CHANGES IN EXPOSURE TO INDUSTRIAL AIR POLLUTION ACROSS THE UNITED STATES FROM 1995 TO 2004:

THE ROLE OF RACE, INCOME AND SEGREGATION

by

Kerry J. Ard

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Sociology and Natural Resources and Environment)
in the University of Michigan
2013

Doctoral Committee:

       Associate Professor Sarah Andrea Burgard, Chair
       Professor Daniel G. Brown
       Associate Professor David James Harding
       Professor Dorceta E.Taylor

DEDICATION

This is dedicated to the four generations of my family that provide me with daily inspiration and support.

ACKNOWLEDGEMENTS

I have many individuals to thank. First of all, I would like to thank my committee. Thank you to Professor Sarah Burgard for investing her time and energy in me. Your unequivocal availability and support were invaluable. Your ability to ask the perfect question, in the most diplomatic way continuously impresses me and makes me strive to be a better scholar. Another big thank you to Professor Taylor, I cannot understate the importance of your presence in my life to getting me to where I am today. You have shown me how to have confidence in my abilities and trust myself, something I will be forever grateful for. Thank you to Professors David Harding and Dan Brown who have opened my mind to the worlds of urban sociology and geography. Professor Harding, the independent study course I took with you gave me much of the theoretical foundation for this work and future work. Professor Brown your course in Geographic Information Systems provided me with the inspiration to ask questions no one had thought to ask before and the tools to answer them.

A number of University of Michigan staff that have helped me throughout this process. Thank you to Jennifer Perkins and Judy Byington who I could always count to bring positivity and helpfulness to my day. Thank you to Shannon Brines whose insights and patience helped me get through a number of tough spots with GIS. Thank you to Bennet Fauber for sharing some of his limitless energy and insights on how to navigate a Linux system remotely in order to write and run computer codes to run statistical programs that I never thought I would have to interact with. Giselle Kolenic and Kathy Welch who taught me through example how to be a beautiful, down to earth, statistician, something I hope to pass on to my students in the future. I am a more confident individual and scholar because of them.

Thank you to my friends who have provided me with emotional support. Thank you to my writing buddy Vanessa Fabien whose daily emails kept a smile on my face and let me know I wasn't alone. Her ability to find enjoyment in life and allow it to propel her to greater heights as a scholar is something I will always try to emulate; I cannot wait for her upcoming book. Thank you to Rachel Styer whose tenacity for life is continuously

astonishing to me. Your ability to live life on your terms, in the most beautiful and creative way possible is something I envy and strive for in my own life. Thank you to Carrie Buckingham whose ability to never let anything get her down or get in her way of happiness is always inspiring to me. Your quick wit to counteract my insecurities and strong belief in yourself has taught me to trust my instincts and provided me with inspiration for how I want to be in this world. Thank you to Julia Lerner. Your ability to maintain your focus on joy, and quest for being the happiest most fulfilled you, even in the face of the yucky realities life brings, is awe inspiring. I am so blessed to have you ladies in my life. Thank you to my oldest and dearest friend Teresa, whose wisdom transcends this earth. I could never thank you enough for the peace and joy you have brought into my life. Thank you for being an inspiration to me to live life fully, never give up searching for answers and making sure to breath and enjoy.

Finally, I want to thank my family, my sister Lisa for being there for me even when life was already requiring every ounce of her. For my beautiful niece Ciarra whose amazing ability to love and feel life is an inspiration to all who meet her. To my handsome nephew David whose creativity is incredible and continually blossoming. To my mother who showed me how to be tough and smart and my father who showed me to be sensitive and giving.

Lastly, I want to thank my adopted family who has shown me more love and support than I could have ever imagined possible. To my brother-in-laws Ethan and Seth, who are two incredibly charming and intelligent men and provide the best company anyone could ask for. To their intelligent and beautiful wives Hannah and Rabia whose love and support I am lucky to have and cherish. Thank you to my father-in-law Josh who was always available to read my work. I could have never gotten to this point without you. Your dry wit and amazing culinary skills kept me fed and laughing.

Thank you to Sue. I have a hard time finding the words of thanks that encompass the gratitude I feel for you. Thank you for believing in me when I didn't. Thank you for making me feel that I was never alone and always had your support. Thank you for answering my teary calls at two in the morning when you were in a far-off country. Thank you for being an incredible mother and grandmother. Thank you for your

willingness to laugh and share your joy with me, Aaron and Sam. To my grandmother and grandfather Nonny and Garvey who saw me begin this process and knew I would make them proud even if they couldn't be here to see it. The love, knowledge, memories and family they gave me has changed my life. I work daily to be worthy of it.

Thank you to my husband: my backbone, my life, my best friend. Aaron you are the most incredible person I have ever known. I have relied on your strength, intelligence and love more than air at some points in this process. More than anyone in this world, you have loved and believed in me. I cannot thank you enough for that. Thank you for sacrificing so much to allow me to reach this goal and always pushing me to be myself. You make me the best me; you are all I ever need to be happy.

Thank you to my beautiful son Samuel Zemon Ard. You sat on my lap while I wrote most of this dissertation. Even in the hardest points you brought me joy. You make me laugh, and think, and appreciate every breath I take next to you. Every time I wanted to quit I would look at you and remember I was doing this for you. We want you to have the kind of childhood that life in academia encourages. A childhood that is conducive to traveling the world, experiencing life, learning, and making the world a better place. Your intelligence, curiosity for life, and ability to laugh at yourself make me positive you will make the most of this.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

A core research concern in the field of environmental justice is to understand how exposure to industrial toxins varies by race/ethnic and class. However, as the field has evolved there have been dramatic declines in air pollution, the toxicity levels of these pollutants, and shifts in the residential settlement patterns of racial and economic groups in the United States. Current work in this field has rarely taken these trends over time into account. Because environmental justice theories in this area are based on the manufacturing industry and how it puts some populations at risk more than others, to understand how toxic emissions from these industries are changing over time is important for evaluating the continued usefulness of current theory. This dissertation addresses these limitations by examining the annual exposure for the years 1995 to 2004 of non-Hispanic whites (herein referred to as whites), African-Americans and Hispanics across the United States to 572 industrial chemicals weighted by their toxicity to human health.

The first essay provides a foundational understanding for how pollution exposure has changed for different racial/ethnic and socio-economic groups across the U.S. from 1995 to 2004. Results indicate that pollution exposure is declining over time for every socio-demographic group. However, there remains a gap between African-Americans and whites, with African-Americans having greater pollution exposure than whites, and Hispanics having similar exposures to that of whites. Interestingly, Hispanics were shown to be exposed to smaller total amounts of pollution, but more toxic substances. Within race/ethnic groups, households with higher income have greater protection from toxic substances. However, between races, African-Americans with a higher income and education still have greater exposure than whites and Hispanics with lower incomes.

The second essay assesses the links between racial residential segregation and pollution exposure, and how this association is changing over time. I use relative centralization, an alternative measure of segregation than has the one most frequently used and one that more precisely captures the clustering of African-Americans around the central city, a spatial pattern that is argued to be at the base of unequal exposure to industrial toxins by race/ethnic in the U.S. Results show that racial segregation of metropolitan areas is significantly related to pollution exposure of block groups in these areas; however this association is decreasing over time. This paper also tests hypotheses

from the literature about the dynamics of industrial pollution exposure in central cities and outside these areas. I show that counter to what has been previously theorized, central city locations have higher pollution exposure than areas central cities, and block groups with larger proportions of African-Americans outside cities experience greater industrial toxin exposure than areas with larger proportions of whites.

The third essay examines how the concentration of poverty in a metropolitan area is related to the toxic pollution exposure of block groups located within it. Findings demonstrate that those metro areas with greater poverty segregation have on average higher rates of toxic pollution exposure. In addition, those block groups with greater proportions of impoverished residents are more likely to have greater exposure to industrial toxins in metro areas with higher levels of poverty segregation.

Together these three essays contribute to the environmental justice literature by examining how exposure to industrial toxins has changed across the continental United States in the 1995 to 2004 decade for different racial and socioeconomic groups. Insights about the role of the central city, and poverty concentration, are drawn out by bringing the concepts of racial and economic segregation to this investigation. Results demonstrate the need to take into account secular changes in industrial pollution and the spatial patterning of different demographic groups while developing environmental justice theory and executing analyses.

CHAPTER 1

Introduction

The environmental justice field studies the unequal exposure to environmental risk by race and social class. This body of scholarship has grown dramatically since the 1980s, particularly studies investigating the racial and economic inequality associated with exposure to air pollution. However, since this time there have been dramatic changes in air pollution and racial and economic segregation that have not yet been adequately incorporated into empirical research. This dissertation addresses this limitation by examining how declining trends in industrial air toxins emissions from the mid-1990s to mid-2000s may have differentially benefitted U.S. residents, depending on the racial and economic segregation of their communities. The primary focus of this collection of papers is to understand the relationship between racial and economic segregation in the United States and the evolution of differential pollution exposure from 1995-2004. Collectively, this work has implications for environmental justice scholars interested in how exposure to industrial pollution varies by race and class over time, for sociologists interested in the relationship between community level inequality and its manifestation of individual risk, as well as for policy-makers interested in eliminating differential exposure to toxic substances that have been theorized to have a hand in health inequality by race in the U.S.

Motivating Theories in the Field of Environmental Justice

A large share of the environmental justice literature investigates whether industrial facilities are disproportionately located in poor and predominately minority communities. Theories to explain environmental inequalities rely heavily on sociological, political science, and economic scholarship. The theories that have developed to explain unequal environmental risk by race and class are reviewed here to illustrate the theoretical grounding of this dissertation and the body of literature that motivated it. I break these

1

theories down into three complementary categories: rational choice, sociopolitical, and racial discrimination theories.

Those theories I group in the rational choice category are based on Adam Smith's classical microeconomics theory, which holds that individual behavior can be explained by the fact that agents act according to their perceived self-interests. In keeping with this theory, it would be economically rational for industry actors to establish polluting facilities in areas that have cheaper land values, which are often in predominately minority and low-income communities (Pastor, Sadd and Hipp 2001). It would also be rational for residents of these areas who have the economic ability to move away from a polluting industry, concentrating in these communities poorer or minority residents who do not have the option to move. Most studies using rational choice theory focus on whether polluting facilities are placed in impoverished and predominately minority areas, or rather if areas that these industries moved into took on these characteristics after the facility moved in.

The results from these examinations have been mixed. Some scholars have found that polluting facilities were placed in areas with higher percentages of minority and low-income populations (Been 1994; Pastor, Sadd and Hipp 2001), while others found no evidence for disproportionate siting (Been 1994; Oakes, Anderton and Anderson 1996). Moreover, some studies have shown that the proportion of minority residents in communities around polluting facilities increased after siting (Been 1994; Mitchell, Thomas, and Cutter 1999; Stretesky and Hogan 1998), while in some cases it did not (Been and Gupta 1997; Oakes, Anderton and Anderson 1996; Pastor, Sadd and Hipp 2001). The only known study to utilize individual-level data showed that some of the differential exposure of pollution experienced by African-Americans is due to variation in the propensity for African-Americans to move to, and stay in, more polluted areas (Crowder and Downey 2010).

The second category of environmental justice theories can be classified as sociopolitical. They are based on the idea that industries deciding where to locate take the path of least political and economic resistance. This argument is based on the assumption that low income people and minorities represent the path of least resistance, meaning it is these communities that are politically and economically vulnerable and

2

unlikely to successfully resist siting proposals. Empirical studies have shown support for this idea. One of the earliest examples is provided by Hamilton (1995), who examined expansion decisions for 84 commercial hazardous waste facilities and found all zip codes of the surrounding areas had factors associated with vulnerable populations (e.g., percentage of voter turnout and renters). Pastor, Sadd and Hipp (2001) also found supportive evidence in their longitudinal study of toxic storage and disposal facilities in Los Angeles County. They found that areas with high turn-over of minority residents, areas they assumed to be less politically organized and invested, were more likely to receive a polluting facility.

The final category of theories is based on the idea that unequal exposure to environmental risk can be explained by racial discrimination, which is broken down into overt and institutional discrimination. The overt discrimination perspective holds that minority communities are intentionally targeted for environmental hazards because of beliefs in racial superiority and/or an intention to protect whites from environmental harms. Bullard (1990: p.103) exemplifies this perspective by arguing that African-American communities are targeted for local unwanted land uses because they are considered "sacrifice zones". Pulido (2000) gives this overt discrimination argument a broader perspective by arguing that environmental inequalities result from 'white privilege', a form of racism she describes as a social order intent on preserving the privilege of white people above all other groups, providing them with greater social, political and economic opportunity. Although this type of racial discrimination does not require that whites intentionally discriminate, Pulido (2000) argues that whites are consciously aware of such privilege and fight when it is threatened.

Reviewing the evidence for theories of overt discrimination can be problematic for the reasons expounded on by Pulido (2000), who notes that previous court decisions require proof of an industry's intention to racially discriminate. So while scholars can demonstrate that industries are disproportionately located in disadvantaged neighborhoods, they often cannot show the motivations behind firm's decision. This does not mean that there has been no supportive evidence for this model. In fact, Stretesky and Hogan (1998) presented a communication to the state of California that

suggested low socioeconomic areas be targeted for placement of LULUs.   However, this type of evidence is rare.

Without direct testimony that specific neighborhoods are targets, researchers are left to surmise how institutional discrimination contributes to environmental inequities. For example, Stretesky and Hogan (1998: p283) argue that the results of their longitudinal analysis of 53 Superfund sites in Florida, "provide us with evidence that indirect discrimination may be largely responsible for the environmental injustice observed." They showed that the number of African-Americans in areas surrounding Superfund sites has been increasing over years, which they suggest is resultant from housing discrimination, because as they state, "these results imply that in 1990 blacks have fewer choices in deciding where they will live than in 1980" (Stretesky and Hogan 1998: p281). While studies investigating housing discrimination, industrial zoning, and other forms of institutional discrimination have all shown general support for the institutional Racial Discrimination model, these studies often point to a web of social issues that create environmental injustices which are often hard to untangle and address (Pulido 2000; Stretesky and Hogan 1998).

Urban Sociology

At the foundation of this dissertation is an idea presented in the urban sociology literature which holds that during the Great Migration in the early 1900's United States, central cities were hubs of industrial manufacturing providing low skilled jobs for African-Americans migrating from the South (Farley, Danziger and Holzer 2000). This historical fact made African-Americans particularly vulnerable to economic shifts in manufacturing (Wilson 1996) and also to the pollution from these facilities (Downey 2005). As deindustrialization moved job opportunities outside of the central city. Residential segregation limited African-Americans from following these jobs and these historically industrial areas became increasingly impoverished, thereby concentrating African-Americans in polluted and economically nonviable areas (Wilson 1996; Downey 2005; Smith 2009).

After Civil Rights legislation made overt housing discrimination illegal, a socially mobile black middle class began moving out of the central cities (Wilson 1987).

However, Quillian (1999) showed that as this group moved outside of the city, whites responded by moving even further out into suburban areas, creating a gradient of vulnerability out from the central city. This left lower income African-Americans located in the historically industrial urban center, middle-class African-Americans located just outside the city, lower-income whites further out, and upper-class whites located the furthest away from the city.

What does it mean for environmental inequality that African-Americans, regardless of their income, tend to live closer to cities, the historic hubs of America's manufacturing industries, than whites? The consequences of deindustrialization are that as America's economy moved away from its reliance on manufacturing over what historical period?, the number of functioning industrial facilities in the U.S. declined (Sugrue1996). Does this mean that the pollution risk in America's cities has also declined? Some have argued that because changes in the U.S. economy in the 1970's and 1980's caused job opportunities to move from cities to suburbs[1], newer facilities were built outside of the city, reducing city residents' exposure to pollution and making racial segregation perversely protective for African-Americans (Downey 2005). An alternative scenario is that older industrial facilities are choosing to be grandfathered out of newer environmental regulations which require factories to adhere to stricter environmental protection practices. Thus, the older and dirtier facilities in U.S. cities are exposing those living there to greater risk than their suburban counterparts (Robertson 1995).

Understanding Dynamics

Previous work in the environmental justice literature has been important in helping us understand that broader structural inequality, like racial and economic segregation, are related to pollution exposure. However the nuances of this association and how it has changed over time have yet to be examined. This primary goal of this dissertation is to better understand the association between pollution and segregation in the United States over the past decade. The project is designed to address the following limitations in the environmental justice literature.

---

[1] This argument is based on the sociological concept of "spatial mismatch" (See Mouw 2000 for a recent empirical test of this concept).

The first limitation addressed is the lack of a dynamic and historical view of the segregation-pollution association in current environmental justice research. Research has shown that racial segregation has declined over recent decades while economic segregation has increased (Watson 2009; Farrell 2008). Moreover, new environmental regulations and deindustrialization since the 1970's has led to a broad decline in air pollution across the nation in the past several decades (Kahn 1999; EPA 2012a). However, we are unsure if the benefits of these changes are occurring equally for all population groups. Previous work has shown that there are class- and race-based disparities in the enforcement of environmental policies (Konisky and Schario 2010). If those areas that are predominately white and wealthy are more likely to have enforcement of environmental regulations over the past several decades, then it is possible that pollution risk has become increasingly concentrated in America's marginalized communities. Moreover, environmental policy analysts suggest that grandfather loopholes in environmental regulations have allowed older facilities to opt out of stricter pollution controls, providing an incentive to continue operating older dirtier industries in the central city. Without longitudinal examination of pollution trends and how they differ spatially and for different demographics, these possibilities remain unexplored.

The second major limitation of current research on segregation and pollution is the lack of integration of the empirical realities of the urbanization process of American cities that has motivated spatial patterns of pollution and people. Sociologist Thomas Sugrue(1996) argues that in order to understand urban inequality we must grapple with how the history of a city both constrains and opens up possibilities in the present. This call for a perspective on process should be heeded by those studying segregation and pollution. Scholars need to keep an eye to the broader trends their findings are located within. Recent work has taken steps towards this by incorporating the urban sociology literature dealing with concentrated poverty.

The environmental justice literature has borrowed from the urban sociology literature examining the increase in concentrated poverty in America's central cities during the 1970s and 80s. A chief argument in this literature is posed by Wilson (1997) who contends that the rise of concentrated poverty in America's central cities was due primarily to deindustrialization. He notes that during the great migration in the early

1900's, southern African-Americans were disproportionately drawn to manufacturing jobs in industrializing cities (Farley, Danziger and Holzer 2000). Wilson argued this historical fact made African-Americans particularly vulnerable to these economic shifts. These migrations patterns would also mean that historically large communities of African-Americans would have settled in central cities, nearer to their primary employment locations, now aging industrial facilities. Previous work has shown that racial segregation, often in the presence of poverty, is an important indicator of pollution exposure (Lopez 2002; Morello-Frosch and Jesdale 2006). However, none of these studies have examined poverty segregation separately from racial segregation or the role of the central city in these relationships. Moreover, few to none have examined how these processes change over time. In order to understand the causes of unequal exposure to environmental risk it is important to give each contributing process separate examination as well as taking into account their trajectories over time.

Three Papers on Social Stratification and Industrial Pollution Exposure

All of these environmental justice theories are grounded in the realities of manufacturing and residential settlement patterns. However, there have been large scale declines in U.S. manufacturing with disparate impacts on communities (Helper et al. 2010). To investigate the potential connections between trends of industrial pollution exposure and racial and economic segregation I analyze data from the Environmental Protection Agency's (EPA) Risk Screening Environmental Indicators Geographic Microdata (RSEI-GM). These are annual estimates of 572 industrial toxins for the years 1995 to 2004. These data are modeled using climate and molecular information to determine which areas they expose and then weighted by their toxicity to human health to provide a comparable assessment of risk for over 100,000 block groups across the continental United States.

Chapter 2: "Changing Exposures to Industrial Toxins in the U.S. from 1995 to 2004," provides the foundation work for understanding how pollution to industrial toxins has changed over the examined decade. This work provides estimated exposures for the average African-American, Hispanic, and white American living in the U.S. during this time period, as well as for the average household making over $50,000 annually (middle

to upper class) or less than $50,000 (lower class). Results show that there have been large scale declines in industrial pollution experienced by all groups. However, the relative burdens have remained stable. While Hispanics and whites share similar exposure patterns, African-Americans consistently have higher exposure levels. For example, when broken down by income, results show that upper and lower-class African-Americans experience greater pollution exposure than lower class white and Hispanics.

Chapter 3: "The Changing Dynamics of Racial Residential Segregation and Pollution: Unexamined Trends" examines how communities with different levels of racial residential segregation are being affected differently over time. Using repeated measures for over 100,000 block groups in 320 metropolitan areas, I use multilevel models to determine if a metropolitan area's racial residential segregation level is related to their levels of pollution exposure in 1995 and the rate of decline over the following decade. I find that those metropolitan areas with higher levels of racial segregation start out with higher exposure to pollution. However, the association between a metropolitan area's racial segregation and average exposure of areas within it is significantly declining over time. This paper also tests hypotheses developed in the environmental justice literature as to whether the relative pollution exposure of areas within and outside of the central city are changing over time, as well as examining differences in exposure rates between African-Americans and whites living outside of the central city. Results show that living in a central city is positively associated with toxicity-weighted pollution exposure. In addition, African-Americans outside of the central city are exposed to more pollution than whites in these areas. This contradicts current predictions that suggest outside of the central city, African-Americans are more likely to have less pollution exposure than whites. This paper contributes to the literature by examining how declining rates of racial segregation relate to declining rates of pollution exposure.

Chapter 4: "Poverty Segregation and Pollution Exposure: Evaluating the Concentration of Poverty" is an examination of how a metropolitan area's level of concentrated poverty is related to the pollution exposure of block groups in that metro area in the mid-1990s, and how this association may have varied over the ensuing decade. This paper helps to address limitations of current research that integrates the concept of concentrated poverty in the urban sociology literature with environmental justice research

8

by more precisely measuring the concept of concentrated poverty and determining how changes in this measure over time relate to pollution exposure. Results show that poverty segregation is strongly related to exposure. In addition, block groups with the highest proportion of those living in poverty experience significantly greater rates of pollution exposure and this is especially true for those located in metropolitan areas with high rates of poverty segregation.

