolitan area such as Houston, where variations in size of the geographic analytical units as well as their number (886 census tracts and 2,705 block groups) could potentially lead to different findings regarding inequitable environmental outcomes.

4.6 Presentation of Statistical Analysis Results

The results of environmental justice analyses associated with the four dependent variables (Figure 7) are discussed in the following four chapters (chapters 5 to 8). Each chapter begins with a brief introduction of the research question followed by specific methodologies and data used to answer each question, and the results associated with summary statistics, bivariate correlation, conventional multiple regression, and spatial autoregressive models, at both the census tract and block group levels. The conclusion chapter combines all the discussions and allows for a comprehensive interpretation of the results.
Figure 7: Organizational Chart of Study
5. LOCATIONAL ANALYSIS OF INDUSTRIAL POLLUTION SOURCES

This chapter focuses on the analysis of environmental justice with regard to the location of facilities with toxic air releases listed in the USEPA’s Toxic Release Inventory (TRI). The goal is to examine the association between locations of these industrial pollution sources in the Houston MSA and selected demographic and socioeconomic variables from the Census 2000, in order to determine the presence of inequity with respect to the racial/ethnic and poverty status of the population.

This analysis begins with an examination of bivariate parametric correlations between the frequency of TRI facilities at three different search radii (0, 0.5, and 1 mile) from each analytical unit (census tract and block group) and explanatory variables described in Chapter 4. Because of the skewed distribution of TRI frequency, the square root (SR) of the number of TRI facilities in each census unit was used for the statistical description and analyses presented in Tables 6 to 9. Summary statistics for all variables analyzed are provided in Tables 6 and 7, respectively, based on census tract and block group level data. Tables 6 and 7 show that census tracts contain a greater number of TRI facilities than block groups and the average number of facilities hosted increase as the search radius increases from 0 to 1 mile from the boundary.

Pearson’s correlation coefficients associated with TRI frequency within the three distances of each analytical unit are presented in Table 8 for census tract level and Table 9 for block group level analyses. The bivariate correlation analysis at the census tract level (Table 8) shows that at 0 miles from the boundary, percent Hispanic has the highest
positive correlation with the frequency of TRIs, followed by the overall minority percentage and percent below the poverty line. Additionally, population density and labor force indicate the greatest negative correlation followed by percent Asian and percent owner occupied housing. Percent Black, however, does not show a significant relationship with the frequency of TRIs at this level.

At 0.5 miles from the census tract boundary, percent Hispanic continues to indicate the highest positive correlation in relation to TRI frequency, followed by percent below poverty and percent minority. Additionally, percent Asian has the greatest negative correlation followed by labor force and percent owner occupied housing. Population density and percent Black does not show any significant association with the frequency of TRIs at this level.

At 1 mile from the census tract boundary, percent Hispanic continues to indicate highest positive correlation in relation to TRI frequency, followed by percent minority and percent below poverty line. Percent Asian again indicates the greatest negative correlation, followed by labor force and percent owner occupied housing. Population density and percent Black does not show a significant relationship with the frequency of TRIs at this level.

At the block group level (Table 9), the correlational analysis indicates that Hispanic percentage has the highest positive correlation with the frequency of TRIs at 0 miles from the boundary followed by the overall minority percentage and percent below poverty. Additionally, population density has the greatest negative correlation followed by labor force, percent Asian, and percent owner occupied housing. Percent Black does not show a significant relationship with the frequency of TRIs at this level.
At 0.5 miles from the block group boundary, percent Hispanic has the highest positive correlation with TRI frequency followed by the overall percent minority and percent below poverty. Additionally, labor force has the greatest negative correlation followed by percent owner occupied housing and percent Asian. Population density and percent Black do not show a significant association with the frequency of TRIs at this level.

At 1 mile from the block group boundary, percent Hispanic has the highest positive correlation with TRI frequency, followed by percent minority and percent below poverty. Additionally, percent Asian had the greatest negative correlation, followed by labor force and percent owner occupied housing. Population density and percent Black does not show a significant relationship with the frequency of TRIs at this level.

In summary, the correlation analysis indicates that the percentage of Hispanics has the strongest and most significant positive linear association with the presence of TRI facilities, at both the census tract and block levels. The environmental inequity hypothesis is supported by three variables (overall minority percentage, percent Hispanic, and percent below poverty) which consistently exhibit a significant and positive relationship with TRI frequency at all search radii and at both the census tract and block group levels. The percentage of Asians, percent owner occupied housing, and labor force suggest a negative linear relationship at all distances and levels of aggregation.

Population density, on the other hand, is negatively correlated with the number of TRI facilities only at the boundaries (0 mile search radius) of census tracts and the block groups. Although percent Black is not significantly related to TRI frequency at any level or unit, the overall minority percentage which encompasses percent Black as well as the
remaining racial/ethnic minority groups indicates a significant and positive correlation. This finding underscores the necessity to evaluate race/ethnicity variables both jointly and separately when analyzing the social distribution of environmental pollution sources.

While correlation analysis provides a preliminary view of the statistical association between each demographic and socioeconomic variable and TRI frequency, multivariate regression is used to analyze the simultaneous statistical effects of the explanatory variables on the location of TRI facilities at the census tract and block group level, respectively. The binary logistic regression approach was utilized to model the presence or absence of TRI facilities within each analytical unit in the study area, based on Census 2000 data. Although the number of facilities could have been used as a quantitative dependent variable, there are two reasons why a dichotomous measure (presence/absence) was implemented. First, few census tracts and block groups in the study area contained more than one or two TRI facilities. Second, binary logistic regression is a standard approach that has been used to examine inequities in the spatial distribution of pollution sources in previous studies (Daniels and Friedman 1999; Pastor Jr et al. 2004; United Church of Christ Commission for Racial Justice 2007).

The dependent variable in this analysis is thus a binary measure of TRI location which was coded as 1 if one or more TRI facilities were present in a analytical unit, and 0 if there were no such facilities in any unit. The logistic regression models were estimated on the basis of the maximum likelihood method. The results associated with each type of analytical unit are described below.
5.1 Census Tract Level Analysis

The results of the logistic regression analysis at the census tract level, for each of the three distance definitions (0 mile, 0.5 mile, and 1 mile from each tract boundary), are summarized in Tables 10 to 12, respectively. These tables provide the logistic regression coefficients and the odds ratios associated with each independent variable, for the four logistic models that were fitted to predict TRI locations at the tract level. This ratio can be interpreted as a multiplier of the odds of hosting a TRI facility within a census tract. When this odds ratio exceeds one, the probability of hosting a TRI facility increases that many times for each unit of increase in the explanatory variable in the model. An odds ratios smaller than one, in contrast, implies that the probability of hosting a TRI facility decreases with an increase in the value of the explanatory variable.

Table 10 summarizes the logistic regression analysis results for TRI location within the boundary of census tracts (0 mile). Models 1 and 2 both indicate that the odds of hosting a TRI facility increases significantly with an increase in the overall percentage of minorities, even after controlling for the statistical effects of socioeconomic variables (model 2). When the minority sub-groups are analyzed separately (models 3 and 4), the odds of the hosting a TRI within the census tract increases by 4 and 5 percent, respectively, with every one percent increase in the Hispanic population. This suggests that the minority population in this study area probably comprises a large proportion of Hispanics. Additionally, it stresses the importance of analyzing each racial/ethnic sub-group individually and collectively to gain clarity on their environmental justice implications. For models 2 and 4, the odds of TRI facilities being hosted within the census tract significantly increases as the size of the labor force increases. In all four
models, the odds of TRI location significantly decreases with an increase in population
density. The inclusion of socioeconomic variables in models 1 and 3 do not indicate a
significant change in the coefficients or odds ratios of the race/ethnicity variables.

At 0.5 mile from the boundary of the census tracts (Table 11), the results for the
racial/ethnic variables are similar to those observed at 0 mile from the tracts. For models
1 and 2, the odds of hosting a TRI facility increase significantly as the overall percentage
of minority residents increases. Furthermore, for models 3 and 4, the odds of TRI
location significantly increase with an increase in the Hispanic percentage. Model 3 is
the only regression model where the odds of hosting a TRI facility at 0.5 mile from a
census tract increase significantly with an increase in the percentage of Black residents.
Percent Black term becomes non-significant, however, when socioeconomic variables are
included in model 4. This could be a possible consequence of a strong and positive linear
correlation between the Black percentage and poverty rate \( (r = 0.52) \). For both models 2
and 4, the odds of hosting a TRI increases significantly by 4 and 3 percent respectively,
with every one percent increase of the percent below poverty. For all models, at 0.5 mile
from the tract boundary, the odds of hosting a facility again significantly decrease as the
population density increases. With the exception of percent Black in model 4, the
addition of socioeconomic variables does not cause a significant change in the
coefficients or odds ratios of the race/ethnicity variables.

At 1 mile from the boundary of the census tracts (Table 12), models 1 and 2
indicate a positive statistical effect of the overall minority percentage and percent
Hispanic (models 3 and 4) on the odds of hosting a TRI facility that is consistent with the
results at 0 and 0.5 miles from tract boundaries. As observed at a distance of 0.5 mile
from the tract boundary, the odds of hosting a TRI facility increases significantly when percent Black increases. For model 2 only, the odds of hosting a TRI facility significantly increases by 3 percent with every one percent increase in the percent below poverty. For all models at 1 mile from the boundary, the odds of hosting a TRI facility significantly decreases as the population density increases. With the exception of percent Black in model 4, the inclusion of socioeconomic variables does not cause a significant change in the coefficients or odds ratios of the race/ethnicity variables.

5.2 Block Group Level Analysis

The results of the logistic regression analysis at the block group level, for each of the three distance definitions (0 mile, 0.5 mile, and 1 mile from each block group boundary), are summarized in Tables 13 to 15, respectively. These tables provide the regression coefficients and the odds ratios associated with each independent variable, for the four logistic models that were fitted to predict TRI location at the block group level.

Table 13 summarizes the logistic regression analysis results for TRI location within the boundary of block groups (0 mile). At the boundary of the block group, for both models 1 and 2, the odds of hosting a TRI facility significantly increases with an increase in the minority percentage. When the minority sub-groups are analyzed separately for both models 3 and 4, the odds of hosting a TRI facility significantly increases by 3 and 4 percent respectively, as the percent Hispanic increases by one percent. As with the census tracts, this suggests that the minority population is mostly comprised of Hispanics in this study area. However, for model 3 alone, the odds of hosting a TRI facility at the block group boundary significantly increases as the Black percentage increases. The Black term becomes non-significant when socioeconomic
variables are added in model, possibly because of its strong association with lower socioeconomic status. Additionally, it stresses the importance of modeling racial/ethnic terms collectively and individually to gain clarity of their impacts on the dependent variable. For all models, the odds of hosting a facility within the block group boundary significantly decreases as the population density increases. The addition of socioeconomic variables did not suggest a significant change in the coefficients or odds ratios of race/ethnicity variables, except for percent Black in model 4.

At 0.5 miles from the block group boundary, for both models 1 and 2 the odds of hosting a TRI facility increases significantly with the overall minority and Hispanic percentages, similarly to what was observed at 0 miles from the block group (Table 14). Additionally, the sign and significance of the Black percentage for model 3 matches the results at 0 mile from the boundary-- the odds of TRI location increase with percent Black. For models 2 and 4, the odds of hosting a TRI facility decreases with an increase of the percent owner occupied housing. The odds of TRI location significantly decrease by 3.1 and 2.5 percent, respectively as labor force increases, in models 2 and 4. For all models at 0.5 miles from the block group boundary, the odds of hosting a facility significantly decreases as the population density increases. After the addition of socioeconomic variables to the models there were no significant changes in the coefficients or odds ratios of race/ethnicity variables except for the percent Black in model 4.

At 1 mile from the boundary of block groups (Table 15), the regression results are similar to those observed at 0 and 0.5 miles; the odds of hosting a TRI facility significantly increases as the overall minority percent and Hispanic percent increases.
Percent Black shows a significant statistical effect in model 3, but not in the presence of other socioeconomic variables in model 4. The odds of hosting a facility significantly decrease again with increases in labor force and population density. A notable exception is the percent below poverty which shows a significant and positive statistical effect on TRI location in both models 2 and 4.

5.3 Discussion and Interpretation

The results reveal that location of TRI facilities in this MSA is significantly related to population density, the overall minority percentage, and the Hispanic percentage at the census tract level. While densely populated tracts are less likely to contain TRI facilities, the presence of racial/ethnic minorities and Hispanics, in particular, indicate a positive statistical effect on TRI location at all distances, even after controlling for the statistical effects of other explanatory variables. The Black percent shows a significant and positive statistical effect, but only when socioeconomic variables are not included in the model. This implies that for the Black sub-group, economic status provides a better statistical explanation for the presence of TRI sites at the tract level. Additionally, the poverty rate and labor force are the only two socioeconomic variables to show significance at the census tract level. Labor force shows a positive statistical effect on the odds of hosting a TRI site only at the boundary which suggests that the presence of a readily available workforce plays a key role in the location of these industrial facilities. Furthermore, the statistical effect of people in poverty is more pronounced only at half mile from the boundary.

As observed at the census tract level, population density, minority percent, and percent Hispanic, are again the most influential variables in explaining the location of
TRI facilities at the block group level. TRI facilities are significantly more likely to locate in block groups containing a higher proportion of racial/ethnic minorities and Hispanic populations, in all models and distance definitions. Furthermore, the Black percent has a significant and positive statistical effect on TRI location when socioeconomic variables are not included. As for the other socioeconomic variables, the presence of owner occupied housing significantly increases the odds of hosting a TRI facility at only 0.5 miles, while labor force suggests a negative association at 0.5 and 1 mile. Poverty rate shows a significant and positive statistical effect at the block group level only at 1 mile.

In summary, the results suggest that statistical effects of race/ethnicity on TRI location become stronger and more significant as the search radius increases at both the census tract and block levels of aggregation. An exception is the Hispanic percentage which retains a significant statistical effect at all three distances and aggregation levels. The significant statistical effect of population density also does not diminish with distance and as the search radius distance increases for both units of analysis, the significance of poverty increases. These findings suggest that although the proportion of Black and below poverty residents has less significance in determining the location of facilities than the Hispanic proportion and population density, the shape and size of the census tract and block group units of analyses may not capture all of the potential effects associated with these populations. Consequently, a large number of Blacks and those in poverty probably reside in census tracts and block groups that are adjacent to those hosting TRI sites. Thus the necessity of implementing a more spatially sensitive analysis which is not limited by arbitrary boundary configurations is necessary to incorporate the
impact of industrial pollution sources which are located at the edge of the boundaries of analytical units.

While the analyses presented in this chapter provide an assessment of inequities in the location of TRI facilities, a more detailed spatial exploration of the quantities of emitted pollutants is necessary to obtain a better understanding of the disproportionate risk burdens imposed by such industrial facilities in the Houston MSA.
Table 6: Descriptive Statistics for Variables at the Census Tract Level. n=886

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<thead>
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<th>Variables</th>
<th>Simple Statistics</th>
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<tr>
<td></td>
<td>Mean</td>
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<td>TRI frequency (SR): 0 Miles</td>
<td>0.105</td>
</tr>
<tr>
<td>TRI frequency (SR): 0.5 Miles</td>
<td>0.167</td>
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<tr>
<td>TRI frequency (SR): 1 Mile</td>
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</tr>
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<td>% Black</td>
<td>18.140</td>
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<tr>
<td>% Asian</td>
<td>4.140</td>
</tr>
<tr>
<td>% Hispanic</td>
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<tr>
<td>% Minority</td>
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<td>Population Density (LN)</td>
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<tr>
<td>% Below Poverty</td>
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<tr>
<td>% Owner Occupied</td>
<td>61.010</td>
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<td>Labor Force (SR)</td>
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Table 7: Descriptive Statistics for Variables at the Block Group Level. n=2705

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<th>Variables</th>
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<td></td>
<td>Std Dev: 0.305</td>
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<td></td>
<td>Min: 0.000</td>
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<td></td>
<td>Max: 3.794</td>
</tr>
<tr>
<td>TRI frequency (SR): 0.5 Miles</td>
<td>Mean: 0.134</td>
</tr>
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Table 8: Pearson Correlation Coefficients at the Census Tract Level Associated with the Square Root of TRI Frequency.  \( n=886 \)

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<td>% Black</td>
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<td>-0.010</td>
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<tr>
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<td>&lt;0.001</td>
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<td>0.010</td>
<td>-0.110</td>
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Table 9: Pearson Correlation Coefficients at the Block Group Level Associated with the Square Root of TRI Frequency.  n=2705

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Tables 11: Logistic Regression Analysis of TRI Location at Half Mile from Census Tract Boundary. n=886

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Tables 12: Logistic Regression Analysis of TRI Location at One Mile from Census Tract Boundary. n=886

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Tables 13: Logistic Regression Analysis of TRI Location at Zero Mile from Block Group Boundary. n=2705

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*p<0.05
6. ANALYZING THE QUANTITY OF EMISSIONS FROM INDUSTRIAL POLLUTION SOURCES

This chapter focuses on the use of pounds of toxic chemicals emitted by facilities listed in the USEPA’s Toxic Release Inventory (TRI) as an indicator of potential exposure to chronic air pollution in the analysis of environmental justice in the Houston-Galveston-Brazoria metropolitan statistical area (HBG-MSA). The goal is to examine the association between the total quantity (pounds) of pollutants released from TRI facilities and selected demographic and socioeconomic variables from Census 2000, in order to determine the presence of inequity with respect to the racial/ethnic and poverty status of the population.

The analysis begins with an examination of bivariate parametric correlations between the density (pounds per square mile) of atmospheric pollutants released at three different search radii (0, 0.5, and 1 mile) and relevant explanatory variables at the census tract and block group levels of aggregation. The density of atmospheric pollution (all emitted chemicals) from TRI facilities were calculated for each analytical unit following the technique for modeling point density described previously in Chapter 4. For each census tract or block group, the areal density of pounds released is measured by dividing the total quantity of pounds emitted from their host facilities by the area enclosed, at three different distances from the tract or block group boundary (0, 0.5, and 1 mile). Because of the skewed distribution of this variable, the natural logarithm (LN) of the density of pounds emitted was used for all statistical analyses presented in this chapter. The use of the natural log reduces outliers and yields a normal-style distribution of the dependent variable that is more consistent with the requirements of regression modeling. Summary
statistics for all variables analyzed are provided in Tables 16 and 17 for census tract and block group level data, respectively. The descriptive statistics show that census tracts contain a larger density of pounds of emitted pollutants than block groups. In addition, the density of pounds emitted increase as the search radius increases from 0 to 1 mile from the boundary due to the possible inclusion of more TRI facilities at larger distances from each unit.

Pearson’s correlation coefficients associated with the density of pounds emitted within the three distances of each analytical unit are presented in Table 18 for census tract level and Table 19 for block group level analyses. The correlation analysis at the census tract level shows that at 0 miles from the boundary, percent Hispanic has the highest positive correlation with the density of pounds emitted followed by the percent below poverty. Additionally, population density has the greatest negative correlation followed by percent Asian, labor force, and percent Black. Percent owner occupied housing and the overall minority percent does not indicate a significant correlation with the density of pounds emitted at this level.

At 0.5 mile from the census tract boundary, percent Hispanic again has the highest positive correlation in relation to pounds emitted followed by percent below poverty. Additionally, population density has the greatest negative correlation followed by percent Asian, percent Black and labor force. Percent owner occupied housing and overall minority percent again do not show a significant correlation with pounds emitted at the tract level.

At 1 mile from the census tract boundary, percent Hispanic has the highest positive correlation in relation to pounds emitted followed by percent below poverty and
overall percent minority. Additionally, percent Asian has the greatest negative
correlation followed by population density and labor force. Percent owner occupied
housing and percent Black do not show a significant correlation with pounds emitted at
this level.

At the block group level, the correlation analysis indicates that at 0 miles from the
boundary percent Hispanic has the highest positive correlation with the pounds emitted.
Additionally, population density has the greatest negative correlation followed by labor
force, percent Asian, and percent Black. Percent owner occupied housing, percent below
poverty and percent minority do not show a significant correlation with pounds emitted at
this level.

At 0.5 mile from the block group boundary, percent Hispanic has the highest
positive correlation in relation to pounds emitted followed by percent below poverty and
percent minority. Additionally, population density has the greatest negative correlation
followed by percent Asian, labor force and percent owner occupied housing. Percent
Black does not show a significant correlation with pounds emitted at this level.

At 1 mile from the block group boundary, percent Hispanic has the highest
positive correlation in relation to pounds emitted followed by percent minority and
percent below poverty. Additionally, percent Asian has the greatest negative correlation
followed by labor force, population density and percent owner occupied housing. Percent
Black does not show a significant correlation with pounds emitted at this level.

In summary, the correlation analysis indicates that the percentage of Hispanics
has the strongest and most significant positive linear association with the pounds of
chemicals released by TRI facilities into the atmosphere, at both the census tract and
block levels. The environmental inequity hypothesis is supported by the overall percent Hispanic variable which consistently exhibits a significant and positive relationship with density of pounds emitted at all search radii and at both the census tract and block group levels. The percentage of Asians, population density, and labor force suggest a negative linear relationship at all distances and levels of aggregation. Blacks, on the other hand, have a negative relationship with density of pounds emitted at 0 and 0.5 mile for census tracts and at 0 miles only for block groups. Additionally, the presence of minorities becomes significant as the search radii approach 1 mile (1 mile at block group; and 0.5 and 1 mile at census tract). This suggests that once again the Hispanic population has the greatest association with the minority percentage since the coefficient overall for the minority percentage is positive while all of the remaining minority sub-groups yield negative coefficients. Additionally, the negative correlation of owner occupied housing at the block group level only reinforces the need to address environmental justice variables at different resolutions.

While correlation analysis provides a preliminary view of the statistical association between each demographic and socioeconomic variable and density of pounds emitted, it does not clarify the underlying pattern in sufficient detail. Multivariate regression is therefore used to analyze the simultaneous statistical effect of the explanatory variables on the density of pounds emitted by TRI facilities at the census tract and block group level, respectively.

The ordinary least squares (OLS) regression approach is first utilized to model the association of explanatory variables with the density of pounds released from TRI facilities within each analytical unit in the study area, based on the three search radii (0,
0.5 and 1 mile). The results from the OLS regression models for the four different combinations of explanatory variables are summarized in the first set of tables (Tables 20-22 and 30-32). This set of tables also provides results from an analysis of spatial dependence using both the contiguity based and distance based methodologies for identifying spatial neighbors. The results in the OLS tables contain regression coefficients that are bolded, z-scores which are in parentheses and p-values which are identified utilizing the single ($\alpha=0.05$) and double ($\alpha=0.10$) asterisk. Additionally these tables contain the values of Moran’s I for each model which is used for testing the presence of spatial autocorrelation.

The second phase of the analysis uses the spatial autoregressive models (SAR) that include an autoregressive coefficient to account for spatial autocorrelation. The appropriate SAR function (spatial lag or spatial error) was determined using the Lagrange-Multiplier test statistic results (Anselin 2006) obtained while running the corresponding OLS model. As mentioned previously, the SAR models use a spatial weights matrix specified by three configurations of neighboring census units: queen-based contiguity, rook-based contiguity, and distance-based bands. Separate queen and rook contiguity analysis was therefore performed in hopes of finding the best fitted model that minimizes the effects of spatial dependence. Additionally, three to five distance bands were constructed to identify neighboring analytical units in order to identify the most appropriate distance from the search radius which yields the best fit model and minimizes the effects of spatial dependence. After the completion of the analyses, the best model was selected based upon the achievement of non-significant ($p<0.05$) Moran’s I which signifies no spatial autocorrelation and the lowest Akaike Information Criterion.
(AIC) which is used to determine the overall fit of the model. The census tract results are listed in Tables 23-24 and the block groups in Tables 33-40. The results in the tables contain regression coefficients which are bolded, z-scores which are in parentheses, and p-values which are identified utilizing the single (α=0.05) and double (α=0.10) asterisk.

The histograms in Figure 8 summarize the connectivity distribution for census tracts, based on the number of neighbors in each configuration. For queen contiguity, Figure 8(a) shows that the majority of the census tracts have 4 to 6 neighbors and peaks at 6 neighbors. For the rook contiguity in Figure 8(b), the number of neighbors peaks at 4 but the census tracts noticeably had a positive skew. The histogram for the distance-based configuration in Figure 8(c) provides the connectivity distribution at 0.50 mile from the centroid of each unit and indicates that a majority of census tracts have no neighbors at this distance. The connectivity distributions for census block groups are summarized in Figure 9. The histogram for queen contiguity in Figure 9(a) shows that the majority of the block groups have 5 to 7 neighbors and peaks at 6 neighbors. For the rook contiguity in Figure 9(b), the number of neighbors peaks at 5 and noticeably has a positive skew. The histogram for the distance-based configuration in Figure 9(c) provides the connectivity distribution at 0.19 mile from the centroid of each unit and indicates that the number of block groups with no neighbors at this distance is considerably higher than the number of census tracts with no neighbors in Figure 9(c).
Figure 8: Census tract connectivity histograms used for modeling pounds emitted
Figure 9: Block group connectivity histograms used for modeling pounds emitted
6.1 Census Tract Level Analysis

Ordinary Least Squares Regression This section focuses on multivariate regression analysis of the areal density of pounds emitted at the census tract level, at zero (0), half (0.5) and one (1) mile search radii, based on the application of ordinary least squares (OLS) and spatial autoregressive (SAR) techniques. Table 20 summarizes the results of OLS regression analysis at the boundary of the census tracts. Models 1 and 2 both indicate that the overall minority percent shows a significant and positive statistical effect on the density of pounds released. Additionally, when the minority sub-groups are analyzed separately for models 3 and 4, the Hispanic percent indicates a significant and positive association with the density of pounds emitted. This suggests that the minority population of tracts with larger quantities of TRI emissions probably comprises a large proportion of Hispanics. Additionally, it stresses the importance of analyzing each racial/ethnic sub-group individually and collectively to gain clarity on their environmental justice implications. Percent Black term for model 3 is significant and becomes non-significant when socioeconomic variables are included in model 4. As mentioned previously, this could be a possible consequence of a strong and positive linear correlation between the Black percentage and poverty rate \((r = 0.52)\) at the tract level. In all four models, the density of pounds emitted significantly increases with a decrease in population density.

At 0.5 mile from the boundary of the census tracts (Table 21), the results for the racial/ethnic variables are similar to those observed at 0 mile from the tracts. For models 1 and 2, the density of pounds emitted increases significantly as the overall percentage of minority residents increases. Furthermore, for models 3 and 4, the Hispanic percentage...
has a significant and positive statistical effect on the density of pounds released. For both models 2 and 4, the density of pounds emitted increase significantly as the overall labor force increases. For all models, at 0.5 mile from the tract boundary, the density of pounds emitted significantly increases with a decrease in population density.

At 1 mile from the boundary of the census tracts (Table 22), models 1 and 2 indicate a positive statistical effect of the overall minority percentage and percent Hispanic (models 3 and 4) on the density of pounds emitted which is consistent with the results at 0 and 0.5 miles from tract boundaries. As observed at a distance of 0 mile from the tract boundary, percentage Black becomes non-significant when socioeconomic variables are included (model 4). For model 2 only, the density of pounds emitted is positively associated with percent below poverty. As with the 0 and 0.5 mile from the tract boundary, the density of pounds emitted significantly increases with a decrease in population density.

Moran’s I for the regression models based on queen and rook contiguities show significance at 0, 0.5, and 1 miles search radii indicating the presence of significant spatial autocorrelation in the data and justifying the need to account for spatial dependence by using a SAR model. However, at 0.5 mile from the boundary when using the distance band for both 0 and 0.5 miles search radii, the Moran’s I was not statistically significant. Consequently, spatial dependence was not detected and the spatial autoregressive function was not implemented. However, at the 1 mile search radii for the 0.5 mile distance band, models 1 and 2 only were found to be significant indicating the presence of significant spatial autocorrelation in the data and the need to use the SAR model. As a result of the statistically significant Moran’s I, SAR was run to account for
spatial dependence. This distance band configuration was chosen based on the best fit using AIC and the achievement of non-significant spatial autocorrelation based on Moran’s I. Following the assessment for spatial dependence, the SAR model was thus implemented for all OLS models in which significant spatial autocorrelation was detected.

**Spatial Regression** At the boundary of the census tract level for the queen contiguity (Table 23), models 1 and 2 indicate a significant and positive association between the density of pounds at 0 miles and the overall minority percent. Additionally, for models 3 and 4, the Asian and Hispanic populations positively affect the density of pounds released. Labor force however, has a positive statistical effect on density of pounds emitted only for model 2 which ceases to be significant when the minority sub-groups are separated. For all models 0 miles from the tract boundary, density of pounds emitted significantly increases when population density decreases. The queen contiguity SAR models differs from OLS in that Black percentage becomes non-significant while percent Asian and labor have a positive statistical effect on the density of pounds released.

At the boundary of the census tract level for the rook contiguity (Table 24), all SAR models exhibit the same statistical associations as observed in the model for queen contiguity and had similar differences from the corresponding OLS models.

Models for the distance band at 0.5 mile were not run because Moran’s I from the OLS regression were not significantly different from zero when determining spatial autocorrelation.

At 0.5 mile from the boundary of census tracts (Table 25) for the queen contiguity models 1 and 2, percent minority has a positive association with the density of pounds
emitted. Additionally, for models 3 and 4 the percent of Asians and Hispanics independently have a significantly positive statistical effect on the density of pounds emitted, as well as labor force for models 2 and 4. For all models at the boundary, population density is a negative predictor of the density of pounds emitted. At the queen contiguity SAR models differ from OLS in that Asian percentage for models 3 and 4 are significant and have a positive statistical effect on the density of pounds emitted unlike the OLS model.

For the rook contiguity models at 0.5 mile from the boundary of census tracts (Table 26), percent minority, percent Asian, and labor force exhibit the same positive statistical effect as the queen contiguity, while population density has the same negative prediction for density pounds emitted. Percent Hispanic, however, has a positive statistical effect on the density of pounds emitted at model 3, but not in model 4 when the socioeconomic variables are introduced. This suggests that economic factors have a greater influence on the density of TRI emissions than the presence of Hispanics when the minority sub-groups are examined separately. The rook contiguity SAR models differ from OLS in that Asian percentage for models 3 and 4 are significant and have a positive statistical effect on the density of pounds emitted unlike the OLS model and that percent Hispanic becomes non-significant for model 4 in the SAR model.

Models for the distance band at 0.5 mile were not run because the distance band at 0.5 mile in the OLS regression was found to be non-significant for spatial autocorrelation using Moran’s I.

At 1 mile from the boundary of census tracts (Table 27) for queen contiguity, percent minority positively associated with the density of pounds emitted, in model 1.
Additionally, for models 3 and 4, the Hispanic population has a positive statistical effect on the density pounds emitted. For all models at 1 mile from the boundary, population density is a negative predictor of the density of pounds emitted. The queen contiguity SAR models differ from the OLS model in that Black percentage is non-significant. In model 2 only, percent minority and percent below poverty become non-significant.

At 1 mile from the boundary of the census tracts (Table 28) for the rook contiguity, percent minority and percent Hispanic exhibits the same positive statistical effect as the queen contiguity, while population density has the same negative statistical effect on pounds emitted. The SAR model exhibits the same difference for the rook contiguity at 1 mile as for the queen contiguity.

A distance band of 0.37 mile was constructed for models 1 and 2 only beginning at 1 mile from each census tract boundary to identify neighboring tracts for assessing spatial dependence (Table 29). This distance was chosen based on a selection criteria that comprised the minimization of the likelihood term (AIC) and significance of spatial autocorrelation using Moran’s I. Percent Hispanic in models 3 and 4 and percent minority in model 1 exhibit the same positive statistical effects on density of pounds emitted as observed in the rook-based contiguity model, while population density has the same negative statistical effect. Additionally, percent below poverty in model 2 and percent Black in model 3 is positively associated with the density of pounds emitted. The 0.37 mile distance band did not show any difference for SAR as compared to the OLS models.
6.2 Block Group Level Analysis

**Ordinary Least Squares Regression** This section focuses on multivariate regression analysis of the areal density of pounds emitted at the block group level, at zero (0), half (0.5) and one (1) mile search radii based on the application of ordinary least squared regression and spatial autoregressive techniques. Table 30 summarizes the results of OLS regression analysis for at the boundary of the block groups. Models 1 and 2 both indicate that the overall percent minority shows a significant and positive statistical effect on the density of pounds released. Additionally, when the minority sub-groups are analyzed separately for models 3 and 4, the Hispanic percent indicates a significant and positive association with the density of pounds emitted. This suggests that the minority population at the block group level with larger quantities emissions probably comprises a large proportion of Hispanics. Additionally, it stresses the importance of analyzing each racial/ethnic sub-group individually and collectively to gain clarity on their environmental justice implications. Percent Black term becomes non-significant, however, when socioeconomic variables are included in model 4. This could be a possible consequence of a strong and positive linear correlation between the Black percentage and poverty rate ($r = 0.45$) at the block group level. In all four models, the density of pounds emitted significantly increases with a decrease in population density.

At 0.5 mile from the boundary of the block groups (Table 31), the results for the racial/ethnic variables are similar to those observed at 0 mile from the block groups. For models 1 and 2, the effect on density of pounds emitted increases significantly as the overall percentage of minority residents increases. Furthermore, for models 3 and 4, the Hispanic percentage has a significant and positive statistical effect on the density of
pounds emitted while in model 3 percent Black retains a positive statistical effect on density of pounds. For both models 2 and 4, the density of pounds emitted increases significantly as the overall percent below poverty and labor force increase. For all models, at 0.5 mile from the block group boundary, the density of pounds emitted increases significantly with a decrease in population density.

At 1 mile from the boundary of the block groups (Table 32), models 1 and 2 indicate a positive statistical effect of the overall minority percentage, along with percent Black at model 3 and percent Hispanic (models 3 and 4) on the density of pounds emitted that is consistent with the results at 0 and 0.5 miles from block group boundaries. As with 0.5 mile, the density of pounds emitted is positively affected by percent below poverty. For all models, at 1 mile from the block group boundary, the density of pounds emitted significantly increases with a decrease in population density.

Moran’s I for the regression models based on queen-based and rook-based contiguities show significance at 0.5 mile and 1 miles search radii indicating the presence of significant spatial autocorrelation in the data and justifying the need to account for spatial dependence by using the SAR model. However, at 0.19 mile from the boundary when using the distance band for 0 miles search radii only, the distance band was found to yield a non-significant Moran’s I. Consequently, spatial dependence was not detected and the spatial autoregressive function was therefore not implemented. This distance band configuration was chosen based on the best fit using AIC and the achievement of non-significance for spatial autocorrelation using Moran’s I. Following the assessment for spatial dependence, the SAR model was thus implemented for all OLS models in which significant spatial autocorrelation was detected.
**Spatial Regression** At the boundary of the block group level (Table 33) for the queen contiguity in models 1 and 2, a significant and positive association is observed between the density of pounds at 0 miles and the overall minority percent. Additionally, in models 3 and 4 the Hispanic population positively predicts the amount of pounds released. Percent Black however, positively affects density of pounds emitted at model 3, but not when the economic terms were introduced. For all models, the density of pounds emitted significantly increases with a decrease in population density. The queen contiguity SAR models differs from OLS in that owner occupied housing is non-significant for models 2 and 4 when the SAR term is introduced.

At the boundary of the block group level (Table 34) for the rook contiguity, all SAR models exhibit the same statistical associations as observed in the model for queen contiguity and had similar differences from the corresponding OLS models. The rook contiguity differed from the OLS model the same as the queen contiguity where owner occupied housing is non-significant for models 2 and 4 when SAR is introduced.

Models for the distance band at 0 miles was not run because the distance band at 0.19 mile for all models in the OLS regression was found to be non-significant when testing for spatial autocorrelation using Moran’s I.

At 0.5 mile from the boundary of the block group level (Table 35) for the queen contiguity, for models 1 and 2 percent minority positively predict the density of pounds emitted. Additionally, models 3 and 4, the Hispanic population and labor force (models 2 and 4) independently and significantly has a positive statistical effect on density of pounds released. Percent Asian however, positively predicts density of pounds emitted at model 3, but is not a predictor in model 4 when the economic term was introduced.
Percent below poverty positively affects the density of pounds emitted at model 4, but not in model 3 when there was not an economic term. For all models, the density of pounds emitted significantly increases with a decrease in population density. The queen contiguity SAR models differ from OLS in that in percent Black in model 3 and percent below poverty in model 2 are no longer significant, but percent Asian gains significance and has a positive statistical effect on density of pounds released.

At 0.5 mile from the boundary of block groups (Table 36) in the rook contiguity model, percent minority, percent Asian, percent Hispanic and labor force exhibit the same positive statistical effect as the queen contiguity, while population density has the same negative prediction on density of pounds emitted. However, percent below poverty and percent owner occupied housing for both models 2 and 4 have positive statistical effects on density of pounds emitted. The rook contiguity SAR models differ from OLS in that the percent Black in model 3 is no longer significant. However, percent Asian gains significance in model 3 without the economic terms and percent owner occupied for both model significant and have a positive statistical effect on density of pounds released.

A distance band of 0.19 mile (Table 37) was constructed beginning from 0.5 mile from each block group boundary to identify neighboring tracts for assessing spatial dependence. Percent minority, percent Hispanic, and percent below poverty exhibit the same positive statistical effect of density of pounds emitted as the rook-based contiguity model, while population density has the same negative association reported earlier. Percent Black, however, positively predicts pounds emitted in model 3, but is not a significant predictor in model 4 when the socioeconomic terms are introduced.
Additionally, labor force positively predicts density of pounds emitted in model 4, but is not a predictor in model 3 when socioeconomic variables are included. The SAR models for the distance-based model at 0.19 mile from the boundary differ from OLS in that labor force in exhibits a positive and significant statistical effect in model 4, but ceases to be significant in model 3.

At 1 mile from the boundary (Table 38) of block groups for the queen contiguity models 1 and 2, percent minority has similar statistical effect as in the SAR models for 0 and 0.5 miles. Additionally, in models 3 and 4 the Hispanic population has a positive association with the density of pounds released while labor force has a positive association in models 2 and 4. For all models, the density of pounds emitted significantly increases with a decrease in population density. The queen contiguity SAR models differ from OLS in that in percent Black in model 3 no longer significant. Additionally, percent Asian (models 3 and 4) and percent below poverty (models 2 and 4) lose significance and no longer contribute to density of pounds released. Labor force on the other hand shows a significant statistical effect on emission density for models 2 and 4.

At 1 mile from the boundary of block groups for the rook contiguity, percent minority, percent Hispanic, and labor force exhibit the same positive statistical effect on the density of pounds emitted as the queen contiguity, while population density has the same negative statistical effect on the density of pounds emitted. The rook contiguity SAR models exhibit the same difference from OLS as the queen contiguity.

A distance band of 0.19 mile (Table 40) was constructed beginning from 1 mile from the block group boundary. Percent minority and percent Hispanic show the same
positive prediction as the rook contiguity, while population density had the same negative statistical effect on the density of pounds emitted. Additionally, percent below poverty is positively associated with the density of pounds emitted at model 2 and 4 and percent Black at model 3. Percent Asian however, is negatively associated with the density of pounds emitted at models 3 and 4. The distance-based SAR models do not exhibit any significant difference from the OLS models.

6.3 Discussion and Interpretation

The analyses presented on this chapter focuses on the geographic distribution of pollution burdens measured in terms of the quantity of emissions from industrial point sources. The results reveal that the areal density of pounds released by TRI facilities in the Houston-MSA are significantly associated with population density, the overall proportion of minorities, and the Hispanic proportion at the census tract level, regardless of whether conventional or spatial regression was utilized. While densely populated tracts are less likely to contain TRI facilities and associated emission quantities, the presence of racial/ethnic minorities and Hispanics, in particular, indicate a positive statistical effect on the density of pounds released at all distances, even after controlling for the statistical effects of other explanatory variables. The percentage of Asians living within or near census tract boundaries are only significant when spatial autocorrelation is removed. The Black percentage shows a significant and positive statistical effect in two separate cases. The first case occurs only when socioeconomic variables are not included in the model, near the tract boundary and when ordinary regression modeling is applied. This implies that for the Black sub-group, economic status provides a better statistical explanation for the presence of pounds at the tract level. The second case where Black
percentage is significant is when the density of emissions is measured at one mile from the tract boundary, for both ordinary and spatial regression. This suggests that less affluent Blacks and those in poverty could be residing closer to TRI facilities with higher quantities of emissions than more affluent Blacks. Furthermore, labor force and poverty rate are the only two socioeconomic variables to show significance at the census tract level. Labor force shows a positive statistical effect on the density of pounds only when spatial autocorrelation is accounted for. This suggests that the presence of a readily available workforce plays a key role in the location of these industrial facilities.

As observed at the census tract level, population density, minority percent, and percent of Hispanics, are again the most influential variables related to the density of pounds emitted at the block group level. There tends to be a significantly greater density of pounds in block groups containing a higher proportion of racial/ethnic minorities and Hispanic populations, in all models and distance definitions. Furthermore, unlike the census tract level, the Black population is significantly associated with emission density at all distances with and without the adjustment for spatial autocorrelation. This suggests that a higher concentration of both Black and Hispanic residents can be found near TRI facilities with greater density of pounds, at the block group level. Again poverty rate and labor force are the only two socioeconomic variables to show a significant statistical effect on emission density at distances of 0.5 and 1 mile from the block group boundaries, for both conventional and spatial regression techniques.

In summary, the results suggest that statistical effects of race/ethnicity on density of pounds released are influential at all search radii and at both the census tract and block levels of aggregation. More specifically, the overall minority and Hispanic population
and the number of people per square mile are the most significant explanatory factors in
determining the density of pounds released at all search radii, all aggregations, and both
regression modeling techniques. Additionally, the proportion of Asians is only
significant when spatial autocorrelation is removed and the significance of labor force
increases when spatial dependence is accounted for as well. This finding indicates how
spatial autocorrelation can mask the effects of specific variables (e.g., percent Asian and
labor force) when determining their statistical association with the magnitude of pollution
and justifies the need to control for spatial dependence in regression analysis of
environmental justice. The proportion of Blacks was found to be significant when
emission density was measured at the boundaries of census tracts, but not at the block
group boundaries. Additionally, the Black sub-group was significant only at the farthest
distance (1 mile) away from tract boundaries and at all three distances from the block
group boundaries, for both regression modeling techniques. This confirms the
importance of analyzing data at more than one spatial resolution because the nuances
between the distances were not evident at a single analytical unit.

While the analyses presented in this chapter provide an assessment of inequities in
the distribution of TRI emission amounts, it is important to consider that the density of
pounds released into the atmosphere does not account for how ambient chemicals
metabolically impact humans. The introduction of toxicity-weighted hazard scores,
therefore, is necessary to address this limitation and provide a more refined assessment of
disproportionate risk burdens imposed on the population in the Houston MSA.
Table 16: Descriptive Statistics for Variables at the Census Tract Level. n=886

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Table 17: Descriptive Statistics for Variables at the Block Group Level.  n=2705

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<thead>
<tr>
<th>Variables</th>
<th>Simple Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density of Pounds (LN): 0 Miles</td>
<td>Mean</td>
</tr>
<tr>
<td>Density of Pounds (LN): 0.5 Miles</td>
<td></td>
</tr>
<tr>
<td>Density of Pounds (LN): 1 Mile</td>
<td></td>
</tr>
<tr>
<td>% Black</td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td></td>
</tr>
<tr>
<td>% Below Poverty</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td></td>
</tr>
</tbody>
</table>

|                            | 0.770 | 3.200  | 0.000 | 23.200 |
| Density of Pounds (LN): 0.5 Miles | 2.290 | 5.000  | 0.000 | 21.990 |
| Density of Pounds (LN): 1 Mile   | 3.990 | 5.990  | 0.000 | 21.060 |
| % Black                         | 17.560| 25.760 | 0.000 | 100.000 |
| % Asian                         | 3.760 | 6.660  | 0.000 | 68.160 |
| % Hispanic                      | 28.860| 25.590 | 0.000 | 100.000 |
| % Minority                      | 52.210| 31.630 | 0.000 | 100.000 |
| Population Density (LN)         | 7.710 | 1.580  | 0.000 | 11.150 |
| % Below Poverty                 | 14.490| 12.190 | 0.000 | 73.360 |
| % Owner Occupied                | 63.110| 27.430 | 0.000 | 100.000 |
| Labor Force (SR)                | 34.140| 10.650 | 0.000 | 83.610 |
Table 18: Pearson Correlation Coefficients Associated with the Density of Pounds (Natural Log) Released at the Census Tract Level. n=886

<table>
<thead>
<tr>
<th>Variables</th>
<th>0 Mile</th>
<th></th>
<th>0.5 Mile</th>
<th></th>
<th>1 Mile</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r</td>
<td>p-Value</td>
<td>r</td>
<td>p-Value</td>
<td>r</td>
<td>p-Value</td>
</tr>
<tr>
<td>% Black</td>
<td>-0.080</td>
<td>0.020</td>
<td>-0.080</td>
<td>0.020</td>
<td>-0.020</td>
<td>0.530</td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.110</td>
<td>0.002</td>
<td>-0.110</td>
<td>0.002</td>
<td>-0.170</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.160</td>
<td>&lt;0.001</td>
<td>0.150</td>
<td>&lt;0.001</td>
<td>0.260</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>% Minority</td>
<td>0.060</td>
<td>0.110</td>
<td>0.050</td>
<td>0.170</td>
<td>0.170</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.300</td>
<td>&lt;0.001</td>
<td>-0.310</td>
<td>&lt;0.001</td>
<td>-0.160</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.080</td>
<td>0.020</td>
<td>0.070</td>
<td>0.040</td>
<td>0.170</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.020</td>
<td>0.520</td>
<td>0.030</td>
<td>0.400</td>
<td>-0.040</td>
<td>0.280</td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.100</td>
<td>0.003</td>
<td>-0.100</td>
<td>0.003</td>
<td>-0.130</td>
<td>0.001</td>
</tr>
</tbody>
</table>

p<0.05
Table 19: Pearson Correlation Coefficients Associated with the Density of Pounds (Natural Log) Released at the Block Group Level.  n=2705

<table>
<thead>
<tr>
<th>Variables</th>
<th>0 Mile</th>
<th>0.5 Mile</th>
<th>1 Mile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r</td>
<td>p-Value</td>
<td>r</td>
</tr>
<tr>
<td>% Black</td>
<td>-0.050</td>
<td>0.010</td>
<td>-0.040</td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.070</td>
<td>0.001</td>
<td>-0.110</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.080</td>
<td>&lt;0.001</td>
<td>0.220</td>
</tr>
<tr>
<td>% Minority</td>
<td>0.030</td>
<td>0.170</td>
<td>0.140</td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.280</td>
<td>&lt;0.001</td>
<td>-0.160</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.080</td>
<td>0.060</td>
<td>0.150</td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.010</td>
<td>0.530</td>
<td>-0.060</td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.120</td>
<td>&lt;0.001</td>
<td>-0.110</td>
</tr>
</tbody>
</table>

p<0.05
Table 20: Least Squares Regression Results for Density of Pounds Released (Natural Log) at Zero Miles from Census Tract Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.0085* (1.380)</td>
<td>0.003 (0.374)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.037 (1.440)</td>
<td>0.041 (1.55)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.061* (8.920)</td>
<td>0.055* (6.090)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>%Minority</td>
<td>0.032* (5.960)</td>
<td>0.025* (3.210)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-1.130* (-11.290)</td>
<td>-1.170* (-10.620)</td>
<td>-1.220* (-11.890)</td>
<td>-1.240* (-11.290)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.027 (1.240)</td>
<td>0.026 (1.120)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.107 (0.107)</td>
<td>0.004 (0.546)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>0.011 (1.220)</td>
<td>0.007 (0.762)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.128</td>
<td>0.130</td>
<td>0.170</td>
<td>0.171</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>64.600*</td>
<td>26.370*</td>
<td>45.000*</td>
<td>25.940*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5097.290</td>
<td>5100.570</td>
<td>5057.580</td>
<td>5061.730</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-2545.640</td>
<td>-2544.280</td>
<td>-2523.790</td>
<td>-2522.870</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.185*</td>
<td>0.188*</td>
<td>0.153*</td>
<td>0.156*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.179*</td>
<td>0.183*</td>
<td>0.144*</td>
<td>0.148*</td>
</tr>
<tr>
<td>Moran’s I-0.50 mile</td>
<td>0.003</td>
<td>0.002</td>
<td>-0.002</td>
<td>-0.004</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 21: Least Squares Regression Results for Density of Pounds Released (Natural Log) at Half-Mile from the Census Tract Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.004</td>
<td>0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.682)</td>
<td>(0.458)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.032</td>
<td>0.037</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.290)</td>
<td>(1.490)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.0520*</td>
<td>0.051*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(8.050)</td>
<td>(5.920)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.025*</td>
<td>0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.090)</td>
<td>(3.170)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-1.290*</td>
<td>-1.490*</td>
<td>-1.390*</td>
<td>-1.580*</td>
</tr>
<tr>
<td></td>
<td>(-10.650)</td>
<td>(-10.360)</td>
<td>(-11.180)</td>
<td>(-10.990)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.023</td>
<td></td>
<td>0.022</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.140)</td>
<td></td>
<td>(1.020)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.005</td>
<td></td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.733)</td>
<td></td>
<td>(1.180)</td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>0.030*</td>
<td>0.027*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.020)</td>
<td></td>
<td>(2.780)</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.115</td>
<td>0.125</td>
<td>0.150</td>
<td>0.164</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>57.230*</td>
<td>25.240*</td>
<td>40.020*</td>
<td>24.550*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>4997.450</td>
<td>4992.680</td>
<td>4961.510</td>
<td>4957.070</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-2495.730</td>
<td>-2490.340</td>
<td>-2475.750</td>
<td>-2470.540</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.186*</td>
<td>0.192*</td>
<td>0.156*</td>
<td>0.163*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.179*</td>
<td>0.187*</td>
<td>0.146*</td>
<td>0.155*</td>
</tr>
<tr>
<td>Moran’s I-0.50 mile</td>
<td>0.005</td>
<td>0.003</td>
<td>0.001</td>
<td>-0.002</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 22: Least Squares Regression Results for Density of Pounds Released (Natural Log) at One-Mile from the Census Tract Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.014**</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.680)</td>
<td>(1.160)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.048</td>
<td>-0.040</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.290)</td>
<td>(-1.060)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.091*</td>
<td>0.092*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(9.610)</td>
<td>(7.060)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.050*</td>
<td>0.038*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.750)</td>
<td>(3.330)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-1.430*</td>
<td>-1.460*</td>
<td>-1.450*</td>
<td>-1.500*</td>
</tr>
<tr>
<td></td>
<td>(-6.930)</td>
<td>(-5.520)</td>
<td>(-6.910)</td>
<td>(-5.850)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.056*</td>
<td></td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.810)</td>
<td></td>
<td>(0.476)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.010</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.060)</td>
<td>(1.120)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.010</td>
<td>0.008</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.612)</td>
<td>(0.510)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.072</td>
<td>0.076</td>
<td>0.132</td>
<td>0.134</td>
</tr>
<tr>
<td></td>
<td>(0.610)</td>
<td>(0.510)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-Statistic</td>
<td>34.390*</td>
<td>14.560*</td>
<td>33.570*</td>
<td>19.400*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5731.710</td>
<td>5733.730</td>
<td>5676.450</td>
<td>5680.740</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-2862.860</td>
<td>-2860.870</td>
<td>-2833.230</td>
<td>-2832.370</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.536*</td>
<td>0.537*</td>
<td>0.502*</td>
<td>0.505*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.570*</td>
<td>0.571*</td>
<td>0.539*</td>
<td>0.541*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moran’s I-0.50 mile</td>
<td>0.012*</td>
<td>0.013*</td>
<td>0.006</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.

b. *p<0.05, **p<0.10
Table 23: Spatial Regression Results for Density of Pounds Released (Natural Log) at Zero Mile of Census Tract Boundary Using Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.012</td>
<td>0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.530)</td>
<td>(1.560)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td></td>
<td></td>
<td>0.061*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(2.000)</td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.060*</td>
<td>0.052*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.220)</td>
<td>(4.920)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.003*</td>
<td>0.027*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.950)</td>
<td>(2.910)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-1.150*</td>
<td>-1.250*</td>
<td>-1.220*</td>
<td>-1.300*</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.033</td>
<td></td>
<td>0.038</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.420)</td>
<td></td>
<td>(1.610)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.005</td>
<td></td>
<td>0.915</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.717)</td>
<td></td>
<td>(0.360)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.018**</td>
<td></td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.880)</td>
<td></td>
<td>(1.480)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.387*</td>
<td>0.397*</td>
<td>0.342*</td>
<td>0.354*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5029.910</td>
<td>5030.330</td>
<td>5009.110</td>
<td>5010.090</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-2511.956</td>
<td>-2509.167</td>
<td>-2499.550</td>
<td>-2497.040</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>-0.009</td>
<td>-0.009</td>
<td>-0.006</td>
<td>0.007</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 24: Spatial Regression Results for Density of Pounds Released (Natural Log) at Zero Mile of Census Tract Boundary Using the Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.008</td>
<td>0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.380)</td>
<td>(0.440)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.051*</td>
<td>0.062*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.010)</td>
<td>(2.050)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.051*</td>
<td>0.052*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.420)</td>
<td>(5.050)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.033*</td>
<td>0.027*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.030)</td>
<td>(2.960)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-1.100*</td>
<td>-1.200*</td>
<td>-1.050*</td>
<td>-1.260*</td>
</tr>
<tr>
<td></td>
<td>(-9.710)</td>
<td>(-9.510)</td>
<td>(-10.110)</td>
<td>(-10.240)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.0310</td>
<td></td>
<td>0.037</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.330)</td>
<td></td>
<td>(1.540)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.004</td>
<td>0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.556)</td>
<td></td>
<td>(0.780)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.019*</td>
<td>0.0150</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.000)</td>
<td></td>
<td>(1.560)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.323*</td>
<td>0.333*</td>
<td>0.268*</td>
<td>0.289*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5043.770</td>
<td>5044.140</td>
<td>5050.190</td>
<td>5022.380</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-2518.890</td>
<td>-2516.070</td>
<td>-2504.730</td>
<td>-2503.190</td>
</tr>
<tr>
<td>Moran's I-rook</td>
<td>-0.014</td>
<td>-0.014</td>
<td>-0.015</td>
<td>-0.011</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 25: Spatial Regression Results for Density of Pounds Released (Natural Log) at Half-Mile of Census Tract Boundary Using the Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.004</td>
<td>0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.783)</td>
<td>(0.505)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.046**</td>
<td>0.057*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.950)</td>
<td>(1.970)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.041*</td>
<td>0.047*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.550)</td>
<td>(4.720)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.027*</td>
<td>0.025*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.250)</td>
<td>(2.850)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.220*</td>
<td>-1.580*</td>
<td>-1.190*</td>
<td>-1.650*</td>
</tr>
<tr>
<td></td>
<td>(-9.140)</td>
<td>(-9.400)</td>
<td>(-9.610)</td>
<td>(-9.980)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.031</td>
<td>0.036</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.430)</td>
<td>(1.620)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.008</td>
<td>0.090</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.250)</td>
<td>(1.470)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>0.036*</td>
<td>0.033*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.520)</td>
<td>(3.320)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.390*</td>
<td>0.402*</td>
<td>0.331*</td>
<td>0.363*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>4929.080</td>
<td>4919.690</td>
<td>4910.900</td>
<td>4901.780</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-2461.540</td>
<td>-2453.850</td>
<td>-2449.240</td>
<td>-2442.890</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>-0.008</td>
<td>-0.009</td>
<td>-0.001</td>
<td>-0.006</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 26: Spatial Regression Results for Density of Pounds Released (Natural Log) at Half-Mile of Census Tract Boundary Using the Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.004</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.797)</td>
<td>(0.338)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.046**</td>
<td>0.050*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.940)</td>
<td>(2.070)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.042*</td>
<td>0.041</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.690)</td>
<td>(4.790)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.026*</td>
<td>0.025*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.260)</td>
<td>(2.880)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-1.170*</td>
<td>-1.510*</td>
<td>-1.190*</td>
<td>-1.350*</td>
</tr>
<tr>
<td></td>
<td>(-8.830)</td>
<td>(-9.190)</td>
<td>(-9.640)</td>
<td>(-9.300)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.029</td>
<td>0.022</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.330)</td>
<td>(1.070)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.007</td>
<td>0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.080)</td>
<td>(0.744)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.036*</td>
<td>0.022*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.520)</td>
<td>(2.350)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.327*</td>
<td>0.337*</td>
<td>0.290*</td>
<td>0.280*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>4943.310</td>
<td>4934.060</td>
<td>4918.240</td>
<td>4917.070</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-2468.650</td>
<td>-2461.030</td>
<td>-2453.120</td>
<td>-2449.540</td>
</tr>
<tr>
<td>Moran's I-rook</td>
<td>-0.014</td>
<td>-0.114</td>
<td>-0.016</td>
<td>-0.003</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 27: Spatial Regression Results for Density of Pounds Released (Natural Log) at One Mile of Census Tract Boundary Using the Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.003</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.517)</td>
<td>(-0.181)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.013</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.511)</td>
<td>(0.557)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.026*</td>
<td>0.028*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.030)</td>
<td>(3.140)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.009**</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.850)</td>
<td>(1.250)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.628*</td>
<td>-0.732*</td>
<td>-0.718*</td>
<td>-0.814*</td>
</tr>
<tr>
<td></td>
<td>(-4.560)</td>
<td>(-4.130)</td>
<td>(-4.990)</td>
<td>(-4.520)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.004</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.187)</td>
<td>(0.056)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.001</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.060)</td>
<td>(0.227)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.011</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.020)</td>
<td>(0.914)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.829*</td>
<td>0.829*</td>
<td>0.814*</td>
<td>0.814*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5129.530</td>
<td>5134.470</td>
<td>5118.730</td>
<td>5123.750</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-2560.770</td>
<td>-2560.230</td>
<td>-2553.370</td>
<td>-2552.880</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>-0.004</td>
<td>-0.001</td>
<td>-0.003</td>
<td>0.001</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 28: Spatial Regression Results for Density of Pounds Released (Natural Log) at One Mile of Census Tract Boundary Using the Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td></td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.426)</td>
<td>(0.067)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.012</td>
<td>0.012</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.488)</td>
<td>(0.490)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.026*</td>
<td>0.029*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.150)</td>
<td>(3.390)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.009*</td>
<td>0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.000)</td>
<td>(1.510)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.608*</td>
<td>-0.719*</td>
<td>-0.694*</td>
<td>-0.793*</td>
</tr>
<tr>
<td></td>
<td>(-4.600)</td>
<td>(-4.230)</td>
<td>(-5.020)</td>
<td>(-4.590)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>-0.001</td>
<td></td>
<td>-0.004</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.041)</td>
<td></td>
<td>(-0.210)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.001</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.146)</td>
<td></td>
<td>(0.118)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.011</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.287)</td>
<td>(0.964)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.824*</td>
<td>0.825*</td>
<td>0.810*</td>
<td>0.810*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5084.700</td>
<td>5089.540</td>
<td>5073.570</td>
<td>5078.450</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-2538.350</td>
<td>-2537.770</td>
<td>-2530.790</td>
<td>-2530.220</td>
</tr>
<tr>
<td>Moran's I rook</td>
<td>-0.002</td>
<td>0.002</td>
<td>-0.001</td>
<td>0.002</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 29: Spatial Regression Results for Density of Pounds Released (Natural Log) at One Mile of Census Tract Boundary Using Distance