CHAPTER 2

Changing Exposures to Industrial Toxins in the U.S. from 1995 to 2004

Abstract

This study investigates trends in exposure to industrial toxins from 1995 to 2004 for different racial and income groups in the United States. Demographic data on race and income is interpolated from the 1990, 2000 and 2010 censuses to provide annual population estimates at the block group level. Using geographic methods these data are overlaid with modeled air pollution exposure for 572 industrial chemicals, weighted by their toxicity to human health for every 1 kilometer square in the continental United States. Results suggest that there are two stories when it comes to recent industrial pollution exposure trends in the U.S. First, absolute exposure to industrial toxins is declining for everyone. However, important differences by race and income remain. Hispanics are exposed to lesser amounts of pollution than whites, but are breathing in more toxic substances. African-Americans experienced larger absolute declines in exposure over the time period compared to whites and Hispanics, but still experience on average 1.7 times more toxic weighted pollution than whites. These results suggest that the benefits of broad declines in pollution exposure from industry did not greatly reduce the relative burden of African-Americans compared to whites.

Introduction

The environmental justice (EJ) field began as an academic discipline in the early 1980's as a response to protesters arguing that their predominately impoverished, African-American communities were being targeted for the dumping of toxic substances (see Taylor 2000 for a review of the history). These claims set off a wave of quantitative research aimed at documenting this phenomenon (UCC 1987; Bullard 1990; Been 1994). The field has grown substantially since this time. Yet quantitative EJ scholars have been focused on determining the relative importance of race verses class leaving broader trends in changes in pollution and population unexamined.

For example, since the field began there have been large declines in industrial, air-borne toxins (Kahn 1997; EPA 2012a). However, to date there has been no research investigating if these declines are experienced equally amongst different racial and socioeconomic groups across America. This raises the question: have these declines mitigated the racial environmental inequality that was apparent at the birth of the environmental justice field? Furthermore, there have been dramatic demographic shifts in the United States since the field began, most centrally a booming Hispanic population (Guzmán 2000) and a growing black middle class (Frey 2003). How have these changes

in sociodemographic composition of the U.S. population altered pollution exposure inequalities?   Existing longitudinal studies give us some insight into how exposure to industrial air pollution has changed over time for different racial and socioeconomic groups. However, because no longitudinal studies focus on comparing trends in industrial pollution exposure across racial and socioeconomic groups, readers of this research are unclear if the broad declines in pollution exposure affect social groups differently. In addition, no known studies cover the whole of the continental United States. Rather, most longitudinal studies focus only on metropolitan areas across the U.S.

Furthermore, current research has faced measurement limitations due to a lack of data on pollution exposure and the resulting analyses have been restrictive. For example, a typical EJ analysis would determine whether a census area (e.g., census tract) has a polluting facility located in it, and then determine how the demographic characteristics of residents of those tracts differ from those residents of tracts without a facility. This seems a reasonable approach until the irregularity of census boundaries and the fact that they vary dramatically in size are taken into account. An analysis by Mohai and Saha (2006) found tracts range from 0.85 square miles to 916.5 square miles. This could mean that the demographics of one side of an oddly shaped polygon might be starkly different than those nearer to the facility. In addition, Mohai and Saha (2006) found that that roughly 71% of all facilities lay within a half a mile from their census block border. This would mean that the population located within the census boundary might not be the most exposed. Rather in those cases some residents in the neighboring tract would be among the more exposed, yet most approaches would code these individuals as unexposed. Standard methods also do not take into account that there are multiple facilities and chemicals contributing to individuals' exposure and that being located near one polluting facility may not be equally as toxic as being near another facility. Because facilities cluster in space, and emit various amounts and toxicities of chemicals, these assumptions could lead to erroneous conclusions.

This paper contributes to the literature by determining how the average exposure to industrial air toxins has changed from 1995 to 2004 for individuals of different racial and socioeconomic groups in the United States. This analysis uses a longer time period of observation, larger land area coverage, more refined geographic unit of analysis, and

11

more precise estimates of pollution exposure than previous EJ studies. This study gives us needed insights into how exposure to industrial pollution is changing over time for previously unexamined social groups. Such work is necessary in order to understand if diverse populations are benefiting equally from the broad declines in pollution reported to be associated with deindustrialization and stricter environmental regulation (Kahn 1997; Maasoumi and Millimet 2005).

Background

Trends in Pollution Exposure by Race/Ethnicity and Income

The consequences of the spatial clustering of African-Americans in America's central cities have been a primary sociological area of study for decades (DuBois 1996(1899); Park 1915; Hawley 1971). One such effect under study has been African-Americans' exposure to industrial pollution from manufacturing facilities, with much research finding that people of color have greater pollution exposure than whites (Pastor, Sadd and Hipp 2001; Bullard et al. 2007; Lopez 2002; Morello-Frosch and Jesdale 2006). Studies that have investigated longitudinal changes in air pollution exposure consistently report declines nationwide (Kahn 1997; 1999; Maasoumi and Millimet 2005). Economists have termed the declines in pollution exposure due to deindustrialization the "silver lining" of deindustrialization (Kahn 1999). No known prior studies have investigated if these large scale declines in industrial pollution have been felt equally across demographic groups. Some researchers have hypothesized that the large scale decommissioning of industrial plants associated with deindustrialization have decreased African Americans' exposure to industrial pollution (Downey 2005).

White Americans, on the other hand, have had different spatial settlement patterning than African-Americans. Reflecting levels of racial segregation, non-Hispanic whites are more concentrated in the suburbs compared to African-Americans (Charles 2003). The racial residential settlement patterns of whites in the suburbs and African-Americans in the cities were the basis of Kain's (1968) spatial mismatch theory, which holds that as manufacturing has declined in the U.S., jobs have moved further away from the cities towards the suburbs. This effect of deindustrialization has been shown to

provide suburban residents with better access to jobs and limited access to central city African-American residents (Farley, Danzinger and Holzer 2000; Massey and Denton 1993; Mouw 2000; Sugrue1996). Downey (2005) argues this theory can be applied to the environmental justice literature and reasons that as job opportunities moved from cities to suburbs, any new factories being built would be placed away from the cities, thereby increasing exposure of suburban populations. This leads Downey (2005) to hypothesize that over time, whites will become more exposed to air pollution while African-Americans will become less exposed. Thus, the ratio of average exposure for African-Americans relative to whites may be decreasing, at the same time absolute exposures for all groups would be going down.

Like African-Americans, the Hispanic population in the U.S. is extremely urbanized, with over 90% living in metro areas in the year 2000 (Kandel and Cromartie 2004).[2] Thus their exposure to industrial is expected to be similar to that of African-Americans. However, unlike the African-American population, which is concentrated in the South and Midwest, the Hispanic population is largely located in the Southwestern United States (Kandel and Cromartie 2004). This means this population's exposure to industrial toxins, and the resulting changes in this due to deindustrialization, may differ from those of African-Americans. Specifically, I hypothesize that this group is less exposed to industrial toxins more generally, and declines in this exposure will be minimal compared to African-Americans. This is because African-Americans are more likely to live in areas more affected by deindustrialization in the time period under examination. The Brookings Institute (Wial and Friedhoff 2006) found that deindustrialization was more extensive in Indiana, Wisconsin, Michigan and southern states during the period 1980-2005. Sixty-one percent of the African-American population resided in these areas in 2000, whereas only 35% of the Hispanic population was located here. 3

---

[2] It is important to note that classifying the "Hispanic" population is often problematic due to their heterogeneity in socioeconomic, immigrant status and residential patterning. Nonetheless, due to space constraints, teasing out these differences will have to be left for another paper. Therefore, in this paper I use the 2000 U.S. Census classification of Hispanic or Latino as "a person of Cuban, Mexican, Puerto Rican, South or Central American, or other Spanish culture or origin regardless of race."

[3] These numbers were calculated from the total number of Hispanics and African-Americans living in the U.S. South and the mentioned states, divided by the total number of Hispanics or Black or African-American alone population in the census (McKinnon 2001; Guzmán 2001).

In addition to providing temporal trends in pollution exposure for different racial groups, this paper also contributes to the literature by providing evidence of exposure for racial groups broken down by socioeconomic status. There have been major demographic shifts across the United States in recent years that EJ research has yet to fully consider. For example the black middle class has grown substantially (Marsh et al. 2007; Frey 2003; Farley and Frey 1994). Frey's indicator of middle-class status, an average household income of $50k or above, can be used to assess this group's growth and size in the most recent census, as well as where they stand in comparison to non-Hispanic whites and Hispanics. In 2010 roughly 36% of African-American households had an average household income of $50k. This is up from 27.4% in 2000, but still below the 56% of non-Hispanic whites and 41% of Hispanics.[4]

The current EJ discourse holds that the more economic wherewithal someone has the less likely they will be subject to pollution exposure. This would suggest that as more African-Americans attain the economic status of middle-class they would be less exposed to industrial toxins. Thus, I hypothesize that within racial groups, those with higher incomes will be more protected from environmental toxins. However, within income categories I still hypothesize there will be differences by race, so that African-Americans and Hispanics will be more exposed than whites in the same income brackets. Such an expectation arises from Logan and Stults' (2011) analysis of all metropolitan areas in 2005-2009. Using ACS data, he found that, "[t]he average affluent black or Hispanic household lives in a poorer neighborhood than the average lower-income white resident." Thus even the more affluent African-American and Hispanics are more likely to have poor neighbors than whites of similar standing. If impoverished individuals are more likely to breathe in toxins, this would mean that those middle-class African-Americans and Hispanics living nearby will experience greater amounts of exposure than whites of similar socioeconomic standing.

---

[4] Data were calculated using American Community Survey's 2010 five-year estimates accessed through Social Explorer variable "Household Income In The Past 12 Months."

14

Prior Longitudinal Environmental Justice Studies: Key Limitations

Current EJ studies that have taken a longitudinal perspective have not focused on how exposure is changing over time, rather they have primarily set out to investigate whether the demographics around a polluting facility changed once a facility moved into the area. While these studies are informative for evaluating whether the unequal distribution of pollution can be explained by demographic transitions around facilities, they are less helpful in determining answers to the policy relevant question: how has exposure to industrial toxins changed over time for individuals of different racial and socioeconomic groups? These studies are limited in answering this question for a few reasons.

The first is that much of current research has focused mainly on metropolitan areas, leaving out possibly important variations in pollution exposure. Fully 80.7% of the U.S. population was located in metro areas in 2010 (Census 2010), and Bullard et al. (2007) found that 83% of commercial hazardous waste facilities operating in the U.S. in 2000 were located in metropolitan areas. These studies would signify that metropolitan areas would be the most important spaces to study if we want to understand pollution exposure. However, Atlas (2002, p.372) found that for the 100 largest, large-quantity-generators (LQG) of hazardous waste, "most of these LQGs did not have substantial numbers of people nearby." This would imply rural areas need to be included in analyses that attempt to determine how pollution exposure varies by race and class. Excluding spaces outside of metro areas makes it difficult to assess how deindustrialization and the suburbanization of jobs have affected pollution exposure trends because of a lack of representation of less urban areas. In order to evaluate empirical evidence on how such trends might have affected exposure differently, a larger spatial area needs to be taken into account than just metro areas. To rectify this, this study uses estimates of pollution exposure for every $1km^2$ in the contiguous United States that has been aggregated to the block group level. This is a larger area and more refined geographic unit analysis than previous studies have presented.

To overcome limitations presented by a lack of data on exposure to pollution, recent studies have begun to use modeled pollution data that take into account the toxicity of chemicals and estimates of where these chemicals are located in the environment. One of the most comprehensive spatial studies to date used pollution estimates for 1 km^2 grid

cells aggregated up to the census tract level (Downey et al. 2008). Looking at the pollution exposure experienced in the year 2000 in 329 metropolitan areas, Downey and his co-authors found that while African-Americans were likely to be the most polluted group in 32.5% of metro areas, whites were actually the most polluted group in 4.3% of these areas. This supports findings from earlier work done on a smaller sample of metro areas that showed environmental inequality varies across the United States (Downey 2007). Such work demonstrates the need to take into account a broader spatial and temporal view. This paper extends analyses in all of those directions as well as considering how the changing social demography of the United States complicates the picture.

Another limitation of current longitudinal EJ research is that they often do not take into account the complication of wind patterns. One well known example where this limitation would pose a problem can be found in the South Basin of California, which is considered to have some of the worst air quality in the country (Brajer and Hall 1992). The greater Los Angeles area is sandwiched between the ocean on the west and mountains on the east. The ocean breeze pushes the smog up against the mountain, where it settles and disproportionately showers pollution on the population who resides at the base of the mountains. Eastern Los Angeles counties have been shown to have twice the average increase risk of premature death due to pollution exposure than their wealthier and more westerly counterparts (Brajer and Hall 1992). Common methods in EJ research would conclude that those areas to the west, where the polluting facilities are located, would have the most exposed population. However, when wind patterns are taken into account the most polluted population would be determined to be those downwind.

Finally, researchers rarely have had the data to accurately consider the toxicity of chemicals and exposure to multiple chemicals. Rather, many assume being near one facility is equivalent to being near another facility, even though these facilities might vary in the toxicity of the pollution they are putting in the air. Assuming equal toxicity between pollutants neglects the overwhelming evidence that some chemicals (e.g. asbestos) are much worse for human health than others (National Cancer Institute 2009). In addition, industries concentrate in areas in order to minimize the cost of doing business

(Weber 1909; Hawley 1971). This clustering of pollution sources means that individuals are being exposed to multiple chemicals at once. As argued by Kim and colleagues (2009, p.565) "[i]t is becoming increasingly evident that the incidence of neurodevelopmental toxicity is dependent on co-exposure to multiple neurotoxicants." To effectively evaluate exposure to pollution in order to understand health and health inequalities such complexities need to be measured. For these reasons current longitudinal studies that determine exposure to only one, or a handful, of toxins are likely to grossly underestimate pollution, and thereby health risk, experienced by communities. The present study is designed to overcome the above limitations by using geographic information systems (GIS) software to overlay census block group data with estimates of exposure to 572 industrial toxins.

Because both deindustrialization and environmental regulation affect racial groups differently my hypotheses for trends in exposure over time varies by demographic group. More specifically, I expect that African-Americans will experience a greater decline in air pollution exposure from industrial sources than whites, due to their denser populations in urban centers, historically a primary location for manufacturing facilities (Sugrue1996), but places that have lost industrial facilities over recent decades.

Data and Methods

Pollution Exposure Data

Pollution data were obtained from the U.S. Environmental Protection Agency's (EPA) Risk Screening Environmental Indicators Geographic Microdata (RSEI-GM). The RSEI-GM database is made up of Toxic Release Inventory (TRI) data that has been modeled in order to estimate the risk these chemicals pose to the population. The EPA models the fate of TRI chemicals in the environment using information about the amount of chemical a facility released measured in micrograms per cubic meter (μ/mg^3), molecular weight, rate of decay, as well as the source of the release (e.g., smokestack height, valve leak, etc.), wind patterns, temperature, and topography around a facility. The final product is an estimate of the yearly amount of chemical estimated to be in the air over a 101 km by 101 km square around each facility. This 101 km by 101 km square

17

is further broken down into 1 km^2 grid cells. Each of these grid cells is assigned a value for the total summed amount of a specific chemical estimated to be in the air for the whole year. The amount of 572 chemicals from multiple facilities landing in each 1 km^2 grid cell that makes up the contiguous Unites States have been estimated. This type of modeling is referred to as plume modeling and provides a potentially more accurate picture of pollution exposure than the simple proximity measures described above (Chakraborty and Armstrong 1997).

In addition to geographic modeling, the RSEI-GM database has also calculated the health risk of the chemicals being modeled. The effect a chemical is expected to have on public health is determined by peer-reviewed studies completed by both EPA and external scientists.[5] Using this literature, chemicals are assigned a toxicity weight with the goal of making different chemicals comparable to one another on a common metric (EPA 2007). Factors that are used to assign toxicity weights are: the number of potential chronic human health effects associated with a chemical, the severity of these effects, and the potency of the chemical (EPA 2007).

The RSEI-GM database weights the estimated amount (or concentration) of a chemical expected to be in a grid cell by its toxicity to create a "toxic concentration" value. This toxic concentration value can be summed across multiple chemicals that are estimated to be in the air above each of the 1 km^2 grid cells. The total toxic concentration is the major indicator of pollution exposure used in this study and is derived by equation 1 below.

$$TC = \sum_{i=0}^{N} \; (T_i * C_i)$$

(eq. 1)

In this equation TC= the total toxic concentration (sum of the toxicity weighted amount of chemicals) of one 1 km^2 grid cell, T_i = toxicity weight of chemical i, C_i = concentration of chemical i and N is the number of chemicals falling in the grid cell. The toxicity weight of chemical i, is multiplied by the concentration (amount) of chemical i landing in a cell, this process is repeated across all N chemicals and then these values are

---

[5] Such as the EPA's Integrated Risk Information System (IRIS), EPA Office of Pesticide Programs' Toxicity Tracking Reports (OPP), Agency for Toxic Substances and Disease Registry final, and other sources.

summed. Total toxic concentration values are available for every grid cell in the contiguous U.S.[6] for every year between 1988 and 2007 (see EPA 2009 p19-20 for a more detailed description of this process).

Limitations and Restrictions of RSEI-GM data

Because RSEI-GM is based on TRI data, the limitations and restrictions associated with TRI affect these data as well.[7] For example, the list of chemicals for which facilities are required to report emissions to the TRI changes over time. For those studying trends it is critical to constrain the summed scores to include the consistent set of chemicals across years. This will help ensure that any changes observed over time are not the result of a new chemical coming under observation that might create an apparent jump in toxic concentration (EPA 2012b).   In 1995 the EPA added 286 chemicals to the list of those that facilities were required to report their emissions. The EPA has made changes to the required reportable chemical list in: 1988, 1991, 1995,1998, 2000 and 2001, with varying number of changes each time. When changes are made the EPA publishes a list of "core chemicals," identifying chemicals that were not added, removed, or for which the method of reporting changed drastically from a specific year onward.   Because these analyses in this paper use data from 1995 to 2004, I have used the core chemicals for 1995 to create measures for all the years. However, as some of the chemicals added to the list after 1995 have been linked to environmental health disparities (e.g., lead and mercury) they are of specific concern and should be considered in future research. To evaluate the implications of differences in sets of chemicals considered, I have calculated trends with 1998, 2000 and 2001 core chemicals and find similar patterns (see Appendix A).

In addition to accounting for changes over time in the required reportable chemicals, I also address misreporting errors in the data.   Because the TRI are reported by facilities rather than detected by monitoring in the atmosphere, there is a possibility of human error. This often takes the form of moving a decimal place over in the reported amount

---

[6] Note not all grid cells have been estimated to have pollution in them. Only those grid cells that are within 101 kilometers of TRI facilities are in this model. Thus those cells outside of these areas have an estimated pollution value of zero, even though there might be other sources of pollution in these areas that are not captured by the TRI data.

[7] For a thorough explanation of the limitations of the RSEI data see the Political Economy Resource Institute's webpage "How Accurate are the RSEI Data on Toxic Air Pollution?" at: http://www.peri.umass.edu/accurate/

of a chemical that was released. The consortium of RSEI-GM users are provided with a list of facilities which have incorrectly filled out their forms submitted to the TRI. I follow the practice of researchers in this group and remove those facilities with unreliable data for the year of misreporting (Pastor 2008).

While those errors corrected by facilities can be accounted for, there is also the error associated with misreported data that is not recognized and reported to the EPA. The non-profit organization The Environmental Integrity Project compared measured data against reported data in Texas for the year 2000. They conclude that the TRI underestimates pollution from the petrochemical industry by four to five times (EIP 2004). The only other known analysis comparing detected exposure data with reported RSEI data was completed for nine to fifteen schools in the state of Michigan. The RSEI-GM version 2.1.5, the same version of data used in this paper, was generally not significantly different between the five chemicals examined from the 2002 RSEI and the 2002 air monitoring stations estimates at one and two kilometers (Lee, Mohai and Kweon 2010).[8] This means that the results provided in this paper are likely to be underestimating pollution exposures.

Demographic Data

Demographic measures were determined for all block groups in the continental United States (N=206,746).[9] I used 1990, 2000 and 2010 Census data obtained from Social Explorer, professional version (2012). These data were then interpolated using Equation 2 below to obtain annual estimates for different racial and socioeconomic groups in census block groups.

$$y_{ai3} = y_{ai1} + (x_3 - x_1)\, \frac{y_{ai2} - y_{ai1}}{x_2 - x_1} \qquad \text{(eq.2)}$$

In equation 2, y_{ai3} is the population of racial group a for census block group i in year 3; y_{ai2} and y_{ai1} are the populations for racial group a in census block group i for the census years I am using

---

[8] The authors report Pearson correlations between RSEI-GM 2002 estimates for 1,2 and 3 km around 9-15 Michigan schools and 2002 air quality monitoring data for Chromium, Cobalt, Lead, Manganese and Nickel. These were not significantly different from one another at the 1 and 2km radii but Chromium and Nickel were mildly significant at 3km.

[9] The number of block groups outside the continental U.S., and thus the pollution dataset, are: Alaska (N= 533), Hawaii (N=646) and Puerto Rico (N=2477) for a total of 4,522 block groups taken out of the data per year.

to interpolate. The value x_3 is the year that I am interpolating for and will thus take on the value of the years between censuses (1991-1999 and 2001-2009). The value of x_1 and x_2 are the census years which data were collected and between which I am interpolating (where $x_2 > x_1$). Using equation 2, I obtained annual block group-level population estimates for the following racial categories: (1) non-Hispanic African-American (herein referred to as African American) (2) white (herein referred to as white) and (3) Hispanic origin individuals of any race.[10]

Household income data, broken down by race, were also obtained for census block groups from the U.S. Census via Social Explorer. Using Frey's (2003) indicators, household incomes were broken down into a dichotomous variable (1) high income: those making $50,000 or above and (2) low income: those making less than $50,000. However, unlike data on race, these data are not available for 100 percent of the population; rather one in every six households receives a long-form from the census requesting these data. This one in six household statistic holds true for the 1990 and 2000 censuses, however, in 2010 the U.S. Census Bureau moved collecting these long-form data from the decennial census to the American Community Survey (ACS). The ACS process of collecting data differs from that used by the U.S. Census. Unlike the U.S. Census, the ACS doesn't collect data at one point in time. The sample size is smaller than the one in six persons collected by the long-form decennial census and in order to protect privacy of individuals the ACS uses values derived from several years of smaller aggregated samples. For example, the ACS 2010 estimates were created from data collected in the years 2006 to 2010.[11]

Merging Data and Determining Average Exposure

Recall that the RSEI-GM data are made up of 1 km^2 grid cells; the total number of RSEI-GM grid cells that make up the continental United States is 14,249,226. Using GIS I overlaid these grid cells with state block group shapefiles from the U.S. Census

---

[10] All of these racial categories refer to those of only one race. In addition, the racial categories Asian/Pacific Islander, Native American and 'Other' are not included here as the sample size of these groups was so small that slight fluctuations of pollution exposure in these groups were magnified and not generalizable.