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 (0.37 mile)</th>
<th>Model 2 (0.37 mile)</th>
<th>Model 3 (0.37 mile)</th>
<th>Model 4 (0.37 mile)</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.37</td>
<td>0.37</td>
<td>0.37</td>
<td>0.37</td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.048</td>
<td>-0.040</td>
<td>-1.290</td>
<td>-1.060</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.014**</td>
<td>0.014</td>
<td>(1.680)</td>
<td>(1.160)</td>
</tr>
<tr>
<td>% Minority</td>
<td>0.014</td>
<td>0.014</td>
<td>(6.790)</td>
<td>(3.460)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>-1.400*</td>
<td>-1.430*</td>
<td>-1.450*</td>
<td>-1.500*</td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-6.860</td>
<td>(-5.450)</td>
<td>(-6.910)</td>
<td>(-5.850)</td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.012</td>
<td>0.010</td>
<td>(1.810)</td>
<td>(0.476)</td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.009</td>
<td>0.008</td>
<td>(1.340)</td>
<td>(1.120)</td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.490*</td>
<td>0.502*</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Akaike Info Coefficient</td>
<td>5726.120</td>
<td>5727.720</td>
<td>5676.450</td>
<td>5680.740</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-2860.060</td>
<td>-2857.860</td>
<td>-2833.230</td>
<td>-2832.370</td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.019</td>
<td>0.002</td>
<td>0.006</td>
<td>0.006</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
c. X-represents data provided in related OLS table
Table 30: Least Squares Regression Results for Density of Pounds Released (Natural Log) at Zero Mile from Block Group Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.005*</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.110)</td>
<td>(1.260)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.011</td>
<td>0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.210)</td>
<td>(1.220)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.025*</td>
<td>0.023*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(9.800)</td>
<td>(7.360)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.015*</td>
<td>0.013*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.250)</td>
<td>(4.670)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.689*</td>
<td>-0.681*</td>
<td>-0.718*</td>
<td>-0.712*</td>
</tr>
<tr>
<td></td>
<td>(-17.070)</td>
<td>(-15.99)</td>
<td>(-17.500)</td>
<td>(-16.620)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>-0.001</td>
<td></td>
<td>-0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.740)</td>
<td></td>
<td>(-0.216)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.006*</td>
<td>-0.005*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.320)</td>
<td></td>
<td>(-2.020)</td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.009</td>
<td>-0.008</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.460)</td>
<td></td>
<td>(-1.330)</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.097</td>
<td>0.100</td>
<td>0.112</td>
<td>0.133</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>145.757*</td>
<td>60.023 *</td>
<td>85.200*</td>
<td>49.623*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>13695.000</td>
<td>13693.000</td>
<td>13654.600</td>
<td>13654.500</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-6844.520</td>
<td>-6840.490</td>
<td>-6822.320</td>
<td>-6819.240</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.141*</td>
<td>0.137*</td>
<td>0.125*</td>
<td>0.122*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.153*</td>
<td>0.148*</td>
<td>0.137*</td>
<td>0.132*</td>
</tr>
<tr>
<td>Moran’s I-0.19 mile</td>
<td>0.001</td>
<td>0.001</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 31: Least Squares Regression Results for Density of Pounds Released (Natural Log) at Half Mile from Block Group Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.009*</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.380)</td>
<td>(0.728)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.007</td>
<td>-0.008</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.504)</td>
<td>(-0.547)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.058*</td>
<td>0.053*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(14.740)</td>
<td>(10.570)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.032*</td>
<td>0.023*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10.290)</td>
<td>(5.350)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.800*</td>
<td>-1.140*</td>
<td>-1.130*</td>
<td>-1.260*</td>
</tr>
<tr>
<td></td>
<td>(-11.660)</td>
<td>(-10.130)</td>
<td>(-12.090)</td>
<td>(-11.270)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.037*</td>
<td>0.028*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.240)</td>
<td>(2.390)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>&lt;0.001</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.390)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>0.018**</td>
<td>0.026*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.640)</td>
<td>(2.430)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.063</td>
<td>0.067</td>
<td>0.104</td>
<td>0.108</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>90.310*</td>
<td>38.870*</td>
<td>78.660*</td>
<td>46.590*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>16217.700</td>
<td>16210.600</td>
<td>16098.500</td>
<td>16093.900</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-8105.830</td>
<td>-8099.290</td>
<td>-8044.260</td>
<td>-8038.950</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.515*</td>
<td>0.722*</td>
<td>0.483*</td>
<td>0.488*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.534*</td>
<td>0.537*</td>
<td>0.503*</td>
<td>0.508*</td>
</tr>
<tr>
<td>Moran’s I-0.19 mile</td>
<td>0.011*</td>
<td>0.011*</td>
<td>0.009*</td>
<td>0.009*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
## Table 32: Least Squares Regression Results for Density of Pounds Released (Natural Log) at One-Mile from Block Group Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.011*</td>
<td>0.005</td>
<td>0.016*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.540)</td>
<td>(3.660)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.034**</td>
<td>-0.001**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.950)</td>
<td>(-0.135)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.075*</td>
<td>0.016*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(16.270)</td>
<td>(11.830)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.042*</td>
<td>0.003*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(11.33)</td>
<td>(5.830)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.190*</td>
<td>-1.140*</td>
<td>-1.210*</td>
<td>-1.330*</td>
</tr>
<tr>
<td></td>
<td>(-9.290)</td>
<td>(-6.550)</td>
<td>(-9.400)</td>
<td>(-7.780)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.049*</td>
<td>0.032*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.560)</td>
<td>(2.320)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.005</td>
<td>0.007</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.060)</td>
<td>(1.450)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>0.004</td>
<td>0.020</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.290)</td>
<td>(1.400)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.058</td>
<td>0.062</td>
<td>0.112</td>
<td>0.115</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>82.770*</td>
<td>35.770*</td>
<td>85.240*</td>
<td>49.820*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>17213.400</td>
<td>17206.700</td>
<td>17056.600</td>
<td>17055.300</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-8603.710</td>
<td>-8597.350</td>
<td>-8523.290</td>
<td>-8519.660</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.672*</td>
<td>0.672*</td>
<td>0.639*</td>
<td>0.642*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.692*</td>
<td>0.692*</td>
<td>0.658*</td>
<td>0.663*</td>
</tr>
<tr>
<td>Moran’s I-0.19 mile</td>
<td>0.018*</td>
<td>0.018*</td>
<td>0.017*</td>
<td>0.016*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 33: Spatial Regression Results for Density of Pounds Released (Natural Log) at Zero Miles from Block Group Boundary Using the Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.005**</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.840)</td>
<td>(0.944)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.010</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.020)</td>
<td>(0.898)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.023*</td>
<td>0.020*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.480)</td>
<td>(5.600)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.014*</td>
<td>0.011*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.650)</td>
<td>(3.660)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.732*</td>
<td>-0.733*</td>
<td>-0.736*</td>
<td>-0.748*</td>
</tr>
<tr>
<td></td>
<td>(-15.620)</td>
<td>(-14.700)</td>
<td>(-15.960)</td>
<td>(-15.150)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.004</td>
<td></td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.586)</td>
<td>(0.468)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td></td>
<td>-0.004</td>
<td></td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-1.460)</td>
<td></td>
<td>(-1.430)</td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.0003</td>
<td></td>
<td>0.0003</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.056)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.305*</td>
<td>0.303*</td>
<td>0.281*</td>
<td>0.280*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>13574.100</td>
<td>13576.800</td>
<td>13556.200</td>
<td>13559.300</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-6784.030</td>
<td>-6782.380</td>
<td>-6773.110</td>
<td>-6771.640</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>-0.006</td>
<td>-0.005</td>
<td>-0.004</td>
<td>-0.004</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 34: Spatial Regression Results for Density of Pounds Released (Natural Log) at Zero Miles from Block Group Boundary Using the Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.005**</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.860)</td>
<td>(0.958)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.011</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.070)</td>
<td>(0.964)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.023*</td>
<td>0.020*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.510)</td>
<td>(5.620)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.014*</td>
<td>0.011*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.690)</td>
<td>(3.680)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.716*</td>
<td>-0.717*</td>
<td>-0.733*</td>
<td>-0.735*</td>
</tr>
<tr>
<td></td>
<td>(-15.350)</td>
<td>(-14.450)</td>
<td>(-15.730)</td>
<td>(-14.930)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.005</td>
<td>0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.679)</td>
<td>(0.555)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.003</td>
<td>-0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.280)</td>
<td>(-1.240)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.001</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.086)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.297*</td>
<td>0.295*</td>
<td>0.275*</td>
<td>0.273*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>13567.300</td>
<td>13570.400</td>
<td>13549.400</td>
<td>13552.900</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-6780.650</td>
<td>-6779.210</td>
<td>-6769.690</td>
<td>-6768.430</td>
</tr>
<tr>
<td>Moran's I-rook</td>
<td>-0.002</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 35: Spatial Regression Results for Density of Pounds Released (Natural Log) at Half-Mile from Block Group Boundary Using the Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.003</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.130)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td></td>
<td>0.003**</td>
<td></td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.130)</td>
<td></td>
<td>(1.430)</td>
</tr>
<tr>
<td>% Hispanic</td>
<td></td>
<td>0.019*</td>
<td></td>
<td>0.017*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(6.690)</td>
<td></td>
<td>(4.600)</td>
</tr>
<tr>
<td>% Minority</td>
<td>0.010*</td>
<td>0.008*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.680)</td>
<td>(2.530)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.512*</td>
<td>-0.642*</td>
<td>-0.566*</td>
<td>-0.699*</td>
</tr>
<tr>
<td></td>
<td>(-7.680)</td>
<td>(-7.890)</td>
<td>(-8.250)</td>
<td>(8.500)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td></td>
<td>0.013</td>
<td></td>
<td>0.014**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.570)</td>
<td></td>
<td>(1.700)</td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.003</td>
<td></td>
<td>-0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.060)</td>
<td></td>
<td>(-0.697)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.024*</td>
<td></td>
<td>0.025*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.150)</td>
<td></td>
<td>(3.270)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.783*</td>
<td>0.783*</td>
<td>0.771*</td>
<td>0.771*</td>
</tr>
<tr>
<td></td>
<td>(14679.400)</td>
<td>14671.700</td>
<td>14660.800</td>
<td>14652.600</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-7335.720</td>
<td>-7328.840</td>
<td>-7324.420</td>
<td>-7317.280</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>0.013</td>
<td>0.016</td>
<td>0.013</td>
<td>0.017</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 36: Spatial Regression Results for Density of Pounds Released (Natural Log) at Half-Mile from Block Group Boundary Using the Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.003</td>
<td>0.008</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.230)</td>
<td>(1.410)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.018**</td>
<td>0.017</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.730)</td>
<td>(1.240)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.020*</td>
<td>0.023*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.880)</td>
<td>(4.240)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.011*</td>
<td>0.016*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.850)</td>
<td>(3.450)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.501*</td>
<td>-1.200*</td>
<td>-0.555*</td>
<td>-1.210*</td>
</tr>
<tr>
<td></td>
<td>(-7.650)</td>
<td>(-10.130)</td>
<td>(-8.230)</td>
<td>(10.190)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.027*</td>
<td>0.026*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.080)</td>
<td>(2.960)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.009*</td>
<td>0.008*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.710)</td>
<td>(2.590)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>0.066*</td>
<td>0.067*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.050)</td>
<td>(7.100)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.770*</td>
<td>0.787*</td>
<td>0.759*</td>
<td>0.781*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>14641.300</td>
<td>14601.100</td>
<td>14621.800</td>
<td>14595.500</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-7316.660</td>
<td>-7294.530</td>
<td>-7304.890</td>
<td>-7291.250</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>-0.012</td>
<td>0.006</td>
<td>0.008</td>
<td>0.006</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 37: Spatial Regression Results for Density of Pounds Released (Natural Log) at Half-Mile from Block Group Boundary Using Distance

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 0.19 mile</th>
<th>Model 2 0.19 mile</th>
<th>Model 3 0.19 mile</th>
<th>Model 4 0.19 mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.009* (2.460)</td>
<td>0.004 (0.764)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.007 (-0.487)</td>
<td>-0.008 (-0.539)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.058* (14.700)</td>
<td>0.052* (10.530)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.032* (10.290)</td>
<td>0.023* (5.330)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.080* (-11.700)</td>
<td>-1.130 (-10.100)</td>
<td>-1.130 (-12.120)</td>
<td>-1.250* (-11.240)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.036* (3.180)</td>
<td>0.027* (2.360)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.001 (-0.197)</td>
<td>0.001 (0.244)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.016 (1.510)</td>
<td>0.024* (2.310)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.290* (16208.900)</td>
<td>0.286* (16202.000)</td>
<td>0.261* (16091.700)</td>
<td>0.252* (16087.600)</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-8101.430</td>
<td>-8095.020</td>
<td>-8040.850</td>
<td>-8035.800</td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 38: Spatial Regression Results for Density of Pounds Released (Natural Log) at One Mile from Block Group Boundary Using the Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.001</td>
<td>0.0004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.599)</td>
<td>(0.134)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.010</td>
<td>0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.040)</td>
<td>(1.060)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.016*</td>
<td>0.015*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.910)</td>
<td>(4.510)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.008*</td>
<td>0.007*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.870)</td>
<td>(2.390)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.449*</td>
<td>-0.605*</td>
<td>-0.491*</td>
<td>-0.670*</td>
</tr>
<tr>
<td></td>
<td>(-6.230)</td>
<td>(-6.150)</td>
<td>(-6.650)</td>
<td>(-6.730)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.011</td>
<td>0.012</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.510)</td>
<td>(1.520)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.001</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.458)</td>
<td>(0.786)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.021*</td>
<td>0.024*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.690)</td>
<td>(2.940)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.876*</td>
<td>0.876*</td>
<td>0.868*</td>
<td>0.868*</td>
</tr>
<tr>
<td></td>
<td>14517.100</td>
<td>14514.400</td>
<td>14500.800</td>
<td>14496.500</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-7254.540</td>
<td>-7250.210</td>
<td>-7244.420</td>
<td>-7239.240</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>-0.008</td>
<td>-0.004</td>
<td>-0.007</td>
<td>-0.003</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 39: Spatial Regression Results for Density of Pounds Released (Natural Log) at One Mile from Block Group Boundary Using the Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.002</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.865)</td>
<td>(0.339)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.009</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.996)</td>
<td>(1.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.016*</td>
<td>0.016*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.140)</td>
<td>(4.690)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.008*</td>
<td>0.007*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.160)</td>
<td>(2.550)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-0.450*</td>
<td>-0.610*</td>
<td>-0.493*</td>
<td>-0.673*</td>
</tr>
<tr>
<td></td>
<td>(-6.400)</td>
<td>(-6.350)</td>
<td>(-6.800)</td>
<td>(-6.930)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.012</td>
<td>0.012</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.600)</td>
<td>(1.550)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.001</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.425)</td>
<td>(0.744)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.022*</td>
<td>0.024*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.810)</td>
<td>(3.080)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.866*</td>
<td>0.866*</td>
<td>0.858*</td>
<td>0.858*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>14449.300</td>
<td>14446.200</td>
<td>14433.200</td>
<td>14428.000</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-7220.830</td>
<td>-7216.080</td>
<td>-7210.610</td>
<td>-7205.020</td>
</tr>
<tr>
<td>Moran's I-rook</td>
<td>-0.017</td>
<td>-0.012</td>
<td>-0.015</td>
<td>-0.010</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 0.19 mile</th>
<th>Model 2 0.19 mile</th>
<th>Model 3 0.19 mile</th>
<th>Model 4 0.19 mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.012* (2.750)</td>
<td>0.006 (1.020)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.035* (-2.060)</td>
<td>-0.033** (-1.880)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.075* (16.230)</td>
<td>0.069* (11.680)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.042* (11.380)</td>
<td>0.030* (5.720)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.180* (-9.280)</td>
<td>-1.110* (-6.410)</td>
<td>-1.200* (-9.360)</td>
<td>-1.290* (-7.610)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.050* (3.670)</td>
<td></td>
<td>0.033* (2.430)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.004 (0.830)</td>
<td></td>
<td>0.006 (1.240)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.001 (0.070)</td>
<td></td>
<td>0.017 (1.180)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.401* (9.280)</td>
<td>0.408* (6.410)</td>
<td>0.385* (9.360)</td>
<td>0.384* (7.610)</td>
</tr>
<tr>
<td>Akaike Info Coefficient</td>
<td>17193.000</td>
<td>17185.200</td>
<td>17038.300</td>
<td>17037.300</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-8593.480</td>
<td>-8586.600</td>
<td>-8514.170</td>
<td>-8510.670</td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.005</td>
<td>0.005</td>
<td>0.003</td>
<td>0.005</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
7. ANALYZING THE TOXICITY OF EMISSIONS FROM INDUSTRIAL POLLUTION SOURCES

This chapter focuses on the use of hazard scores calculated from points sources listed in the USEPA’s Toxic Release Inventory (TRI) as an indicator of exposure to chronic air pollution in the analysis of environmental justice in the Houston-Galveston-Brazoria metropolitan statistical area (HGB-MSA). The goal is to explore the association between toxicity-weighted quantities of emissions (hazard score) from chronic industrial air pollution sources and selected demographic and socioeconomic variables from Census 2000, in order to determine the presence of inequity with respect to the racial/ethnicity and poverty status of the population.

The analysis begins with an examination of bivariate parametric correlations between the toxicity-weighted quantities of emissions (hazard scores) at three search radii (0, 0.5, and 1 mile) and relevant explanatory variables at the census tract and block group level of aggregation. The hazard scores of atmospheric pollution (all emitted chemicals) from TRI facilities were calculated for each geographic analytical unit following the technique for modeling point density described previously in Chapter 4. For each census tract or block group, the areal density of hazard scores is measured by dividing the total toxicity-weighted hazard scores from their host facilities by the area enclosed, at three different distances from the tract or block group boundary (0, 0.5, and 1 mile). Because of the skewed distribution of this variable, the natural logarithm (LN) of the density of hazard scores was used for all statistical analyses presented in this chapter. The use of
the natural log reduces outliers and yields a normal-style distribution of the dependent variable that is more consistent with the requirements of regression modeling.

Summary statistics for all variables analyzed are provided in Tables 41 and 42, respectively, for census tract and block group level data. The descriptive statistics show that census tracts contain a larger density of hazard scores from pollutants than block groups. In addition, the density of hazard scores increase as the search radius increases from 0 to 1 mile from the boundary due to the possible inclusion of more TRI facilities at larger distances from each unit.

Pearson’s correlation coefficients associated with the density of hazard scores within the three distances of each analytical unit are presented in Table 43 for census tract level and Table 44 for block group level analyses. The correlation analysis at the census tract level show that at 0 miles from the boundary, percent Hispanic has the highest positive correlation with the density of hazard scores followed by percent below poverty and percent minority. Additionally, population density has the greatest negative correlation followed by percent Asian, labor force, and percent Black. Percent owner occupied housing does not indicate significant correlation with density of hazard scores at this level.

At 0.5 mile from the census tract boundary, percent Hispanic again has the highest positive correlation in relation to density of hazard scores followed by percent below poverty and percent minority. Additionally, percent Asian has the greatest negative correlation followed by population density, and labor force. Percent owner occupied housing and percent Black does not indicate a significant correlation with density of hazard scores at this level.
At 1 mile from the census tract boundary, percent Hispanic has the highest positive correlation in relation to density of hazard scores followed by percent minority and percent below poverty. Additionally, percent Asian has the greatest negative correlation followed by labor force and population density. Percent owner occupied housing and percent Black do not indicate a significant correlation with density of hazard scores at this level.

At the block group level, the correlation analysis show that at 0 miles from the boundary percent Hispanic has the highest positive correlation to the density of hazard scores followed by percent below poverty and percent minority. Additionally, population density has the greatest negative correlation followed by labor force, percent Asian, and percent Black. Percent owner occupied housing does not indicate a significant correlation with density of hazard scores at this level.

At 0.5 mile from the block group boundary, percent Hispanic has the highest positive correlation in relation to density of hazard scores followed by percent below poverty and percent minority. Additionally, population density has the greatest negative correlation followed by labor force, percent Asian, and percent owner occupied housing. Percent Black does not indicate a significant correlation with density of hazard scores at this level.

At 1 mile from the block group boundary, percent Hispanic has the highest positive correlation in relation to hazard scores followed by percent minority and percent below poverty. Additionally, percent Asian along with labor force has the greatest negative correlation followed by population density and percent owner occupied housing.
Percent Black does not show a significant correlation with density of hazard scores at this level.

In summary, the correlation analysis indicates that the percent Hispanic has the strongest positive correlation and most significant positive linear association with the toxicity-weighted quantities of chemicals released by TRI facilities into the atmosphere, at both the census tract and block levels. The environmental inequity hypothesis is supported by three variables (overall percent Hispanic, percent minority, and percent below poverty) which consistently exhibit a significant and positive relationship with density of hazard scores at all search radii and at both the census tract and block group levels. The percentage of Asians, population density, and labor force suggest a negative linear relationship at all distances and levels of aggregation. Blacks, on the other hand, have a negative relationship with density of hazard scores at 0 miles only for both census tracts and block groups. Additionally, the presence of minorities becomes significant as the search radii approach 1 mile (1 mile at block group; and 0.5 and 1 mile at census tract). This suggests once again that the Hispanic population has the greatest statistical effect on the minority proportion since the coefficient for overall minority percentage is positive while all of the remaining minority sub-groups are negative. Additionally, the negative correlation of owner occupied housing at the block group level only reinforces the need to address environmental justice variables at different resolutions. The negative correlation for the percent Asian on the other hand becomes stronger as the search radius increases from the boundary to 1 mile for both analytical units, while population density became less influential. This suggests that more Asians could reside at the edge or outside of analytical units characterized by higher hazard scores.
While correlation analysis provides a preliminary view of the statistical association between each demographic and socioeconomic variable and the density of hazard scores, it does not clarify the underlying pattern in sufficient detail. Multivariate regression is therefore used to analyze the simultaneous statistical effects of the explanatory variables on the density of hazard scores derived on the basis of the toxicity of chemicals released from TRI facilities at the census tract and block group level, respectively.

The ordinary least squares (OLS) regression approach is first utilized to model the statistical effect of explanatory variables on the density of hazard scores within each analytical unit in the study area, based on the three search radii (0, 0.5 and 1 mile). The results from the OLS regression models for the four different combinations of explanatory variables are summarized in the first set of tables (Tables 45-47 and 56-58). Following Chapter 6, this set of tables also provides results from an analysis of spatial dependence using both the contiguity-based and distance-based methodologies. The results in the OLS tables contain regression coefficients that are bolded, z-scores which are in parentheses and p-values which are identified utilizing the single ($\alpha=0.05$) and double ($\alpha=0.10$) asterisk. Additionally, these tables contain Moran’s I which is used for testing for the existence of spatial autocorrelation.

The second phase of the analysis uses the spatial autoregressive function (SAR) by utilizing an autoregressive coefficient to account for spatial autocorrelation. The appropriate SAR function (spatial lag or spatial error) was determined using the Lagrange-Multiplier test statistic results (Anselin 2006) obtained while running the corresponding OLS model. As mentioned previously, the SAR models use a spatial
weights matrix specified by three configurations of neighboring census units: queen-based contiguity, rook-based contiguity, and distance-based bands. Separate queen and rook contiguity analysis was therefore performed in hopes of finding the best fitted model that minimizes the effects of spatial dependence. Additionally, separate analysis for distance bands were constructed selecting between 3 and 5 distances which were used as adjustments to eliminate spatial autocorrelation. After the completion of the analyses, the best model was selected based upon the achievement of non-significant \((p<0.05)\) Moran’s I which signifies no spatial autocorrelation and the lowest Akaike Information Criterion (AIC) which is used to determine the fit of the model. The census tract results are listed in Tables 48-55 and the block groups in Tables 59-66. The results in the tables contain regression coefficients which are bolded, z-scores which are in parentheses, and p-values which are identified utilizing the single \((\alpha=0.05)\) and double \((\alpha=0.10)\) asterisk.

The histograms in Figure 10 summarize the connectivity distribution for census tracts, based on the number of neighbors in each configuration. For queen contiguity, Figure 10(a) shows that the majority of the census tracts have 5 to 8 neighbors and peaks at 7 neighbors. For the rook contiguity in Figure 10(b), the number of neighbors peaks at 4 but the census tracts noticeably had a positive skew. The histogram for the distance-based configuration in Figure 10(c) provides the connectivity distribution at 0.50 and (d) 0.38 mile from the centroid of each unit and indicates that a majority of census tracts have no neighbors at this distance. The connectivity distributions for census block groups are summarized in Figure 11. The histogram for queen contiguity in Figure 11(a) shows that the majority of the block groups have 5 to 7 neighbors and peaks at 6 neighbors. For the rook contiguity in Figure 11(b), the number of neighbors peaks at 5
and noticeably has a positive skew. The histogram for the distance-based configuration in Figure 11(c) provides the connectivity distribution at 0.19 mile from the centroid of each unit and indicates that the number of block groups with no neighbors at this distance is considerably higher than the number of census tracts with no neighbors in Figure 11(c).
Figure 10: Census tract connectivity histograms used for hazard scores
Figure 11: Block group connectivity histograms used for hazard scores

a. Queen Contiguity

b. Rook Contiguity

c. Distance-Based Configuration (0.19 miles)
7.1 Census Tract Level Analysis

Ordinary Least Squares Regression This section compares the density of hazard scores as computed from toxicity-weighted quantities of emissions at the census tract level, at zero (0), half (0.5) and one (1) mile search radii, based on the application of ordinary least squares (OLS) and spatial autoregressive (SAR) techniques. Table 45 summarizes the results of OLS regression analysis at the boundary of the census tracts. Models 1 and 2 both indicate that the overall percent minority shows a significant and positive statistical effect on the density of hazard scores. Additionally, when the minority subgroups are analyzed separately for models 3 and 4, the Hispanic percent indicates a significant and positive association with the density of hazard scores. This suggests that the minority population in tracts exposed to the most toxic emissions probably comprises a large proportion of Hispanics. Additionally, it stresses the importance of analyzing each racial/ethnic sub-group individually and collectively to gain clarity on their environmental justice implications. In all four models, the density of hazard scores significantly increases with a decrease in population density.