[11] Roughly 1.9 million households were interviewed each year from 2006-2010. As there were 116 million households in the U.S. in 2010, roughly 8.2% of the population is represented in the ACS 2010 samples.

Bureau.[12] I then determined the percentage of the block group covered by the grid cell, by calculating the area of the block group and then intersecting it with RSEI grid cells. Figure 1 shows an example; the solid line outlines a block group in Madison, Wisconsin. The dashed line is a RSEI-GM grid cell. In this instance the grid cell has a toxic concentration value of five.[13] I then calculated the area of the block group and the area that the RSEI grid cell intersected (or overlaid) with that block group. Dividing the intersected area with the block group area it was determined that this grid cell took up 40% of the block group, and thus it contributed a toxicity of two (5 *0.40) to the block group's total toxic concentration.[14] Figure 1 shows only one RSEI grid cell for clarity. In reality, the whole of the block group is covered by grid cells, each contributing their own weighted toxicity to the block group. Once the pollution exposure for all grid cells are weighted according to the amount of space they took up in a block group, they were then summed up to the 2000 census boundaries.

The process described above yielded pollution exposure scores for every block group in the contiguous U.S. (N= 207,612)[15] for the years 1995 to 2004. Pollution estimates were aggregated up to 2000 census block group boundaries. However, demographic data obtained for the 1990 and 2010 Censuses were associated with the boundaries for their respective years. These boundaries were overlaid with 2000 boundaries, and using the same weighting system described above, demographics of the block group were weighted according to the proportion they took up of the 2000 boundary. For example, if a 1990 block group covered 40% of a 2000 block group and the 1990 population was 50 individuals, then the 1990 population would be weighted by 0.40 (50 *0.40) and then aggregated up to the new 2000 boundary to equal 20 individuals who resided within the 2000 boundary of that block group.

---

[12] GIS shapefiles were obtained from: http://www.census.gov/geo/www/cob/bdy_files.html and a RSEI grid cell shapefile from ABT Associates on 8/13/2011 via Professor Michael Ash, Professor of Economics and Public Policy and Chair of Economics at the University of Massachusetts, Amherst.
[13] Note these values are rounded for this heuristic.
[14] It's important to remember that these scores that have magnitude relative to one another. The total amount of pollution that landed in this grid cell was weighted by the toxicity of the pollution in order to make the score comparable to scores for other cells. A score of two is meaningful in reference to other scores which may have larger or smaller magnitude. The range of these values is from 0 to roughly 110,000 with an average of 9.7, indicating a highly skewed distribution.
15 The total number of block groups in the 2000 Census was 211,268. Because I only have pollution estimates for the contiguous U.S. I excluded Alaska (N= 533), Hawaii (N=646) and Puerto Rico (2477).

Once every block group had an estimated pollution score for the years 1995 to 2004, and was merged with the corresponding year's interpolated demographic data, I was able to determine average exposure for each demographic group. For example, if the block group in Figure 1 had an aggregated estimated exposure of 10 in the year 1995, and the total interpolated population for that year was 75 individuals (25 white, 25 African-Americans and 25 Hispanics) then I would have a data frame with 75 observations, each having a toxic concentration of ten associated with it, and 25 having a race variable coded as white, 25 African-American and 25 Hispanic. Once the data were reshaped from block groups to individuals I was able to determine an average exposure for individuals in each demographic group by summing the individuals' associated pollution score across racial and economic groups and then dividing by the total number of individuals in that group in the U.S. as a whole. All statistical analyses were performed in STATA 12.1.

Results

Figure 2 shows the average amount of industrial toxins experienced by individuals in different racial groups for the years 1995 to 2004. African-Americans experience the highest absolute amount of pollution at a maximum of 0.080 μ/mg^3 in the year 1995 down to 0.008 μ/mg^3. Whites stay consistently in the middle ground, ranging across the years from 0.023 – 0.003 μ/mg^3 and Hispanics are consistently the least exposed group ranging from 0.008-0.001 μ/mg^3.[16] These results show the large degree to which the amount of pollution has declined across the U.S. over this period. Whites experienced 8.79 times less pollution (0.023 μ/mg^3/0.003 μ/mg^3) in 2004 than in 1995, Hispanics almost 6 times less (0.008 μ/mg^3/0.001 μ/mg^3) and African-Americans 9.67 times less (0.079 μ/mg^3/0.008 μ/mg^3).

---

[16] These results were calculated without the outlier of Miami-Dade County. This county was considered an outlier for this analysis because it had an overabundance of the chemical Phenol being produced from 1996-2001 (RTK 2012). This chemical rose to one of the top four chemicals released in this city in 1996, its amounts rose slowly to peak in 1998 as the third most released chemical in the county and then arched downward to become absent from the release list in 2001. Because this chemical is not considered highly toxic in the RSEI database its contribution to the health risk is minimal and therefore does not affect the results for health risk. However, because it was released in such large amounts it was able to skew the data for this one county and because of the dense Hispanic population there skewed the estimated amount of pollution this group was exposed to. Analyses not broken down for Hispanic population are not as affected by this outlier and thus the remaining analyses in this dissertation include these counties.

When I weight the chemical concentrations in Figure 2 by their toxicity to human health we see a similar picture for African-Americans (see Figure 3 below).[17] In addition to the burden of greater amounts of pollution, African-Americans also consistently suffer from the greatest health risk from industrial toxins. Hispanics are generally exposed to smaller amounts of pollution than whites (Figure 2). However, when these amounts are weighted by their toxicity to human health, their risk is equivalent to whites. This means that although they are exposed to smaller amounts of pollution than whites, they are generally exposed to more toxic substances. The most striking take away from these results is that there are clearly two stories taking place. While the average amount of toxins and associated health risk experienced by African-Americans and whites is declining, the relative amount and risk is staying roughly the same.

Subtracting the average amount of toxic concentration experienced by African-Americans and Hispanics from the average amount of toxic concentration experienced by whites tells the story (Figures 4 and 5). The absolute difference between whites and African-Americans posed by industrial pollution has sharply declined, with a slope of -3.49. The absolute difference between Hispanics and whites has decreased very slightly, with a slope of -0.13. While the absolute risk from industrial toxins has declined over all, the relative risk is such that African-Americans are still over one and a half more exposed than whites (Figure 5); with an average difference in slope over the years equal to roughly zero (-0.04). Similarly, the relative difference between Hispanics and whites has remained unchanged from 1995 to 2004 with a slope also equal to roughly zero (-0.01).

Figure 6 shows how income differences within racial groups relate to pollution exposure. Recall that the high income category is those households making $50,000 a year or more, and the low income category were those households making less.[18] As expected, those with lower income are at greater risk for exposure to industrial toxins. Interestingly, the larger difference in exposure is between income groups rather than ethnic groups. Low-income Hispanics' and low-income whites' exposure profiles are more similar to each other than the low and high income groups of a given ethnic group.

---

[17] Note that because these are population data any difference found between groups is statistically significant.
[18] These results were also replicated with poverty status by race with the same substantive results. These are available upon request.

Low income whites have a greater rate of decline in exposure than the other groups in Figure 5, with a slope of -3.33. Low-income Hispanics have the next fastest rate of decline with a slope of -2.96. The high income categories experienced a slower rate of decline from a lower base level in 1995.

Figure 7 demonstrates that African-Americans of high income have exposure levels that never fall far below those of whites in the lower income category. Moreover, African-Americans of low income clearly experience greater absolute levels of risk than all other groups discussed thus far, reaching a risk of over 1.5 relative to high income whites in 1996. The absolute difference between these groups has declined, moving from a roughly 40 point difference between groups in 1995 to a ten point difference in 2004. However, the relative difference has not budged much (Figure 5). Although the slope is roughly zero (-0.084), low-income African-Americans experienced almost two and a half times[19] as much exposure as high-income whites in 1995 to 1.9 times more exposure in 2004. Similarly, within income categories, high-income African-Americans experience 1.53 times more exposure than high-income whites in 1995 and this stays roughly the same ending at 1.45 in 2004. Likewise, in 1995 low-income African-Americans were 1.81 times more exposed than whites of similar income in 2004 this declined to 1.35, the second greatest amount of change in these groupings, with a slope of -0.080.

The sensitivity analyses presented in figure 8 in Appendix A shows the average toxic pollution exposure for African-Americans, whites and Hispanic using chemicals that were consistently reported from 1998 onward (aka: 1998 core chemicals). These results consistently show African-Americans with the most pollution exposure and Hispanics and whites having similar exposures with Hispanics averages fluctuating around whites. The Hispanics fluctuations could be due to the fact that this population is densely populated in specific areas in California where there are also high levels of toxic pollution. The reported emissions in these areas are not known to have not been corrected with the EPA and thus are possibly accidental releases and should therefore remain in the data. The same interpretation holds for figures 9 and 10, which graph averages based on 2000 and 2001 core chemicals respectively. Figures 11 through 13 graph averages based on core chemicals for each income group. Low income African-Americans consistently

---

[19] This ratio was 2.38 in 1995 and 2.51 in 1996.

have the highest exposure for each set of core chemicals. However, the group with the next lowest exposure is often low income whites. The fluctuations in these results make it hard to identify a consistent pattern for which racial/income group is exposed to the most toxic pollution. Future exploration into possible outliers is necessary to untangle these findings.

Discussion

The results presented in this paper provide novel evidence for the evolution of environmental inequalities in America. These analyses utilize a longer time span, finer geographic resolution, more complete coverage of the continental United States, and better measures of exposure to industrial toxins, than previous longitudinal, national-level studies. From these analyses we can see that the absolute exposure to health risk from industrial toxins is declining for all racial groups. The average amount of, and health risk from, industrial toxins for all Americans in the continental U.S. was halved during the period 1995 to 2004. The declines in air pollution seen across the U.S. since the 1970s have been linked to both deindustrialization and environmental regulation (Kahn 1997; 1999).

Although the absolute exposure and health risk of all racial groups declined over the time period examined, there were differences by race. African-Americans had the most dramatic absolute decline in exposure to industrial toxins. The amount of pollution they were exposed to, as measured in micrograms per cubic meter, declined by almost tenfold. Similarly, when these pollutants were weighted by toxicity, African-Americans' exposure decreased by over half from 1995 to 2004. While the cause of this decline was not examined, these results are consistent with the hypothesis the African-Americans will experience greater declines than other racial groups because of their over representation in areas affected by deindustrialization (Downey 2005).

Compared to African Americans, Hispanics were consistently exposed to one and a half times less risk. Although not tested directly here, this is congruous with the hypothesis that Hispanics are less exposed to industrial toxins generally due to their smaller populations in historically industrial regions of the U.S., like the Midwest. Future work should consider how these results might vary if regional and ethnic group

differences are considered. Interestingly, although Hispanics were exposed to smaller amounts of pollution than whites, when these pollutants were weighted by their toxicity their exposure was equivalent to whites. This means that although Hispanics are exposed to smaller amounts of pollution than whites they are exposed to more toxic substances. This finding points to an interesting area for future research. Perhaps those facilities in Hispanic neighborhoods are less likely to have strict enforcement of pollution controls laws in their neighborhoods and are thereby exposed to more accidental releases. This theory is consistent with findings from Lynch, Stretesky and Burns (2004) who found that the mean penalties levied against petroleum refineries for violating the Clean Air Act, the Clean Water Act, and/or the Resource Conservation and Recovery Act were significantly greater in non-Hispanic tracts as compared to Hispanic tracts.

When results were broken down by both race and income, Hispanics, African-Americans and whites of lower income were exposed to more industrial toxins than those of higher incomes in their same racial group. This is consistent with the hypothesis that those of high income will be better protected from pollution than those of a lower income. However, comparing across racial groups, African-Americans in higher income categories had a similar exposure profile to whites of the low income category. In fact, African-Americans of the high income group were on average 1.14 times more exposed than whites of lower income.

While these findings are novel and add considerably to our understanding of the evolution of inequality in pollution exposure, the study has some important limitations. One of the most central limitations of these data is that they do not include mobile sources of pollution. This is of concern because research suggests that mobile sources also contribute to racial health disparities (Morello-Frosch and Jesdale, 2006). This concern is particularly warranted in research investigating differential exposure by race, as highways have been used in American history to segregate residential locations based on race and income, thereby spatially clustering individuals and their exposure to airborne toxins (Venkatesh 2000). However, this paper's focus is specifically on exposure to toxins from industrial sources. This paper seeks to update and expand upon previous national-level examinations, which have primarily focused on exposure from industry. These data are well suited to address this goal. Although mobile sources are

outside of this paper's scope, past studies of mobile sources suggest that inclusion of this additional data would magnify the differences shown here. Roads with a large number of mobile sources of pollution, like trucks, will be spatially correlated with industry as these are the paths mainly used for transporting to and from industrial facilities (Hawley 1971). Nonetheless, future research should consider these patterns using a variety of pollution sources.

The results of this paper raise some questions for future research. First, why is absolute exposure between African-Americans and whites declining sharply while relative exposure is staying roughly the same? In addition, why are African-Americans of higher income not as protected as whites of similar income? Finally, why are Hispanics exposed to less amounts of pollution, but more toxic substances? To answer these questions, EJ scholars would do well to examine the larger social structures determining pollution exposure patterns. For example, are the barriers of racial segregation still preventing middle-class African-Americans from utilizing their greater socioeconomic position to access cleaner air?

There have only been a handful of cross-sectional studies that have investigated the segregation-pollution relationship and results tend to be mixed, with earlier studies showing a positive association between a metropolitan area's segregation levels and unequal distribution of pollution exposure (Lopez 2002; Morello-Frosch and Jesdale 2006) and later studies concluding that segregation rates explain little of the difference in environmental exposure experienced by different racial groups (Downey 2007; Downey et al. 2008). However, few to none of these studies investigated how these results might vary when taking into account different socioeconomic characteristics of the different racial groups, or change over time in pollution and segregation levels.

FIGURES

Figure 2.1: Example of a RSEI-GM grid cell (thin line) overlaid with a Census Block Group (thicker line)
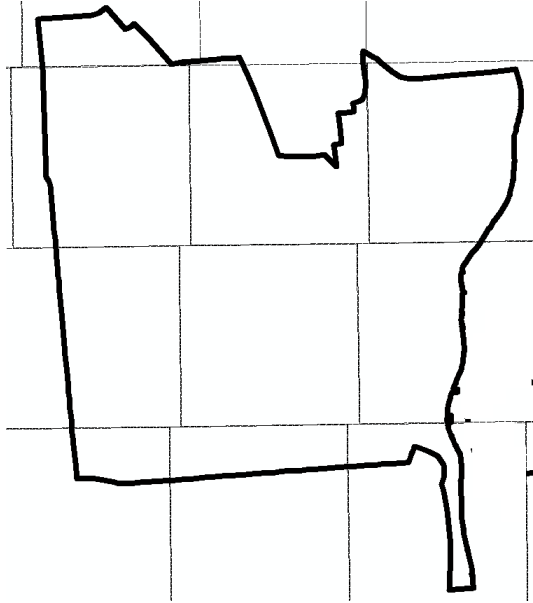
Figure 2.2: Estimated Amount (μ/mg3) of Air Toxins Experienced by Different Racial Groups
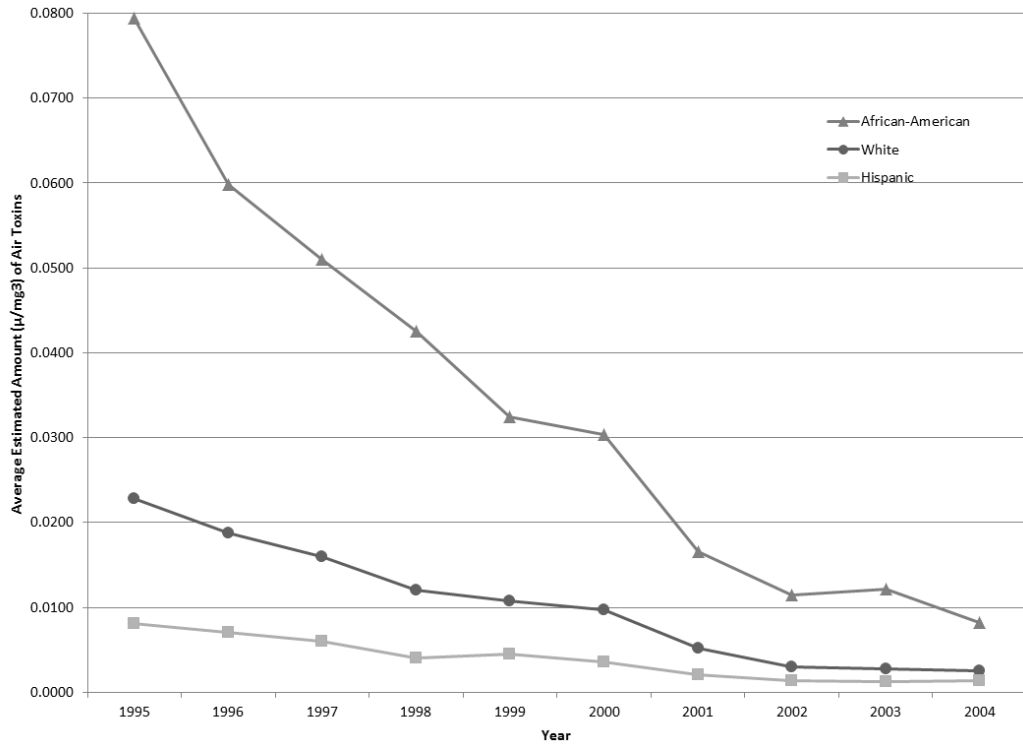
Figure 2.3: Estimated Toxic Concentration from Exposure to Industrial Air Toxins Experienced by Different Racial Groups