At 0.5 mile from the tract boundary (Table 46), the results for the racial/ethnic variables are similar to those observed at 0 mile from the tracts. For models 1 and 2, the density of hazard scores increases significantly as the overall percentage of minority residents increases. Furthermore, for models 3 and 4, the Hispanic percentage has a significant and positive statistical effect on the density of hazard scores. Percent Black however, has a positive and significant statistical effect on hazard scores at model 3, but not in model 4 when the socioeconomic terms are introduced. Furthermore, percent
below poverty increases significantly for models 2 and 4. For all models at the boundary, population density is a negative predictor of hazard score density.

At 1 mile from the boundary of census tracts (Table 47) models 1 and 2 indicate a positive statistical effect of the overall minority percentage and percent Hispanic (models 3 and 4) on the density of hazard scores, which is consistent with the results at 0 and 0.5 miles from tract boundaries. Percentage Black is again positive and significant in model 3. Percent below poverty on the other hand is significant in model 2, but becomes non-significant when the individual minority subgroups are introduced. In all four models, the density of hazard scores significantly increases with a decrease in population density.

Moran’s I for the regression models based on queen and rook contiguities shows significance at 0, 0.5, and 1 mile search radii indicating the presence of significant spatial autocorrelation in the data and justifying the need to account for spatial dependence by using a SAR model. However, at 0.5 mile from the 0 mile boundary when using the distance band at all search radii the distance band was found to be non-significant. Consequently, spatial dependence was not detected and the spatial autoregressive function was therefore not implemented. The distance band was also found to be non-significant at 0.37 mile at 0.5 and 1 mile search radii for models 3 and 4 only. Consequently, spatial dependence was not detected and the spatial autoregressive function was implemented only for models 1 and 2. Following the assessment for spatial dependence, the SAR model was thus implemented for all OLS models in which significant spatial autocorrelation was detected.

**Spatial Regression** At the boundary of the census tract level for the queen contiguity (Table 48), models 1 and 2 indicate a significant and positive association between the
density of hazard scores at 0 miles and the overall minority percent. Additionally, for models 3 and 4, the Asian and Hispanic populations positively affect the density of hazard scores. Labor force however, has a positive statistical effect on density of hazard scores only for model 2, but is not significant when the minority sub-groups are separated. For all models at 0 mile from the tract boundary, density of hazard scores significantly increases when population density decreases. The queen contiguity SAR models differ from OLS in that Asian percentage and labor force becomes significant and has a positive statistical effect on the density of hazard scores.

At the boundary of the census tract level for the rook contiguity (Table 49), all SAR models exhibit the same statistical associations as observed in the model for queen contiguity and had similar differences from the corresponding OLS models.

Models for the distance band at 0.5 mile were not run because the Moran’s I from the OLS regression were not significantly different from zero when determining spatial autocorrelation.

At 0.5 mile from the boundary of census tracts (Table 50) for the queen contiguity, percent minority is positively associated with the density of hazard scores (model 1) only in the absence of socioeconomic variables. Additionally, for models 3 and 4, percent Hispanic has a significantly positive statistical effect on the density of hazard scores, along with labor force and percent below poverty for models 2 and 4. For model 2, the density of hazard scores increases significantly only when percent owner occupied increases, but not when the minority sub-groups are separated. For all models at the boundary of tracts, population density is a negative predictor of the density of hazard scores. The queen contiguity SAR models differ from OLS in that the Black
percent becomes non-significant for model 3 and percent minority becomes non-significant for model 2 only. Additionally, percent owner occupied housing and labor force have a positive statistical effect and are significant and for models 2 only on the density of hazard scores unlike the OLS model.

At 0.5 mile from the boundary of the census tracts for the rook contiguity (Table 51), explanatory variables in all SAR models exhibit the same statistical associations as observed in the models for queen contiguity except percent occupied housing and labor which were both non-significant in this contiguity. Additionally, rook contiguity achieved the same significance and non-significance as the corresponding OLS model.

A distance band of 0.37 mile was constructed for models 1 and 2 only beginning 0.5 mile from each census tract boundary to identify neighboring tracts for assessing spatial dependence (Table 52). This distance was chosen based on a selection criteria that comprised the minimization of the likelihood term (AIC) and significance of spatial autocorrelation using Moran’s I. Percent Hispanic for models 3 and 4 has a significantly positive statistical effect on the density of hazard scores, as well as percent minority for models 1 and 2, and percent below poverty for models 2 and 4. The distance band did not show any difference for SAR as compared to the OLS models.

At 1 mile from the boundary of census tracts (Table 53) for queen contiguity, percent minority positively statistical effects the density of hazard scores in model 1. Additionally, for models 3 and 4, the Hispanic population has a positive statistical effect on the density of hazard scores. For all models at 1 mile from the boundary, population density is a negative predictor of the density of hazard scores. The queen contiguity SAR
models differ from OLS in that Black percentage is not significant. In model 2 only, percent minority and percent below poverty become non-significant.

At 1 mile from the boundary of the census tracts (Table 54) for the rook contiguity model, percent Hispanic exhibits the same positive prediction as in the queen contiguity model, while population density has the same negative statistical effect on the density of hazard scores. Percent minority is significant and a positive predictor of density of hazard scores for models with and without the socioeconomic variables. The SAR model exhibits the same difference for the rook contiguity at 1 mile as for the queen contiguity, except the minority percent for model 2 is significant.

A distance band of 0.37 mile was constructed for models 1 and 2 only at 1 mile from each census tract boundary to identify neighboring tracts for assessing spatial dependence (Table 55). This distance was chosen based on selection criteria that comprised the minimization of the likelihood term (AIC) and significance of spatial autocorrelation using Moran’s I. Percent Hispanic and percent minority exhibit the same positive statistical effects on density of hazard scores as in the rook contiguity model, while population density has the same negative statistical effect. Additionally, percent below poverty and percent owner occupied in model 2, and labor force and percent Black in model 3 show a positive and significant statistical effect on the density of hazard scores. The distance-based model did not show any difference for SAR as compared to the OLS model, except that percent owner occupied housing and labor force became significant while using the distance-based SAR model.
7.2 Block Group Level Analysis

Ordinary Least Squares Regression This section focuses on multivariate regression analysis of the areal density of hazard scores at the block group level, at zero (0), half (0.5), and one (1) mile search radii based on the application of ordinary least squared regression and spatial autoregressive techniques. Table 56 summarizes the results of OLS regression analysis at the boundary of the block groups. Models 1 and 2 both indicate that the overall percent minority shows a significant and positive statistical effect on the density of hazard scores. Additionally, when the minority sub-groups are analyzed separately in models 3 and 4, the Hispanic percent and Black percent indicates a significant and positive association with the density of hazard scores. Additionally, percent owner occupied is a negative predictor in models 3 and 4, while the density of hazard scores significantly increases with a decrease in population density in all four models.

At 0.5 mile from the boundary of the block groups (Table 57), the results for the racial/ethnic variables are similar to those observed at 0 mile from the block groups. For models 1 and 2, the effect on density of hazard scores increase significantly as the overall percentage of minority residents increases. Furthermore, for models 3 and 4, the Hispanic percentage has a significant and positive statistical effect on the density of hazard scores while in model 3 percent Black retains a positive statistical effect on density hazard scores. For both models 2 and 4, the density of hazard scores increases significantly as the percent below poverty increases. For all models, at 0.5 mile from the block group boundary, the density of hazard scores significantly increases with a decrease in population density.
At 1 mile from the boundary of block groups (Table 58), models 1 and 2 indicate a positive statistical effect of the overall minority percentage, along with percent Black and percent Hispanic (models 3 and 4) on the density of hazard scores that is consistent with the results at 0 miles from block group boundaries. As with 0.5 mile density of hazard scores is positively associated by percent below poverty. Additionally, the hazard scores increases significantly as percent Asian decreases for model 3 alone and for all models with a decrease in population density.

Moran’s I for the regression models based on the queen and rook contiguities show significance at 0.5 and 1 miles search radii indicating the presence of significant spatial autocorrelation in the data, therefore justifying the need to account for spatial dependence by using the SAR model. However, at 0.19 mile from the boundary when using the 0 mile search radii only, the distance band was found to be non-significant. Consequently, spatial dependence was not detected and the spatial autoregressive function was therefore not implemented. This distance band configuration was chosen based on the best fit using AIC and the achievement of non-significance for spatial autocorrelation using Moran’s I. Following the assessment for spatial dependence the SAR model was thus implemented for all OLS models in which significant spatial autocorrelation was detected.

**Spatial Regression** At the boundary of block groups (Table 59) for the queen contiguity in models 1 and 2, the overall minority percent indicates a significant and positive association with the density of hazard scores. Additionally, in models 3 and 4, the Hispanic percent has a positive statistical effect on the density of hazard scores. Percent Black however, positively influences density of hazard scores in model 3, but not when
the socioeconomic variables are introduced. For all SAR models, the density of hazard scores significantly increases with a decrease in population density. Hazard scores also increase when the presence of percent owner occupied housing decreases in models 2 and 4. The queen contiguity SAR models differs from OLS in that the Black percent becomes non-significant in model 4, while it remains significant in model 3 when socioeconomic terms are absent.

At the boundary of the block group level (Table 60) for the rook contiguity, all SAR models exhibit the same statistical associations as observed in the model for queen contiguity and similar differences from the corresponding OLS models. The rook contiguity differed from the OLS model the same as the queen contiguity where owner occupied housing is non-significant for models 2 and 4 when SAR is introduced and labor force became significant in model 4.

Models for the distance band at 0 miles was not run because the distance band at 0.19 mile for all models in the OLS regression was found to be non-significant when testing for spatial autocorrelation using Moran’s I.

At 0.5 mile from the block group boundary (Table 61) for the queen contiguity, percent minority shows a positive statistical effect on the density of hazard scores in models 1 and 2. Additionally, in models 3 and 4, the Hispanic population has significantly a positive statistical effect on density of hazard scores. In models 2 and 4, percent below poverty, percent owner occupied, and labor force independently and significantly has a positive statistical effect on density of hazard scores. Percent Black however, positively predicts density of hazard scores at model 3, but is not a predictor in model 4 when the socioeconomic terms are introduced. For all models, the density of
hazard scores significantly increases with a decrease in population density. The queen contiguity SAR models differ from OLS in that the percent owner occupied housing and labor force have a positive statistical effect on density of hazard scores.

At 0.5 mile from the boundary at the block group level (Table 62) for rook contiguity, percent minority and percent Hispanic exhibit the same positive statistical effect as the queen contiguity, while population density has the same negative prediction on density of hazard scores. Additionally, percent Asian has a positive statistical effect on density of hazard scores for models 3 and 4. However, percent below poverty (model 2) and labor force (model 4) both have positive statistical effects on density of hazard scores. The rook contiguity SAR models differ from OLS in that the percent Black in model 3 is no longer significant. However, percent Asian gains significance in models 3 and 4 and labor force gains significance in the model with separate minority sub-groups. The Black percentage on the other hand loses significance for model 3 while below poverty percentage loses significance when minority sub-groups are included.

A distance band of 0.19 mile (Table 63) was constructed beginning from 0.5 mile from each block group boundary to identify neighboring tracts for assessing spatial dependence. Percent minority and percent Hispanic exhibit the same positive statistical effect of density of hazard scores as the rook contiguity, while population density has the same negative prediction. Additionally, percent below poverty is a positive predictor for both models. Percent Black however, positively predicts hazard scores at model 3, but is not a predictor in model 4 when the economic terms were introduced. Labor force is positively associated with the density of hazard scores in model 4, but is not a predictor in model 3 when the minorities are classified into sub-groups. Lastly, percent owner
occupied is a significant and negative predictor of density of hazard scores. The SAR models for the distance band model at 0.19 mile from the boundary differ from OLS in that percent owner occupied and labor force in model 3 are both significant and exhibits a positive statistical effect in model 4 on density of hazard scores.

At 1 mile from the boundary of block groups (Table 64) for queen contiguity, percent minority and percent Hispanic has similar positive statistical effect in the SAR models as 0 and 0.5 mile while population has a similar negative statistical effect on density of hazard scores. Hazard scores also increase as labor force increases for models 2 and 4. The queen contiguity SAR models differ from OLS in that in percent Black in models 3 and 4 are no longer significant. Additionally, percent Asian (model 3) and percent below poverty (models 2 and 4) lose significance and no longer contribute to density of hazard scores. Labor force on the other hand gains significance for models 2 and 4.

At 1 mile from the boundary of block groups (Table 65) for rook contiguity, percent minority, percent Hispanic, and labor force exhibit the same positive statistical effect on the density of hazard scores as the queen contiguity, while population density has the same negative statistical effect on the density of hazard scores.

The rook contiguity SAR models exhibit the same difference from OLS as the queen contiguity models.

A distance band of 0.19 mile (Table 66) was constructed beginning from 1 mile from the block group boundary. Percent minority and percent Hispanic show the same positive prediction as the rook contiguity, while population density had the same negative statistical effect on of density of hazard scores. Additionally, percent below poverty has
a positive association with the density of hazard scores at model 2 and 4 and percent Black at models 3 and 4. Percent Asian however, has a negative association with the density of hazard scores at model 3. The distance-based SAR models do not exhibit any significant differences from the OLS models.

7.3 Discussion and Interpretation

The analyses presented in this chapter focuses on the geographic distribution of pollution burdens measured in terms of the toxicity-weighted quantities of emissions (hazard scores) from industrial point sources. The results reveal that the areal density of hazard scores from TRI facilities in the Houston-MSA are significantly associated with population density, the overall proportion of minorities, and the Hispanic proportion at the census tract level, regardless of whether conventional or spatial regression was utilized. While densely populated tracts are less likely to be exposed to the most toxic emissions, the presence of racial/ethnic minorities and Hispanics, in particular, indicate a positive statistical effect on the density of hazard scores at all distances, even after controlling for the effects of other explanatory variables. Additionally, the percentage of Asians living within the census tract boundaries are only significant when spatial autocorrelation is removed. The Black percentage shows a significant and positive statistical effect when the density of hazard scores is measured at 0.5 mile from the tract boundary, for both ordinary regression and spatial regression based on distance-based contiguity (0.37 mile). The poverty rate also shows a positive relationship with hazard scores at 0.5 mile. Additionally, the percentage of owner occupied housing at distances (0.5 and 1 mile) away from the census tract boundaries are only positive and significant when spatial autocorrelation is removed. Labor force shows a positive statistical effect
on the density of hazard scores near the boundary only when spatial autocorrelation is taken into account. This suggests that the presence of a readily available workforce plays a key role in the location of these industrial facilities.

As observed at the census tract level, population density, minority percent, and percent of Hispanics, are again the most influential variables related to the density of hazard scores at the block group level. Hazard scores are found to be significantly greater in block groups containing a higher proportion of racial/ethnic minorities and Hispanic populations, in all models and distance definitions. Furthermore, unlike the census tract level, the Black population is significantly associated with hazard score density at all distances with and without the adjustment for spatial autocorrelation. This suggests that a higher concentration of both Black and Hispanic residents can be found near TRI facilities releasing chemicals of greater toxicity, at the block group level. It also again suggests that the minorities facing the greatest exposure to the most toxic TRI chemicals are overwhelmingly Hispanics. Again the Asian population is significant only when spatial dependence is removed. As for poverty rate, a positive and significant statistical effect is found only when hazard scores are measured at distances that extend beyond block group boundaries (0.5 mile; and 1 mile-0.19 mile distance based), with and without adjusting for spatial autocorrelation. Additionally, the percentage of owner occupied housing at distances (0 and 0.5 mile) away from the block group boundaries are negative and significant using both ordinary and spatial regression techniques, while labor force is positive and significant at almost all distances.

In summary, the results suggest that the toxicity-weighted quantities of TRI emissions increase significantly with an increase in the proportion of racial/ethnic
minorities at all search radii and at both the census tract and block levels of aggregation. More specifically, the overall minority, Hispanic population, and population density are the most significant explanatory factors in determining the density of hazard scores at all search radii, all data resolutions, and for both regression modeling techniques. Additionally, the proportion of Asians is only significant when spatial autocorrelation is removed and the significance of labor force increases when spatial dependence is accounted for as well. This finding indicates how spatial autocorrelation can mask the effects of specific variables (e.g., percent Asian and labor force) when determining their statistical association with the toxicity-weighted magnitude of emissions and justifies the need to control for spatial dependence in regression analysis of environmental justice. The Black population was found to be positive and significant at the boundary of the tract level for the OLS models only. Additionally, this variable was found to be significant at the 0.5 and 1 mile search radii and the 0.5 search radii using the 0 distance-based SAR models that did not include socioeconomic variables. However, at the block group level, Black population was significant at all distances and in majority of the models tested with and without the socioeconomic variables. It should be noted that owner occupied housing had a positive statistical effect on the hazard scores at the census tract level but exhibited a negative statistical effect at the block group level. This confirms the importance of analyzing data at more than one spatial resolution because the nuances between the distances were not evident at a single analytical unit.

While the analyses presented in this chapter provide an assessment of inequities based on toxicity of chemicals emitted from TRI facilities, it is important to consider that the toxicity-weighted quantities (hazard scores) do not account for the environmental fate
and transport of released chemicals. Thus, the human health risks of exposure to toxic emissions within and outside the analytical unit containing the TRI facilities are not considered. The application of modeled risk scores, therefore, is necessary to address this limitation and provide a more exact assessment of disproportionate risk burdens imposed on the population in the Houston MSA.
Table 41: Descriptive Statistics for Variables at the Census Tract Level Associated with Hazard Scores. n=886

<table>
<thead>
<tr>
<th>Variables</th>
<th>Hazard Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
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<td>Density of Hazard Scores (LN):</td>
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</tr>
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<td>0 Miles</td>
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<tr>
<td>Density of Hazard Scores (LN):</td>
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<td>0.5 Mile</td>
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<td>Density of Hazard Scores (LN):</td>
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<tr>
<td>% Black</td>
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<tr>
<td>% Asian</td>
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<tr>
<td>% Hispanic</td>
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<tr>
<td>% Minority</td>
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<td>Population Density (LN)</td>
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<tr>
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</tr>
<tr>
<td>% Owner Occupied</td>
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<tr>
<td>Labor Force (SR)</td>
<td>60.270</td>
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Table 42: Descriptive Statistics for Variables at the Block Group Level Associated with Hazard Scores. n=2705

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<td>Std Dev</td>
<td>Min</td>
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</tr>
<tr>
<td>% Black</td>
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<td>25.760</td>
<td>0.000</td>
<td>100.000</td>
</tr>
<tr>
<td>% Asian</td>
<td>3.760</td>
<td>6.660</td>
<td>0.000</td>
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<tr>
<td>% Hispanic</td>
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<td>25.590</td>
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<tr>
<td>% Minority</td>
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<td>% Below Poverty</td>
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<td>12.190</td>
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<td>% Owner Occupied</td>
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<td>Labor Force (SR)</td>
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Table 43: Pearson Correlation Coefficients Associated with the Density of Hazard Scores (Natural Log) at the Census Tract Level. n=886

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<td>p-Value</td>
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<td>% Hispanic</td>
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<td>% Minority</td>
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<td>0.204</td>
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<td>&lt;0.001</td>
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<td>% Below Poverty</td>
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<td>% Owner Occupied</td>
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p<0.05
Table 44: Pearson Correlation Coefficients Associated with the Density of Hazard Scores (Natural Log) at the Block Group Level. n=2705

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<td>p-Value</td>
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<td>% Black</td>
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<td>% Asian</td>
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<td>0.001</td>
<td>-0.107</td>
<td>&lt;0.001</td>
<td>-0.130</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.086</td>
<td>&lt;0.001</td>
<td>0.240</td>
<td>&lt;0.001</td>
<td>0.292</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>% Minority</td>
<td>0.039</td>
<td>0.043</td>
<td>0.161</td>
<td>&lt;0.001</td>
<td>0.212</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.283</td>
<td>&lt;0.001</td>
<td>-0.156</td>
<td>0.004</td>
<td>-0.102</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.042</td>
<td>0.030</td>
<td>0.166</td>
<td>&lt;0.001</td>
<td>0.204</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.019</td>
<td>0.331</td>
<td>-0.074</td>
<td>0.001</td>
<td>-0.076</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.124</td>
<td>&lt;0.001</td>
<td>-0.116</td>
<td>&lt;0.001</td>
<td>-0.130</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

p<0.05
Table 45: Least Squares Regression Results for Density of Hazard Scores (Natural Log) at Zero Miles of Census Tract Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.013</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.580)</td>
<td>(0.807)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.050</td>
<td>0.052</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.400)</td>
<td>(1.420)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.088*</td>
<td>0.083*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(9.320)</td>
<td>(6.640)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.046*</td>
<td>0.040*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.310)</td>
<td>(3.650)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-1.560*</td>
<td>-1.620*</td>
<td>-1.680*</td>
<td>-1.720*</td>
</tr>
<tr>
<td></td>
<td>(-11.240)</td>
<td>(-10.680)</td>
<td>(-11.860)</td>
<td>(-11.330)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.027</td>
<td></td>
<td>0.022</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.919)</td>
<td></td>
<td>(0.686)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.001</td>
<td></td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.129)</td>
<td></td>
<td>(0.267)</td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>0.0180</td>
<td></td>
<td>0.012</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.350)</td>
<td></td>
<td>(0.916)</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.128</td>
<td>0.130</td>
<td>0.172</td>
<td>0.173</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>64.630*</td>
<td>26.330*</td>
<td>45.810*</td>
<td>26.310*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5671.740</td>
<td>5675.280</td>
<td>5629.360</td>
<td>5634.070</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-2832.870</td>
<td>-2831.640</td>
<td>-2809.680</td>
<td>-2809.040</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.176*</td>
<td>0.179*</td>
<td>0.141*</td>
<td>0.144*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.168*</td>
<td>0.172*</td>
<td>0.130*</td>
<td>0.135*</td>
</tr>
<tr>
<td>Moran’s I-0.5 mile</td>
<td>0.003</td>
<td>0.002</td>
<td>-0.003</td>
<td>-0.004</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 46: Least Squares Regression Results for Density of Hazard Scores (Natural Log) at Half-Mile from the Census Tract Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.025*</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.220)</td>
<td>(0.542)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.075</td>
<td>-0.057</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.580)</td>
<td>(-1.18)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.121*</td>
<td>0.105*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(9.800)</td>
<td>(6.310)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.069*</td>
<td>0.039*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.230)</td>
<td>(2.650)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-1.870*</td>
<td>-1.860*</td>
<td>-1.860*</td>
<td>-1.920*</td>
</tr>
<tr>
<td></td>
<td>(-7.950)</td>
<td>(-6.610)</td>
<td>(-7.770)</td>
<td>(-6.900)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.128*</td>
<td></td>
<td>0.079**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.240)</td>
<td></td>
<td>(1.890)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.015</td>
<td>0.015</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.220)</td>
<td>(1.280)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>0.015</td>
<td>0.012</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.800)</td>
<td>(0.645)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.086</td>
<td>0.098</td>
<td>0.146</td>
<td>0.150</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>41.740*</td>
<td>19.030*</td>
<td>37.570*</td>
<td>22.150*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>6178.330</td>
<td>6173.400</td>
<td>6122.810</td>
<td>6124.240</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-3086.170</td>
<td>-3080.700</td>
<td>-3056.410</td>
<td>-3054.120</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.433*</td>
<td>0.436*</td>
<td>0.387*</td>
<td>0.393*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.461*</td>
<td>0.465*</td>
<td>0.419*</td>
<td>0.425*</td>
</tr>
<tr>
<td>Moran’s I-0.37 mile</td>
<td>0.013*</td>
<td>0.014*</td>
<td>0.006</td>
<td>0.007</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.032*</td>
<td>0.026</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.670)</td>
<td>(1.550)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.063</td>
<td>-0.047</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.240)</td>
<td>(-0.897)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.137*</td>
<td>0.134*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10.450)</td>
<td>(7.440)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.080*</td>
<td>0.059*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.870)</td>
<td>(3.740)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-2.030*</td>
<td>-1.920*</td>
<td>-2.050*</td>
<td>-2.010*</td>
</tr>
<tr>
<td></td>
<td>(-7.110)</td>
<td>(-5.240)</td>
<td>(-7.04)</td>
<td>(-5.580)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.096*</td>
<td>0.040</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.520)</td>
<td>(0.883)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.021</td>
<td>0.021</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.620)</td>
<td>(1.690)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.001</td>
<td>-0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(-0.098)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.086</td>
<td>0.092</td>
<td>0.146</td>
<td>0.149</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>41.480*</td>
<td>17.870*</td>
<td>37.690*</td>
<td>21.960*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>6307.650</td>
<td>6307.510</td>
<td>6251.260</td>
<td>6254.260</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-3150.820</td>
<td>-3147.760</td>
<td>-3120.630</td>
<td>-3119.130</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.530*</td>
<td>0.528*</td>
<td>0.496*</td>
<td>0.497*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.561*</td>
<td>0.559*</td>
<td>0.531*</td>
<td>0.521*</td>
</tr>
<tr>
<td>Moran’s I-0.37 mile</td>
<td>0.012*</td>
<td>0.013*</td>
<td>0.007</td>
<td>0.008</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 48: Spatial Regression Results for Density of Hazard Scores (Natural Log) at Zero Mile from Census Tract Boundary Using Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.016</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.570)</td>
<td>(0.740)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.085**</td>
<td>0.078**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.790)</td>
<td>(1.840)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.085*</td>
<td>0.078*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.510)</td>
<td>(5.360)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.047*</td>
<td>0.041*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.080)</td>
<td>(3.190)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-1.560*</td>
<td>-1.710*</td>
<td>-1.670*</td>
<td>-1.780*</td>
</tr>
<tr>
<td></td>
<td>(-9.010)</td>
<td>(-9.620)</td>
<td>(-10.580)</td>
<td>(-10.290)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.033</td>
<td>0.037</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.020)</td>
<td>(1.130)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.004</td>
<td>0.022</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.368)</td>
<td>(1.630)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.027*</td>
<td>0.022</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.030)</td>
<td>(1.630)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.372*</td>
<td>0.381*</td>
<td>0.322*</td>
<td>0.333*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5610.470</td>
<td>5611.420</td>
<td>5587.530</td>
<td>5589.570</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-2802.230</td>
<td>-2799.710</td>
<td>-2788.760</td>
<td>-2786.790</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>-0.008</td>
<td>-0.009</td>
<td>-0.005</td>
<td>0.006</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 49: Spatial Regression Results for Density of Hazard Scores (Natural Log) at Zero Mile from Census Tract Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.012</td>
<td>0.007</td>
<td>(1.490)</td>
<td>(0.637)</td>
</tr>
<tr>
<td>% Asian</td>
<td>0.066**</td>
<td>0.068**</td>
<td>(1.910)</td>
<td>(1.900)</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.073*</td>
<td>0.068*</td>
<td>(7.730)</td>
<td>(5.440)</td>
</tr>
<tr>
<td>% Minority</td>
<td>0.047*</td>
<td>0.041*</td>
<td>(5.210)</td>
<td>(3.240)</td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.500*</td>
<td>-1.650*</td>
<td>-1.450*</td>
<td>-1.490*</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.033</td>
<td>0.023</td>
<td>(1.030)</td>
<td>(0.730)</td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.003</td>
<td>-0.001</td>
<td>(0.302)</td>
<td>(-0.063)</td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.029*</td>
<td>0.010</td>
<td>(2.160)</td>
<td>(0.795)</td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.309*</td>
<td>0.319*</td>
<td>0.252*</td>
<td>0.252*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5623.860</td>
<td>5624.380</td>
<td>5598.410</td>
<td>5603.280</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-2808.930</td>
<td>-2806.190</td>
<td>-2793.200</td>
<td>-2792.640</td>
</tr>
<tr>
<td>Moran's I-rook</td>
<td>-0.013</td>
<td>-0.013</td>
<td>-0.006</td>
<td>-0.002</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.010</td>
<td>-0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.110)</td>
<td>(-0.396)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.006</td>
<td>0.016</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.166)</td>
<td>(4.240)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td></td>
<td></td>
<td>0.051*</td>
<td>0.360*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(5.090)</td>
<td>(2.710)</td>
</tr>
<tr>
<td>% Minority</td>
<td>0.027*</td>
<td>0.023</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.580)</td>
<td>(1.380)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-1.010*</td>
<td>-1.670*</td>
<td>-1.090*</td>
<td>-1.160*</td>
</tr>
<tr>
<td></td>
<td>(-5.440)</td>
<td>(-5.390)</td>
<td>(-5.640)</td>
<td>(-5.130)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.111*</td>
<td></td>
<td>0.062**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.020)</td>
<td></td>
<td>(1.860)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.019**</td>
<td></td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.720)</td>
<td></td>
<td>(0.337)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.040*</td>
<td></td>
<td>0.011*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.320)</td>
<td></td>
<td>(0.747)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.717*</td>
<td>0.735*</td>
<td>0.692*</td>
<td>0.691*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5812.130</td>
<td>5805.870</td>
<td>5802.380</td>
<td>5804.430</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-2902.060</td>
<td>-2896.930</td>
<td>-2895.190</td>
<td>-2893.220</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>-0.005</td>
<td>0.000</td>
<td>0.004</td>
<td>0.009</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 51: Spatial Regression Results for Density of Hazard Scores (Natural Log) at Half-Mile from Census Tract Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.010</td>
<td>0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.210)</td>
<td>(-0.313)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.006</td>
<td>0.016</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.161)</td>
<td>(0.437)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.051*</td>
<td>0.037*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.240)</td>
<td>(2.850)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.027*</td>
<td>0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.750)</td>
<td>(1.040)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.951*</td>
<td>-0.997*</td>
<td>-1.030*</td>
<td>-1.100*</td>
</tr>
<tr>
<td></td>
<td>(-5.280)</td>
<td>(-4.630)</td>
<td>(-5.480)</td>
<td>(-5.000)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.064*</td>
<td>0.061**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.140)</td>
<td>(1.890)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.002</td>
<td>0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.202)</td>
<td>(0.470)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.013</td>
<td>0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.928)</td>
<td>(0.773)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.715*</td>
<td>0.711*</td>
<td>0.691*</td>
<td>0.691*</td>
</tr>
<tr>
<td></td>
<td>(5783.210)</td>
<td>(5783.920)</td>
<td>(5772.850)</td>
<td>(5774.810)</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>-2887.600</td>
<td>-2884.960</td>
<td>-2880.420</td>
<td>-2878.400</td>
</tr>
<tr>
<td>Moran's I- rook</td>
<td>0.006</td>
<td>0.013</td>
<td>0.006</td>
<td>0.011</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 52: Spatial Regression Results for Density of Hazard Scores (Natural Log) at Half-Mile from Census Tract Boundary Using Distance Band

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 0.37 mile</th>
<th>Model 2 0.37 mile</th>
<th>Model 3 0.37 mile</th>
<th>Model 4 0.37 mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.025* (2.220)</td>
<td>0.009 (0.542)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.075 (-1.580)</td>
<td>-0.057 (-1.180)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.121* (9.800)</td>
<td>0.105* (6.310)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.068* (7.150)</td>
<td>0.038* (2.600)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.840* (-7.850)</td>
<td>1.820* (-6.550)</td>
<td>-1.860* (-7.770)</td>
<td>-1.920* (-6.900)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td></td>
<td></td>
<td>0.131* (4.800)</td>
<td>0.079** (1.890)</td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td></td>
<td></td>
<td>0.0170 (1.410)</td>
<td>0.015 (1.280)</td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td></td>
<td></td>
<td>0.016 (0.864)</td>
<td>0.012 (0.645)</td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.417</td>
<td>0.438</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>6173.950</td>
<td>6168.310</td>
<td>6122.810</td>
<td>6124.240</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-3082.990</td>
<td>-3077.150</td>
<td>-3056.410</td>
<td>-3054.120</td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.003</td>
<td>0.003</td>
<td>0.006</td>
<td>0.007</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
c. X-represents data provided in related OLS table
Table 53: Spatial Regression Results for Density of Hazard Scores (Natural Log) at One Mile from Census Tract Boundary Related Using Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.001</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.135)</td>
<td>(-0.022)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.014</td>
<td>0.018</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.394)</td>
<td>(0.500)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.040*</td>
<td>0.041*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.380)</td>
<td>(3.330)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.016*</td>
<td>0.015</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.310)</td>
<td>(1.400)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.900*</td>
<td>-1.010*</td>
<td>-1.020*</td>
<td>-1.120*</td>
</tr>
<tr>
<td></td>
<td>(-4.670)</td>
<td>(-4.080)</td>
<td>(-5.050)</td>
<td>(-4.460)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.012</td>
<td>0.007</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.432)</td>
<td>(0.242)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.002</td>
<td>0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.268)</td>
<td>(0.546)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.020</td>
<td>0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.831)</td>
<td>(0.715)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.823*</td>
<td>0.823*</td>
<td>0.807*</td>
<td>0.807*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5718.480</td>
<td>5723.560</td>
<td>5707.190</td>
<td>5712.250</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-2855.240</td>
<td>-2854.780</td>
<td>-2847.600</td>
<td>-2847.130</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>-0.014</td>
<td>-0.010</td>
<td>-0.012</td>
<td>0.008</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.

b. *p<0.05, **p<0.10
Table 54: Spatial Regression Results for Density of Hazard Scores (Natural Log) at One Mile from Census Tract Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.001</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.109)</td>
<td>(0.215)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td></td>
<td></td>
<td>0.009</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.270)</td>
<td>(0.333)</td>
</tr>
<tr>
<td>% Hispanic</td>
<td></td>
<td></td>
<td>0.041*</td>
<td>0.044*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.570)</td>
<td>(3.670)</td>
</tr>
<tr>
<td>% Minority</td>
<td>0.016*</td>
<td>0.017**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.450)</td>
<td>(1.670)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.868*</td>
<td>-0.987*</td>
<td>-0.977*</td>
<td>-1.090*</td>
</tr>
<tr>
<td></td>
<td>(-4.670)</td>
<td>(-4.130)</td>
<td>(-5.030)</td>
<td>(-4.480)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.006</td>
<td></td>
<td>-0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.208)</td>
<td></td>
<td>(-0.065)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.002</td>
<td></td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.224)</td>
<td></td>
<td>(0.470)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.012</td>
<td></td>
<td>0.011</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.866)</td>
<td></td>
<td>(0.752)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.816*</td>
<td>0.816*</td>
<td>0.800*</td>
<td>0.800*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5681.920</td>
<td>5687.050</td>
<td>5669.280</td>
<td>5674.280</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-2836.960</td>
<td>-2836.520</td>
<td>-2828.640</td>
<td>-2828.140</td>
</tr>
<tr>
<td>Moran's I rook</td>
<td>-0.013</td>
<td>-0.010</td>
<td>-0.011</td>
<td>-0.007</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 55: Spatial Regression Results for Density of Hazard Scores (Natural Log) at One Mile from Census Tract Boundary Using Distance Band

<table>
<thead>
<tr>
<th>Independent Variables (m)</th>
<th>Model 1 (0.37 mile)</th>
<th>Model 2 (0.37 mile)</th>
<th>Model 3 (0.37 mile)</th>
<th>Model 4 (0.37 mile)</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.032* (2.670)</td>
<td>0.026 (1.55)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.063 (-1.240)</td>
<td>-0.047 (-0.897)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.137* (10.450)</td>
<td>0.134* (7.440)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.080* (7.910)</td>
<td>0.060* (3.870)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-2.000* (-7.090)</td>
<td>-1.880* (-5.200)</td>
<td>-2.050* (-7.040)</td>
<td>-2.010* (-5.580)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.094* (2.250)</td>
<td>0.040 (0.883)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.024** (0.012)</td>
<td>0.021 (1.690)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.001* (-0.002)</td>
<td>-0.002 (-0.098)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.501*</td>
<td>0.517*</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Akaike Info Coefficient</td>
<td>6301.750 6300.590 6251.260 6254.260</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-3147.870 -3144.440 -3120.630 -3119.130</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.003 0.003 0.007 0.008</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
c. X-represents data provided in related OLS table
Table 56: Least Squares Regression Results for Density of Hazard Scores (Natural Log) at Zero Mile from the Block Group Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.009*</td>
<td>0.008**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.640)</td>
<td>(1.850)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.016</td>
<td>0.017</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.300)</td>
<td>(1.300)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.026*</td>
<td>0.035*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10.480)</td>
<td>(8.050)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.022*</td>
<td>0.020*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.970)</td>
<td>(5.350)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-0.958*</td>
<td>-0.948*</td>
<td>-0.999*</td>
<td>-0.811*</td>
</tr>
<tr>
<td></td>
<td>(-17.410)</td>
<td>(-16.320)</td>
<td>(-17.850)</td>
<td>(-16.970)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>-0.005</td>
<td>-0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.478)</td>
<td>(-0.584)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.009*</td>
<td>-0.008*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.580)</td>
<td>(-2.290)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.013</td>
<td>-0.012</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.630)</td>
<td>(-1.480)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.101</td>
<td>0.104</td>
<td>0.117</td>
<td>0.119</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>152.155*</td>
<td>62.890*</td>
<td>89.090*</td>
<td>52.045*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>15374.000</td>
<td>15370.500</td>
<td>15331.300</td>
<td>15329.900</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-7683.990</td>
<td>-7679.270</td>
<td>-7660.650</td>
<td>-7656.960</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.139*</td>
<td>0.134*</td>
<td>0.123*</td>
<td>0.118*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.151*</td>
<td>0.145*</td>
<td>0.134*</td>
<td>0.129*</td>
</tr>
<tr>
<td>Moran’s I-0.19 mile</td>
<td>0.001</td>
<td>0.001</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.017*</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.280)</td>
<td>(1.460)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.002</td>
<td>-0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.102)</td>
<td>(-0.173)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.087*</td>
<td>0.080*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(15.960)</td>
<td>(11.510)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.050*</td>
<td>0.038*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(11.540)</td>
<td>(6.230)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.540*</td>
<td>-1.590*</td>
<td>-1.620*</td>
<td>-1.770*</td>
</tr>
<tr>
<td></td>
<td>(-11.950)</td>
<td>(-10.190)</td>
<td>(-12.460)</td>
<td>(-11.400)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.047*</td>
<td>0.034*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.950)</td>
<td>(2.090)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.003</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.508)</td>
<td>(-0.088)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>0.018</td>
<td>0.030</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.230)</td>
<td>(2.020)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.071</td>
<td>0.075</td>
<td>0.114</td>
<td>0.117</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>102.640*</td>
<td>43.520*</td>
<td>86.990*</td>
<td>50.990*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>18009.600</td>
<td>18003.090</td>
<td>17883.700</td>
<td>17881.400</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-9001.780</td>
<td>-8995.940</td>
<td>-8936.850</td>
<td>-8932.710</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.505*</td>
<td>0.506*</td>
<td>0.469*</td>
<td>0.474*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.524*</td>
<td>0.526*</td>
<td>0.488*</td>
<td>0.494*</td>
</tr>
<tr>
<td>Moran’s I-0.19 mile</td>
<td>0.010*</td>
<td>0.011*</td>
<td>0.008*</td>
<td>0.008*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 58: Least Squares Regression Results for Density of Hazard Scores (Natural Log) at One Mile from the Block Group Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.024*</td>
<td>0.016*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.920)</td>
<td>(1.990)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.041**</td>
<td>-0.036</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.690)</td>
<td>(-1.470)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.114*</td>
<td>0.011*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(17.690)</td>
<td>(12.800)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.067*</td>
<td>0.050*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(13.000)</td>
<td>(6.850)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.650*</td>
<td>-1.480*</td>
<td>-1.680*</td>
<td>-1.750*</td>
</tr>
<tr>
<td></td>
<td>(-9.220)</td>
<td>(-6.070)</td>
<td>(-9.300)</td>
<td>(-7.320)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.069*</td>
<td>0.045*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.620)</td>
<td>(2.320)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.007</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.080)</td>
<td>(2.320)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.007</td>
<td>0.015</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.339)</td>
<td>(0.776)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.069</td>
<td>0.073</td>
<td>0.124</td>
<td>0.126</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>99.550*</td>
<td>42.730*</td>
<td>95.460*</td>
<td>55.500*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>19032.20</td>
<td>19024.40</td>
<td>18870.70</td>
<td>18870.50</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-9513.10</td>
<td>-8597.35</td>
<td>-9430.35</td>
<td>-9427.26</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.663*</td>
<td>0.661*</td>
<td>0.628*</td>
<td>0.630*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.682*</td>
<td>0.680*</td>
<td>0.648*</td>
<td>0.650*</td>
</tr>
<tr>
<td>Moran’s I-0.19 mile</td>
<td>0.020*</td>
<td>0.021*</td>
<td>0.019*</td>
<td>0.018*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 59: Spatial Regression Results for Density of Hazard Scores (Natural Log) at Zero Miles from Block Group Boundary Using Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.009*</td>
<td>0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.260)</td>
<td>(1.370)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.015</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.090)</td>
<td>(0.966)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.033*</td>
<td>0.030*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(8.110)</td>
<td>(6.190)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.010*</td>
<td>0.020*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.260)</td>
<td>(4.190)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density</td>
<td>-1.020*</td>
<td>-1.020*</td>
<td>-1.040*</td>
<td>-1.040*</td>
</tr>
<tr>
<td>(LN)</td>
<td>(-15.990)</td>
<td>(-15.020)</td>
<td>(-16.350)</td>
<td>(-15.500)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.004</td>
<td></td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.387)</td>
<td></td>
<td>(0.223)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.006**</td>
<td></td>
<td>-0.006**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.680)</td>
<td></td>
<td>(-1.650)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.001</td>
<td></td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.118)</td>
<td></td>
<td>(-0.101)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.301*</td>
<td>0.297*</td>
<td>0.275*</td>
<td>0.273*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>15256.900</td>
<td>15259.200</td>
<td>15237.100</td>
<td>15239.800</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-7625.470</td>
<td>-7623.620</td>
<td>-7613.570</td>
<td>-7611.920</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>-0.006</td>
<td>-0.005</td>
<td>-0.004</td>
<td>-0.004</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 60: Spatial Regression Results for Density of Hazard Scores (Natural Log) at Zero Miles from Block Group Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.009*</td>
<td>0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.270)</td>
<td>(1.330)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.016</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.120)</td>
<td>(1.010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.033*</td>
<td>0.031*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(8.120)</td>
<td>(6.300)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.021*</td>
<td>0.018*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.280)</td>
<td>(4.200)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.999*</td>
<td>-0.997*</td>
<td>-1.020*</td>
<td>-0.961*</td>
</tr>
<tr>
<td></td>
<td>(-15.730)</td>
<td>(-14.770)</td>
<td>(-16.130)</td>
<td>(-13.730)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.005</td>
<td></td>
<td>0.008</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.497)</td>
<td></td>
<td>(0.854)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.005</td>
<td></td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.460)</td>
<td></td>
<td>(2.690)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.001</td>
<td></td>
<td>-0.089*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.105)</td>
<td></td>
<td>(-2.610)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.293*</td>
<td>0.289*</td>
<td>0.269*</td>
<td>0.261*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>15250.100</td>
<td>15253.000</td>
<td>15230.400</td>
<td>15228.600</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-7622.070</td>
<td>-7620.510</td>
<td>-7610.190</td>
<td>-7606.310</td>
</tr>
<tr>
<td>Moran's I-rook</td>
<td>-0.003</td>
<td>-0.003</td>
<td>-0.002</td>
<td>-0.001</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.013**</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.740)</td>
<td>(1.260)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.028</td>
<td>0.018</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.360)</td>
<td>(0.906)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.033*</td>
<td>0.030*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.770)</td>
<td>(3.890)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.024*</td>
<td>0.021*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.120)</td>
<td>(3.070)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.010*</td>
<td>-1.810*</td>
<td>-1.010*</td>
<td>-1.820*</td>
</tr>
<tr>
<td></td>
<td>(-8.250)</td>
<td>(-10.720)</td>
<td>(-8.280)</td>
<td>(-10.750)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.036*</td>
<td>0.035*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.860)</td>
<td>(2.730)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.009**</td>
<td>-0.008**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.870)</td>
<td>(1.760)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.091*</td>
<td>0.092*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.820)</td>
<td>(6.850)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.786*</td>
<td>0.793*</td>
<td>0.780*</td>
<td>0.788*</td>
</tr>
<tr>
<td></td>
<td>(6.820)</td>
<td>(6.850)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>16539.000</td>
<td>16495.500</td>
<td>16537.600</td>
<td>16493.600</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-8266.600</td>
<td>-8241.710</td>
<td>-8263.800</td>
<td>-8238.800</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>0.002</td>
<td>0.001</td>
<td>0.003</td>
<td>0.002</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 62: Spatial Regression Results for Density of Hazard Scores (Natural Log) at Half-Mile from Block Group Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.006 (1.590)</td>
<td>0.002 (1.495)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.028** (1.940)</td>
<td>0.024** (1.670)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.030* (7.350)</td>
<td>0.030* (5.150)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.016* (5.300)</td>
<td>0.013* (3.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.737* (-7.970)</td>
<td>-0.900* (-7.990)</td>
<td>-0.819* (-8.600)</td>
<td>-0.987* (-8.650)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.015* (1.380)</td>
<td>0.017 (1.490)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.005 (-1.270)</td>
<td>-0.003 (-0.893)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.030 (2.810)</td>
<td>0.031* (2.940)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.763* (2.810)</td>
<td>0.763* (2.810)</td>
<td>0.750* (2.810)</td>
<td>0.751* (2.810)</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>16492.500</td>
<td>16486.500</td>
<td>16471.600</td>
<td>16465.200</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-8242.230</td>
<td>-8236.240</td>
<td>-8229.670</td>
<td>-8223.590</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>0.012</td>
<td>0.015</td>
<td>0.012</td>
<td>0.016</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 0.19 mile</th>
<th>Model 2 0.19 mile</th>
<th>Model 3 0.19 mile</th>
<th>Model 4 0.19 mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.017*</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.370)</td>
<td>(1.500)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.002</td>
<td>-0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.095)</td>
<td>(-0.174)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.087*</td>
<td>0.079*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(15.890)</td>
<td>(11.450)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.050*</td>
<td>0.037*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(11.530)</td>
<td>(6.210)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.540*</td>
<td>-1.580*</td>
<td>-1.620*</td>
<td>-1.760*</td>
</tr>
<tr>
<td></td>
<td>(-11.970)</td>
<td>(-10.150)</td>
<td>(-12.470)</td>
<td>(-11.360)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.046*</td>
<td>0.033*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.900)</td>
<td>(2.080)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.004</td>
<td>-0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.674)</td>
<td>(-0.218)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.016</td>
<td></td>
<td>-0.028**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.100)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.279*</td>
<td>0.279*</td>
<td>0.233*</td>
<td>0.229*</td>
</tr>
<tr>
<td></td>
<td>(1.100)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Akaike Info Coefficient</td>
<td>18001.300</td>
<td>17995.600</td>
<td>17878.400</td>
<td>17876.300</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-8997.670</td>
<td>-8991.810</td>
<td>-8934.190</td>
<td>-8930.160</td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.003</td>
<td>0.003</td>
<td>0.008</td>
<td>0.002</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 64: Spatial Regression Results for Density of Hazard Scores (Natural Log) at One Mile from Block Group Boundary Using Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.003</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.944)</td>
<td>(0.430)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.015</td>
<td>0.015</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.080)</td>
<td>(1.090)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.024*</td>
<td>0.023*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.300)</td>
<td>(4.810)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.013*</td>
<td>0.011*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.270)</td>
<td>(2.650)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-0.637*</td>
<td>-0.807*</td>
<td>-0.702*</td>
<td>-0.901*</td>
</tr>
<tr>
<td></td>
<td>(-6.240)</td>
<td>(-5.810)</td>
<td>(-6.660)</td>
<td>(-6.410)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.014</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.300)</td>
<td>(1.270)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.001</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.279)</td>
<td>(0.608)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.024*</td>
<td>0.027*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.100)</td>
<td>(2.360)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.873*</td>
<td>0.873*</td>
<td>0.864*</td>
<td>0.863*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>16400.000</td>
<td>16400.500</td>
<td>16382.600</td>
<td>16381.900</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-8196.000</td>
<td>-8193.240</td>
<td>-8185.320</td>
<td>-8181.950</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>-0.009</td>
<td>-0.006</td>
<td>-0.008</td>
<td>-0.005</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 65: Spatial Regression Results for Density of Hazard Scores (Natural Log) at One Mile from Block Group Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.004</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.250)</td>
<td>(0.630)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>0.014</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.986)</td>
<td>(0.985)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.024*</td>
<td>0.024*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.520)</td>
<td>(4.940)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.013*</td>
<td>0.011*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.570)</td>
<td>(2.780)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>-0.630*</td>
<td>-0.806*</td>
<td>-0.690*</td>
<td>-0.898*</td>
</tr>
<tr>
<td></td>
<td>(-6.310)</td>
<td>(-5.950)</td>
<td>(-6.700)</td>
<td>(-6.530)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.015</td>
<td></td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.450)</td>
<td></td>
<td>(1.340)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.001</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.213)</td>
<td>(0.527)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>0.025*</td>
<td>0.028*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.240)</td>
<td>(2.520)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.863*</td>
<td>0.863*</td>
<td>0.854*</td>
<td>0.854*</td>
</tr>
<tr>
<td></td>
<td>(2.240)</td>
<td>(2.520)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>16339.500</td>
<td>16339.000</td>
<td>16322.300</td>
<td>16320.600</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-8165.750</td>
<td>-8162.510</td>
<td>-8155.140</td>
<td>-8151.320</td>
</tr>
<tr>
<td>Moran's I-rook</td>
<td>0.017</td>
<td>-0.013</td>
<td>-0.013</td>
<td>-0.012</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 66: Spatial Regression Results for Density of Hazard Scores (Natural Log) at One Mile from Block Group Boundary Using Distance Band

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 0.19 mile</th>
<th>Model 2 0.19 mile</th>
<th>Model 3 0.19 mile</th>
<th>Model 4 0.19 mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.025* (4.120)</td>
<td>-0.016* (2.030)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.044** (-1.840)</td>
<td>-0.040 (-1.630)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.114* (17.590)</td>
<td>0.105* (12.650)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.067* (13.000)</td>
<td>0.049* (6.750)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>-1.640* (-9.200)</td>
<td>-1.430* (-5.920)</td>
<td>-1.660* (-9.270)</td>
<td>-1.700* (-7.130)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.070* (3.700)</td>
<td></td>
<td>0.460* (2.400)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>0.006 (0.861)</td>
<td></td>
<td>0.008 (1.260)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.011 (-0.553)</td>
<td></td>
<td>0.011 (0.566)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.421* (13.000)</td>
<td>0.427* (6.750)</td>
<td>0.405* (12.650)</td>
<td>0.405* (12.650)</td>
</tr>
<tr>
<td>Akaike Info Coefficient</td>
<td>19008.100</td>
<td>18999.300</td>
<td>18849.300</td>
<td>18849.200</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-9501.070</td>
<td>-9493.660</td>
<td>-9419.630</td>
<td>-9416.590</td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.005</td>
<td>0.005</td>
<td>0.004</td>
<td>0.004</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
8. ANALYZING THE HEALTH RISKS OF EMISSIONS FROM INDUSTRIAL POLLUTION SOURCES

This chapter focuses on the use of human health risks from points sources listed in the USEPA’s Toxic Release Inventory (TRI) as an indicator of exposure to chronic air pollution in the analysis of environmental justice in the Houston-Galveston-Brazoria metropolitan statistical area (HGB-MSA). The goal is to explore the association between health risks (modeled risk scores) from chronic exposure to industrial air pollution sources and selected demographic and socioeconomic variables from Census 2000, in order to determine the presence of inequity with respect to the racial/ethnicity and poverty status of the population.

Risk scores from the Risk Screening Environmental Indicators (RSEI) model are used to assess health risks from chronic exposure of industrial pollution from TRI facilities. To estimate the relative risks to chronic human health posed by toxic chemical releases, the model integrates toxicity weights for individual chemicals and chemical categories and exposure estimates, based upon pathway-specific reporting of releases to air, water, and land, and the size of the potentially exposed residential population. The toxicity weights are assigned separately for the oral and inhalation exposure pathways, and include both cancer and non-cancer effects. Chemical release data from the TRI and pathway-specific fate and transport models that consider factors such as wind patterns and stream flow are used to calculate the doses to which people may be exposed (Bouwes et al. 2001).
The RSEI model combines toxicity weights with the surrogate dose delivered by each release to obtain a partial score for each square kilometer grid cell that represents the toxicity-adjusted potential human health effects from chronic exposure. The partial scores resulting from TRI emissions at different facilities are summed to obtain an aggregated risk score for each 1km by 1km grid cell for the Houston-MSA. Areal interpolation based on proportional allocation was used to assign risk scores from the 1km by 1km grid cells to the boundaries of census tracts and block groups in the study area, resulting in each analytical unit containing a non-zero value representing health risks throughout the MSA. Although the 1km by 1km grids provide a finer spatial resolution than census tracts or block groups, the grids were not used as analytical units to maintain consistency with the equity analyses associated with the other pollution indicators that are based on census units.

The final risk score of atmospheric pollution (all emitted chemicals) from TRI facilities were then calculated for each geographic analytical unit following the technique for modeling point density described previously in Chapter 4. For each census tract or block group, the areal density of risk scores is measured by dividing the total modeled risk scores from their host facilities by the area enclosed, at three different distances from the tract or block group boundary (0, 0.5, and 1 mile). Because of the skewed distribution of this variable, the natural logarithm (LN) of the density of risk scores was used for all statistical analyses presented in this chapter. The use of the natural log reduces outliers and yields a normal-style distribution of the dependent variable that is more consistent with the requirements of regression modeling.
Summary statistics for all variables analyzed are provided in Tables 67 and 68, respectively, for census tract and block group level data. The descriptive statistics show that census tracts contain a larger density of risk scores than block groups. In addition, the density of risk scores increase as the search radius increases from 0 to 1 mile from the boundary due to the possible inclusion of more pollution emissions at larger distances from each unit.

The analysis begins with an examination of bivariate parametric correlations between the risk score density at three search radii (0, 0.5, and 1 mile) and relevant explanatory variables at the census tract and block group level of aggregation. Pearson’s correlation coefficients associated with the density of risk scores at the three distances from each analytical unit are presented in Table 69 for census tract level and Table 70 for block group level analyses. The correlation analysis at the census tract level shows that at 0 miles from the boundary, population density has the highest positive correlation with the density of risk scores followed by percent minority, percent Hispanic, percent below poverty, and percent Black. Additionally, percent owner occupied housing has the greatest negative correlation. Labor force and percent Asian do not indicate significant correlation with density of risk scores at this level.

At 0.5 mile from the census tract boundary population density again has the highest positive correlation with the density of risk scores followed by percent minority, percent Hispanic, percent below poverty, and percent Black. Additionally, owner occupied housing has the greatest negative correlation followed by labor force. Percent Asian does not indicate a significant correlation with density of risk scores at this level.
The correlations at 1 mile from the tract boundary are similar to those observed at 0.5 mile, for all variables.

At the block group level, the correlation analysis shows that at 0 miles from the boundary population density has the highest positive correlation with the density of risk scores followed by percent minority, percent Hispanic, percent below poverty, and percent Black. Additionally, owner occupied housing has the greatest negative correlation followed by labor force. Percent Asian does not indicate a significant correlation with density of risk scores at this level. At both 0.5 mile and 1 mile from the block group boundary, the correlations for all explanatory variables are similar to those observed at 0 mile.