Figure 2.4: Absolute Difference in Estimated Health Risk from Industrial Toxins for African-Americans and Hispanics When Compared to Whites
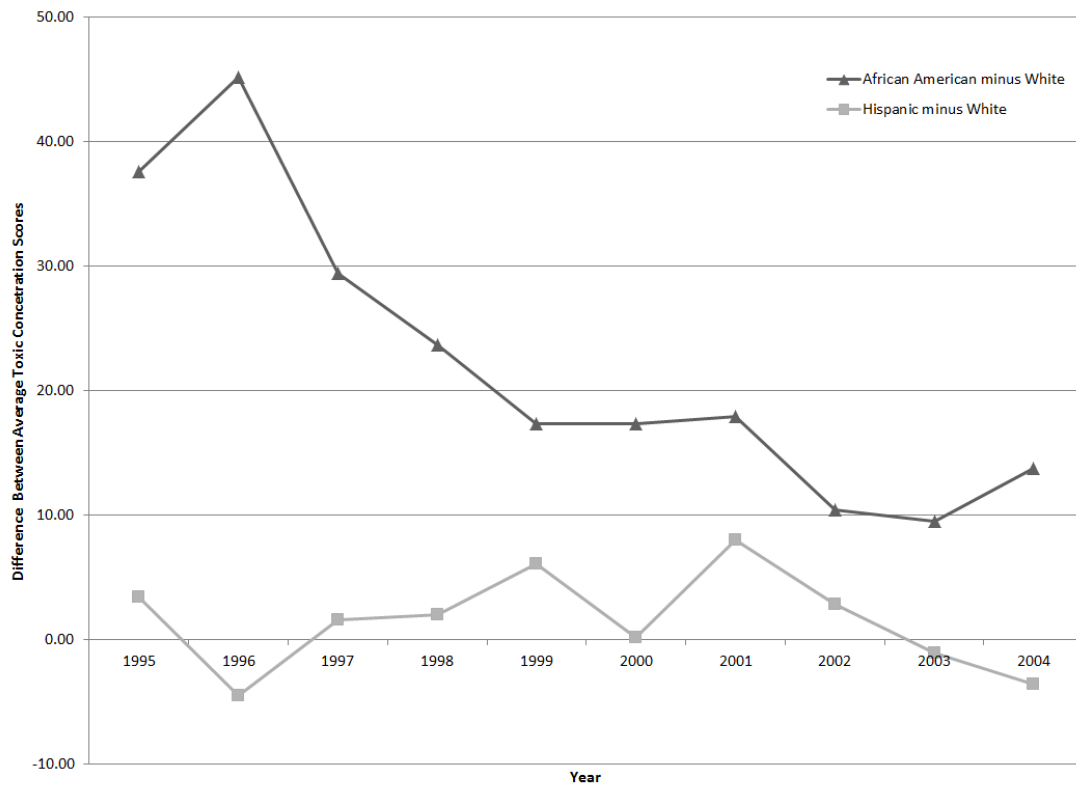
Figure 2.5: Relative Difference in Estimated Health Risk from Industrial Toxins for African-Americans and Hispanics When Compared to whites
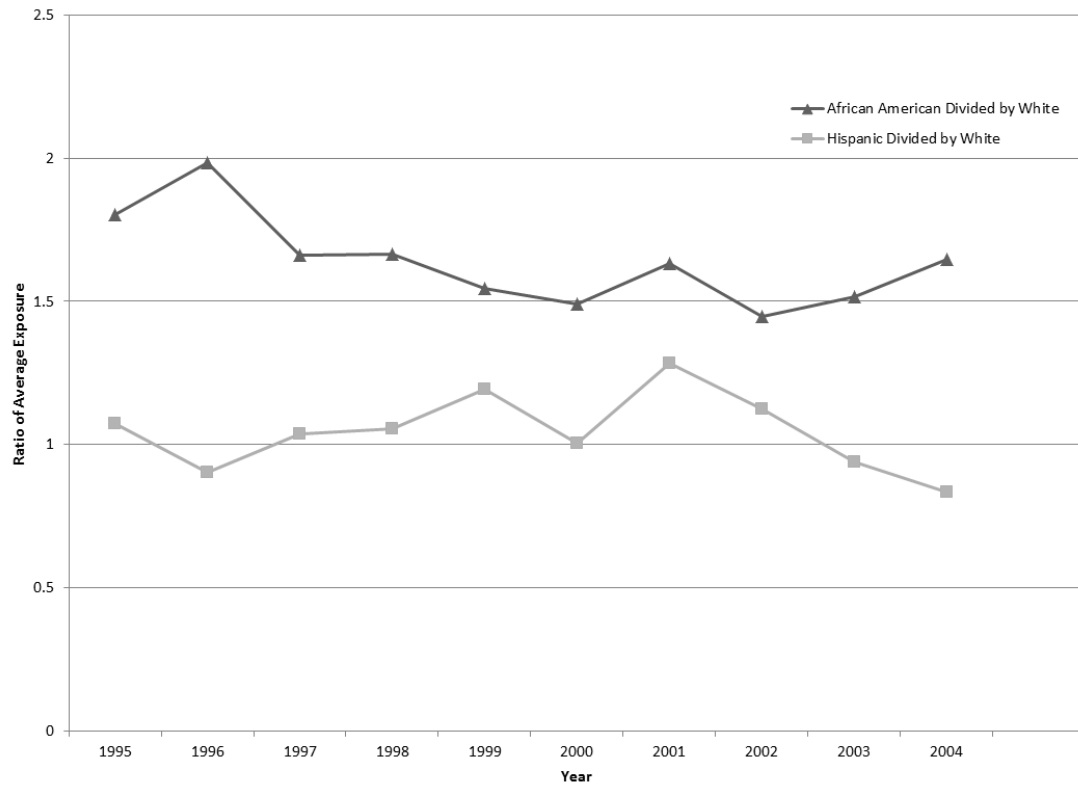
Figure 2.6: Average Estimated Health Risk from Industrial Toxins for Hispanics and Whites Broken Down by High (over 50K) and Low (less 50K) Income Groups
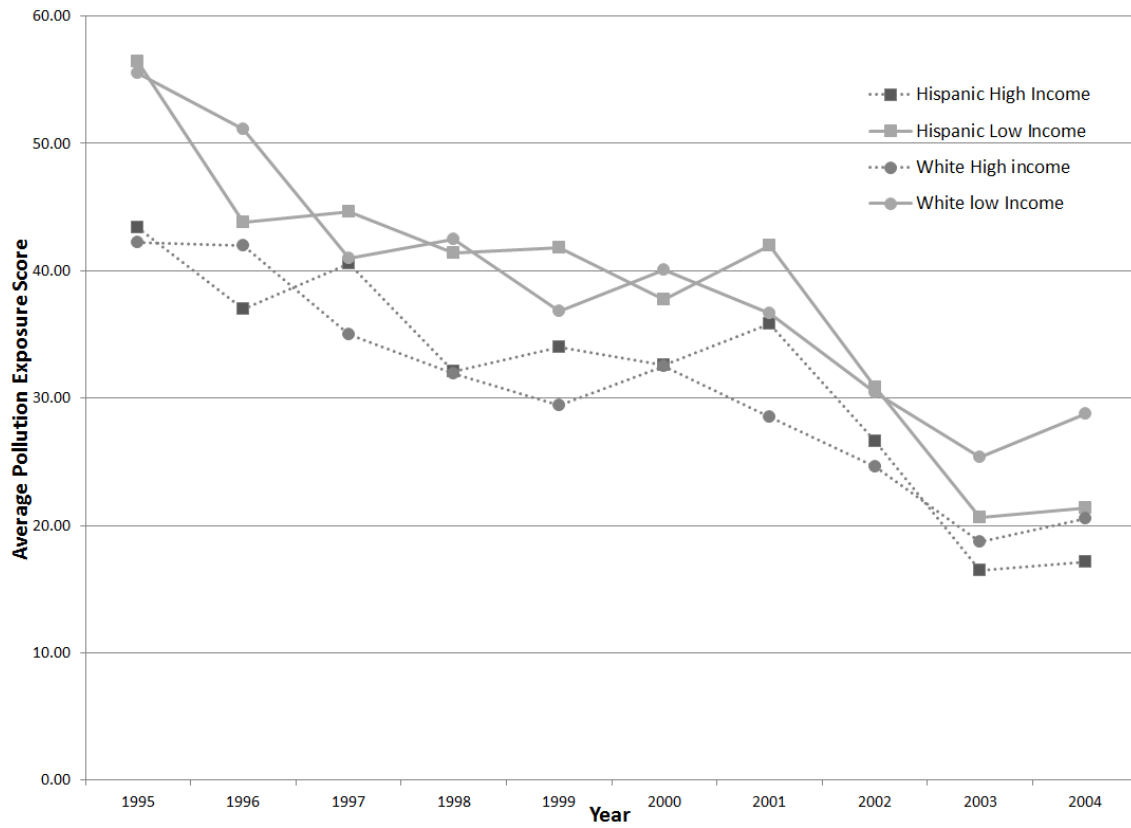
Figure 2.7: Average Estimated Health Risk from Industrial Toxins for African American Households and non-Hispanic White Households in High (over 50K) and Low (less 50K) Income Groups
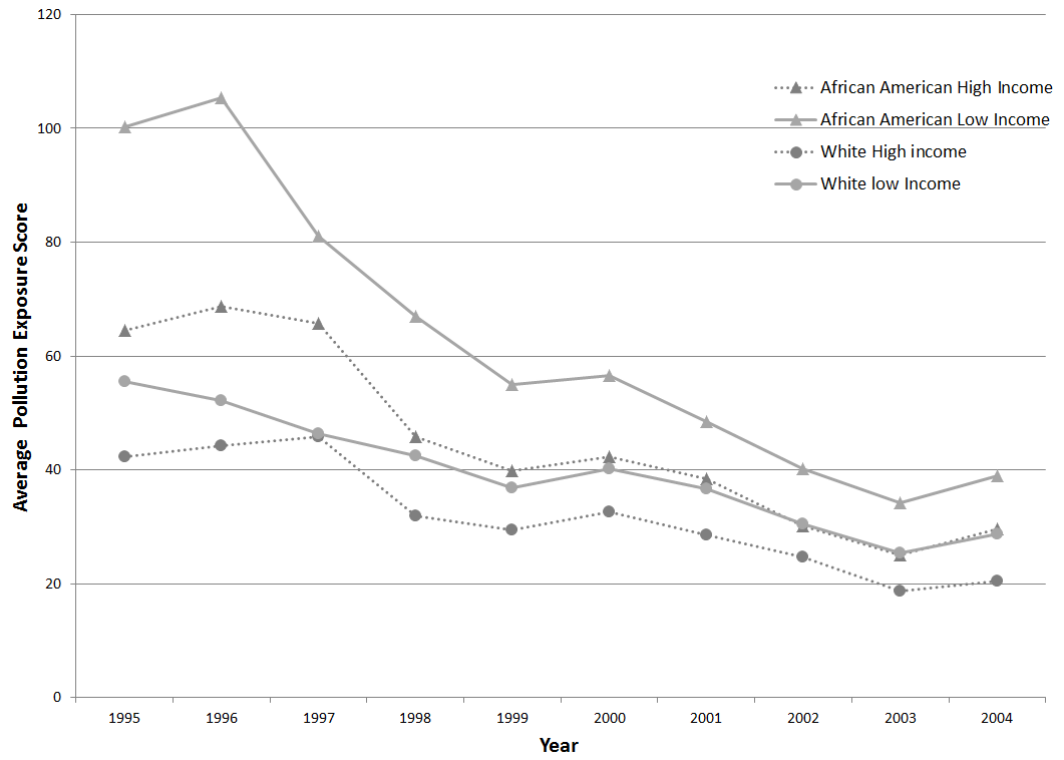
Appendix A

Figure 2.8: Estimated Toxic Concentration from Exposure to Industrial Air Toxins Experienced by Different Racial Groups with 1998 Core Chemicals
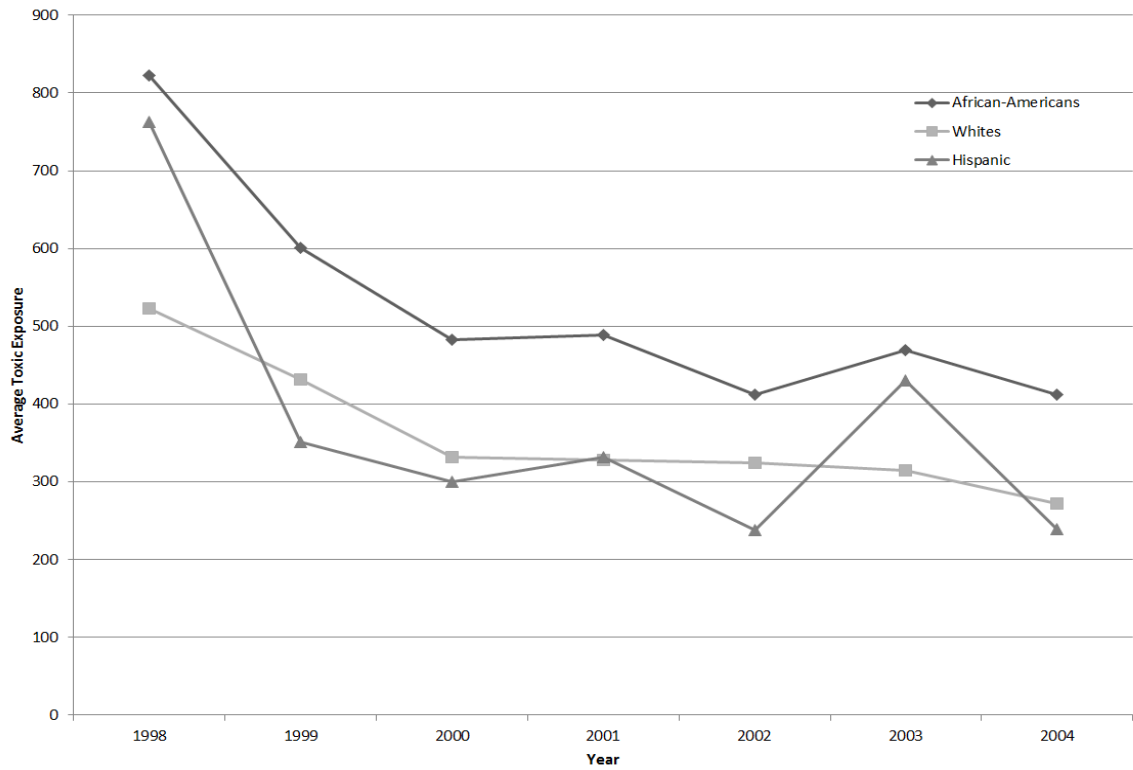
Figure 2.9: Estimated Toxic Concentration from Exposure to Industrial Air Toxins Experienced by Different Racial Groups with 2000 Core Chemicals
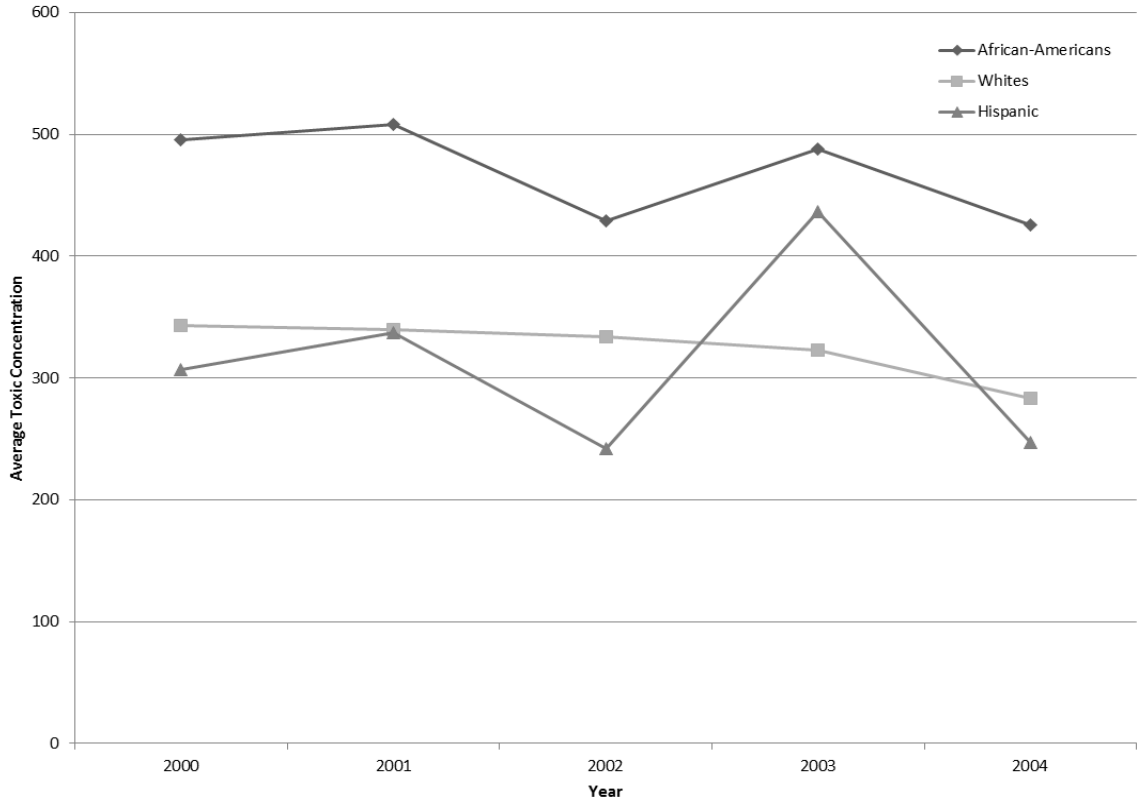
Figure 2.10: Estimated Toxic Concentration from Exposure to Industrial Air Toxins Experienced by Different Racial Groups with 2001 Core Chemicals
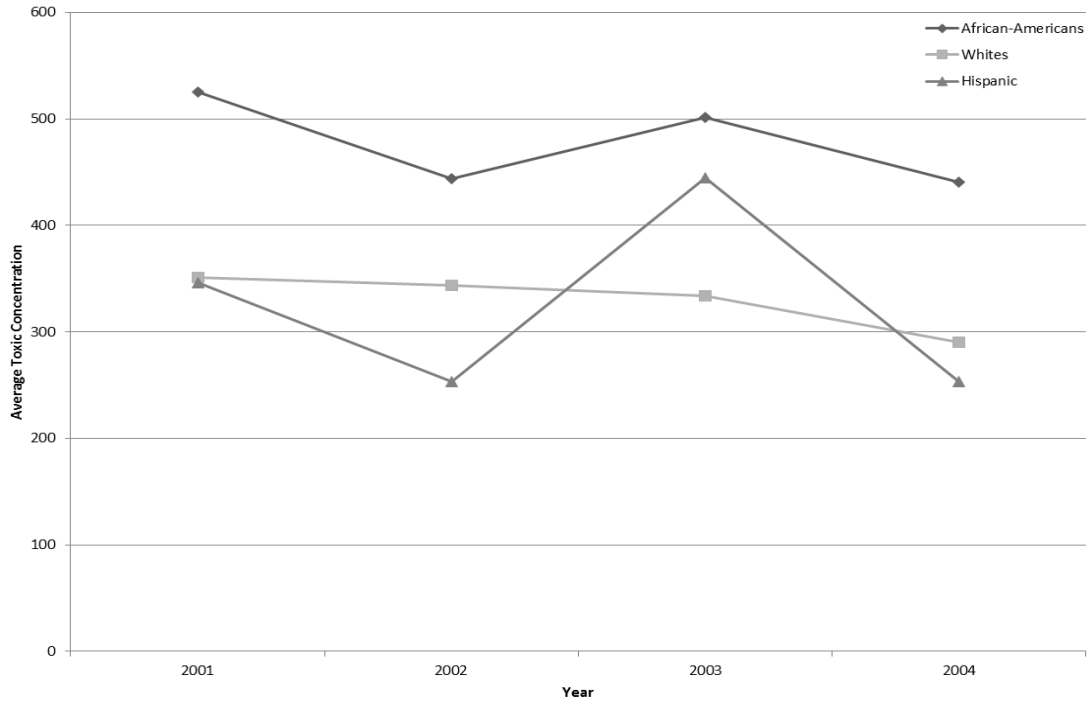
Figure 2.11: Average Estimated Health Risk from Industrial Toxins for African-Americans, Hispanics and whites. Broken down by High (over 50K) and Low (less 50K) Income Groups for 1998 Core Chemicals
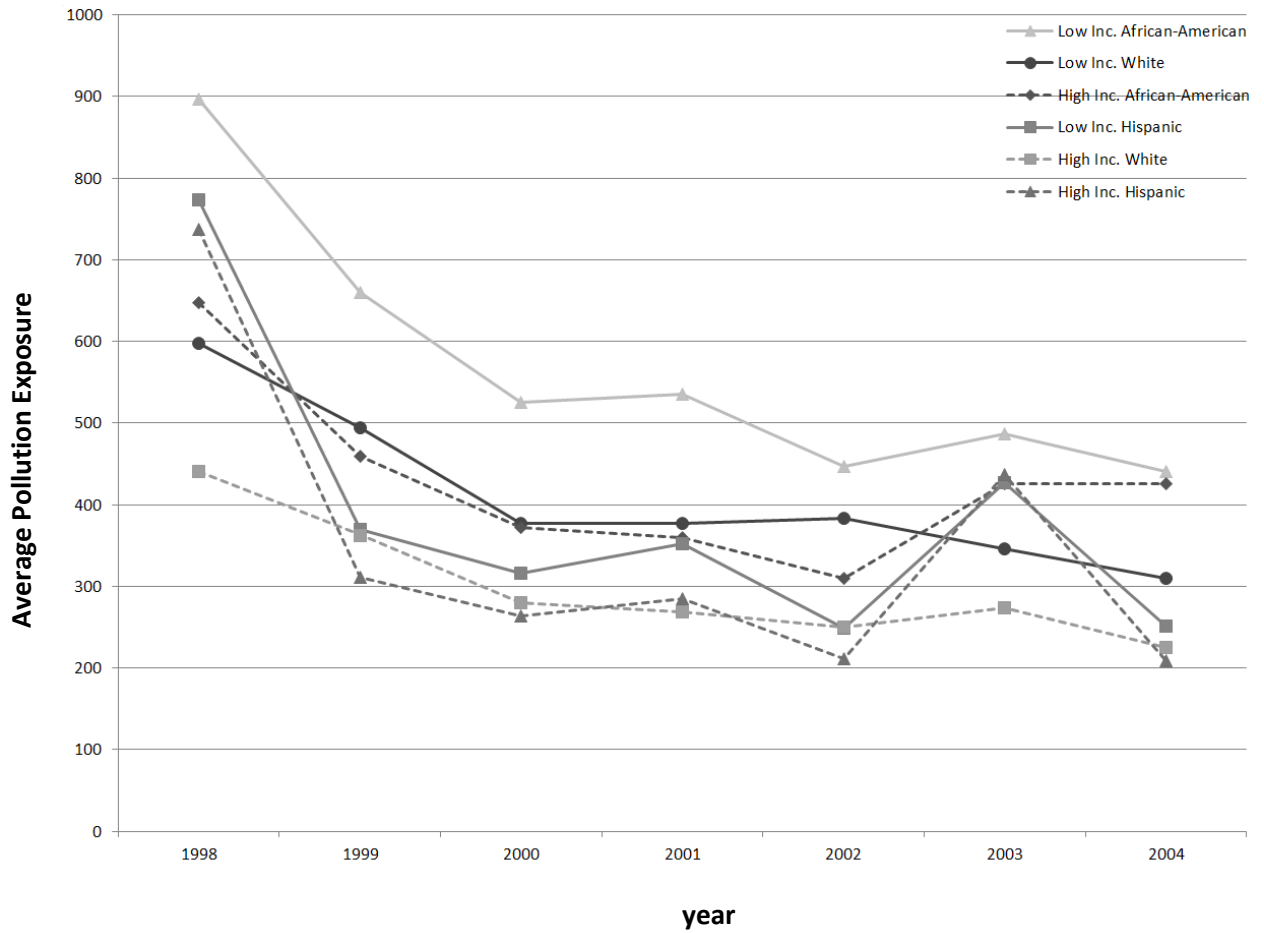
Figure 2.12: Average Estimated Health Risk from Industrial Toxins for African-Americans, Hispanics and whites. Broken Down by High (over 50K) and Low (less 50K) Income Groups for 2000 Core Chemicals
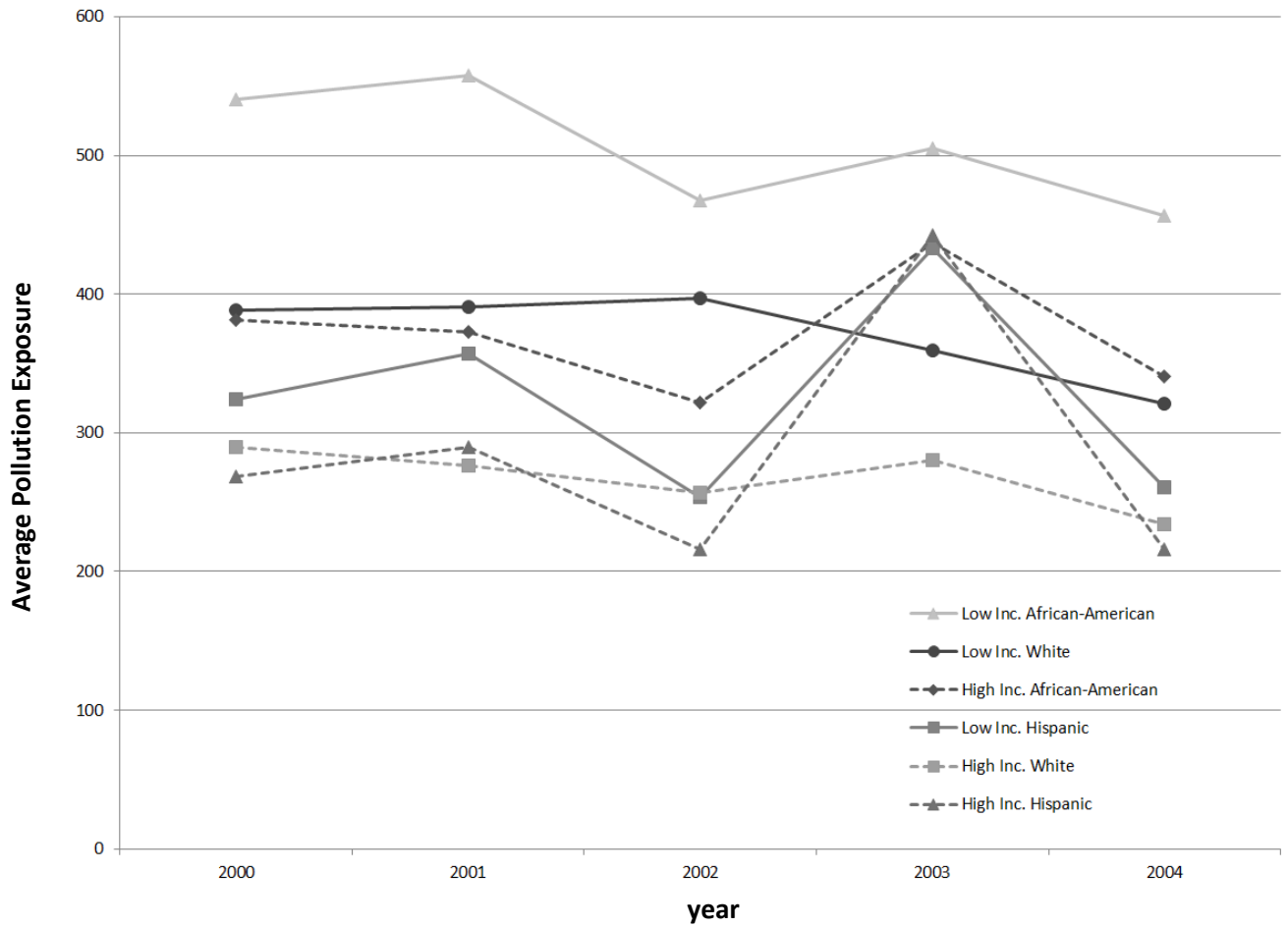
Figure 2.13: Average Estimated Health Risk from Industrial Toxins for African-Americans, Hispanics and whites. Broken down by High (over 50K) and Low (less 50K) Income Groups for 2001 Core Chemicals
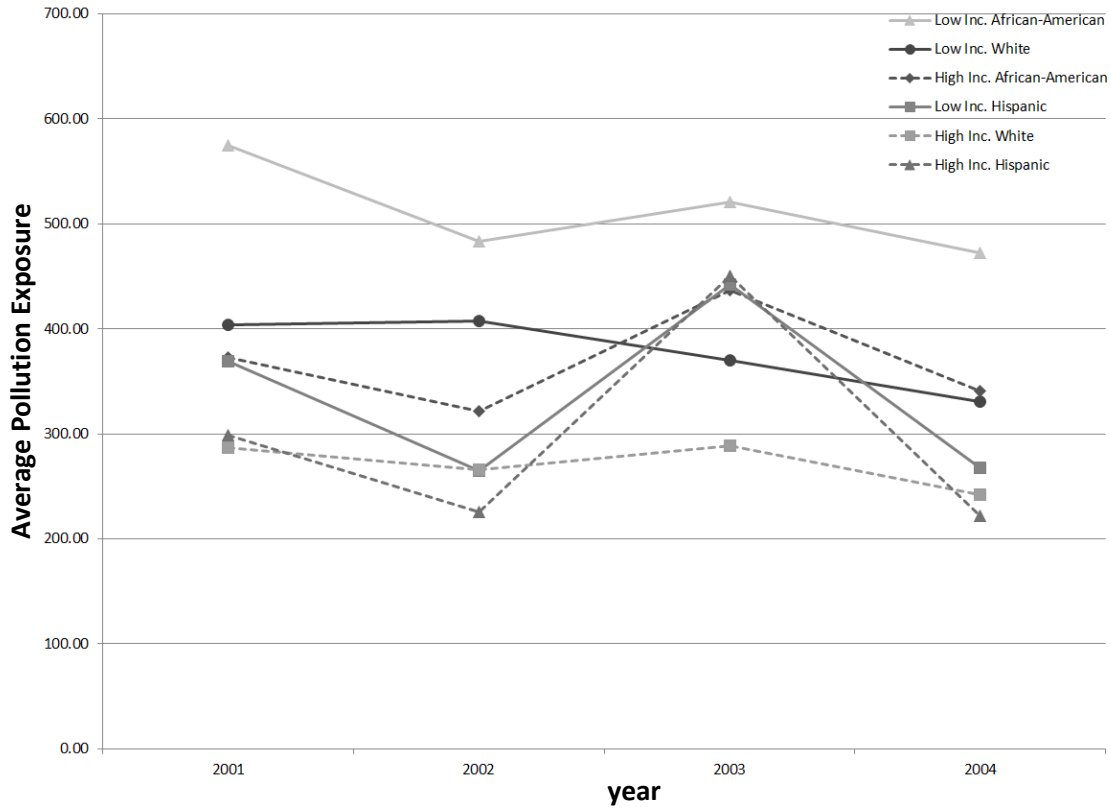
CHAPTER 3

The Changing Dynamics of Racial Residential Segregation and Pollution in the United States: Unexamined Trends

Abstract

Current research investigating the relationship between racial segregation and pollution exposure has not yet considered important temporal trends in both explanatory and outcome variables. Moreover, past studies have generally used the dissimilarity index to capture segregation, but this measure captures only one dimension of segregation. This paper addresses these limitations by using annual repeated measures on the pollution exposure of block groups in 320 metropolitan areas from 1995 to 2004. Exposure data for 572 industrial chemicals were obtained from the Environmental Protection Agency's (EPA) Risk Screening Environmental Indicator data. These data have been geographically modeled to determine exposure paths and weighted for toxicity to human health. Segregation is measured using an indicator of centralization, relative centralization, and these results are compared with results from the typically-used dissimilarity index. Results show that racial segregation of African-Americans in a metropolitan area was positively and significantly associated with industrial pollution exposure at the block group level, however this association is decreasing significantly over time. This paper also tests hypotheses about how pollution exposure changed inside and outside of the central city, showing that block groups located in the central city have significantly higher rates of toxic pollution. In addition, outside of the central city, block groups with greater proportions of African-American residents experience more pollution exposure than block groups outside the city with greater proportions of whites.

Introduction

The concept of "segregation" plays an important role in the environmental justice literature, which focuses on social disparities in exposure to environmental risk. Scholars have theorized that the institutional discrimination in housing and zoning policies that has led to racial residential segregation (Brodkin 1998) has also put poor and minority communities in the United States at greater risk for exposure to industrial toxins and environmental harms more generally (Taylor 2009; Maantay 2002; Pulido 2000; Stretesky and Hogan 1998). Importantly, levels of both racial segregation and industrial pollution have changed in recent decades in the United States, but much of the current empirical literature uses cross-sectional data on both segregation and industrial air

42

pollution.   The present paper is among the few to use data from multiple recent years to assess whether the segregation-pollution association is changing over time.

According to the U.S. Environmental Protection Agency's (EPA) National Air Toxics Assessment (NATA), the contribution of industry to the United States' total air pollution exposure is significant. In 2005 the EPA estimated that industrial toxins contributed almost 26% to the nation's neurological risk, almost 6% to the nation's cancer risk, and over 1% to the nation's respiratory risk.[20]   However, underneath these exposure statistics are trends that have been relatively unexamined in the environmental justice literature. In 1990 the EPA began collecting data on Hazardous Air Pollutants (HAP) in order to implement the U.S. Clean Air Act. From 1990 to 2004 the EPA found that, "air toxics emissions declined by approximately 42 percent from all sources" (EPA 2005). Despite these striking declines in pollution emissions, quantitative environmental justice work has not taken into account these trends over time. Overlooking the temporal aspect of pollution exposure in such a mutable environment makes it difficult to draw conclusions about if and how exposure to industrial toxins varies for racial/ethnic groups living in differentially-segregated communities.

This problem becomes especially challenging when changing patterns of racial segregation are also considered. Although recent studies show that African-Americans are still the most segregated racial/ethnic group (Iceland and Nelson 2008), racial segregation between blacks and whites has declined over the past four decades (Farrell 2008; Timberlake and Iceland 2007; Frey and Myers 2005; Iceland 2004). Census data shows that from 1970 to 2009, black isolation fell below 50 percent; that is, the typical African American in a U.S. metropolitan area no longer lives in a neighborhood that is majority black (Iceland et al. 2010). Current research investigating the relationship between segregation and pollution has not yet taken account of these changes in segregation.

In addition to ignoring change over time, research on segregation and pollution has not considered whether the association varies if different measures of segregation are used. There are currently 19 measures of segregation that are widely used in the racial

---

[20] The percentage of major sources contribution to the total risk was calculated from the EPA's National Air Toxics Assessment 2005 data.

segregation literature (Census 2013). Factor analyses have shown that these measures reflect five different dimensions of segregation: clustering, exposure, concentration, centralization, and evenness. Because the majority of the literature investigating pollution and segregation has used some version of the dissimilarity index (DI), a measure of evenness, the rest of these dimensions have gone largely unexamined. This omission is particularly important because other dimensions may be more theoretically important for the study of how air pollution is disproportionately borne by African-Americans compared to whites. For example, the urban sociology literature suggests that America's manufacturing firms, and thus the associated industrial pollution, have historically been located in central cities. Because some measures of segregation more explicitly capture residence in the "central city" than others, an evaluation of these different measures of segregation is warranted, as is inclusion of information about central city location in analyses.

A final limitation of prior research is inadequate attention to spatial associations in data that capture pollution exposure and segregation. Both measures are inherently spatial, as is the association between them. Industrial air pollution comes from a stationary source in the environment. Thus air emissions of pollution by facilities will expose those individuals living closer to them to greater risk from the toxicity of these emissions than those living further away. Segregation is also inherently spatial. It is a characteristic of a larger area, such as a metropolitan area, that reflects the spatial pattern of individual units that make up that area, such as census block groups. If both the dependent variable, pollution exposure, and the primary explanatory variable, segregation, are generated by spatial processes, then we cannot assume the errors are uncorrelated. The assumption needed for ordinary least squares linear regression of independent observations is violated, because the errors associated with one observation are correlated with errors of another observation. Correlated errors are a property of processes that are varying continuously over space, like pollution exposure from a stationary source. Thus a major assumption of linear regression models is violated, although this has been the primary method in current research used to determine how pollution and segregation are related across America. This paper overcomes such limitations by using multilevel models that account for the dependence of observations on

44

the same block group over time, with estimated spatial correlations that account for the spatial dependence of census block groups closer or further away from one another.

This paper contributes to the environmental justice literature in three primary ways: by taking into account changes in pollution over time, changes in segregation over time, and the spatial relationship of these measures. In addition, I explore the robustness of the association between segregation and pollution by empirically assessing a variety of segregation measures. The larger aim of this paper is to determine if and how the block group level exposure to industrial toxins varies by the segregation level of a metropolitan area in the mid-1990s United States, and if this relationship changes over the subsequent decade. I also compare how conclusions might vary when using the dissimilarity index – the most commonly used measure - to a segregation measure that captures the concentration of African-Americans in the central city, a measure of segregation that is more theoretically consistent with the literature investigating how pollution is related to segregation. Finally, I examine how being located in the central city affects a block group's exposure to industrial toxins and how this relationship changes over time.

Background

Prior Studies of Segregation and Pollution Exposure

Research examining the link between pollution exposure and segregation has thus far been largely cross-sectional and yielded mixed results. Lopez (2002) compared 1990 EPA Air Toxics Data and the dissimilarity index of 44 U.S. metropolitan areas with populations greater than one million. His rationale for using the Dissimilarity Index was that it is one of the most common used measures of segregation and he limited his study to metro areas because they best reflect local housing markets and function as coherent economic and social units. He used ordinary least square regression to predict the net difference score, a measurement he developed that represents the probability that a randomly chosen African-American is living in a census tract with a higher amount of air toxins than a white person. He found a positive association between a metropolitan area's dissimilarity index and unequal distribution of pollution exposure by race.

Morello-Frosch and Jesdale (2006) also found segregation was positively associated with increasing environmental risk. However, they used different measures and a larger sample, looking across the United States. Their dependent variable was tract level estimates of the cancer risk posed by 188 hazardous air pollutants listed in the Clean Air Act, including diesel particulate matter, obtained from the EPA's 1990 National Air Toxics data. They linked this data with the multigroup Dissimilarity Index of 309 metropolitan areas. This variable is version of the typical Dissimilarity Index that has been adjusted to apply to multiple racial/ethnic groups. They found that segregation amplified cancer risks for all racial groups, and the racial disparity seen in cancer risk widened with increasing levels of segregation.

More recently, scholars have come to different conclusions. Using 2000 census data, and 2000 RSEI-GM data, Downey et al. (2008) linked the average toxic concentration for 329 metropolitan areas with dissimilarity index measures. The authors concluded that segregation explained very little of the variance in pollution exposure (Downey et al. 2008). This study expanded on Downey's previous work (2007) which examined the cross-sectional relationship between environmental inequality and segregation in 61 of the largest metro areas in the U.S. His results showed that those cities with the highest degree of segregation were not the same cities with the largest racial disparities in pollution exposure.

With only a few studies investigating the relationship between pollution and segregation, and their subsequent mixed results, scholars are left to question if these discrepant findings be explained by the fact that the relationship between pollution and segregation levels has changed over time. The fact that on the whole later studies concluded racial segregation was not a significant indicator of environmental pollution risk, while the earlier studies did, leads to the following hypothesis:

Hypothesis 1: The relationship between pollution exposure and metropolitan level segregation has declined over time.

Downey (2005) offers one of the few papers to test sociological theories that might explain why racial segregation is related to pollution exposure. In this paper he used 1970, 1980 and 1990 census data to test explanatory models of changes in environmental

inequality in and around the city of Detroit, Michigan. He concludes that over time, racial segregation has actually reduced the proximity of African-Americans to pollution sources, perversely protecting African-Americans from toxic exposures. Being limited to one metropolitan area, he did not measure racial segregation at the metropolitan area level, but instead calculated changes in the African-American population of census tracts over time. He tests the hypothesis that pollution exposure, and change in exposure, will be positively associated with the change in the number of resident African-Americans over time. If this is true, he argues, this suggests that segregation is preventing African-Americans from living in more industrial areas outside of the central city, thereby exposing them to greater pollution outside of the central city. He created a measure of exposure by breaking up census tracts (N=416) into 25 by 25 meter cells. He then calculated the distance to the nearest transportation equipment, chemical, primary metal, and fabricated metal facility within a quarter of a mile from the center of these cells, as well as how many of these types of facilities were in this radius.

Downey's (2005) results showed that over time, the number of facilities declined or remained constant in tracts with greater percentages of African-Americans. He theorized that racial segregation prevented African-Americans from moving into Warren, the most heavily industrialized suburb in Downey's data, thereby protecting African-Americans from pollution exposure. While these results were informative, they were based on the city of Detroit, which has had a unique combination of being consistently one of the most segregated areas in the country and has an economy based on automotive manufacturing that migrated dramatically to suburban areas over this period. The present analyses test these theories on data for the entire United States.

Urban Underclass Literature

Downey's (2005) theories are based on the sociological literature dealing with the development of the U.S. "urban underclass". This literature addresses how the legacy of deindustrialization and segregation has affected Americans' economic well-being. Scholars argue that the historical processes of racially-discriminatory lending, locations of receiving communities during the great migration of African Americans northward, and deindustrialization, all have spatial patterns which still affect the life chances of

47

individuals today. Lessons from this literature are directly applicable to the understanding of environmental inequality (Smith 2009; Downey 2005) and its evolution.

Brodkin (1998) argues the passage of the GI Bill during WWII ushered in America's modern era of segregation. The GI Bill provided low interest loans to veterans to purchase new homes in America's rapidly developing suburbs. While these suburban neighborhoods were available to whites, they were not readily available to returning black veterans (Lieberson 1980). This allowed whites to leave more historically industrial urban centers, segregating African-Americans in these more toxic areas. Scholars have argued that the interaction of these industrial settlement patterns with segregation and deindustrialization have had profound impacts on the opportunities of individuals (Wilson 1987; Massey and Denton 1993; Mouw 2000), which have also been argued to be related to individuals' exposure to air pollution (Downey 2005).

These spatial patterns undergird one of the most applicable aspects of the urban poverty literature, 'spatial mismatch theory'. Spatial mismatch theory is based on the idea that racial prejudice in housing markets (Brodkin 1998; Lieberson 1980) and the expansion of transportation routes out of the central city (Kasarda 1972) allowed for the outmigration of white residents from historically industrial centers in the central city. Furthermore, as America's economy deindustrialized, businesses followed this white flight away from the city towards the suburbs (Kain 1968). These processes have been shown to socially, physically, and economically isolate African-Americans in America's central cities because the jobs they need are not located in the places where they reside (Mouw 2000; Sugrue1996) and have also been applied to environmental justice analysis (Downey 2005). Downey (2005) argued that as job opportunities moved from cities to the suburbs, any new industrial facilities being built would follow other businesses and locate in the suburbs. This process would thereby increase the exposure of suburban populations to air pollution relative to central city areas. This leads to the following hypotheses:

Hypothesis 2: **Block groups located outside of the central city will experience higher exposure over the period examined to toxic pollution than block groups inside central cities during the period examined.**

Hypothesis 3: The difference between the pollution exposure of block groups located outside of the central city compared to those located inside will be increasing over time.

Downey (2005) further theorized that these economic patterns of industry might be affecting the relative exposure to toxins for different racial groups. Wilson (1987; 1997) argued that after Civil Rights legislation made overt discrimination in the housing markets illegal, middle-class African-Americans moved out from the central cities, concentrating African-American poverty in the central cities. Massey and Denton (1993) argued that middle-class African-Americans moving out from the central cities were unable to fully integrate into surrounding white communities, and Quillian (1999) found support for this showing that as middle-class African-Americans moved into white neighborhoods, whites with the economic ability moved even further out. Downey (2005) theorized that because middle-class African-Americans moving out of the central city were unable to fully integrate into white neighborhoods, and industry was following white populations out of the central city, racial segregation was perversely protecting African-Americans. This leads to the following hypotheses:

Hypothesis 4: For block groups outside of the central city, those with larger proportions of African-American residents will experience lower exposure to toxic pollution than block groups with larger proportions of whites over the time period examined.

Data and Methods

Pollution Exposure Data

I use data from the Environmental Protection Agency's Risk Screening Environmental Indicators Geographic Microdata (RSEI-GM). This data is thought to provide the most "realistic information on potential human health effects from air pollutants that has been available" (Ash and Fetter 2004: 447). The following analyses are completed on data from the year 1995 to 2004. During these years facilities required to report the Toxic Release Inventory, the information which these data are modeled, had a standardized way to report their releases. From 1995 to 2004 the EPA allowed less

polluting, smaller facilities to file a "Form A"[21] (EPA 2013). A form A is a less precise form which facilities are allowed to choose from a range of preset categories representing their annual emissions and the EPA lists the midpoint of this range. This makes data from the smaller industries less reliable than larger ones. After the year 2004, larger, more polluting industries were also allowed to use this form which would make their data less reliable after this point, so I restrict the data to the years 1995 to 2004. In addition, when aggregated RSEI data for the year 1998 is much greater than the other years so I have taken this outlier year out for the following analyses.

Because reporting requirements change every few years, the following analyses only utilize those 572 chemicals that were consistently monitored for the years 1995 to 2004.[22] RSEI data models the emission routes of over 600 toxic chemicals from a variety of manufacturing, mining, utility operations, hazardous waste treatment, and disposal facilities, as well as from chemical distributors and federal facilities. The EPA uses information on the velocity at which chemicals are emitted into the environment, weather patterns, and properties of the chemicals to estimate where these particles exist in a 101 by 101 kilometer square around reporting facilities in the continental United States. These 101 by 101 kilometer squares are further broken down into one by one kilometer grid cells.

The EPA weights the amount of the chemical in this grid cell by its toxicity to human health using epidemiological evidence to make chemicals commensurate across health outcomes (EPA 2009). [23] This process creates a unitless score of pollution exposure for each 1 kilometer square that makes them comparable across types of polluting facilities and areas. Because some facilities have been found to have incorrectly reported their emissions to the EPA, I have followed the standard of the consortium of researchers using these data to leave out those facilities with unreliable data, which make up 1.9 percent of the total 50,368 number of facilities.

---

21 These regulations were in place until the 2005 reporting year, however because facilities report for the year prior a 2005 reporting year means 2004 emissions data.
22 Trends in these data were consistent for other years of "core chemicals" (1998, 2000, and 2001).
23 These weights take into account the severity of a chemical's health effects and its potency. For further information on how these weights were developed see:
www.epa.gov/oppt/rsei/pubs/technical_appendixa_toxicity.pdf

To address the hypotheses outlined previously, I constructed measures of annual toxic pollution exposure score at the block group level for ten years: 1995 to 2004. I have overlaid 1990, 2000 and 2010 block group boundaries with these one kilometer square RSEI-GM grid cells and then determined the proportion that each grid cell makes up of a block group. I then weight the toxicity of this grid cell by this proportion and aggregate it up to the block group level. This gives me my dependent variable, the annual toxic pollution exposure score of a block group from 1995 to 2004. The values for the pollution measures are highly skewed to the right, so a base-10 log of this score is used, making the dependent variable more normally distributed. The data are made up of over 1.5 million time period observations for over 150,000 block groups. On aggregate, pollution exposure estimates for the year 1998 were much greater than the other years examined, this outlier year was removed from the following analyses.

I standardized 1990 and 2010 census block groups to 2000 census block group boundaries. Standardizing block groups is potentially important as boundaries change to some extent with every census. Overlaying 1990, 2000 and 2010 block groups in Arc GIS 10.1 I determined the proportion that each 1990 and 2010 block group made up of the 2000 block group. I then apply these weights to census data and aggregate them up to the 2000 block group boundaries. This procedure gives me 1990 and 2010 census data in the year 2000 block group boundaries. Once all three censuses were standardized I then linearly interpolated the following population data for the census block group: the number of African-Americans, whites, the total population, and population of racial groups that did not fall into the above mentioned categories (Hispanic, Asian-Pacific Islander, Native American). The rate of change in each block group from the year 1990 to the year 2000 was applied linearly to each year of census data from 1995 to 1999. Year 2000 census data was used for the year 2000. Then the rate of change of block group population from the year 2000 to 2010 was linearly applied to census data from 2001 to 2004.

Segregation Measures

As noted above, residential discriminating has historically confined African-Americans to declining central cities (Quillian 1999; Massey and Denton 1993).

Moreover, much of the sociological theory cited to explain how and why segregation is related to pollution exposure relies on the concept of how centralized African-Americans are to the central city compared to whites (Downey 2005). Therefore, the following analyses use the relative centralization measure as a measure of residential segregation. This measure captures the degree to which African-Americans are spatially located near the central business district of a metropolitan area compared to whites.

The most basic version of this measure is just the percentage of the African-American population in a MSA that is located in the central business district. The proportion of African-Americans in the center is calculated as the total number of African-Americans living in the center, divided by the total number of African-Americans in the metropolitan area. Such a measure, however, does not indicate the actual distribution of African-Americans compared to any other group. To obtain a measure of this the relative centralization measure must be calculated.

The relative centralization measure represents the relative share of the African-American population that would have to move to match the relative centralization of whites in the MSA (Massey 1998). The score varies from negative one to positive one, with positive values indicating that African-Americans are closer to the center of the MSA's central business district and negative values representing the opposite. This is calculated using equation 1 below.

$$\sum_{i=1}^{m}(X_{i-1}Y_i) - \sum_{i=1}^{m}(X_iY_{i-1}) \qquad \text{(eq.1)}$$

In equation 1, m is equal to the total number of block groups that make up a MSA ranked by their increasing distance from the central business district.[24] X is the total population of African-Americans in a block group and Y is the total population of whites in a block group, summed over all block groups.