In summary, the correlation analysis consistently indicates that the population density has the strongest positive correlation and most significant linear association with the risk scores at both the census tract and block levels. The premise of environmental inequity is supported by three variables (overall population density, percent minority, percent Hispanic, percent below poverty, and percent Black) which consistently exhibit a significant and positive relationship with density of risk scores at all search radii and at both the census tract and block group levels. The percentage of owner occupied housing units suggests a negative linear relationship at all distances and levels of aggregation along with labor force except at the boundary of the tract level. Additionally, the Asian percentage does not exhibit a significance association with the risk scores for any level or aggregation.

While correlation analysis provides a preliminary view of the statistical association between each demographic and socioeconomic variable and the density of
risk scores, it does not clarify the underlying pattern in sufficient detail. Multivariate regression is therefore used to analyze the simultaneous statistical effects of the explanatory variables on the density of risk scores as related to the health effects of toxic chemicals released from TRI facilities at the census tract and block group level, respectively.

The ordinary least squares (OLS) regression approach is first utilized to model the statistical effect of explanatory variables on the density of risk scores within each analytical unit in the study area, based on the three search radii (0, 0.5, and 1 mile). The results from the OLS regression models for the four different combinations of explanatory variables are summarized in the first set of tables (Tables 71-73 and 77-79). This set of tables also provides results from an analysis of spatial dependence using both the contiguity-based and distance-based methodologies. The results in the OLS tables contain regression coefficients that are bolded, z-scores which are in parentheses and p-values which are identified utilizing the single (α=0.05) and double (α=0.10) asterisk. Additionally, these tables contain Moran’s I which is used for testing for the existence of spatial autocorrelation.

The second phase of the analysis uses the spatial autoregressive function (SAR) by utilizing an autoregressive coefficient to account for spatial autocorrelation. The appropriate SAR function (spatial lag or spatial error) was determined using the Lagrange-Multiplier test statistic results obtained while running the corresponding OLS model (Anselin 2006). As mentioned previously, the SAR models use a spatial weights matrix specified by three configurations of neighboring census units: queen-based contiguity, rook-based contiguity, and distance-based bands. Separate queen and rook
contiguity analysis was therefore performed in hopes of finding the best fitted model that minimizes the effects of spatial dependence. Additionally, separate analysis for distance bands were constructed selecting between 3 and 5 distances which were used as adjustments to eliminate spatial autocorrelation. After the completion of the analyses, the best model was selected based upon the achievement of non-significant (p<0.05) Moran’s I which signifies no spatial autocorrelation and the lowest Akaike Information Criterion (AIC) which is used to determine the fit of the model. The census tract results are listed in Tables 74-82 and the block groups are listed in Tables 86-94. The results in the tables contain regression coefficients which are bolded, z-scores which are in parentheses, and p-values which are identified utilizing the single (α=0.05) and double (α=0.10) asterisk.

The histograms in Figure 12 summarize the connectivity distribution for census tracts, based on the number of neighbors in each configuration. For queen contiguity, Figure 12(a) shows that the majority of the census tracts have 5 to 8 neighbors and peaks at 7 neighbors. For the rook contiguity in Figure 12(b), the number of neighbors peaks at 4 but the census tracts noticeably had a positive skew. The histogram for the distance-based configuration on Figure 12(c) at 0.50 provides the connectivity distribution at from the centroid of each unit and indicates that a majority of census tracts have no neighbors at this distance. The connectivity distributions for census block groups are summarized in Figure 13. The histogram for queen contiguity in Figure 13(a) shows that the majority of the block groups have 4 to 8 neighbors and peaks at 6 neighbors. For the rook contiguity in Figure 13(b), the number of neighbors peaks at 5 and noticeably has a positive skew. The histogram for the distance-based configuration in Figure 13(c) provides the connectivity distribution at 0.19 mile from the centroid of each unit and
indicates that the number of block groups with no neighbors at this distance is considerably higher than the number of census tracts with no neighbors in Figures 12.
Figure 12: Census tract connectivity histograms used for modeling risk scores
Figure 13: Block group connectivity histograms used for modeling risk scores
8.1 Census Tract Level Analysis

Ordinary Least Squares Regression This section compares the density of risk scores as computed from the quantity and physiochemical properties of released chemicals, in conjunction with fate and transport modeling at the census tract level, at zero (0), half (0.5) and one (1) mile search radii, based on the application of ordinary least squares (OLS) and spatial autoregressive (SAR) techniques. Table 71 summarizes the results from OLS regression analysis at the boundary of the census tracts. Models 1 and 2 both indicate that the overall percent minority shows a significant and positive statistical effect on the density of risk scores. When the minority sub-groups are analyzed separately in models 3 and 4, the Hispanic percent indicates a significant and positive association with the density of risk scores while percent Asian has a significant and negative association. Percent Black however, has a positive and significant statistical effect on risk scores in model 3, but not in model 4 when the socioeconomic terms are introduced. This stresses the importance of analyzing each racial/ethnic sub-group individually and collectively to gain clarity on their environmental justice implications. Furthermore, both percent owner-occupied housing and labor force are significant and have a negative association with density of risk scores in models 2 and 4. In all four models, the density of risk scores significantly increases with an increase in population density.

At 0.5 from the boundary of the census tract (Table 72), the results for the racial/ethnic variables are similar to those observed at 0 mile from the tracts. For models 1 and 2, the density of risk scores increases significantly as the overall percentage of minority residents increases. Furthermore, for models 3 and 4, the Hispanic percentage has a significant and positive statistical effect on the density of risk scores while percent
Asian has a significant and negative association for both models. Percent Black however, has a positive and significant statistical effect on risk scores at model 3, but not in model 4 when the socioeconomic terms are introduced. Furthermore, percent owner occupied has a negative and significant statistical effect on risk scores at model 4, but not in model 2 when the minority subgroups are combined. Again labor force is significant and has a negative association with density of risk scores for models 2 and 4. In all four models, the density of risk scores significantly increases with an increase in population density.

At 1 mile from the boundary of the census tracts (Table 73) models 1 and 2 indicate a positive statistical effect of the overall minority percentage and percent Hispanic (models 3 and 4) on the density of risk scores, which is consistent with the results at 0 and 0.5 miles from the tract boundary. Percentage Black is again positive and significant in model 3, while percent Asian has a negative association at model 3 only. Percent owner occupied housing and labor force are both consistent with 0 mile, where they both have a negative and significant association with density of risk scores. In all four models, the density of risk scores significantly increases with an increase in population density.

Moran’s I for the queen and rook contiguities as well as the distance-based (0.5 mile) configuration shows significance at 0, 0.5, and 1 miles search radii, indicating the presence of significant spatial autocorrelation in the data and justifying the need to account for spatial dependence by using a SAR model. Following the assessment for spatial dependence the SAR model was thus implemented for all OLS models where spatial autocorrelation remained.
**Spatial Regression** At the boundary of the census tract level for the queen contiguity (Table 74), models 1 and 2 indicate a significant and negative association between the density of risk scores at 0 miles and the overall minority percent. Additionally, for models 3 and 4, the Black and Asian percentages have a negative statistical effect on the density of risk scores. Percent owner occupied housing, however, has a negative statistical effect on density of risk scores for model 4 only, but is not influential when the minorities are classified into sub-groups. For all models at 0 mile from the tract boundary, the density of risk scores significantly increases when population density increases. Labor force, however, has a positive statistical effect on density of risk scores only for model 2, but is not influential when the minority sub-groups are included. The queen contiguity SAR models differ from OLS in that the minority and Black percentages indicate negative associations while the Hispanic percentage and labor force becomes non-significant.

At the boundary of the census tract level for the rook contiguity (Table 75), all SAR models exhibit the same statistical associations as observed in the model for queen contiguity and have similar differences from the corresponding OLS models, except for percent owner occupied housing which is negative and significant in model 2.

Several distance bands were constructed based on selection criteria resulting in minimization of the likelihood term (AIC) and significance of spatial autocorrelation using Moran’s I (Table 76). Distance bands for models 1 and 3 were constructed at 0.93 mile while models 2 and 4 were constructed at 1.24 miles. Percent Black in model 1 has a positive and significant association with density of risk scores. Percent Hispanic for models 3 and 4 has a significantly positive statistical effect on the density of risk scores,
as well as percent minority for model 1 only. All socioeconomic variables (percent below poverty, percent owner occupied, and labor force) have a negative and significant association with density of risk scores for models 2 and 4. The only difference between the SAR and the OLS models is that percent below poverty became significant and percent Asian became non-significant when spatial dependence was taken into account.

At 0.5 mile from the boundary of census tracts for the queen contiguity (Table 77), models 1 and 2 indicate a significant and negative association between the density of risk scores at 0.5 mile and the overall minority percent. Additionally, for models 3 and 4, the Black and Asian proportions negatively affect the density of risk scores. Percent owner occupied housing and labor force, however, independently have a negative statistical effect on density of risk scores in both models 2 and 4. For all models at 0.5 mile from the tract boundary, density of risk scores significantly increases when population density increases. The queen contiguity SAR models differ from OLS in that the minority and Black percentages show a negative association while the Hispanic percentage for both models becomes non-significant. Additionally, percent owner occupied housing for model 2 becomes significant while maintaining the same negative sign.

At 0.5 mile from the boundary of census tracts for the rook contiguity (Table 78), all SAR models exhibit the same statistical associations as observed in the model for queen contiguity and had similar differences from the corresponding OLS models.

Several distance bands were constructed based on selection criteria resulting in minimization of the likelihood term (AIC) and significance of spatial autocorrelation using Moran’s I (Table 79). Model 1 was constructed at 0.37 mile, model 2 at 0.62 mile
and models 3 and 4 at 0.5 mile. Percent Black in model 1 has a positive and significant association with density of risk scores. Percent Hispanic for models 3 and 4 has a significantly positive statistical effect on the density of risk scores, as well as percent minority for models 1 and 2. Percent Asian on the other hand, has a negative and significant association with density of risk scores. Percent owner occupied and labor force indicates a negative and significant association with density of risk scores for models 2 and 4. The only difference between the SAR as compared to the OLS models is that percent owner occupied housing in model 2 became significant when spatial dependence was negated.

At 1 mile from the boundary of the census tract level for the queen contiguity (Table 80), model 2 indicates a significant and negative association between the density of risk scores at 1 mile and the overall minority percent. Additionally, percent Black in model 4 has a significant and negative association with density of risk scores. Percent Asian is significant and negative for both models with and without the socioeconomic variables. Percent owner occupied housing and labor force however, independently have a negative statistical effect on density of risk scores on both models 2 and 4. For all models 1 mile from the tract boundary, the density of risk scores increases significantly when population density increases. The queen contiguity SAR models differ from OLS in that the overall minority percent indicates a negative association in model 2 and minority percent becomes non-significant in model 1. Black percentages also show a negative association and become significant in model 4. The Hispanic percentage, on the other hand, becomes non-significant in both models. Additionally, the Asian percentage becomes significant in both models while maintaining the same negative sign.
At 1 from the boundary of the census tract level for the rook contiguity (Table 81), all SAR models exhibit the same statistical associations as observed in the model for queen contiguity and had similar differences from the corresponding OLS models.

Several distance bands at 1 mile were constructed based on selection criteria resulting in minimization of the likelihood term (AIC) and significance of spatial autocorrelation using Moran’s I (Table 82). Models 1 and 3 were constructed at 0.5 mile, model 2 at 0.62 mile, and model 4 at 0.37 mile. Percent Black in model 1 has a positive and significant association with density of risk scores. Percent Hispanic for models 3 and 4 has a significantly positive statistical effect on the density of risk scores, as well as percent minority for models 1 and 2. Percent owner occupied and labor force had a negative and significant association with density of risk scores for models 2 and 4. The only difference between the SAR as compared to the OLS models is that percent owner occupied housing in model 2 became significant when spatial dependence was negated and percent Asian for both models became non-significant.

8.2 Block Group Level Analysis

*Ordinary Least Squares Regression* This section compares the density of risk scores as computed from the quantity and physiochemical properties of released chemicals, in conjunction with fate and transport modeling at the block group level, at zero (0), half (0.5) and one (1) mile search radii, based on the application of ordinary least squares (OLS) and spatial autoregressive (SAR) techniques. Table 83 summarizes the OLS regression analysis at the boundary of the block groups. Models 1 and 2 both indicate that the overall percent minority shows a significant and positive statistical effect on the density of risk scores. Percent Asian has a significant and negative association in model
3, but is non-significant when the minority sub-groups are included separately for model 4. Percent Black and percent Hispanic have a significant and positive association with density of risk scores. All socioeconomic variables (percent below poverty, percent owner occupied, and labor force) show a negative and significant association with density of risk scores for models 2 and 4. In all four models, the density of risk scores significantly increases with an increase in population density.

At 0.5 mile from the boundary of the block group (Table 84), the results for the racial/ethnic variables are similar to those observed at 0 mile from the block groups.

At 1 mile from the boundary of the block group (Table 85), the results for the racial/ethnic variables are also similar to those observed at 0 mile from the block groups. The only difference is that the Asian percentage is non-significant at 1 mile from the boundary.

Moran’s I for the queen and rook contiguities as well as the distance-based (0.5 mile) configuration shows significance at 0, 0.5, and 1 mile search radii indicating the presence of significant spatial autocorrelation in the data and justifying the need to account for spatial dependence by using a SAR model. Following the assessment for spatial dependence, the SAR model was thus implemented for all OLS models where spatial autocorrelation was detected.

**Spatial Regression** At the boundary of block groups for the queen contiguity (Table 86), models 1 and 2 indicate a significant and negative association between the density of risk scores at 0 miles and the overall minority percent. Additionally, for models 3 and 4, the Black and Asian populations negatively affect the density of risk scores. For all models 0 miles from the block group boundary, density of risk scores significantly increases when
population density increases. Percent Hispanic and all socioeconomic variables are non-significant and have no overall statistical effect on the density of risk scores. The queen contiguity SAR models differ from OLS in that the Asian percentage became significant for model 4 and all the socioeconomic variables yield non-significant coefficients.

At the boundary of block groups for the rook contiguity (Table 87), all SAR models exhibit the same statistical associations as observed in the model for queen contiguity and had similar differences from the corresponding OLS models.

A distance band of 0.19 mile (Table 88) was constructed beginning from 0.5 mile from each block group boundary to identify neighboring block groups for assessing spatial dependence. The distance bands were constructed based on selection criteria resulting in minimization of the likelihood term (AIC) and significance of spatial autocorrelation using Moran’s I. Models 1 and 2 both indicate that the overall percent minority shows a significant and positive statistical effect on the density of risk scores. Percent Asian has a significant and negative association in model 3, but is non-significant when the economic terms fare introduced in model 4. Percent Black and percent Hispanic have a significant and positive association with density of risk scores. Percent owner occupied and labor force have a negative and significant association with density of risk scores for models 2 and 4, while percent below poverty is negative and significant only in model 4. In all four models, the density of risk scores significantly increases with an increase in population density. The distance SAR models differ from OLS in that percent below poverty in model 3 becomes non-significant.

At 0.5 mile from the boundary of block groups for the queen contiguity (Table 89), models 1 and 2 indicate a significant and negative association between the density of
risk scores at 0.5 mile and the overall minority percent. Additionally, for models 3 and 4, the Black and Asian populations negatively affect the density of risk scores. Percent Hispanic, however, is significant only in the model that contains the socioeconomic terms. Labor force has a negative statistical effect on density of risk scores on both models 2 and 4, while Percent owner occupied housing has a significant and negative statistical effect in model 4 only. For all models at 0.5 mile from the block group boundary, density of risk scores significantly increases when population density increases. The queen contiguity SAR models differ from OLS in that the percent Asian loses significance when the socioeconomic terms are introduced. Hispanic percentage also becomes non-significant for model 3. Additionally, percent owner occupied housing for model 2 loses significance while maintaining the same signage and percent below poverty loses significance for both models.

At 0.5 mile from the boundary of block groups for the rook contiguity (Table 90), all SAR models exhibit the same statistical associations as observed in the model for queen contiguity and had similar differences from the corresponding OLS models.

A distance band of 0.19 mile (Table 91) was constructed beginning from 0.5 mile from each block group boundary to identify neighboring block groups for assessing spatial dependence. The distance bands were constructed based on selection criteria resulting in minimization of the likelihood term (AIC) and significance of spatial autocorrelation using Moran’s I. There are no statistical differences between the SAR models as compared to the OLS models for the 0.5 mile distance band.

At 1 mile from the boundary of block groups for the queen contiguity (Table 92), model 2 indicates a significant and negative association between the density of risk
scores at 1 mile and the overall minority percent. Additionally, percent Black and percent Hispanic in model 4 have a significant and negative association with density of risk scores. Percent Asian is significant and negative for both models with and without the economic variables. Percent owner occupied housing and labor force however, independently have a negative statistical effect on density of risk scores in both models 2 and 4. For all models at 1 mile from the block group boundary, density of risk scores significantly increases when population density increases. The queen contiguity SAR models differ from OLS in that the percent minority gains a negative association and model 1 becomes non-significant. Additionally, Black and Hispanic percentages gain negative association and lose significance for model 3. Asian percentage for both models also becomes significant while maintaining the same signage. Lastly, percent below poverty loses significance.

At 1 mile from the boundary of block groups for the rook contiguity (Table 93), all SAR models exhibit the same statistical associations as observed in the model for queen contiguity and had similar differences from the corresponding OLS models, except percent owner occupied housing became non-significant in the model with separate minority sub-groups.

A distance band of 0.19 mile (Table 94) was constructed beginning from 0.5 mile from each block group boundary to identify neighboring block groups for assessing spatial dependence. The distance bands were constructed based on selection criteria resulting in minimization of the likelihood term (AIC) and significance of spatial autocorrelation using Moran’s I. Percent Black and percent Hispanic in models 3 and 4 indicate a positive and significant association with the density of risk scores, as well as
percent minority for models 1 and 2. All socioeconomic variables are significant and have a positive statistical effect on the density of risk scores. The only difference between the SAR as compared to the OLS models is that percent Asian for model 4 became significant.

8.3 Discussion and Interpretation

The analyses presented in this chapter focuses on the geographic distribution of pollution burdens measured in terms of human health risks from industrial point sources. The results reveal that the areal density of modeled risk scores in the Houston-MSA is significantly associated with population density, the overall proportion of minorities, and the Hispanic percentage at the census tract level, regardless of whether conventional or spatial regression was utilized. The findings from the analysis of risk scores reveals distinct differences between the OLS, contiguity-based SAR, and distance-based SAR techniques. The OLS and distance-based methodologies provide similar statistical results at each level of aggregation and distance from the analytical unit. The presence of racial/ethnic minorities and Hispanics, in particular, indicate a positive statistical effect on the density of risk scores at all distances, even after controlling for the effects of other explanatory variables, in OLS and distance-based SAR models. Additionally, the percentage of Asians living within the census tract boundaries indicates a significantly negative statistical effect at all search radii in the OLS models and when spatial autocorrelation is removed at the 0.5 mile distance band (0.5 mile). The Black percentage shows a significant and positive statistical effect when the density of risk scores is measured at all search radii from the tract boundary, for both ordinary regression and when using the spatial regression at all distance bands. The poverty rate
also shows a negative relationship with the density of risk scores at the 0 mile search radius while using the distance band only. Additionally, the percentages of owner occupied housing units are negative and significant only when spatial autocorrelation is removed using the distance bands. Labor force shows a negative statistical effect on the density of risk scores using OLS and when spatial autocorrelation is taken into account using the distance bands. Lastly, population density has a positive association with the risk scores at all aggregation, search radii and distances using all methodological techniques.

The contiguity-based SAR models exhibit results that are similar to those from the OLS and distance-based techniques, except that the Black and minority percentages become negative and more significant. This indicates how the definition of neighborhood for measuring spatial dependence affects the sign and significance of a key explanatory variable (i.e., Black percentage). Additionally, the Asian percentage is negative and significant at all levels and aggregations using the queen and rook contiguities, except when using the distance band at 0 and 1 mile search radii. This suggests that a large proportion of the Asian population in this MSA is located outside and away from census tracts facing the greatest risks from industrial pollution sources. Furthermore, the positive significance of Hispanics at all levels using the distance-based SAR suggests that a large proportion of the Hispanic population resides in tracts that are adjacent to those facing greater health risks from toxic emissions.

As observed at the census tract level, population density, minority percent, and percent of Hispanics, are again the most influential variables related to the density of risk scores at the block group level. Again, the OLS and distance-based SAR models indicate
similar statistical results at each aggregation and distance. The presence of racial/ethnic minorities and Hispanics (OLS and distance bands only), in particular, indicate a positive statistical effect on the density of risk scores at all distances, even after controlling for the effects of other explanatory variables. Additionally, the percentage of Asians living within the block group boundaries shows negative significance using OLS at all search radii and when spatial autocorrelation is removed. The Black percentage shows a significant and positive statistical effect when the density of risk scores is measured at all search radii from the tract boundary, for both ordinary regression and when using the spatial regression at all distance bands for the models. The poverty rate also shows a negative relationship to risk scores overall using OLS and distance bands at all search radii. Additionally, the percentage of owner occupied housing and labor force are negative and significant using OLS and when spatial autocorrelation is removed using the distance bands. Lastly, population density has a positive association with the risk scores at all aggregation, search radii, and distances for both regression techniques.

In summary, the results suggest that the density of risk scores from industrial toxic emissions increase significantly with an increase in the proportion of racial/ethnic minorities at all search radii and at both the census tract and block levels of aggregation. More specifically, the overall minority, Black, and Hispanic proportions and population density are the most significant explanatory factors in determining the density of risk scores at all search radii, all aggregations, and both regression modeling techniques. Blacks and Asians were found to reside outside of areas with the highest health risk. Therefore, it can be surmised that minorities facing the highest health risks are primarily comprised of the Hispanic population, particularly when using the contiguity-based
spatial regression models. Furthermore, the distance bands provide evidence that a large percentage of the Hispanic population resides along the edges of analytical units and are exposed to higher health risks. Additionally, risk scores decrease consistently across all search radii as home ownership rates decline and the significance of the negative association between the Asian proportion and risk scores increases at the block group resolution. Lastly, the analytical units with higher population density were found to be exposed to greater health risks. The combination of the aforementioned findings suggests that the Hispanic residents comprise the largest component of the potentially exposed population. The locations of this minority sub-group coincide spatially with areas facing the greatest health risks from industrial air pollution in the Houston-Galveston-Brazoria-MSA.
Table 67: Descriptive Statistics for Variables at the Census Tract Level. n=886

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density of Risk Scores (LN): 0 Miles</td>
<td>5.110</td>
<td>1.880</td>
<td>0.010</td>
<td>9.660</td>
</tr>
<tr>
<td>Density of Risk Scores (LN): 0.5 Miles</td>
<td>5.190</td>
<td>1.830</td>
<td>0.010</td>
<td>9.050</td>
</tr>
<tr>
<td>Density of Risk Scores (LN): 1 Mile</td>
<td>5.210</td>
<td>1.800</td>
<td>0.010</td>
<td>8.800</td>
</tr>
<tr>
<td>% Black</td>
<td>18.140</td>
<td>24.290</td>
<td>0.000</td>
<td>98.160</td>
</tr>
<tr>
<td>% Asian</td>
<td>4.140</td>
<td>5.890</td>
<td>0.000</td>
<td>37.710</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>28.380</td>
<td>23.310</td>
<td>0.000</td>
<td>100.000</td>
</tr>
<tr>
<td>% Minority</td>
<td>52.700</td>
<td>29.830</td>
<td>0.000</td>
<td>100.000</td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>7.550</td>
<td>8.020</td>
<td>0.000</td>
<td>10.390</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>14.210</td>
<td>10.920</td>
<td>0.000</td>
<td>66.690</td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>61.010</td>
<td>25.440</td>
<td>0.000</td>
<td>100.000</td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>60.270</td>
<td>16.530</td>
<td>0.000</td>
<td>115.450</td>
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Table 68: Descriptive Statistics for Variables at the Block Group Level. n=2705

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density of Risk Scores(LN): 0 Miles</td>
<td>5.160</td>
<td>1.920</td>
<td>0.000</td>
<td>9.930</td>
</tr>
<tr>
<td>Density of Risk Scores(LN): 0.5 Miles</td>
<td>5.270</td>
<td>1.850</td>
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<td>9.350</td>
</tr>
<tr>
<td>Density of Risk Scores(LN): 1 Mile</td>
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<td>1.810</td>
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<td>9.210</td>
</tr>
<tr>
<td>% Black</td>
<td>17.560</td>
<td>25.760</td>
<td>0.000</td>
<td>100.000</td>
</tr>
<tr>
<td>% Asian</td>
<td>3.760</td>
<td>6.660</td>
<td>0.000</td>
<td>68.160</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>28.860</td>
<td>25.590</td>
<td>0.000</td>
<td>100.000</td>
</tr>
<tr>
<td>% Minority</td>
<td>52.210</td>
<td>31.630</td>
<td>0.000</td>
<td>100.000</td>
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<tr>
<td>Population Density (LN)</td>
<td>7.710</td>
<td>1.580</td>
<td>0.000</td>
<td>11.150</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>14.490</td>
<td>12.190</td>
<td>0.000</td>
<td>73.360</td>
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<tr>
<td>% Owner Occupied</td>
<td>63.110</td>
<td>27.430</td>
<td>0.000</td>
<td>100.000</td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>34.140</td>
<td>10.650</td>
<td>0.000</td>
<td>83.610</td>
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Table 69: Pearson Correlation Coefficients Associated with the Density of Risk Scores (Natural Log) Released at the Census Tract Level. n=886

<table>
<thead>
<tr>
<th>Variables</th>
<th>0 Mile</th>
<th>0.5 Mile</th>
<th>1 Mile</th>
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<tbody>
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<td></td>
<td>r</td>
<td>p-Value</td>
<td>r</td>
</tr>
<tr>
<td>% Black</td>
<td>0.122</td>
<td>0.001</td>
<td>0.130</td>
</tr>
<tr>
<td>% Asian</td>
<td>0.028</td>
<td>0.404</td>
<td>0.026</td>
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<td>% Hispanic</td>
<td>0.418</td>
<td>&lt;0.001</td>
<td>0.432</td>
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<tr>
<td>% Minority</td>
<td>0.429</td>
<td>&lt;0.001</td>
<td>0.446</td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.648</td>
<td>&lt;0.001</td>
<td>0.577</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.332</td>
<td>&lt;0.001</td>
<td>0.354</td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.349</td>
<td>&lt;0.001</td>
<td>-0.361</td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.017</td>
<td>0.616</td>
<td>-0.046</td>
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p<0.05
Table 70: Pearson Correlation Coefficients Associated with the Density of Risk Scores (Natural Log) Released at the Block Group Level. n=2705