Results from models using relative centralization as a measure of racial segregation are compared to models using the dissimilarity index, the typical measure of segregation used in studies of this kind. The dissimilarity index is a measure of how evenly distributed the African-American population is within a metropolitan area. This index

---

[24] The census defines a central city as the largest place(s) in a metro area (US Census 2012).

ranges from zero to one, with a one representing complete segregation and a zero representing total even distribution of African-American populations within block groups. This measures is calculated using equation 2 below, where x_i equals the African-Americans population of the ith block group; X equals the total population of African-Americans in the MSA; y_i equals the white population of the ith block group, and Y equals the total white population of the MSA. The absolute values of these percentages are summed across N, the total number of block groups in a MSA.

$$\frac{1}{2}\sum_{i=0}^{N} = \left| \frac{x_i}{X} - \frac{y_i}{Y} \right| \qquad\qquad (eq.2)$$

Central City Location

Information on which block groups were within the central city was determined by overlaying central city boundaries from the US census with 2000 census block group boundaries obtained from the U.S. Census Bureau (Census 2001;Census 2012). Those block groups located within the central city were coded as one, those that fell outside as zero.

Models

Multilevel models are appropriate for repeated measures on a unit, like these annual block group measures of pollution, because they take into account the correlated structure of observations in the estimation of standard errors. Serial observations made on the same census unit are likely to be correlated. The observations in these data are clustered so that each block group, standardized to 2000 census block group boundaries as discussed above, has one measure of pollution exposure for each year between 1995 and 2004. The Intraclass Correlation Coefficient gives the amount of variability in the dependent variable arising from the clustering of annual observations within a block group. The Intraclass Correlation Coefficient was determined using STATA 12.0 and showed that 15% of the variability in the observations comes from the fact that they are repeated measures on the same block group. The p-value of the likelihood ratio test,

which was <0.001, demonstrates the need for a multilevel model that will account for repeated observations on the same block group.

The following two-level multilevel model was specified where all level 1 variables are time varying so that the dependent variable, LOGTC, is the log of the toxic pollution exposure score of block group i, at time point t; π_{1i} (seg) is the time varying segregation level of the metropolitan area; π_{2i}(year) is year centered on 1995, so that zero equals year 1995; π_{3i}(popden) is the time-varying population density of the block group which allows me to control for the fact that population density has been negatively and significantly associated with pollution values from these data (Ash and Fetter 2004). Level 2 equations display the fixed effects for these parameters and includes a random intercept (b_{0i}) for each block group within MSA.   To address the fact that block group observations are correlated with one another across space a spatial power covariance structure was specified was specified in SAS 9.3 using the ProcMixed statement. The covariance of block groups (cov_{bg}) is equal to the estimated covariance of how block groups are associated with one another across space ($\sigma^2(b_{0i})$) which is multiplied by a matrix made up of estimated spatial power covariance for block groups (ρ_{bg}) to the power of the distance between block groups to one another. This distance is based on the latitude and longitude of the block group centroid, e.g. block group 1 and 2 would be specified as: $\rho_{bg}^{d\,1,2}$.   In addition the fact that these data are repeated observations on the same block group means that the observation of block group 1 at time 1 is likely to be associated with observation of block group 1 at time 2. To address this an autoregressive lag (AR1) covariance structure was specified so that the covariance of the residuals ($cov(e_{ti})$) is equal to the variance of these residuals ($\sigma^2_{residuals}$) multiplied by a ten by ten matrix where ρ is equal to the estimated covariance between time periods for each block group to a power of year minus one.

Level 1: $\text{LOGTC}_{ti} = \pi_{0i} + \pi_{1i}(\text{seg}) + \pi_{2i}(\text{year}) + \pi_{3i}(\text{popden}) + e_{ti}$ (eq.3)

Level 2: $\pi_{0i} = \beta_{00} + b_{0i}$

$\qquad \pi_{1i} = \beta_{10}$

$\qquad \pi_{2i} = \beta_{20}$

$\qquad \pi_{3i} = \beta_{30}$

Mixed Model: $\text{LOGTC}_{ti} = \beta_{00} + \beta_{10}(\text{seg}) + \beta_{20}(\text{year}) + \beta_{30}(\text{popden}) + b_{0i} + e_{ti}$

Where:

Spatial Power Covariance Structure:

$$\text{Cov}_{bg} = \sigma^2(b_{0i}) * \begin{bmatrix} 1 & \rho_{bg}^{\,d\,1,2} & \rho_{bg}^{\,d\,1,3} & \rho_{bg}^{\,d\,1,4} \\ & 1 & & \\ & & 1 & \\ & & & 1 \end{bmatrix}$$

Residuals Covariance Structure- Autoregressive Lag:

$$\text{cov}(e_{ti}) = \sigma^2_{\text{residuals}} * \begin{bmatrix} 1 & \rho_t & \rho_t^2 & \rho_t^3 & \rho_t^4 & \rho_t^5 & \rho_t^6 & \rho_t^7 & \rho_t^8 & \rho_t^9 \\ & 1 & & & & & & & & \\ & & 1 & & & & & & & \\ & & & 1 & & & & & & \\ & & & & 1 & & & & & \\ & & & & & 1 & & & & \\ & & & & & & 1 & & & \\ & & & & & & & 1 & & \\ & & & & & & & & 1 & \\ & & & & & & & & & 1 \end{bmatrix}$$

Equation three specifies the simplest model specified in the following analysis. I expand on equation three above by including β_4 which is the coefficient associated with an indicator of the location of a block group in the center of a city (where 1=center and 0=outside of center). This allows me to test Downey's (2005) hypotheses that block groups outside of the central city will have higher pollution exposures than those inside. If this is the case then the relationship between central city and pollution exposure will be negative and statistically significant. In order to test Downey's (2005) hypothesis that pollution exposure is increasing in the block groups located outside the city compared to

those inside, I included an interaction term β_5 that multiplies the central city indicator (1=center, 0=outside) with the centered year variable (e.g. year 1995 =0). If Downey is correct, and pollution exposure is increasing for the areas outside of the city, then when an interaction term between year and central city is included, we should see that the coefficient for year is positive and significantly different from zero. This positive effect would mean that pollution exposure would be increasing in those areas outside of the city.

Finally, to test the idea that African-Americans living outside of central cities have less pollution exposure than whites, as well as determining how the proportion of African-Americans in a block group relates to pollution exposure in these models, I have run a model with only those block groups located outside of the central city, as well as including the following variables: β_6 is the coefficient associated with the proportion of a block group's population that is African-American and β_7 is the coefficient associated with the proportion of non-white, non-African-Americans in the block group. This last variable allows me to make sure the omitted/comparison group is made up of white Americans, allowing me to test the hypothesis that those block groups outside of the central city with greater percentages of African-Americans are more exposed to industrial toxins than those block groups with fewer African Americans.

Results

Table 1, model 1, clarifies the changing relationship between racial segregation and toxic pollution exposure using yearly observations on block group level pollution exposure. The coefficient for segregation in model 1 shows that the effect of segregation on pollution exposure in the year 1995 is 1.433. A one unit increase in the segregation measure means that when a MSA's African-American population becomes 0.01 more concentrated in the central city compared to whites their pollution exposure score will increase significantly by 1.433. The interaction term between segregation and time provides support for the first hypothesis, which asserts that the association between racial segregation and pollution has declined over time. These results illustrate that with every year the effect of segregation on pollution declines significantly by -0.070. This means

that by the year 2004 every one unit increase in segregation will increase pollution exposure by only 0.803 (1.433 + (-0.070*9).

Further nuances of this relationship emerge from examination of Models 2 and 3, which include information about the proportion of African-Americans in a block group. The coefficient of 0.823 for the proportion of African-Americans demonstrates that moving to a block group with a proportion of African-Americans that is 0.01 greater, will increase pollution exposure by 0.823. The Akaike Information Criteria (AIC) shows that model 3 has a better fit than models 2 and 1. Model 3 includes the interaction variables. The coefficient for segregation in this model tells us that the main effect of segregation in the year 1995, when the proportion of African-Americans in a block group is zero is 0.720. The main effect for year tells us that when there is no segregation in an MSA and the proportion of African-Americans is zero the effect of year on pollution exposure scores is -0.111. The main effect for the proportion of African-Americans in model 3 tells us that in year 1995, when there is no segregation in a MSA, with every 0.01 increase in the proportion of African-Americans in a block group the pollution exposure score increases significantly by 1.284.

The interaction term for segregation and year in model 3 tell us that when there is zero proportion of African-Americans in a block group the relationship between the segregation level of a MSA and pollution exposure is decreasing significantly by -0.034 each year. The interaction term for segregation and proportion of African-Americans in model 3 tell us that when year equals zero, that is in the year1995, every 0.01 increase in the MSA level segregation the pollution exposure of a block group decreases by -0.011 for every 0.01 increase in the proportion of African-Americans in that block group. Finally, the three-way interaction tells us how the two-way interaction between segregation and the proportion of African-Americans in a block group is changing over time. We can see that it is decreasing very slightly so that every increase in year decreases this relationship by -0.002.

Models 4 through 7 help us to test the remaining hypotheses arising from Downey's (2005) work. Model 4 includes information about whether a block group is located in the central city. Model 4 tests Downey's hypothesis that block groups located outside of the central city will experience higher exposure to toxic pollution than block groups inside

central cities during the period examined by including a variable for whether a block group is located in the central city. This hypothesis was not supported. Results show that those block groups located in the central city have 0.276 greater toxic pollution scores than those outside of the central city, a significant difference. I have excluded the segregation and year interaction in these variables to facilitate interpretation of the central city interaction with year. In addition, including this variable decreased the fit in these models as demonstrated by an increased AIC value. Model 5 tests hypothesis three, that the difference between the pollution exposure of block groups located outside of the central city compared to those located inside will be increasing over time. Although significant, the coefficient for the interaction between time and central city is virtually zero. The large sample size makes it more likely estimates will be significant. Nonetheless, these findings do not provide support for the idea that over time those block groups outside of the central city are becoming more polluted.

Model 6 helps support this idea by only looking at those block groups outside of the central city. If pollution was in fact increasing outside of these areas, the time coefficient would be positive. However, from Model 6 it can be seen that year is negatively related to pollution exposure in these areas. Although this model provides no comparison with central city block groups, it is clear that over time pollution is declining in areas outside of the central city. Model 6 also helps to test the final hypothesis that for block groups located outside of the central city, those with larger proportions of African-American residents will experience lower pollution exposure than those with lesser proportion of African-Americans. These results do not support this hypothesis. In fact, moving to a block group with a 0.01 greater proportion of African-American residents will significantly increase one's pollution exposure by 0.703.

In order to compare these results with previous research I have also run Models 1-6 using the dissimilarity index as the measure of racial residential segregation. These results can be found in Table 2. The dissimilarity index ranges from zero to one, with zero representing no segregation and one representing total segregation. The models show that with every one unit increase in this index increases the logged pollution exposure by 3.537. Unlike the relative centralization measure, the relationship between

a metropolitan area's dissimilarity index and block group exposure has an unstable relationship over time. The most basic models do not show that the relationship between pollution and segregation is declining significantly over time. However, when information about the central city is incorporated into the model the coefficients for year are shown to be significantly negative. Because relative centralization is based on the relative representation of African-Americans in the central city, and the year coefficient becomes significant in the dissimilarity index models when information is incorporated, raises the possibility that it is central city and year are negative cofounders, meaning that the central city is strongly positively related to pollution exposure and year is negatively related so that they cancel one another out and without including information about central city we could not observe any effect of time. As in the relative centralization models in Table 1, block groups with larger proportions of African-Americans outside of the central city are significantly more likely to be exposed to pollution than block groups with larger proportions of whites.

Discussion

This study moves environmental justice research toward an understanding of the dynamic relationship between pollution exposure and segregation. These results show a significantly positive relationship between segregation and pollution exposure. Results from both the relative centralization measure and dissimilarity index show that the ability of racial segregation to explain pollution exposure is declining over time. Such findings lend support that mixed results found from cross-sectional studies on pollution and segregation might be a result of changes in the relationship between these variables over time. The fact that the dissimilarity index and relative centralization differ in their results on the importance of being in the central city in explaining exposure to toxins underscores the need to consider different measures and dimensions of segregation. These results support the idea that the centralization measure is capturing different processes that underlie the segregation and pollution relationship than the measure of evenness.

This paper also tests theories about how being located inside and outside of central cities might affect pollution exposure. Results from the centralization or evenness

measures of segregation do not support the argument that the theorized movement of industry away from America's cities has increased relative exposure to industrial toxins outside of these areas. One possible explanation for the finding that pollution exposure is still higher in central city block groups is grandfather clauses in environmental policy. Grandfather clauses are loopholes put into laws that allow an already existing facility to opt out of stricter environmental regulations (Robertson 1995). Grandfather clauses allow a firm to continue using an older, more toxic facility in the central city, rather than outfitting a new one with more environmental-friendly technology like smoke stack scrubbers (Robertson 1995).[25] Grandfather clauses can apply to many types of environmental regulation. In fact, in comments to Congress, Marcia E. Williams, Director of the EPA's Office of Solid Waste and Emergency Response noted that seventy percent of all land-based hazard waste treatment, storage, and disposal facilities would fail the EPA's current siting criteria for protecting groundwater because of grandfathering opt outs (Garrard 1994).

Garrard (1994) notes that older facilities are being utilized to a greater extent than new facilities are being built. He demonstrates that increasingly stringent environmental regulation since the 1970s has incentivized companies to continue to use older facilities over building new ones that are subject to stricter controls and more community pushback. If older facilities are able to opt out of stricter environmental regulation, and these are more likely to be located in the central city, we would expect that although there has been an overall decline in industrial pollution, central cities will still have higher levels of exposure to these toxins. Future research should test this theory by incorporating information about the date of industrial facility establishment, their use of grandfather clauses and whether this varies the amount and toxicity of the pollution they are emitting over time. Testing this idea would also require capturing the nuanced relationships between outer and inner suburbs, something that could not be captured with just the central city variable. This is important because research has shown that older suburbs located closer to the central city are experiencing socioeconomic declines similar to those of the central city (Lee and Leigh 2007).

---

[25] See Robertson (1995) for a discussion how these have been applied to air pollution.

Results from this paper also suggest that different dimensions of segregation might relate to pollution differently. Researchers investigating pollution and segregation need to ensure that the measure of segregation being utilized is effectively operationalizing the underlying theoretical process relating exposure and race. This might mean considering different dimensions of segregation as well as new measures. While the analyses presented here suggest that the relative centralization measure, a measure of centralization, was the most parsimonious variable to use in these models, this might not be the case with other models or at different spatial and temporal ranges. In addition, segregation measures were only available at the metropolitan level for 1990 and 2000 census data. Future research should incorporate more recent census data as well as considering the possible differences in measuring segregation at a county level or other areas. In addition, with a consistent spatial covariance of 0.99 for the dependent variable, these results suggest that the assumption needed for linear regression models of uncorrelated errors is not supported. Researchers need to incorporate ways to address such spatial relationships wherever possible.

As with all secondary data analysis, the limitations of the previously collected data are passed along.[26] One such limitation is the lack of information on facilities that have closed and are no longer reporting their emissions to the EPA through the Toxic Release Inventory program. It could be that facilities that are shut down are now superfund sites which are abandoned sites that are still toxic to the environment. If it is correct that older facilities are closing down in the central cities, then the number of superfund sites in these areas would be greater than outside of the central cities, and the estimates provided in this paper would be underestimating the environmental risk posed to central city residents. Moreover, these data do not include mobile sources of air pollution. This is particularly important in studies of segregation and pollution, as transportation routes have historically been used segregate neighborhoods in the United States (Venkatesh 2000). Moreover, research suggests that mobile sources contribute to racial health disparities (Geer, Weedon and Bell 2013;Morello-Frosch and Jesdale 200). In addition the pollution exposure measure in these data takes into account the toxicity of the

---

[26] For a thorough explanation of the limitations of the RSEI data see the Political Economy Resource Institute's webpage "How Accurate are the RSEI Data on Toxic Air Pollution?" at: http://www.peri.umass.edu/accurate/

pollutants. There might be very different mechanisms at play in the pathways which distribute certain toxicities differently by demographics than those which would have been uncovered had I used the amount of pollution exposed to that was unweighted by its toxicity.

Although there have been large scale declines in industrial air pollution over recent decades, these results demonstrate that some areas have experienced greater declines than others. Metropolitan areas with greater rates of racial segregation are on average more exposed to industrial toxins overall. Those areas within the central city still have higher exposure to toxins than areas outside the central city. While the resurgence of the neighborhood effects literature has ushered in an increased focus on the effects of racial segregation on the deleterious effect on the health of minorities (Hayanga, Zeliadt and Backhus 2013; Grant et al. 2010), the pathways through which segregation affects health are still being uncovered (see Williams and Sternthal 2010 for a recent review of the literature on segregation and health). One possible explanation is that segregated communities have higher levels of pollution. Thus far this possibility has been understudied (Gee and Payne-Sturges 2004). Those few studies that do investigate if segregated areas have higher rates of pollution have been primarily cross-sectional and found mixed results. This study helps shed light on this relationship and how it might vary over time and for different measures of segregation.

Table 3.1: Descriptives

Year	Mean Segregation	Std Error	Mean Log Pollution	Std Error	Number of Block Groups		White (Percent of Total Pop)		African-American (Percent of Total Pop)	
					Central	Outside	Central	Outside	Central	Outside
1995	0.31501	0.05	2.274	0.006	27369	128763	13.71%	60.33%	2.64%	10.28%
1996	0.31362	0.05	2.115	0.006	27324	128494	13.53%	60.04%	2.72%	10.47%
1997	0.31146	0.05	1.996	0.006	27355	128268	13.30%	59.58%	2.77%	10.64%
1999	0.30992	0.05	1.793	0.006	27151	127793	12.80%	58.85%	2.85%	10.96%
2000	0.3056	0.05	1.822	0.006	27371	128536	12.57%	58.35%	2.89%	11.10%
2001	0.30382	0.05	1.661	0.006	27410	128351	12.39%	57.95%	2.91%	11.21%
2002	0.30197	0.05	1.346	0.006	27425	127971	12.20%	57.46%	2.93%	11.37%
2003	0.30019	0.05	1.067	0.006	27336	128027	11.96%	57.14%	2.95%	11.51%
2004	0.29901	0.05	1.082	0.006	27235	127814	11.76%	56.91%	2.97%	11.66%

Table 3.2: Linear Mixed Model Predicting the Log of Pollution Exposure Scores for Block Groups with Relative Centralization as a Measure of MSA Level Racial Segregation between African-Americans and Whites

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
						OUTSIDE
Segregation	1.433 **	1.485 **	0.720 **	0.037 **	0.037 **	0.034 **
	0.049	0.049	0.058	0.000	0.000	0.000
Year	-0.102 **	-0.102 **	-0.111 **	-0.123 **	-0.123 **	-0.124 **
	0.001	0.001	0.001	0.001	0.001	0.001
Segregation*Year	-0.070 **	-0.072 **	-0.034 **			
	0.002	0.002	0.003			
Prop African-Americans		0.823 **	1.284 **			0.703 **
		0.017	0.040			0.018
Prop African-Americans * segregation			-0.011 **			
			0.001			
Prop African-Americans * year			0.048 **			
			0.004			
Prop African-Americans * year * segregation			-0.002 **			
			0.000			
Central City Location (1=central 0=outside)				0.276 **	0.276 **	
				0.013	0.013	
Central City Location *Interacted with Year (1=central 0=outside)					0.000 **	
					0.001	
Spatial Covariance Parameter	0.990	0.990	0.990	0.990	0.990	0.990
Akaike Information Criterion	4348520	4346310	4344929	4348963	6239063	5117929
Constant	-0.595 **	-0.509 **	-0.587 **	-0.758 **	-0.759 **	-0.504 **
	0.024	0.024	0.025	0.027	0.027	0.026
N Block group observations	1,444,404	1,444,404	1,444,404	1,444,404	1,444,404	1189114
N Block groups	160,559	160,559	160,559	160,559	160,559	132131
N Metropolitan Areas	322	322	322	322	322	322

Robust standard errors are given in parentheses and models control for population density.

ⱡ Stratified sample of just those block groups located outside of the central city.

** significant at a p-value of 0.001 * significant at a p-value of 0.05

Table 3.3: Linear Mixed Model Predicting the Log of Pollution Exposure Scores for Block Groups with Dissimilarity Index as a Measure of MSA Level Racial Segregation between African-Americans and Whites

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6 [1]	
											OUTSIDE CITY	
Segregation	3.537	**	3.5805	**	2.156	**	0.04426	**	0.04426	**	0.0416	**
	0.08063		0.08051		0.092		0.00013		0.00013		0.00015	
Year	-0.00401		-0.00412		-0.049	**	-0.1103	**	-0.1103	**	-0.1077	**
	0.003		0.003		0.003		0.001		0.001		0.001	
Segregation*Year	-0.1746	**	-0.1769	**	-0.106	**						
	0.004		0.004		0.005							
Prop African-Americans			0.5146	**	0.516	**					0.6041	**
			0.007		0.075						0.014	
Prop African-Americans * seg					0.015	**						
					0.001							
Prop African-Americans * year					0.434	**					-0.031	
					0.013						0.002	
Prop African-Americans * year * seg					-0.007	**						
					0.000							
Central City Location (1=central 0=outside)							0.069	**	0.067	**		
							0.005		0.009			
Central City Location * Year (1=central 0=outside)									-0.000			
									0.002			
Spatial Covariance			099		0.99		0.99		0.99		0.99	
AIC	6285404		6280288		6278467		6286922		6286933		5156536	
Constant	-2.0529	**	-1.9293	**	-1.834	**	-1.5981	**	-1.597	**	-1.5189	**
	0.016		0.016		0.018		0.011		0.013		0.012	
Observations	1,445,205		1,445,205		1,445,205		1445205		1445205		1189114	
N Block groups	160,586		160,586		160,586		160586		160586		132131	
N MSA	322		322		322		322		322		322	

Robust standard errors are given in parentheses and models control for population density.

ⱡ Stratified sample of just those block groups located outside of the central city.

** significant at a p-value of 0.001 * significant at a p-value of 0.05

CHAPTER 4
Poverty Segregation and Pollution Exposure:
Evaluating the Concentration of Poverty

Abstract

This study is among the first to examine the changing relationship between metropolitan level segregation of poverty and pollution exposure at the block group level within these areas. These analyses utilize air pollution data on 572 industrial chemicals which have been estimated using air dispersion modeling to determine their effect on over one hundred thousand block groups. These estimates are weighted by their toxicity to human health to provide estimates of exposure to toxic industrial pollutants at the block group level, over time, across the United States. Results show that block groups located in metropolitan areas with higher levels of poverty segregation have, on average, higher rates of pollution exposure. In addition, those block groups with greater proportions of impoverished residents have more exposure to toxic pollutants if they are located in a metro area with higher levels of poverty segregation.

Introduction

Although a number of environmental justice studies consider poverty as a predictor of pollution exposure, none actually measure poverty segregation. This is an important limitation of the environmental justice literature, because a measure of poverty segregation would be a more accurate metric of concentrated poverty, one of the most theoretically cited causes of environmental inequality (Smith 2009; Downey 2005; Lopez 2002). A renewed focus on "concentrated poverty" came about in the urban sociology literature in the late 1980s in the quest to understand the increasing rates of poverty in America's central cities. Insights from this body of literature made it clear that both racial and economic segregation are important for understanding what social groups are located nearer to historically industrial centers in America, and thereby closer to the pollution coming from these facilities. Research investigating the unequal exposure to environmental risk by social class has been criticized for being slow to incorporate sociological theory (Smith 2009; Downey 2005). This paper addresses such criticism by operationalizing the concept of "concentrated poverty" in a way that is more consistent

66

with that laid out in the urban sociology literature being cited by environmental justice studies.

A large body of research has shown that there has been a great deal of change over recent decades in levels of both pollution (EPA 2012a) and economic segregation (Wheeler and La Jeunesse 2008), but these two indicators have had different trajectories. Economic segregation has been increasing. Using census tract-level family income data for 216 U.S. metropolitan areas, Watson (2009) found that top and bottom income quintiles were more isolated in 2000 than in 1970 and income segregation rates have stayed high through the year 2009 (Lichter, Parisi and Taquino 2013). However, hazardous air emissions from industrial facilities have declined dramatically since the early 1990's (EPA 2012a). Kahn (1999) argues this is mainly due to deindustrialization. During the time period of this study, from 1980 to 2009, the United States lost almost 40% of its manufacturing jobs (Helper et al. 2010). Yet current environmental inequality research has not attempted to examine how the association between increasing economic segregation and decreasing pollution has evolved over time to influence unequal exposure to pollution.

This paper will address these limitations by exploring two primary research questions: (1) In the mid-1990s U.S., how did pollution exposure of a census block group vary by the economic segregation of the metropolitan area within which it was situated? (2) How did the relationship between economic segregation and pollution vary over the ensuing decade? I link data from the Environmental Protection Agency's (EPA) Risk Screening Environmental Indicator geographic microdata (RSEI-GM) for 1995 to 2004 to poverty segregation in those years based on the dissimilarity index (DI), a standard measure of segregation. Multilevel models are used that account for clustering of observations over time within block groups and spatial correlation of the observations. This paper helps theoretically advance the EJ literature by offering a more precise measure of concentrated poverty, looking at trends over time and using more precise measures of pollution exposure than have been used in previous studies.

Background

Research from the field of environmental justice has largely showed that stratification of environmental quality mirrors that of other social goods; those of lower

income are disproportionately located in more polluted areas (Crowder and Downey 2010). Recently this field has been criticized for not incorporating important lessons from the discussion of the causes of concentrated poverty in America's cities (Smith 2009; Downey 2005). The urban poverty literature borrows from the field of Human Ecology. Specifically, Weber's (1909) least cost theory holds that new industrial facilities are sited near industries of similar type because these areas already have the necessary infrastructure, access to markets and labor, that companies need to effectively do business. This process creates a 'Zone of Industry'. The broader sociological literature argues that this spatial patterning of industry significantly affects the economic opportunities of individuals within a metropolitan area and the spatial concentration of poverty (Wilson 1996). Because these facilities also emit air pollution, these zones of industry are also zones of exposure to air toxins.

It is often argued that having an industrial facility in the local community provides economic vitality to the area (Cole and Foster 2001; Bullard 1990). If such areas are economic hotspots we would expect to see that overall, places with more industrial facilities would have higher levels of employment, particularly in industrial occupations, and a reasonable amount of personal wealth amongst local citizens. This, however, was not the case for the communities of over 413 commercial hazardous waste facilities operating in the U.S. in the year 1999. National level examination demonstrated that populations within three kilometers of polluting facilities have 1.5 times higher poverty rates and 15% lower mean annual household incomes than other areas (Bullard et al. 2007). One such example is provided by St. James Parish in Louisiana. In the mid-nineties this area had 137 petrochemical facilities, but suffered from 10 to 14 percent higher unemployment rates than the state average (Kurtz 2003). After a community in this area protested a new facility being sited there, corporate officials were forced to admit that they were not anticipating hiring people from the local community, "because the educational level of the local citizens did not meet the company requirement" (Cole and Foster 2001: 78).

Moreover, with increased automation in industrial sectors, the number of jobs industrial facilities can provide has dwindled (Wilson 1996). Wilson (1996) argues that one of the primary reasons for poverty segregation, or a concentration of poverty in

America's metropolitan areas, is the polarization of the labor market into low wage and high wage sectors. The job opportunities that do remain in industrial facilities are reserved for highly skilled workers, who are often brought in from outside of the local community. Wilson (1987, 1996) argues that as deindustrialization has progressed, America's historically industrial centers have shown increased poverty rates due in part to the lack of low wage jobs in these areas, as well as the outmigration of wealthier individuals (Wilson 1987, 1996). If poverty has concentrated around older manufacturing facilities then the next logical step is to ask if this process underlies the unequal distribution of pollution by income.

The environmental justice literature often cites Wilson's (1987; 1996) work in order to explain the importance of including a measure of poverty in statistical models predicting pollution exposure (Smith 2009; Downey 2005; Lopez 2002). However Wilson's argument is not just about poverty per se, but rather the spatial concentration of poverty. Wilson's theories deal explicitly with the concentration of poverty of central cities in the context of a broader, less impoverished metropolitan area. Thus a simple measure of a census unit's poverty doesn't accurately capture whether this area is spatially clustered with other areas with a similar poverty status. It could possibly be that those census units with high areas of poverty are randomly dispersed throughout the metro area. Measuring income inequality at the metro level would capture the mean pollution level for that metro area, but would not indicate whether those areas that are more impoverished in that metro area are the ones most exposed to pollution. To more accurately assess whether being in an impoverished community, surrounded by other impoverished communities, increases the risk of exposure to industrial toxins it is necessary to use a measure of poverty segregation.

Smith (2009) provides one of the few studies that operationalize the concentration of poverty and determine how it is related to pollution exposure in Portland, Oregon and Detroit, Michigan. He wanted to evaluate Wilson's (1987; 1996) theory and capture "concentrated poverty" explicitly. Thus he created an index of economic deprivation for the census tract that included the percentage of residents who were unemployed, in poverty, receiving welfare, living in a female-headed household, lacking a high school diploma, and employed as an executive, and the tract-level median income. He uses this

index to predict whether a census tract had a hazardous waste disposal site located in it. He presented models with estimates for both concentrated poverty at the tract level and racial segregation at the metropolitan level. He found that concentrated poverty was a strong and significant predictor of whether there was superfund site located in the tract, and that this index was a stronger predictor of the presence of a polluting facility than the level of racial segregation.

While the literature investigating pollution and concentrated poverty is not yet robust, there have been a handful of cross-sectional studies that have examined economic inequality and pollution exposure. For example, in their models to assess the effect racial segregation had on environmental outcomes, Downey et al. (2008) ran series of logistic regressions for 329 metropolitan areas in 2000. The dependent variable in these regressions was whether or not the average person in a racial group (e.g. African-Americans) had a higher pollution burden relative to an average person of another racial group (e.g. whites). In these models they incorporated a measure of income inequality which was calculated as the ratio of a racial group's median household income over the median household income of all households in the metropolitan area. The authors found that this measure of income inequality did not account for much of the variation in pollution exposure by race. In a similar paper, Downey (2007) used ordinary least square models predicting the ratio of exposure of African-Americans and whites, African-Americans and Hispanics and whites and Hispanics. In these models Downey (2007) included the median income ratio of African-Americans and whites of a metropolitan area. Again, Downey (2007) did not find that this variable of metropolitan level income inequality was a significant predictor of unequal pollution exposure by race. While these findings are illuminating, their measure of economic inequality is a ratio of median income in a MSA. This tells us nothing about the spatial patterns of the poor in these areas, which is the major mechanism cited in the motivating theory of these papers.

The extant papers are all notably motivated by Wilson's (1987; 1996) theory on metropolitan level concentrated poverty; however, none of them precisely measure it. This paper addresses this limitation by helping to make clear if block groups located in metropolitan areas with higher poverty concentration are significantly more likely to have higher pollution exposure. In addition, the role of block group level poverty is noted in

70

order to determine if in fact those block groups with higher levels of poverty are also the ones experiencing greater levels of pollution. This paper also helps test the idea that for those metropolitan areas with high rates of concentrated poverty, it is those areas of concentrated poverty that are experiencing the greatest environmental risk from industrial toxins.

Data and Methods

The Risk Screening Environmental Indicators geographic microdata (RSEI-GM) was created to augment the current Toxic Release Indicator (TRI) data. TRI data is a compilation of reported releases of over 600 individual chemicals from a variety of manufacturing, mining, utility operations, hazardous waste treatment, and disposal facilities, as well as from chemical distributors and federal facilities (EPA 2012b). TRI data is limited in that it doesn't provide information about what areas are most affected by this exposure or the comparative risk of these amounts and chemicals. The RSEI-GM data overcomes these limitations by using air dispersion modeling. This model takes into account information on a chemical's rate of decay, molecular weight, as well as the source of the release (i.e.: smokestack height, valve leak, etc.), wind patterns, temperature, and topography around a facility, to produce an exposure estimate for a 101 km by 101 km square around each facility. This area is further broken down into one kilometer square grid cells. These amounts are then weighted by their toxicity to human health based on peer-reviewed studies completed by both EPA and external scientists[27] which take into account the number of potential chronic human health effects, severity of these effects, potency of the chemical and uncertainty in differentiating these effects (EPA 2007). Once weights are applied they are added together to create a score for a one by one kilometer grid cell which is comparable across facilities and areas.

Because reporting requirements change every few years, these analyses only examine those 572 chemicals that were consistent across the time period examined. In addition, facilities reporting their emissions to the EPA can retroactively change their reported numbers to correct for errors. I follow the standard of the consortium of researchers that

---

[27] Compiled in the EPA's Integrated Risk Information System (IRIS), EPA Office of Pesticide Programs' Toxicity Tracking Reports (OPP), Agency for Toxic Substances and Disease Registry final, and other sources.

use these data and omit these facilities (N=957), which make up less than one percent of the total facilities in these data (N=50,368). Finally, these years 1995 to 1997 and 1999 to 2004 were utilized because over this period the requirements for what types of facilities could submit cursory emission information was limited to smaller facilities; this allowance was later extended to larger facilities. During this time period smaller facilities were able to submit ranges of their emissions rather than the actual output. The EPA then used the middle of that range as their actual emissions, making these estimates less reliable. After 2004 this allowance was given to larger facilities, expanding the uncertainty in estimates after this time. Pollution estimates in aggregate for the year 1998 were much greater than the other years, thus this outlier was excluded of the following analyses.

In GIS 10.1 I intersected these grid cells with 2000 census block group boundaries. This helped me to determine what percentage each grid cell made up of a census block group. I then weighted the toxicity of this cell by this proportion and aggregated it up to the 2000 block group boundary, giving me an estimate of exposure for that block group boundary. I repeated this for the years 1995 to 2004. Using the same technique, I overlaid 1990 and 2010 census block group boundaries with 2000 census block groups. I determined the percentage each block group made up of the 2000 boundaries, and weighted data on the number of individuals in poverty and not in poverty to the 2000 block group boundaries. This gave me standardized block group boundaries, 1990 and 2010 census data in 2000 block group boundaries. The then was able to linearly interpolate these data, so that the average rate of change from 1990 to the year 2000 was applied to population data for the years 1994 to 1999. The 2000 census data was used for the year 2000, and the average rate of change from 2000 to 2010 was applied to population data for the years 2001 to 2004. This gave me annual varying estimates of block group level poverty and the population density per square mile, which I then matched to yearly pollution estimates from the RSEI-GM data. These analyses include over 150,000 block groups with over 1.4 million observations.

I calculated the proportion of those in poverty in a block group by dividing the total number of individuals in poverty in a block group by the total number of persons in that block group. The distribution of the proportion of block group poverty is skewed so I

broke it down into quintiles. The highest quintile was coded as a four, and so on to the lowest quintile which was coded as zero. It is important to bear in mind that the proportion of a block group's population living in poverty is not necessarily correlated with the level of poverty segregation of the metropolitan area that it is located in. In fact, there was no evidence of multicollinearity between these variables. One is a measure of an MSA characteristic and the other of a block group characteristic.

I calculated the index of dissimilarity of poverty for metropolitan statistical areas (MSA)[28]. MSAs are focused on because in a national examination of commercial hazardous waste facilities operating in 1999, Bullard et al. (2007) found that 83% were located within metropolitan areas (see table 1 for a breakdown of pollution levels for quintiles of poverty segregation). The dissimilarity index is a measure of spatial evenness of poverty across block groups in a metropolitan area, so those metropolitan areas that have greater concentration of poverty will have a higher index value. The Index of Dissimilarity for poverty was calculated at the metropolitan area level for 320 metropolitan areas. Interpretation of the Index of Dissimilarity is for the larger geographic area; in this case it would be a measure of segregation for the MSA. The index can range from 1 (total segregation) to 0 (equal distribution of groups).   It is calculated using equation 1 below, where pi equals the population of the ith block group in poverty; P equals the total population of the MSA in poverty; ni equals the population of the ith block group not in poverty, and N equals the total population of the MSA not in poverty (Farley 2009). The absolute values of these percentages are summed across N, the total number of block groups in a MSA.

$$\frac{1}{2}\sum_{i=0}^{N} = \ \mid \frac{pi}{P} - \frac{ni}{N} \mid \tag{eq.1}$$

The dissimilarity index is the most commonly measured dimension of segregation (Weinburg et al. 2009). Previous scholars have argued that it is preferable to obtain these measures at the metropolitan level because it is at this level that policy decisions on the environment and structural forces affecting segregation take place (Morello-Frosch and Lopez 2006). As Morello-Frosch and Lopez (2006: 183) argue, "economic trends, transportation planning, and industrial clusters tend to be regional in nature, even as

---

[28] 1999 MSA boundaries were obtained from the U.S. census (Census 2001).

zoning, facility siting, and urban planning decisions tend to be local." Furthermore, MSA overlap considerably with real estate markets and are often used as a proxy for these.

Analytic Strategy

Multilevel models are appropriate for repeated measures on a unit, like these annual block group measures of pollution, because they take into account the correlated structure of observations in the estimation of standard errors. Serial observations made on the same census unit are likely to be correlated. The observations in these data are clustered so that each block group, standardized to 2000 census block group boundaries as discussed above, has one measure of pollution exposure for each year between 1995 and 2004. Therefore the following two-level multilevel model was specified where all level 1 variables are time varying so that the dependent variable, LOGTC, is the log of the toxic pollution exposure score of block group i, at time point t; π_{1i} (seg) is the time varying poverty segregation level of the metropolitan area; π_{2i}(year) is year centered on 1995, so that zero equals year 1995; π_{3i}(popden) is the time-varying population density of the block group which allows me to control for the fact that population density has been negatively and significantly associated with pollution values from these data (Ash and Fetter 2004).

Level 2 equations display the fixed effects for these parameters and includes a random intercept (b_{0i}) for each block group within MSA. To address the fact that block group observations are correlated with one another across space a spatial power covariance structure were specified was specified in SAS 9.3 using the ProcMixed statement where the covariance of block groups (cov_{bg}) is equal to the estimated covariance of how block groups are associated with one another across space ($\sigma^2(b_{0i})$) which is multiplied by a matrix made up of estimated spatial power covariance for block groups (ρ_{bg}) to the power of the distance between block groups to one another. This distance is based on the latitude and longitude of the block group centroid, e.g. block group 1 and 2 would be specified as: $\rho_{bg}^{d\,1,2}$. In addition the fact that these data are repeated observations on the same block group means that the observation of block group

1 at time 1 is likely to be associated with observation of block group 1 at time 2. To address this an autoregressive lag (AR1) covariance structure was specified so that the covariance of the residuals ($\text{cov}(e_{ti})$) is equal to the variance of these residuals ($\sigma^2_{residuals}$) multiplied by a ten by ten matrix where ρ is equal to the estimated covariance between time periods for each block group to a power of year minus one. Equation three specifies the simplest model specified in the following analysis. I expand on equation three above by including β_4 which is the coefficient associated with the proportion of those living in poverty in a block group as well as interaction terms between these variables.

Level 1: $\text{LOGTC}_{ti} = \pi_{0i} + \pi_{1i}(\text{seg}) + \pi_{2i}(\text{year}) + \pi_{3i}(\text{popden}) + e_{ti}$ (eq.3)

Level 2: $\pi_{0i} = \beta_{00} + b_{0i}$

$\qquad \pi_{1i} = \beta_{10}$

$\qquad \pi_{2i} = \beta_{20}$

$\qquad \pi_{3i} = \beta_{30}$

Mixed Model: $\text{LOGTC}_{ti} = \beta_{00} + \beta_{10}(\text{seg}) + \beta_{20}(\text{year}) + \beta_{30}(\text{popden}) + b_{0i} + e_{ti}$

Where:

Spatial Power Covariance Structure:

$$\text{Cov}_{bg} = \sigma^2(b_{0i}) \begin{bmatrix} 1 & \rho_{bg}^{d\,1,2} & \rho_{bg}^{d\,1,3} & \rho_{bg}^{d\,1,4} \\ & 1 & & \\ & & 1 & \\ & & & 1 \end{bmatrix} *$$

Residuals Covariance Structure- Autoregressive Lag:

$$\text{cov}(e_{ti}) = \sigma^2_{residuals} * \begin{bmatrix} 1 & \rho_t & \rho_t^2 & \rho_t^3 & \rho_t^4 & \rho_t^5 & \rho_t^6 & \rho_t^7 & \rho_t^8 & \rho_t^9 \\ & 1 & & & & & & & & \\ & & 1 & & & & & & & \\ & & & 1 & & & & & & \\ & & & & 1 & & & & & \\ & & & & & 1 & & & & \\ & & & & & & 1 & & & \\ & & & & & & & 1 & & \\ & & & & & & & & 1 & \\ & & & & & & & & & 1 \end{bmatrix} *$$

75

The previous equation specifies the simplest model in the following analysis. I expand on this by including β_4 which is the coefficient associated with the proportion of those living in poverty in a block group. I also included interaction of this term with the poverty segregation level of the MSA in order to understand if those block groups with greater proportion of those in poverty have higher pollution exposure if they are living in MSAs with greater poverty segregation.

Results

Figure 1 graphs the average logged toxic concentration of block groups by quintile of MSA-level poverty segregation from 1995 to 2004. The pattern of higher pollution rates at higher levels of poverty segregation is apparent for each year examined. Those block groups in the most segregated quintile are the most exposed, those in the second highest are the second most exposed, and the third highest the third most exposed. Below these two quintiles it is less clear cut. Those block groups in the lowest category of segregation are the least exposed in only four of the ten years. Results from an analysis of variance on the sample pooled across all years, shows that the mean pollution between each quintile is all statistically different from one another, with a p-value of <0.001.

Model 1 in Table 1 demonstrates that the poverty segregation level of a metropolitan area is positively and significantly related to the logged pollution exposure of the block groups within it. For every one unit increase in the poverty segregation level of an MSA, the logged pollution exposure value for block groups within that MSA increases by 8.912. The coefficient for year in model 1 demonstrates that for block groups at the lowest level of poverty segregation, the logged pollution exposure decreases by -0.132 per year. Model 2 shows that the interaction between poverty segregation at the metropolitan level and year is negative and statistically significant. This means that over time poverty segregation of a metropolitan area is less related to pollution exposure so that by the year 2004 the poverty segregation level of an MSA is correlated with pollution exposure of a block groups by 7.724 = (8.912-(0.132*9)). However the coefficient is relatively small, and loses significance in the subsequent models.

Up to this point these statistical models have just provided information about how the average pollution exposure of block groups varies by their location in MSAs with different levels of poverty segregation. There is no information about which block groups are more affected. Figure 2 helps us to understand the relationship between the proportion of individuals living in poverty in a block group, their pollution exposure and MSA poverty segregation level. This graph breaks down the average pollution exposure for the five quintiles of block group poverty, by the five quintiles of metropolitan level poverty segregation. The positive relationship between block group poverty and pollution is clear cut for the top two quintiles of metropolitan level poverty segregation. Those block groups with the highest proportion of individuals in poverty also have the greatest pollution exposure, and this increase is linear. However, for the lowest three quintiles of metropolitan level poverty this relationship differs in two ways. The first is that the difference between the highest quintile of block group poverty and lowest decreases. For the MSA with the greatest amount of poverty segregation the difference between the average pollution of the top quintile and bottom is 0.76 (3.22-2.46). For the MSA with the lowest poverty segregation this difference is 0.13, the second lowest 0.30, the third lowest 0.41, and the fourth 0.52. The second difference is that the linear aspect of this relationship is not as apparent in MSAs with lower levels of poverty segregation. In some cases, block groups with the lowest level of poverty have higher average pollution exposure than block groups with higher levels of poverty.

Model 3 helps us to further understand if block groups with greater rates of poverty are more exposed to pollution. The coefficient for the block group level proportion of those living in poverty, shows that moving to a block group with 0.01 a greater proportion of those in poverty increases ones pollution exposure by 0.967. Model 4 includes an interaction term between the proportion of those in poverty in a block group and metropolitan area segregation in order to determine if areas of concentrated poverty have greater pollution burdens in MSAs with higher levels of poverty segregation. The main effect for block group proportion of poverty in this model demonstrates that moving to a block group with a 0.01 greater proportion of those in poverty, increases pollution exposure by 9.051 when there is no metropolitan area level poverty segregation. The positive and significant interaction estimate signifies that those block groups with greater

percentages of poverty have more pollution exposure in MSAs that have higher levels of poverty segregation. Model 5 includes a three-way interaction between block group level poverty proportion, MSA poverty segregation and year. These results show that the association between block group level poverty and MSA level poverty segregation is declining slightly and significantly over time (beta= -0.012).