<table>
<thead>
<tr>
<th>Variables</th>
<th>0 Mile</th>
<th></th>
<th>0.5 Mile</th>
<th></th>
<th>1 Mile</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r</td>
<td>p-Value</td>
<td>r</td>
<td>p-Value</td>
<td>r</td>
<td>p-Value</td>
</tr>
<tr>
<td>% Black</td>
<td>0.094</td>
<td>&lt;0.001</td>
<td>0.105</td>
<td>&lt;0.001</td>
<td>0.111</td>
<td>&lt;0.001</td>
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<tr>
<td>% Asian</td>
<td>0.021</td>
<td>0.275</td>
<td>0.018</td>
<td>0.359</td>
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<td>0.331</td>
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<tr>
<td>% Hispanic</td>
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<td>&lt;0.001</td>
<td>0.406</td>
<td>&lt;0.001</td>
<td>0.409</td>
<td>&lt;0.001</td>
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<tr>
<td>% Minority</td>
<td>0.382</td>
<td>&lt;0.001</td>
<td>0.414</td>
<td>&lt;0.001</td>
<td>0.423</td>
<td>&lt;0.001</td>
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<td>Population Density (LN)</td>
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<td>0.538</td>
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<td>0.450</td>
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<td>% Below Poverty</td>
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<td>0.285</td>
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<td>&lt;0.001</td>
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<td>% Owner Occupied</td>
<td>-0.274</td>
<td>&lt;0.001</td>
<td>-0.294</td>
<td>&lt;0.001</td>
<td>-0.299</td>
<td>&lt;0.001</td>
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<td>Labor Force (SR)</td>
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<td>-0.071</td>
<td>0.001</td>
<td>-0.086</td>
<td>&lt;0.001</td>
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p<0.05
Table 71: Least Squares Regression Results for Density of Risk Scores (Natural Log) at Zero Mile from Census Tract Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.005*</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.390)</td>
<td>(1.290)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.024*</td>
<td>-0.024*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.820)</td>
<td>(-2.870)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.019*</td>
<td>0.017*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(8.420)</td>
<td>(6.120)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>%Minority</td>
<td>0.011*</td>
<td>0.006*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.540)</td>
<td>(2.390)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.676*</td>
<td>0.757*</td>
<td>0.690*</td>
<td>0.713*</td>
</tr>
<tr>
<td></td>
<td>(20.630)</td>
<td>(22.130)</td>
<td>(20.760)</td>
<td>(21.420)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.002</td>
<td></td>
<td>-0.012</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.275)</td>
<td></td>
<td>(-1.590)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.008*</td>
<td>-0.010*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.040)</td>
<td>(-5.080)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.023*</td>
<td>-0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-7.710)</td>
<td>(-5.690)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.446</td>
<td>0.499</td>
<td>0.479</td>
<td>0.514</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>355.720*</td>
<td>175.634*</td>
<td>202.820*</td>
<td>132.850*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>3115.890</td>
<td>3032.270</td>
<td>3065.120</td>
<td>3044.490</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-1554.940</td>
<td>-1510.130</td>
<td>-1527.560</td>
<td>-1496.760</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.643*</td>
<td>0.643*</td>
<td>0.602*</td>
<td>0.612*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.657*</td>
<td>0.656*</td>
<td>0.616*</td>
<td>0.624*</td>
</tr>
<tr>
<td>Moran’s I-0.5 mile</td>
<td>0.060*</td>
<td>0.071*</td>
<td>0.048*</td>
<td>0.055*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.009*</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.220)</td>
<td>(0.680)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.015**</td>
<td>-0.020*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.750)</td>
<td>(-2.470)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.023*</td>
<td>0.017*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10.410)</td>
<td>(6.120)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.015*</td>
<td>0.005*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(9.280)</td>
<td>(2.220)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.715*</td>
<td>1.010*</td>
<td>0.728*</td>
<td>1.010*</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.006</td>
<td>-0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.861)</td>
<td>(-0.920)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.010</td>
<td>-0.010*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.160)</td>
<td>(-5.410)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.038*</td>
<td>-0.038*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-12.130)</td>
<td>(-12.570)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.388</td>
<td>0.507</td>
<td>0.424</td>
<td>0.538</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>280.398*</td>
<td>180.823*</td>
<td>161.823*</td>
<td>145.904*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>3152.400</td>
<td>2967.860</td>
<td>3104.000</td>
<td>2914.400</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-1573.200</td>
<td>-1477.930</td>
<td>-1547.000</td>
<td>-1449.200</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.718*</td>
<td>0.691*</td>
<td>0.681*</td>
<td>0.631*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.729*</td>
<td>0.704*</td>
<td>0.692*</td>
<td>0.675*</td>
</tr>
<tr>
<td>Moran’s I-0.5 mile</td>
<td>0.049*</td>
<td>0.049*</td>
<td>0.039*</td>
<td>0.036*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 73: Least Squares Regression Results for Density of Risk Scores (Natural Log) at One-Mile from Census Tract Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.011*</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.240)</td>
<td>(0.874)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td></td>
<td>-0.006*</td>
<td>-0.015**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.681)</td>
<td>(-1.880)</td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td></td>
<td>0.027*</td>
<td>0.018*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(11.640)</td>
<td>(6.400)</td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.018*</td>
<td>0.006*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10.720)</td>
<td>(2.570)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.671*</td>
<td>1.150*</td>
<td>0.674*</td>
<td>1.140*</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.005</td>
<td></td>
<td>-0.005</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.801)</td>
<td></td>
<td>(-0.800)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.011*</td>
<td></td>
<td>-0.011*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.540)</td>
<td></td>
<td>(-5.700)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.046*</td>
<td></td>
<td>-0.047*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-13.700)</td>
<td></td>
<td>(-14.180)</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.337</td>
<td>0.488</td>
<td>0.373</td>
<td>0.519</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>224.695*</td>
<td>167.553*</td>
<td>130.881*</td>
<td>135.274*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>3196.270</td>
<td>2974.160</td>
<td>3151.540</td>
<td>2922.530</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-1595.130</td>
<td>-1481.080</td>
<td>-1570.770</td>
<td>-1453.270</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.750*</td>
<td>0.701*</td>
<td>0.689*</td>
<td>0.672*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.759*</td>
<td>0.711*</td>
<td>0.727*</td>
<td>0.683*</td>
</tr>
<tr>
<td>Moran’s I-0.5 mile</td>
<td>0.050*</td>
<td>0.046*</td>
<td>0.042*</td>
<td>0.033*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
### Table 74: Spatial Regression Results for Density of Risk Scores (Natural Log) at Zero Mile from Census Tract Boundary Using Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.003*</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.830)</td>
<td>(-1.560)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.016*</td>
<td>-0.018*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.180)</td>
<td>(-4.460)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>-0.001</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.570)</td>
<td>(-0.037)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.002*</td>
<td>-0.003*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.150)</td>
<td>(-2.460)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.230*</td>
<td>0.233*</td>
<td>0.246*</td>
<td>0.247*</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.002</td>
<td>-0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.466)</td>
<td>(-1.270)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.002</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.830)</td>
<td>(-2.36)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.001**</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.462)</td>
<td>(-0.394)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.878*</td>
<td>0.871*</td>
<td>0.869*</td>
<td>0.862*</td>
</tr>
<tr>
<td></td>
<td>(1868.550)</td>
<td>(1840.650)</td>
<td>(1854.030)</td>
<td>(1853.540)</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-930.274</td>
<td>-927.614</td>
<td>-921.013</td>
<td>-917.280</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>0.033</td>
<td>0.030</td>
<td>0.024</td>
<td>0.038*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 75: Spatial Regression Results for Density of Risk Scores (Natural Log) at Zero Mile from Census Tract Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.003*</td>
<td>-0.002**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.770)</td>
<td>(-1.570)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.016*</td>
<td>-0.017*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.200)</td>
<td>(-4.510)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>-0.001</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.670)</td>
<td>(-0.230)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.002*</td>
<td>-0.003*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.160)</td>
<td>(-2.310)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.227*</td>
<td>0.231*</td>
<td>0.242*</td>
<td>0.239*</td>
</tr>
<tr>
<td></td>
<td>(13.270)</td>
<td>(12.100)</td>
<td>(13.030)</td>
<td>(13.130)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.002</td>
<td>-0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.582)</td>
<td>(-1.060)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.002**</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.680)</td>
<td>(-2.280)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.001</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.566)</td>
<td>(0.360)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.870*</td>
<td>0.863*</td>
<td>0.861*</td>
<td>0.857*</td>
</tr>
<tr>
<td></td>
<td>(1855.940)</td>
<td>(1856.870)</td>
<td>(1841.720)</td>
<td>(1840.130)</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>0.029</td>
<td>0.039*</td>
<td>0.018</td>
<td>0.029</td>
</tr>
<tr>
<td></td>
<td>(-923.971)</td>
<td>(-921.437)</td>
<td>(-914.861)</td>
<td>(-912.043)</td>
</tr>
<tr>
<td>Moran's I-rook</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 76: Spatial Regression Results for Density of Risk Scores (Natural Log) at Zero from Census Tract Boundary Using Distance Band

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 0.93 mile</th>
<th>Model 2 1.24 miles</th>
<th>Model 3 0.93 mile</th>
<th>Model 4 1.24 miles</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.93 mile</td>
<td>1.24 miles</td>
<td>0.93 mile</td>
<td>1.24 miles</td>
</tr>
<tr>
<td>% Asian</td>
<td>0.005*</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(2.290)</td>
<td>(0.277)</td>
<td>(0.041)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.016*</td>
<td>0.008*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.560)</td>
<td>(2.880)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.010*</td>
<td>0.004</td>
<td>0.010*</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(5.290)</td>
<td>(1.460)</td>
<td>(5.290)</td>
<td>(1.460)</td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.596*</td>
<td>0.648*</td>
<td>0.598*</td>
<td>0.648*</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>-0.160*</td>
<td>-0.018*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.790)</td>
<td>(-2.980)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.011*</td>
<td>-0.011*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-6.290)</td>
<td>(-6.410)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.017*</td>
<td>-0.018*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-7.060)</td>
<td>(-7.270)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.519*</td>
<td>0.696*</td>
<td>0.489*</td>
<td>0.696*</td>
</tr>
<tr>
<td></td>
<td>(-7.060)</td>
<td>(-7.270)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>3098.620</td>
<td>2728.060</td>
<td>2942.320</td>
<td>2724.570</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-1443.990</td>
<td>-1357.030</td>
<td>-1466.160</td>
<td>-1354.280</td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.034</td>
<td>-0.031</td>
<td>0.033</td>
<td>-0.030</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 77: Spatial Regression Results for Density of Risk Scores (Natural Log) at Half-Mile from Census Tract Boundary Using Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.002*</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.610)</td>
<td>(-2.600)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.011*</td>
<td>-0.012*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.020)</td>
<td>(-4.350)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>-0.001</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.984)</td>
<td>(-1.240)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.001*</td>
<td>-0.007*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.260)</td>
<td>(-5.450)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.205*</td>
<td>0.332*</td>
<td>0.218*</td>
<td>0.257*</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>-0.003</td>
<td></td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.020)</td>
<td></td>
<td>(-0.443)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.005*</td>
<td></td>
<td>-0.002*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-6.760)</td>
<td></td>
<td>(-2.940)</td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.006*</td>
<td></td>
<td>-0.004*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.320)</td>
<td></td>
<td>(-3.640)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.945*</td>
<td>0.982*</td>
<td>0.940*</td>
<td>0.922*</td>
</tr>
<tr>
<td></td>
<td>(5.180)</td>
<td>(5.450)</td>
<td>(5.180)</td>
<td>(5.180)</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>1236.210</td>
<td>1221.290</td>
<td>1224.890</td>
<td>1205.410</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-614.100</td>
<td>-604.650</td>
<td>-606.440</td>
<td>-593.710</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>0.102*</td>
<td>0.060*</td>
<td>0.091*</td>
<td>0.120*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 78: Spatial Regression Results for Density of Risk Scores (Natural Log) at Half-Mile from Census Tract Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.002*</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.640)</td>
<td>(-2.760)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.011*</td>
<td>-0.011*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.170)</td>
<td>(-4.440)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>-0.001</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.220)</td>
<td>(-1.500)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.016*</td>
<td>-0.003*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.410)</td>
<td>(-3.590)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.199*</td>
<td>0.241*</td>
<td>0.212*</td>
<td>0.251*</td>
</tr>
<tr>
<td></td>
<td>14.350</td>
<td>13.630</td>
<td>(15.120)</td>
<td>(14.190)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.003</td>
<td></td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.340)</td>
<td></td>
<td>(-0.239)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.001*</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.170)</td>
<td></td>
<td>(-2.660)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.004*</td>
<td>-0.004*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.810)</td>
<td></td>
<td>(-3.860)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.941*</td>
<td>0.924*</td>
<td>0.937*</td>
<td>0.919*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>1192.440</td>
<td>1171.140</td>
<td>1180.670</td>
<td>1160.880</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-592.218</td>
<td>-578.569</td>
<td>-584.336</td>
<td>-571.438</td>
</tr>
<tr>
<td>Moran's I-rook</td>
<td>0.110*</td>
<td>0.114*</td>
<td>0.968*</td>
<td>0.126*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 79: Spatial Regression Results for Density of Risk Scores (Natural Log) at Half-Mile from Census Tract Boundary Using Distance Band

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 0.37 mile</th>
<th>Model 2 0.62 mile</th>
<th>Model 3 0.5 mile</th>
<th>Model 4 0.5 mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.005*</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.480)</td>
<td>(1.080)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.023*</td>
<td>-0.022*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.760)</td>
<td>(-2.730)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.018*</td>
<td>0.016*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(8.110)</td>
<td>(5.850)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.002*</td>
<td>0.005*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.150)</td>
<td>(2.210)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.230*</td>
<td>0.101*</td>
<td>0.693*</td>
<td>0.761*</td>
</tr>
<tr>
<td></td>
<td>(13.180)</td>
<td>(21.970)</td>
<td>(20.700)</td>
<td>(22.620)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.003</td>
<td>-0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.501)</td>
<td>(-1.550)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.010*</td>
<td>-0.009*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.140)</td>
<td>(-4.280)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.039*</td>
<td>-0.024*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-12.480)</td>
<td>(-8.240)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.227*</td>
<td>0.290*</td>
<td>0.259*</td>
<td>0.295*</td>
</tr>
<tr>
<td></td>
<td>(-12.480)</td>
<td>(-8.240)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>3137.960</td>
<td>2944.410</td>
<td>3053.870</td>
<td>2965.250</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-1564.980</td>
<td>-1466.200</td>
<td>-1521.930</td>
<td>-1457.620</td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>-0.006</td>
<td>0.017</td>
<td>0.010</td>
<td>0.014</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 80: Spatial Regression Results for Density of Risk Scores (Natural Log) at One Mile from Census Tract Boundary Using Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.001</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.470)</td>
<td>(-2.340)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td></td>
<td>-0.006*</td>
<td>-0.007*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-2.630)</td>
<td>(-3.21)</td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td></td>
<td>-0.001</td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.276)</td>
<td>(-1.150)</td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.001</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.140)</td>
<td>(-2.880)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.155*</td>
<td>0.219*</td>
<td>0.163*</td>
<td>0.227*</td>
</tr>
<tr>
<td></td>
<td>(12.270)</td>
<td>(12.600)</td>
<td>(12.590)</td>
<td>(12.920)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.002</td>
<td></td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.849)</td>
<td></td>
<td>(-0.292)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.002*</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.870)</td>
<td>(-3.200)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.005*</td>
<td>-0.005*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.390)</td>
<td>(-5.480)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.974*</td>
<td>0.956*</td>
<td>0.972*</td>
<td>0.952*</td>
</tr>
<tr>
<td></td>
<td>(5-309)</td>
<td>(5-480)</td>
<td>(5-709)</td>
<td>(5-939)</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>902.225</td>
<td>862.775</td>
<td>898.860</td>
<td>859.156</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-447.110</td>
<td>-424.387</td>
<td>-443.430</td>
<td>-420.578</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>0.112*</td>
<td>0.145*</td>
<td>0.111*</td>
<td>0.140*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 81: Spatial Regression Results for Density of Risk Scores (Natural Log) at One Mile from Census Tract Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.001</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.550)</td>
<td>(-2.060)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.006*</td>
<td>-0.007*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.830)</td>
<td>(-3.360)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>-0.001</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.518)</td>
<td>(-1.380)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.001</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.330)</td>
<td>(-3.130)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.149*</td>
<td>0.214*</td>
<td>0.157*</td>
<td>0.222*</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.002</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.050)</td>
<td>(-0.136)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.001*</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.530)</td>
<td>(-2.880)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.005*</td>
<td>-0.005*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.760)</td>
<td>(-5.840)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.971*</td>
<td>0.952*</td>
<td>0.968*</td>
<td>0.949*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>862.448</td>
<td>820.155</td>
<td>858.575</td>
<td>816.490</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-427.224</td>
<td>-403.078</td>
<td>-423.288</td>
<td>-399.245</td>
</tr>
<tr>
<td>Moran's I rook</td>
<td>0.125*</td>
<td>0.152*</td>
<td>0.116*</td>
<td>0.147*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 82: Spatial Regression Results for Density of Risk Scores (Natural Log) at One Mile from Census Tract Boundary Using Distance Band

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 0.5 mile</th>
<th>Model 2 0.62 mile</th>
<th>Model 3 0.5 mile</th>
<th>Model 4 0.37 mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.010* (4.800)</td>
<td>0.002 (0.676)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.008 (-0.971)</td>
<td>-0.020 (-1.920)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.025* (11.380)</td>
<td>0.017* (6.290)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.017* (9.820)</td>
<td>0.006* (2.580)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.667* (13.770)</td>
<td>1.140* (20.620)</td>
<td>0.672* (13.560)</td>
<td>1.140* (20.970)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.003 (0.444)</td>
<td></td>
<td>-0.004 (-0.660)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.011* (-5.520)</td>
<td></td>
<td>-0.010* (-4.280)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.047* (-14.010)</td>
<td></td>
<td>-0.024* (-5.520)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.160* (-14.101)</td>
<td>0.175* (-5.625)</td>
<td>0.162* (-5.520)</td>
<td>0.212* (-5.520)</td>
</tr>
<tr>
<td>Akaike Info Coefficient</td>
<td>3168.430 2929.720</td>
<td>3151.540 2912.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-1564.980 -1466.200</td>
<td>-1521.930 -1447.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.019 0.005 0.008</td>
<td>0.005 0.008 0.005</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 83: Least Squares Regression Results for Density of Risk Scores (Natural Log) at Zero Mile from Block Group Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.004*</td>
<td>0.003*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.410)</td>
<td>(2.080)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.013*</td>
<td>-0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.910)</td>
<td>(-1.280)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.016*</td>
<td>0.014*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-12.720)</td>
<td>(-9.650)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.010*</td>
<td>0.007*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(9.790)</td>
<td>(5.780)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density(LN)</td>
<td>0.682*</td>
<td>0.754*</td>
<td>0.681*</td>
<td>0.741*</td>
</tr>
<tr>
<td></td>
<td>(34.880)</td>
<td>(38.000)</td>
<td>(34.540)</td>
<td>(37.400)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>-0.006**</td>
<td></td>
<td>-0.009*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.740)</td>
<td></td>
<td>(-2.600)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.006*</td>
<td></td>
<td>-0.006*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.330)</td>
<td></td>
<td>(-5.240)</td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.039*</td>
<td></td>
<td>-0.006*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-14.340)</td>
<td></td>
<td>(-13.770)</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.412</td>
<td>0.459</td>
<td>0.430</td>
<td>0.475</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>946.950*</td>
<td>458.330*</td>
<td>516.290*</td>
<td>348.5590*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>9780.500</td>
<td>9560.600</td>
<td>9684.650</td>
<td>9543.390</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-4887.250</td>
<td>-4774.300</td>
<td>-4937.300</td>
<td>-4734.230</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.682*</td>
<td>0.670*</td>
<td>0.661*</td>
<td>0.654*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.692*</td>
<td>0.680*</td>
<td>0.670*</td>
<td>0.665*</td>
</tr>
<tr>
<td>Moran’s I-0.19 mile</td>
<td>0.033*</td>
<td>0.048*</td>
<td>0.033*</td>
<td>0.046*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 84: Least Squares Regression Results for Density of Risk Scores (Natural Log) at Half Mile from Block Group Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.008*</td>
<td>0.004*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.270)</td>
<td>(2.780)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.086**</td>
<td>-0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.93)</td>
<td>(-0.980)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.022*</td>
<td>0.015*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(18.120)</td>
<td>(11.150)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.015*</td>
<td>0.008*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(15.570)</td>
<td>(6.930)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.772*</td>
<td>1.210*</td>
<td>0.777*</td>
<td>1.191*</td>
</tr>
<tr>
<td></td>
<td>(27.100)</td>
<td>(39.830)</td>
<td>(26.980)</td>
<td>(39.230)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>-0.007*</td>
<td></td>
<td>-0.010*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.270)</td>
<td></td>
<td>(-3.160)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.009*</td>
<td></td>
<td>-0.009*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-8.480)</td>
<td></td>
<td>(-8.3600)</td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.078*</td>
<td></td>
<td>-0.075*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-26.650)</td>
<td></td>
<td>(-26.140)</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.347</td>
<td>0.495</td>
<td>0.377</td>
<td>0.513</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>719.690*</td>
<td>529.370*</td>
<td>409.040*</td>
<td>405.528*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>9843.390</td>
<td>9155.830</td>
<td>9721.070</td>
<td>9063.430</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-4918.700</td>
<td>-4571.910</td>
<td>-4855.540</td>
<td>-4523.710</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.777*</td>
<td>0.722*</td>
<td>0.754*</td>
<td>0.706*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.784*</td>
<td>0.729*</td>
<td>0.761*</td>
<td>0.714*</td>
</tr>
<tr>
<td>Moran’s I-0.19 mile</td>
<td>0.011*</td>
<td>0.021*</td>
<td>0.010*</td>
<td>0.020*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 85: Least Squares Regression Results for Density of Risk Scores (Natural Log) at One Mile from Block Group Boundary

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.009*</td>
<td>0.005*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.270)</td>
<td>(3.660)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.006</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.160)</td>
<td>(-0.135)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.023*</td>
<td>0.016*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(17.680)</td>
<td>(-11.830)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.018*</td>
<td>0.009*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(18.740)</td>
<td>(7.870)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.699*</td>
<td>1.470*</td>
<td>0.823*</td>
<td>1.436*</td>
</tr>
<tr>
<td></td>
<td>(20.080)</td>
<td>(37.600)</td>
<td>(22.630)</td>
<td>(36.830)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.009*</td>
<td>-0.012*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.960)</td>
<td>(-3.710)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.020*</td>
<td>-0.010*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-9.700)</td>
<td>(-9.530)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force (SR)</td>
<td>-0.097*</td>
<td>-0.094*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-29.920)</td>
<td>(-29.420)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.290</td>
<td>0.480</td>
<td>0.321</td>
<td>0.497</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>551.670*</td>
<td>498.600*</td>
<td>318.730*</td>
<td>380.913*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>9977.040</td>
<td>9139.550</td>
<td>9861.100</td>
<td>9053.700</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-4985.520</td>
<td>-4563.780</td>
<td>-5097.330</td>
<td>-4518.850</td>
</tr>
<tr>
<td>Moran’s I-queen</td>
<td>0.816*</td>
<td>0.728*</td>
<td>0.796*</td>
<td>0.714*</td>
</tr>
<tr>
<td>Moran’s I-rook</td>
<td>0.821*</td>
<td>0.734*</td>
<td>0.722*</td>
<td>0.722*</td>
</tr>
<tr>
<td>Moran’s I-0.19 mile</td>
<td>0.009*</td>
<td>0.018*</td>
<td>0.008*</td>
<td>0.017*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 86: Spatial Regression Results for Density of Risk Scores (Natural Log) at Zero Miles from Block Group Boundary Using Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td></td>
<td>-0.002*</td>
<td>-0.002*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-3.240)</td>
<td>(-3.150)</td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td></td>
<td>-0.007*</td>
<td>-0.007*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-3.240)</td>
<td>(-3.660)</td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td></td>
<td>0.001</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-1.610)</td>
<td>(-1.850)</td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.001*</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.930)</td>
<td>(-3.270)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.149*</td>
<td>0.153*</td>
<td>0.154*</td>
<td>0.155*</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.002</td>
<td></td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.370)</td>
<td></td>
<td>(0.701)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.001</td>
<td></td>
<td>-0.0002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.187)</td>
<td></td>
<td>(-0.355)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.001</td>
<td></td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.910)</td>
<td></td>
<td>(-0.030)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.912*</td>
<td>0.909*</td>
<td>0.909*</td>
<td>0.907*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>5320.860</td>
<td>5323.080</td>
<td>5311.560</td>
<td>5317.900</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-2656.430</td>
<td>-2654.540</td>
<td>-2649.780</td>
<td>-2649.260</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>0.019</td>
<td>0.019</td>
<td>0.017</td>
<td>0.017</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 87: Spatial Regression Results for Density of Risk Scores (Natural Log) at Zero Miles from Block Group Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.001*</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.040)</td>
<td>(-2.880)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.006*</td>
<td>-0.006*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.650)</td>
<td>(-3.500)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>-0.001</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.290)</td>
<td>(-1.500)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.001*</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.620)</td>
<td>(-2.910)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td><strong>0.147</strong></td>
<td><strong>0.151</strong></td>
<td><strong>0.152</strong></td>
<td><strong>0.154</strong></td>
</tr>
<tr>
<td></td>
<td>(16.700)</td>
<td>(16.100)</td>
<td>(17.120)</td>
<td>(16.340)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.002</td>
<td></td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.190)</td>
<td></td>
<td>(0.543)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.001</td>
<td></td>
<td>-0.0002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.211)</td>
<td></td>
<td>(-0.372)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.0009</td>
<td></td>
<td>-0.0005</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.824)</td>
<td></td>
<td>(-0.470)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td><strong>0.907</strong></td>
<td><strong>0.905</strong></td>
<td><strong>0.904</strong></td>
<td><strong>0.903</strong></td>
</tr>
<tr>
<td></td>
<td>(5284.500)</td>
<td>(5287.510)</td>
<td>(5275.730)</td>
<td>(5280.970)</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-2638.250</td>
<td>-2636.760</td>
<td>-2631.860</td>
<td>-2631.390</td>
</tr>
<tr>
<td>Moran's I-rook</td>
<td>0.010</td>
<td>0.010</td>
<td>0.008</td>
<td>0.008</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 0.19 mile</th>
<th>Model 2 0.19 mile</th>
<th>Model 3 0.19 mile</th>
<th>Model 4 0.19 mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.004* (3.670)</td>
<td>0.002* (1.970)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.013* (-3.020)</td>
<td>-0.006 (-1.310)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.016* (12.860)</td>
<td>0.014* (9.490)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.010* (9.790)</td>
<td>0.097* (5.610)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.682* (34.880)</td>
<td>0.767* (39.250)</td>
<td>0.686* (35.160)</td>
<td>0.755* (38.670)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>-0.005 (-1.440)</td>
<td></td>
<td>-0.008* (-2.280)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.007* (-5.770)</td>
<td></td>
<td>-0.006* (-5.660)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.042* (-15.440)</td>
<td></td>
<td>-0.040* (-14.870)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.501* (9.732.900)</td>
<td>0.579* (9.480.030)</td>
<td>0.507* (9.636.070)</td>
<td>0.581* (9.404.940)</td>
</tr>
<tr>
<td>Akaike Info Coefficient</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-4863.450</td>
<td>-4734.010</td>
<td>-4813.030</td>
<td>-4694.470</td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>0.003</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 89: Spatial Regression Results for Density of Risk Scores (Natural Log) at Half-Mile from Block Group Boundary Using Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.001*</td>
<td>-0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.620)</td>
<td>(-3.860)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td></td>
<td>-0.005*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-5.210)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td></td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-1.62)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.001*</td>
<td>-0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.470)</td>
<td>(-4.230)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.142*</td>
<td>0.196*</td>
<td>0.150*</td>
<td>0.200*</td>
</tr>
<tr>
<td></td>
<td>(20.000)</td>
<td>(21.510)</td>
<td>(20.960)</td>
<td>(21.870)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td></td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.270)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.001</td>
<td></td>
<td>-0.001**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-1.640)</td>
<td></td>
<td>(-1.900)</td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.007*</td>
<td></td>
<td>-0.007*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-9.480)</td>
<td></td>
<td>(-9.150)</td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.966*</td>
<td>0.951*</td>
<td>0.965*</td>
<td>0.950*</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>2339.850</td>
<td>2247.500</td>
<td>2319.100</td>
<td>2236.020</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-1165.930</td>
<td>-1116.750</td>
<td>-1153.550</td>
<td>-1108.010</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>0.121*</td>
<td>0.121*</td>
<td>0.113*</td>
<td>0.118*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 90: Spatial Regression Results for Density of Risk Scores (Natural Log) at Half-Mile from Block Group Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.001*</td>
<td>-0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.530)</td>
<td>(-3.650)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.005*</td>
<td>-0.004*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.040)</td>
<td>(-4.470)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>-0.001</td>
<td>-0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.530)</td>
<td>(-2.650)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.0005*</td>
<td>-0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.360)</td>
<td>(-3.980)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.139*</td>
<td>0.191*</td>
<td>0.146*</td>
<td>0.194*</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.001</td>
<td></td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.060)</td>
<td></td>
<td>(0.318)</td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.004</td>
<td>-0.001**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.600)</td>
<td></td>
<td>(-1.860)</td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.007*</td>
<td>-0.007*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-9.400)</td>
<td></td>
<td>(-9.080)</td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.964*</td>
<td>0.949*</td>
<td>0.963*</td>
<td>0.948*</td>
</tr>
<tr>
<td></td>
<td>(-9.400)</td>
<td></td>
<td>(-9.080)</td>
<td></td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>2259.630</td>
<td>2170.290</td>
<td>2240.330</td>
<td>2159.540</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-1125.810</td>
<td>-1078.140</td>
<td>-1114.170</td>
<td>-1070.770</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>0.114*</td>
<td>0.112*</td>
<td>0.109*</td>
<td>0.109*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.19 mile</td>
<td>0.19 mile</td>
<td>0.19 mile</td>
<td>0.19 mile</td>
</tr>
<tr>
<td>% Black</td>
<td>0.008*</td>
<td>0.004*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.320)</td>
<td>(2.740)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.009**</td>
<td>-0.004**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.920)</td>
<td>(-0.950)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.022*</td>
<td>0.015*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(18.070)</td>
<td>(11.040)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.015*</td>
<td>0.008*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(15.520)</td>
<td>(6.840)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.771*</td>
<td>1.220*</td>
<td>0.776*</td>
<td>1.200*</td>
</tr>
<tr>
<td></td>
<td>(27.140)</td>
<td>(40.270)</td>
<td>(27.020)</td>
<td>(39.660)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>-0.007*</td>
<td>-0.009*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.140)</td>
<td>(-3.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.009*</td>
<td>-0.009*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-8.720)</td>
<td>(-8.580)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.079*</td>
<td>-0.076*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-27.110)</td>
<td>(-26.610)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.287*</td>
<td>0.424*</td>
<td>0.268*</td>
<td>0.416*</td>
</tr>
<tr>
<td></td>
<td>(-27.110)</td>
<td>(-40.270)</td>
<td>(-27.020)</td>
<td>(-39.660)</td>
</tr>
<tr>
<td>Akaike Info Coefficient</td>
<td>9834.870</td>
<td>9480.030</td>
<td>9713.940</td>
<td>9040.300</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-4914.430</td>
<td>-4559.330</td>
<td>-4815.970</td>
<td>-4512.160</td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.003</td>
<td>0.004</td>
<td>0.003</td>
<td>0.004</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 92: Spatial Regression Results for Density of Risk Scores (Natural Log) at One Mile from Block Group Boundary Using Queen Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.001*</td>
<td>-0.001*</td>
<td>-0.001*</td>
<td>-0.001*</td>
</tr>
<tr>
<td></td>
<td>(-0.943)</td>
<td>(-3.270)</td>
<td>(-0.943)</td>
<td>(-3.270)</td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.003*</td>
<td>-0.003*</td>
<td>-0.003*</td>
<td>-0.003*</td>
</tr>
<tr>
<td></td>
<td>(-3.600)</td>
<td>(-3.590)</td>
<td>(-3.590)</td>
<td>(-3.590)</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>-0.001</td>
<td>-0.001*</td>
<td>-0.001*</td>
<td>-0.001*</td>
</tr>
<tr>
<td></td>
<td>(-0.439)</td>
<td>(-2.81)</td>
<td>(-0.439)</td>
<td>(-2.81)</td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.001</td>
<td>-0.008*</td>
<td>-0.008*</td>
<td>-0.008*</td>
</tr>
<tr>
<td></td>
<td>(-0.755)</td>
<td>(-3.780)</td>
<td>(-0.755)</td>
<td>(-3.780)</td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.104*</td>
<td>0.192*</td>
<td>0.110*</td>
<td>0.195*</td>
</tr>
<tr>
<td></td>
<td>(17.220)</td>
<td>(21.950)</td>
<td>(17.920)</td>
<td>(22.170)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.003</td>
<td>-0.005</td>
<td>-0.005</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.488)</td>
<td>(-0.078)</td>
<td>(0.488)</td>
<td>(-0.078)</td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.007*</td>
<td>-0.008*</td>
<td>-0.008*</td>
<td>-0.008*</td>
</tr>
<tr>
<td></td>
<td>(-3.410)</td>
<td>(-3.610)</td>
<td>(-3.410)</td>
<td>(-3.610)</td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.009*</td>
<td>-0.009*</td>
<td>-0.009*</td>
<td>-0.009*</td>
</tr>
<tr>
<td></td>
<td>(-14.010)</td>
<td>(-13.790)</td>
<td>(-14.010)</td>
<td>(-13.790)</td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.985*</td>
<td>0.967*</td>
<td>0.984*</td>
<td>0.966*</td>
</tr>
<tr>
<td></td>
<td>(0.985)</td>
<td>(0.967)</td>
<td>(0.984)</td>
<td>(0.966)</td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>1022.090</td>
<td>821.993</td>
<td>1011.450</td>
<td>817.101</td>
</tr>
<tr>
<td>Log-likelihood queen</td>
<td>-507.047</td>
<td>-403.547</td>
<td>-499.726</td>
<td>-399.55</td>
</tr>
<tr>
<td>Moran's I-queen</td>
<td>0.130*</td>
<td>0.111*</td>
<td>0.117*</td>
<td>0.110*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 93: Spatial Regression Results for Density of Risk Scores (Natural Log) at One Mile from Block Group Boundary Using Rook Contiguity

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>-0.001</td>
<td>-0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.867)</td>
<td>(-3.060)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.003*</td>
<td>-0.003*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.660)</td>
<td>(-3.430)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>-0.001</td>
<td>-0.001*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.437)</td>
<td>(-2.640)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>-0.001*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.714)</td>
<td>(-3.550)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.102*</td>
<td>0.189*</td>
<td>0.107*</td>
<td>0.189*</td>
</tr>
<tr>
<td></td>
<td>(17.400)</td>
<td>(21.860)</td>
<td>(18.060)</td>
<td>(22.070)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>0.001</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.357)</td>
<td>(-0.186)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.001*</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.200)</td>
<td>(-3.410)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.009*</td>
<td>-0.009*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-13.790)</td>
<td>(-13.570)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.983*</td>
<td>0.965*</td>
<td>0.982*</td>
<td>0.965*</td>
</tr>
<tr>
<td></td>
<td>(-13.790)</td>
<td>(-13.570)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Akaike Info Criterion</td>
<td>960.780</td>
<td>767.392</td>
<td>951.258</td>
<td>764.040</td>
</tr>
<tr>
<td>Log-likelihood rook</td>
<td>-476.390</td>
<td>-376.696</td>
<td>-469.629</td>
<td>-373.020</td>
</tr>
<tr>
<td>Moran's I-rook</td>
<td>0.110*</td>
<td>0.962*</td>
<td>0.104*</td>
<td>0.930*</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
Table 94: Spatial Regression Results for Density of Risk Scores (Natural Log) at One Mile from Block Group Boundary Using Distance Band

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 0.19 mile</th>
<th>Model 2 0.19 mile</th>
<th>Model 3 0.19 mile</th>
<th>Model 4 0.19 mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Black</td>
<td>0.011*</td>
<td>0.005*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(9.120)</td>
<td>(3.620)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Asian</td>
<td>-0.001</td>
<td>-0.001**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.183)</td>
<td>(-0.088)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.025*</td>
<td>0.016*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(20.390)</td>
<td>(11.690)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Minority</td>
<td>0.018*</td>
<td>0.009*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(18.130)</td>
<td>(7.770)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population Density (LN)</td>
<td>0.699*</td>
<td>1.480*</td>
<td>0.698*</td>
<td>1.440*</td>
</tr>
<tr>
<td></td>
<td>(20.840)</td>
<td>(37.980)</td>
<td>(20.500)</td>
<td>(37.200)</td>
</tr>
<tr>
<td>% Below Poverty</td>
<td>-0.009*</td>
<td>-0.011*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.850)</td>
<td>(-3.570)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Owner Occupied</td>
<td>-0.010*</td>
<td>-0.010*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-9.920)</td>
<td>(-9.720)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force(SR)</td>
<td>-0.098*</td>
<td>-0.095*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-30.320)</td>
<td>(-29.810)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Autoregressive Coefficient</td>
<td>0.274*</td>
<td>0.409*</td>
<td>0.248*</td>
<td>0.394*</td>
</tr>
<tr>
<td></td>
<td>(18.130)</td>
<td>(37.980)</td>
<td>(20.500)</td>
<td>(37.200)</td>
</tr>
<tr>
<td>Akaike Info Coefficient</td>
<td>9969.930</td>
<td>9118.220</td>
<td>9855.630</td>
<td>9034.850</td>
</tr>
<tr>
<td>Log-likelihood</td>
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<td>-4559.110</td>
<td>-4922.810</td>
<td>-4506.430</td>
</tr>
<tr>
<td>Moran's I-distance</td>
<td>0.005</td>
<td>0.005</td>
<td>0.003</td>
<td>0.005</td>
</tr>
</tbody>
</table>

a. All race variables represent a single race.
b. *p<0.05, **p<0.10
9. CONCLUSIONS

Issues of fairness and equity in the distribution of environmental pollution sources such as industrial manufacturing facilities, landfills, and hazardous waste disposal sites sparked the beginning of the environmental justice movement. The disproportionate placement of polluting sites in predominantly low-income and minority neighborhoods has resulted in an uneven health burden that requires researchers to move beyond locational analyses of facilities to more rigorous methodological approaches that make a connection between exposure to toxic chemical releases and adverse health risks. The siting patterns of industrial facilities and the exploration of their relationship with proximate populations are grounded in geographic principles and spatial techniques are thus necessary to analyze associations between environmental pollution and the characteristics of potentially exposed residents. While numerous environmental justice studies have examined the location pattern of polluting facilities, recent research has emphasized the need to analyze disproportionate exposure to pollutants and related health risks on the basis of chemical-specific emission data and atmospheric modeling techniques.

The goals of this dissertation were to extend quantitative research on environmental justice and address several methodological limitations of previous studies, by: 1) using new indicators of exposure to air pollution and contemporary risk modeling techniques; 2) assessing disparities in human health risks, instead of focusing only on potential exposure or proximity to pollution sources; and 3) implementing multivariate
regression models that consider the effect of spatial autocorrelation and are thus more suitable for analyzing variables derived from census data. These goals were specifically addressed by using the Risk Screening Environmental Indicators model (RSEI) as provided by the US Environmental Protection Agency. This model provides information on toxicity-weighted emissions (hazard scores) and human health risks (modeled risk scores) from air pollutants by including detailed data on the quantity, nature, and dispersion of chemical releases from facilities in the Toxic Release Inventory (TRI). Compared to the measures used in previous studies on the environmental justice implications of TRI facilities, the RSEI data provides two distinct advantages. First, the detailed information on chemical toxicity allows an improved measure of the potential human health effects caused by pollution. Second, the data used are based on a realistic representation of exposure, incorporating chemical fate and transport, as well as stack heights and exit gas velocities. The application of this new data set thus allowed for an extension of the traditional approach for measuring the magnitude of pollution in quantitative analysis of environmental justice. Additionally, the implementation of advanced multivariate and spatial regression techniques instead of traditional bivariate statistical measures and regression models allowed for the indicators of environmental justice to be examined on the basis of different analytical units and distances. Furthermore, the assessment and adjustment for spatial dependence resulted in the use of multivariate models that are less likely to violate the assumptions associated with regression residuals or bias the regression coefficients. Lastly, the use of least likelihood statistics combined with the adjustments for spatial dependence lends to an improved
selection of variables for explaining the geographic distribution of health risks and pollution sources.

Newly emerging themes in the environmental justice research literature (Gee and Payne-Sturges 2004; Maantay 2005; Payne-Sturges and Gee 2006), such as inequities in the levels of pollution and public health risks, were explored in the Houston-MSA by determining the association between various pollution indicators and the racial/ethnic and socioeconomic characteristics of the population. Four quantitative measures of pollution were used for these assessments. First, locations of industrial toxic emissions were examined by assessing the presence or absence of TRI facilities across census units in the study area. Second, the quantity of chemicals (pounds) emitted into the atmosphere was used as a method of exposure assessment on the population. Third, the quantity of pounds emitted was extended by assessing the contribution of toxicity of each chemical as part of the exposure assessment (hazard scores). Modeling the atmospheric dispersion of chemicals in conjunction with their toxic impacts on the population was the fourth and final avenue of risk assessment.

9.1 Evaluating Inequities for the Four Pollution Indicators

The findings from the analyses of the four pollution sources overwhelmingly indicate that the overall minority percentage, the Hispanic percentage, and population density provide the most consistent associations on the magnitude of pollution at all search radii, all aggregations, and both standard and spatial regression modeling techniques. The nuances of these analytical results lend significant findings to this study. Locational analysis of TRI facilities provides evidence that the effect of race/ethnicity on TRI location becomes stronger and more significant as the search radius increases, at
both the census tract and block group levels of aggregation. Thus, choosing both the
correct analytical unit and the correct scale for measuring pollution is essential. Although
higher Hispanic proportions suggested a stronger statistical relationship with TRI
pollution than higher Black proportions and percent below poverty, the results associated
with the Black population and poverty rates provide necessary evidence that not all
statistical effects from pollution sources can be captured by using a single analytical unit.
Thus, it becomes important to utilize more flexible analytical techniques in order to
assess whether minority sub-groups (e.g., Blacks) reside inside or on the edge of
boundaries of census tracts or block groups.

The analysis of racial/ethnic inequity for the density of pounds and density of
hazard scores suggested similar results. As observed in the locational analysis, levels of
pounds and hazard scores are higher in census units containing a greater percentage of
Hispanics. Additionally, a higher percentage of Asians showed a negative statistical
effect while Blacks and labor force indicated a positive statistical effect on levels of
pounds and hazard scores.

The human health risks from toxic emissions, as measured by modeled risk
scores, are also impacted by the proportion of minorities, Hispanics, and population
density. Although census units associated with TRI facilities, higher emission quantities,
and higher hazard scores indicated lower population density, modeled risk scores are
greatest in areas of higher population density. Since the modeled risk scores are
interpolated data which provide consistent scores for all analytical units, it presents an
improved picture of the magnitude of health risks on the studied population. Thus, the
findings of the positive statistical effect of population density on adverse health risks
from air pollution are consistent with other environmental justice and health disparities studies (Krieger and Subramanian 2003; Gee and Payne-Sturges 2004; Maantay 2005; Payne-Sturges and Gee 2006; Krieger 2005; Chen et al. 2006). The Hispanic population represents the minority sub-group exposed to the highest levels of health risk in the study area, while the Asian population is facing the lowest health risks. The Black population, on the other hand, experiences an increase in health risks only when neighbor relationships in the analysis of spatial dependence are based on the distance-based approach. Most of the model results suggest that the Black and Hispanic populations within the boundaries of both the analytical units have the greatest health risks. While these two minority sub-groups share the same spaces in certain parts of the study area, the history of a greater density of Blacks residing within the inner core and Hispanics being more dispersed throughout the Houston-MSA may influence these findings. The findings for owner-occupied housing are also consistent with the results of previous environmental justice studies that found fewer toxic facilities and lower levels of pollution in areas with smaller home ownership rate (Morello-Frosch et al. 2001; Ash and Fetter 2004; Pastor Jr et al. 2005).

9.2 Effect of Regression Methodology and Analytical Unit Selection

*Ordinary Least Squares Regression vs. Spatial Regression* An important goal of this research was to implement multivariate regression models that considered the effect of spatial dependence and do not violate the assumptions of ordinary least squares regression (OLS) regression, in order to obtain a clearer picture of the disproportionate impacts of industrial pollution in the Houston-MSA. OLS regression was the traditional modeling technique utilized to examine the statistical effects of various racial/ethnic and
socioeconomic explanatory variables. The inherent geographic distribution of these population variables along with pollution sources suggested a need to identify if spatial autocorrelation exists and the independence assumptions of OLS are satisfied. SAR models were then used to improve the OLS models and account for spatial autocorrelation in the data. OLS and SAR techniques were not used for the traditional host/non-host analysis of census units that was based on bivariate analysis and logistic regression of TRI locations. Therefore, three quantitative pollution indicators were analyzed to supply evidence that accounting for spatial dependence provides a significant improvement over using OLS regression alone. Additionally, multiple neighborhood configurations were used to identify the set of neighbors which provide the best fit for each regression model while minimizing spatial dependence.

In assessing the influences of racial/ethnic and socioeconomic variables on pounds emitted and toxicity-weighted pounds (hazard scores), the Asian percentage and labor force was found to be significant only when spatial dependence was taken into account. Consequently, these relationships with health risks would not be noticed if spatial autocorrelation existed in the data. Additionally, when looking at the health risks, the Black and minority populations who reside within the boundary of the analytical units experience increased health risks as compared to the same groups outside the boundary. This would not be obvious if the distance-band and contiguity-based approaches were not implemented and compared to each other. Thus, neighbors in the unit boundaries have a greater influence on health risks than neighbors at a greater distance and when spatial dependence is not accounted for when using OLS. The findings clearly demonstrate that
the choice of technique for constructing neighbor relationships on the basis of census units (contiguity-based or distance-based) affects the results of the SAR models.

It is important to consider the limitations associated with the use of buffers (0.5 mile and 1.0 mile) to calculate certain dependent variables (pounds emitted, hazard scores, and modeled risk scores). These buffer distances potentially introduce additional spatial autocorrelation in the dependent variable that could be partially responsible for causing OLS regression residuals to be spatially autocorrelated. The regression results obtained from the analyses of dependent variables at the boundaries of census units (0 mile buffer) are thus more reliable because they are not based on values derived from neighboring census units. The findings associated with the 0.5 mile and 1.0 mile buffers should therefore be interpreted with caution. Although the exact amount of spatial autocorrelation in regression errors introduced by the dependent variable itself cannot be currently estimated, the results indicate that the value of Moran’s I from the OLS regressions increase as the buffer size around census units increases. Future research should focus on the systematic separation of these spatial effects and determining the extent to which spatial autocorrelation in regression residuals is influenced by spatial autocorrelation in the dependent variable.

**Census tract vs. Block group analysis** Another goal of this research was to assess the effects of the modifiable areal unit problem (Anderton et al. 1994; Glickman et al. 1995) on the findings of environmental justice analysis. More specifically, the study attempted to examine whether conducting the same set of analyses at two different spatial resolutions (census tract or block group) lead to different results, when analyzing the
influence of racial/ethnic and socioeconomic explanatory variables on the pollution indicators.

For locational analysis of TRI facilities, it was found that the likelihood of TRI location is related to population density, overall minority percentage, and the Hispanic percentage at both the census tract and block group levels. While racial/ethnic sub-groups were found to be related to the quantity of pollutants emitted from industrial sources, the Black percentage was found to be significant only when emission density was measured at the boundaries of census tracts, but not at the block group boundaries. Additionally, the Black sub-group was significant only at the farthest distance (1 mile) away from tract boundaries and at all three distances from the block group boundaries, for both regression modeling techniques. This confirms the importance of analyzing data at more than one spatial resolution because the nuances between the distances were not evident at a single analytical unit. As for the hazard scores, the Black percentage at the block group level showed significance at all distances and in majority of the models tested with and without the socioeconomic variables. Furthermore, home ownership rate had a positive statistical effect on the hazard scores at the census tract level but exhibited a negative statistical effect at the block group level. Regarding the health risks from toxic emissions, the findings in this study suggest that race/ethnicity and socioeconomic variables are influential at both the census tract and block levels of aggregation. Overall minority, Black, and Hispanic populations, along with population density, are influential at both analytical units. Although the Asian percentage showed a negative association with health risks, the significance of this variable increases when the block group unit of analysis is used. These findings suggest that a quantitative study based on one particular
areal unit is unlikely to produce reliable empirical support for environmental injustice, because the statistical results are affected by the spatial resolution of the data.

9.3 Geographies of Environmental Justice

A variety of theories have been proposed to understand and explain the occurrence of spatial and environmental injustices. These were outlined in Chapter 2 of this dissertation and include theories of social justice, theories of neighborhood change, and economic, residential, and location theories. The results suggest that principles of contractarianism, egalitarianism, and libertarianism are violated because environmental health risks are not evenly distributed across all racial/ethnic and socioeconomic groups in the Houston MSA. Industrial pollution sources were found to be predominantly located in areas containing a higher proportion of minorities, and Hispanics, and to a lesser extent Blacks, in particular. Additionally, the magnitude of pollution was found to be primarily in the same communities with a disproportionate risk burden being placed on these groups. Although equal access to clean air and low health risks is not evident in this research, basic principles of utilitarianism are observed. By placing industrial facilities in confined areas of the MSA it limits the overall exposure to the majority of the population thus supporting a basic utilitarian principle. The contemporary view of the Marxist exploitation principle as outlined by (Smith 1994) is supported by the findings of this research. This idea states that “unfair advantage within broader distribution arrangements which include uneven access to resources in general and to the means of production in particular”. Since neighborhoods populated with minorities contain the majority of pollution sources, greater exposures, and health risks, this group does not receive equal access to clean air. Empirical support for theories of neighborhood change
cannot be established through this research because longitudinal analysis is necessary to understand the process through which the socially disadvantaged groups and pollution sources came to occupy the same spaces.

Examples of the tenets of geographic principles associated with place, scale, and space in relation to environmental justice were addressed in this research. The over-representation of the minority population in the most polluted parts of the study area exhibits the importance of place. The fact that White and Asian populations are located primarily in areas without industrial pollution sources and low health risks show that place matters in the MSA when addressing environmental justice concerns. Furthermore, scale was found to be of substantial importance with respect to the resolution of spatial data (census tracts to block groups). The use of block groups or a finer resolution provided evidence of an increase in the significance of specific explanatory variables and contributed a more detailed understanding of how race/ethnicity and socioeconomic factors relates to pollution sources and the magnitude of pollution. Thus, it is essential to examine the role of geographic scale when analyzing environmental justice and health disparities. Lastly, the effects of space were recognized explicitly in the analysis and findings of this research. In previous environmental justice research, traditional regression modeling has been conducted without taking into account the spatial clustering of pollution and populations. This research demonstrated the importance of assessing and adjusting for spatial dependence in the data. Spatial autocorrelation was found to exist in all analyses based on traditional regression modeling. Furthermore, several variables including the Asian percentage are only significant when spatial dependence is negated. Therefore, understanding the importance of spatial relationships and
geographically referenced data is essential when analyzing environmental injustices and health disparities.

9.4 Public Health Implications

The World Health Organization (WHO) (2007) states that the determinants of health include: the social and economic environment, the physical environment, and the person’s individual characteristics and the behaviors. This research assessed specific aspects of these determinants by evaluating relationships between race/ethnicity and socioeconomic status in relation to pollution sources and indicators of exposure in the Houston MSA. Evidence of disparities related to excess exposure of toxic chemicals was observed using the Risk Screening Environmental Indicators (RSEI) model. Specifically, minorities and the Hispanic population, in particular, were found to be disproportionately exposed to health risks compared to the remainder of the studied population. These results beg for future questions to be posed. From this research, systematic connections between levels of exposure and measurable outcomes such as cancers and asthma rates can be addressed. These results will be provided to the Houston MSA public health community so that they can use these findings as a guide to address the needs of populations that are potentially facing excess toxic chemical exposure.

The importance of conducting public health research in a spatial context versus traditional analytical methods alone was also evident from this study. The research provides evidence that the data and variables commonly selected for health disparities research (e.g., race/ethnicity, income) are inherently spatial. Consequently, analyses conducted with spatial tools and methodologies could provide an improved assessment of relationships. While this study focused on the general population, future research will
utilize a more detailed exploration of specific sub-populations that more susceptible to
the adverse health effects of toxic chemical exposure. These groups will include young
children, fetuses to address prenatal exposure, the elderly, and persons with compromised
immune systems (e.g., persons with HIV/AIDS and liver and kidney disease).

9.5 Limitations and Future Research

This study indicated that certain racial/ethnic or socioeconomic groups are
restricted to specific locations within the Houston metropolitan area and are
disproportionately exposed to the adverse health risks from industrial pollution. These
groups reside in these spaces for numerous reasons, such as economical limitations that
restrict housing choices, employment (dis)opportunities, lack of political representation,
racial/ethnic discrimination or social and cultural links to the local community (Been
1994; Liu 2001). The methodologies implemented in this study capture the pattern of
inequity associated with the geography of pollution sources, racial/ethnic and
socioeconomic factors in the Houston MSA. Although this study provides evidence for
environmental inequity, there are several limitations that can be addressed by future
research. First, the Risk Screening Environmental Indicators (RSEI) modeling data,
although a great improvement on traditional locational information on polluting facilities,
suffer from three limitations. The RSEI data are arbitrary in nature, meaning that the
emissions data can only be compared to each other and toxicity weights may not directly
correlate with criteria used for listing chemicals in the TRI. Therefore, the RSEI should
be used only as a screening tool. Environmental analysis with RSEI data could be
enhanced by conducting a longitudinal study on locations of facilities and nearby
populations over a period of several decades, using consistent census data to determine the population and facilities succession of the area. Additionally, the RSEI model analyzes chronic effects associated with long-term exposure and not acute toxicity to humans or the environment. This limitation could be rectified by performing a similar analysis using data on accidental releases of toxic chemicals in conjunction with explanatory variables from Census 2000. This would provide a more comprehensive picture of the combined effects of chronic and acute human health risk on the residents in this study area. Other limitations are that the toxicity weights used reflect the single most sensitive chronic human health effect dependent upon inhalation and oral pathways (fish consumption only), and not the most severe health effect or the synergistic effects of exposure to multiple chemicals. These issues can contribute to biases in toxicity calculations by positively or negatively skewing the results and by not accounting for the additive effects of simultaneous releases of toxic chemicals. Because the RSEI data provides information for the person with the highest sensitivity to a chemical instead of only a severe health effect, an improvement in understanding the additive and synergistic effects of the chemicals may be the most important extension that can be made to this study.

A second limitation to this study is that no qualitative research was conducted to complement or support the quantitative analysis of environmental justice. Although the RSEI database provides an improvement over environmental data sets used previously to examine industrial air pollution from point sources, qualitative analysis could better help ascertain population exposure to other types of pollution sources (stationary and mobile). Future research should focus on determining occupational exposures of the residents and
exposure from other pollution sources in regards to locations of dwellings. This would allow first-hand historical information concerning possible exposure sources to be obtained and related to the health risks. Additionally, the length of time and other locations where residents have previously resided need to be considered. Research on health disparities would benefit this study if government officials provided historical information of where and how long the polluting industries have existed in the studied areas and any notable patterns of previously detected health effects on the impacted populations.

Finally, there is a need to link data from the RSEI model to measureable health outcomes. The modeled risk scores in the RSEI database are based on toxicity of chemicals and their dispersal in the environment, which cannot be used to determine the actual health outcomes such as the occurrence of a type of cancer or respiratory illness. Studies of environmental justice can be improved substantially by combining the spatial modeling benefits of the RSEI model with data on the spatial distribution of individual cancer cases and other adverse health outcomes to assess potential cause and effect for exposure to toxic emissions.

9.6 Policy Recommendations

Although there are several additional questions which could be asked to improve our understanding of environmental injustice, the findings of this study provide several avenues for public policy recommendations. Regardless of the methodology utilized, Hispanics and Blacks represent the two minority sub-groups that are disproportionately exposed to health risks from industrial pollution in the MSA although Hispanics overwhelmingly received the greatest exposures. This information can be used by local
environmental regulatory agencies to advance environmental justice through the restriction of new industrial facilities near neighborhoods populated by minority residents. The identification of the health disparities reported in this dissertation could provide the local government with the ability to formulate a grassroots effort to assess the health and wellbeing of minority residents. In addition, this study can provide local community groups and environmental activists empirical evidence of unequal exposure and health risks, which can help them achieve improved health surveillance in this metropolitan area or support possible litigation against specific polluting industries.

In conclusion, this research gives credence to the disparate impacts of industrial pollution and the resultant health effects on people and places. It also provides evidence that although lower socioeconomic status is associated with the extent of pollution, race/ethnicity remains one of the strongest predictors of environmental health risks. The results substantiate that environmental injustices and health disparities exist in the Houston MSA, even after controlling for population density and various economic factors that are known to influence industrial location.


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ABOUT THE AUTHOR

Marilyn M. Williams began her collegiate journey at the University of Colorado at Boulder where she received her Bachelor’s degree in Environmental Studies. She then continued her education at Ball State University where she received a Master of Science in Natural Resources and Environmental Management. She then relocated to Chicago, IL where she was employed as an Environmental Scientist for several years.

The author returned to college where she received both a Masters of Public Health in Environmental Health and went on to obtain a Ph.D. at the University of South Florida in Geography and Environmental Science and Policy. While pursuing these degrees she was a team member on several research projects and presented at numerous local and national conferences including the meetings of the American Public Health Association and Association of American Geographers. Today, Ms. Williams is a Lecturer at the University of Denver and is seeking a tenure track position with a focus on Health Geography.