Discussion

These results demonstrate that living in a block group with higher rates of poverty will significantly increase exposure to industrial toxins and this effect is amplified in metropolitan areas with higher rates of poverty segregation. This study improves upon previous studies in several ways. First, I examined the segregation of poverty rather than overall income inequality or tract-level economic deprivation. The segregation of poverty is a spatial measure that provides information about how spatially concentrated poverty is within a metropolitan area; this cannot be captured with metropolitan level measure of economic inequality, because such a measure does not indicate whether areas of concentrated poverty are experiencing more exposure. Additionally, concentrated poverty, in the way Wilson (1987; 1996) talks about it, cannot be measured as just the percentage of people in poverty in a block group, or as another characteristic of a small geographic unit like a census tract, because it could be that tracts with higher rates of poverty are more or less randomly distributed across the metropolitan area. This paper contributes to the literature by defining poverty segregation in a way more consistent with the guiding theory posed by Wilson by measuring areas of concentrated poverty as a metropolitan area characteristic not a census unit characteristic. Finally, I examine changes in poverty segregation and how this relates to industrial pollution exposure over time.

Those block groups with higher rates of poverty were in fact the areas being most exposed to industrial toxins. Statistical models showed that an increase in the level of block group poverty was associated with increasing levels of pollution exposure and compared to the least impoverished block groups, these relationships were significant. It is often assumed that although industrial facilities might pollute, they also bring economic development to the local communities in which they are sited. Such a scenario

78

would suggest that areas with more pollution have greater economic resources. The fact that these results show that block groups with greater proportions of poverty actually have higher pollution exposure, provides motivation for future research to test this assumption more directly.

To explore these findings further, future research should consider how the relationship between segregation and poverty pollution varies regionally. Could it be that those metro areas with less segregation are clustered in the Western United States, where there might be a different relationship between poverty segregation and industrial pollution? This might explain why at lower levels of poverty segregation there is more equal distribution of pollution by proportion of block group poverty. A regional examination could also provide insight as to whether certain industrial sectors contribute differently to the segregation and pollution association. Such work could also help to explain why poverty segregation is declining in its ability to explain pollution exposure, even though economic segregation is increasing in the United States. Current research has shown that there have been steady increases in central city populations (Mather et al. 2011). Regional examinations should consider if varying levels of gentrification in these areas might help explain these trends over time.

Future research should also consider different measurements of segregation. The dissimilarity index has been criticized for being "aspatial" in that it relies on areal units created by census boundaries (Reardon and O'Sullivan 2008). By comparing various measures of segregation, researchers will better be able to grasp how different dimensions of poverty or economic segregation might relate differently to pollution exposure. This could also mean creating different measures of economic segregation, using various combinations of income brackets, as well as breaking these down by race.

Finally, once it is determined to what extent industrial exposures can be explained by economic segregation, measures of racial segregation should be incorporated to see how results change and how the inclusion of a time dimension alters these relationships. Because race and poverty are so intertwined in the U.S., results from statistical models just including one of these variables might be capturing effects of the other. To determine the extent to which each affects environmental inequality, it is important to run

separate models for poverty segregation and racial segregation, as well as finding ways to estimate models that incorporate both.

This study has several limitations. Firstly, it is important to note that these results do not provide evidence of causation. In order to understand if pollution exposure causes increases in poverty levels, or vice versa, information on the relative timing of these indicators would have to be included. For example, one could ask: in areas where there was an increase in pollution exposure, there was a subsequent increase in block group level poverty? Such an examination would be most useful over a longer time period. Finally, as with all secondary data analysis, the limitations of these data are passed on to this study.[29] A limitation of note is that these data do not include mobile sources of pollution. While the theory motivating this paper is based on industrial spatial patterning and pollution emissions, America's transportation systems have been used to segregate communities (Venkatesh 2000). Because mobile pollution has been linked to segregation and unequal exposure by race (Morello-Frosch and Jesdale 2006) future work should incorporate such information.

Environmental justice research finds community-level poverty to be one of the chief indicators of exposure to air pollution (Hamilton, 1995; Smith 2009; Stretesky and Hogan 1998). However, research investigating the unequal exposure to environmental risk by poverty status has not measured poverty segregation in a way that is consistent with the motivating theory. The urban poverty literature that environmental justice researchers have drawn upon to explain how pollution and economic inequality relate to one another, describes the concentration of poverty within a metropolitan area. According to the urban poverty literature, the mechanisms through which poverty affect pollution is a spatial relationship between economic groups across the whole metropolitan area, not just within one neighborhood. This paper addresses that limitation and results suggest that the metropolitan level concentration of poverty is a strong indicator of the overall pollution of the MSA, as well as providing evidence that those living in poverty are exposed to greater industrial toxins if their MSA has a high level of poverty concentration.

---

29 Further information about the limitations of the RSEI data can be found online at:
http://www.peri.umass.edu/accurate/

Table 4.1: Descriptives

Year	Mean Segregation	Std Error	Mean Log Pollution	Std Error	Mean Pollution Quintiles of MSA Level Segregation				
					Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
1995	0.364	<0.000	2.274	0.006	1.280	1.470	2.612	2.768	3.362
1996	0.365	<0.000	2.115	0.006	1.156	1.334	2.124	2.818	3.092
1997	0.367	<0.000	1.996	0.006	1.358	1.026	1.711	2.689	2.932
1999	0.377	<0.000	1.793	0.006	1.222	0.950	1.258	2.201	2.679
2000	0.384	<0.000	1.822	0.006	1.193	0.955	1.391	1.942	2.723
2001	0.372	<0.000	1.661	0.006	1.017	0.803	1.377	2.133	2.584
2002	0.367	<0.000	1.346	0.006	0.595	0.636	1.253	1.698	2.476
2003	0.364	<0.000	1.067	0.006	0.342	0.361	0.971	1.600	2.270
2004	0.365	<0.000	1.082	0.006	0.281	0.450	1.000	1.561	2.273

Figure 4.1: Average Unadjusted Values of Average Logged Toxicity Weighted Pollution Exposure Score of Block Groups by Year, Broken Down by Quintile of Block Group Proportion of Poverty
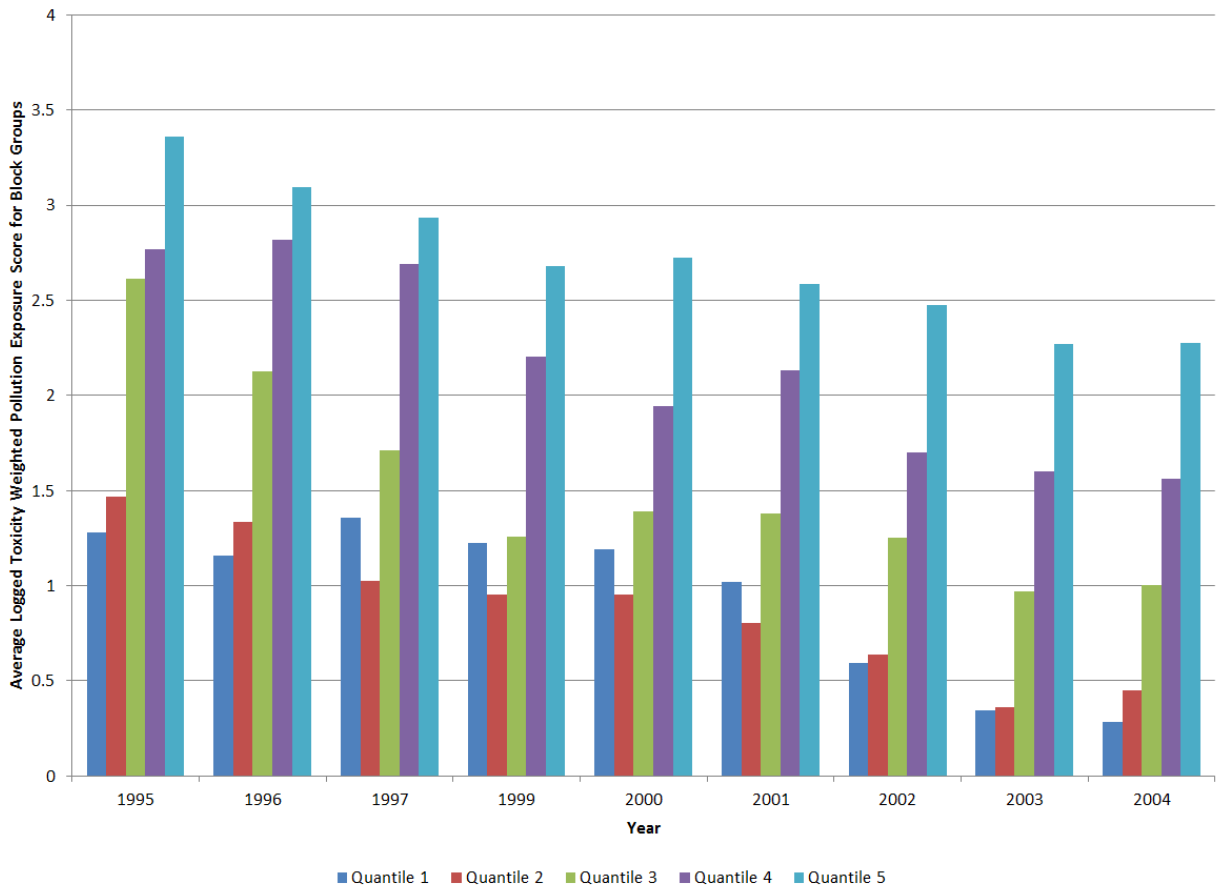
Table 4.2: Linear Mixed Model Predicting the Log of Pollution Exposure Scores for Block Groups

	Model 1	Model 2	Model 3	Model 4	Model 5
Poverty Segregation	8.912 **	9.126 **	9.040 **	9.051 **	9.034 **
	0.028	0.048	0.048	0.048	0.049
Year	-0.132 **	-0.114 **	-0.131 **	-0.130 **	-0.130 **
	0.001	0.003	0.004	0.004	0.004
Poverty Segregation*Year		-0.049 **	0.011	-0.001	-0.001
		0.009	0.009	0.009	0.009
Prop Block Group Poverty			0.967 **	0.840 **	0.792 **
			0.015	0.027	0.030
Prop Block Group Poverty * segregation				0.074 **	0.181 **
				0.012	0.033
Prop Block Group Poverty * segregation * year					-0.012 **
					0.004
Spatial Covariance Parameter	0.990	0.990	0.990	0.990	0.990
Akaike Information Criterion	6299713	6299691	5826709	5826681	5826678
Constant	-2.149	-2.228 **	-2.243 **	-2.231 **	-2.225 **
	0.013	0.019	0.019	0.01954	0.020
N Block group observations	1,444,404	1,444,404	1,444,404	1,444,404	1,444,404
N Block groups	160,559	160,559	160,559	160,559	160,559
N Metropolitan Areas	322	322	322	322	322

Robust standard errors are given in parentheses and models control for population density.

** significant at a p-value of 0.001 * significant at a p-value of 0.05

Figure 4.2: **Average of Unadjusted Logged Toxicity Weighted Pollution Exposure Score of Block Groups Broken Down by Quintile of Proportion of Poverty and Quintile of Metropolitan Level Poverty Segregation**
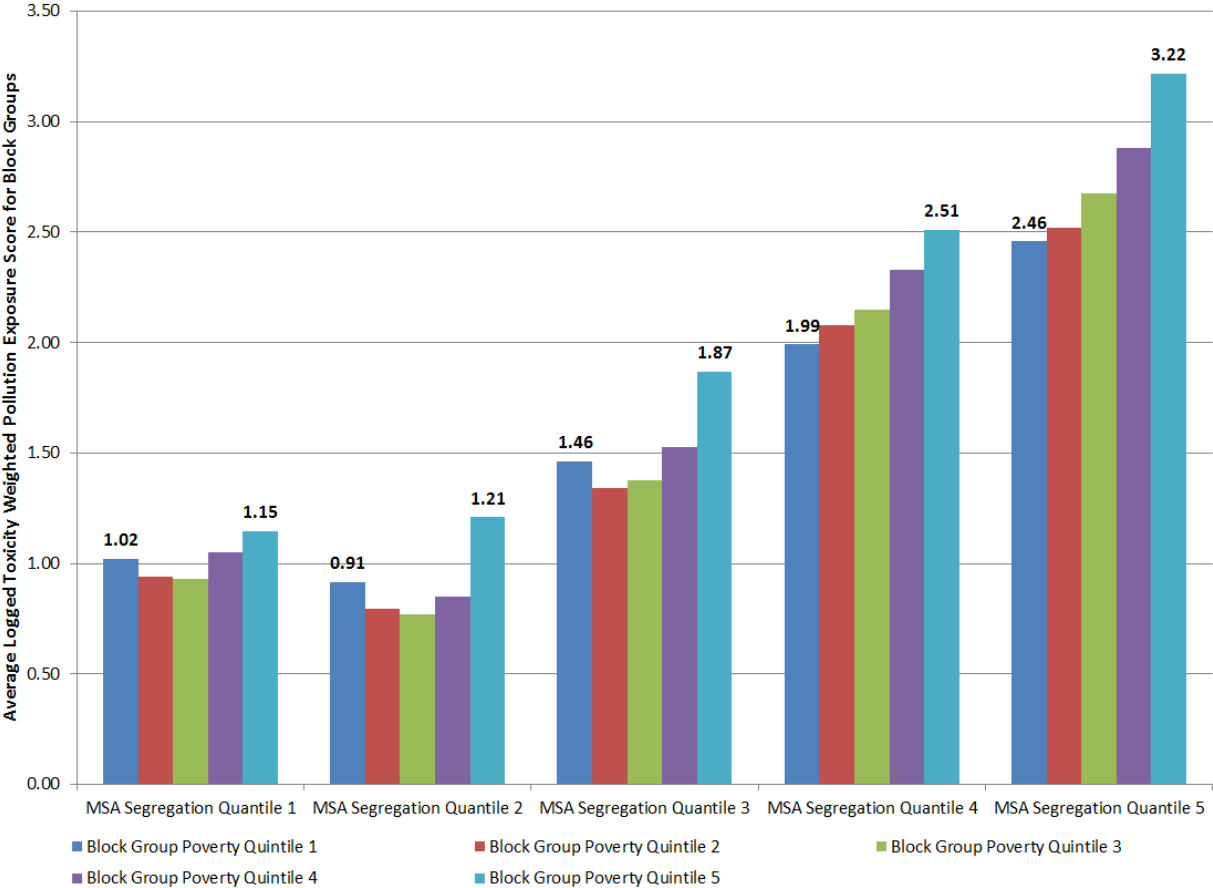
CHAPTER 5

Conclusion

As early as DuBois' 1899 study of the black ghetto in Philadelphia, sociologists have known that residential segregation has a deleterious effect on the health of minorities (DuBois 1996 [1899]). The causes of these negative effects have been greatly expounded upon by scholars over the years.[30] There is now a large body of literature providing evidence that poor and predominately minority communities are overburdened with toxic air pollution. Yet there has been little research asking how residential segregation by race/ethnicity and economic status relates to these unequal environmental risks. This dissertation helps to provide a foundation for such examination. Using detailed pollution exposure data on over 572 industrial chemicals that have been weighted by their toxicity to human health, this collection of work examines how exposure to industrial toxins has changed across racial/ethnic and economic groups from 1995 to 2004 in the United States.

In chapter 2, average exposure to these toxins was calculated for the typical African-American, white and Hispanic individual in the U.S. annually from 1995 to 2004. These results confirmed that pollution exposure was declining over time for every group. When these results were examined for differences by race and income results showed that African-Americans were consistently the most exposed racial group, while whites and Hispanics had similar exposure profiles. It is notable however that Hispanics were exposed to less total amounts of pollution, but overall more toxic substances. Future research should investigate this further to understand if these differences can be explained by incorporation of region and type of industry that might be over represented in certain communities.

---

[30] See Williams and Sternthal 2010 for a recent review of the literature.

When racial groups were also broken down into household income categories, results showed that within racial groups, those with more economic resources were better protected. However when income groups are compared across races results showed that although higher income African-American households were more protected from pollution than lower income African-Americans they were actually more exposed that whites of lower income categories. This has implications for health inequalities as current research has shown that there are racial differences in health that cannot be explained by differences in socioeconomic status (Williams and Sternthal 2010). If African-Americans, regardless of their income, are more exposed to air toxins, then they are at greater risk for the health problems that arise from this exposure, such as cardiovascular disease (Schultz et al. 2005) and asthma (Grineski 2007).

Chapter 3 provides a basis with which to question the straight-forward application of the spatial mismatch hypothesis to the field of environmental justice. The spatial mismatch theory holds that jobs followed white-flight trends out of the central cities, disenfranchising African-Americans from economic opportunity. Applying this directly to the environmental justice literature would imply that as firms moved away from the central city, they took with them the pollution burden they imposed disproportionately on the more urbanized African-American population. The results presented in this paper do not support this theory rather being in the central city is shown to significantly increase one's exposure to industrial air toxins. In addition, counter to current hypotheses, African-Americans outside of the central city are shown to have greater pollution exposure than whites outside of the city. I theorize in this essay that the current EJ literature overlooks the broader context of pollution trends, such as the large-scale declines and stricter regulation of toxins. While such an explicit test of the processes underlying these findings is beyond the scope of this paper, the evidence presented here lays the groundwork for future studies that might evaluate this hypothesis. The fact that results differed using the dissimilarity index as a measure of segregation compared to those using relative centralization as a measure of segregation, make clear that it is important for environmental justice researchers consider what a measure of segregation is capturing. The dissimilarity index, the most commonly used measure of segregation,

measures the spatial clustering of African-Americans in a broader metropolitan area, whereas the relative centralization measure captures the extent to which African-Americans are located in the central city compared to whites. These are different concepts and need to be matched with theory accordingly.

Chapter 4 engages the environmental justice literature on the often cited arguments about the increasing concentration of poverty in America's inner cities posed by Wilson (1978;1996). Wilson argues that deindustrialization concentrated poverty in inner cities by providing economic opportunity outside of the central cities while job opportunities within U.S. cities have declined. This essay links this theory to a metropolitan level measure of concentrated poverty, allowing a more accurate assessment of the idea that areas of poverty, within metropolitan areas where poverty is concentrated, are more exposed to industrial toxins. Results show that as metropolitan level poverty segregation increases, the pollution exposure levels of the most impoverished block groups also increases. However, results show that this relationship is decreasing over time.

Chapters 3 and 4 included models that allow for the comparison across types of segregation. In Chapter 3, model 3 in table 1 presents information for several interactions of racial segregation using the relative centralization measure. This same model is presented in model 3 in table 2 except the dissimilarity index is used as a measure of racial segregation. Finally, in Chapter 4, model 5 includes these same interactions with the proportion of block group poverty replacing the proportion of resident African-Americans. These models are comparable by using the Bayesian Information Criteria (BIC), a popular measure for comparing maximum likelihood models. This model diagnostic determines which set of variables best predicts the outcome without sacrificing parsimony. Unlike the Akaike's Information Criteria used within these chapters, the models being tested do not need to be nested within one another. In other words, I can use the BIC to test which of the possible segregation measures is the best predictor of pollution exposure risk, with those models having lower BICs being better fits. Within the racial segregation models, the BIC for the relative centralization measure of segregation was a much better fit than the dissimilarity index (with a BIC 55,837 points lower than the dissimilarity index BIC). However, the poverty segregation model was relatively the best fit, with a BIC 395,952 points lower than racial segregation models.

While these comparisons are interesting, some scholars have argued that the environmental justice literature has spent too much energy on trying to determine the relative importance of race verses income in explaining disproportionate burdens of pollution exposure (Grant et al. 2010). Such a criticism is warranted as racial and poverty segregation are inherently intertwined in the United States and creating a horse race between them does not easily help explicate patterns of unequal exposure to environmental risk.

These essays are all based on the same data and thus several of the same limitations can be applied across chapters. For example, the dependent variable in all of these studies is the toxicity weighted pollution exposure. The exposure score was calculated by applying weights to the total amount of air pollution (measured in micrograms per cubic meter) to make these chemicals commensurate across health outcomes. This means that scores can only be compared to one another. In addition, these data are modeled from Toxic Release Inventory data, whereby industrial employees provide information to the Environmental Protection Agency about their annual releases of certain industrial toxins. Thus such data are subject to human calculation error. While the Environmental Protection Agency, and non-affiliated groups, make every effort to check these data some error might still be present. On this point it is important to note that these data likely error on the side of underrepresenting pollution exposure. Researcher at the University of Massachusetts have published "top polluters" list from these data for several years and although several firms have contacted them to correct their pollution estimates downward, none have contacted them to correct them in the opposite direction (PERI 2013). Moreover, the environmental integrity project has argued that the Toxic Release Inventory data are systematically underreported (EIP 2004).

In addition, these data are limited to the years 1995 to 2004. While the decline in deindustrialization was consistent with previous years declines, from 1970 to 2009, it would still be judicious to update these exposure estimates as well as incorporate information about other sources of pollution, such as mobile sources, and including information about those facilities that are no longer active, and thus not required to report to the Toxic Release Inventory program, yet still might pose hazards to the local

populations.   Future work needs to include information about the date a facility was established in order to test possible theories revolving around grandfathering of older industries in central cities and how this might be unevenly affecting central city populations.

One of the most fundamental questions in EJ research is related to the siting of industrial facilities: where do facilities locate and who is affected by the resulting pollution? However, there have been large scale declines in manufacturing in the United States over the past several decades (Helper, Krueger, Wial 2012) as well as changes in the spatial patterning of racial and economic groups.

Few to no environmental justice studies have focused on trying to determine if the large scale declines that have been shown to exist in the United States over the past decades have occurred equally across racial and socioeconomic groups. This dissertation addresses these issues and provides a needed foundation for understanding how exposure to industrial toxins has changed over time and how this relates to community level racial and economic inequality.

Bibliography

Amy J. Schulz, Srimathi Kannan, J. Timothy Dvonch, Barbara A. Israel, Alex Allen, III, Sherman A. James, James S. House, James Lepkowski. (2005). Social and Physical Environments and Disparities in Risk for Cardiovascular Disease: The Healthy Environments Partnership Conceptual Model. *Environmental Health Perspectives*. 113(12): 1817–1825.

Ash, M., & Fetter, T. R. (2004). Who Lives on the Wrong Side of the Environmental Tracks? Evidence from the EPA's Risk-Screening Environmental Indicators Model. *Social Science Quarterly*, *85*(2), 441–462.

Atlas, M., & Carolina, N. (2002). Few and Far Between ? An Environmental Equity Analysis of the Geographic Distribution of Hazardous Waste Generation. *83*(1):365-378.

Been, V. and F. Gupta. 1997. "Coming to the Nuisance or Going to the Barrios? A Longitudinal Analysis of Environmental Justice Claims." *Ecology Law Quarterly*. 24:1-56.

Been, Vicki. (1994). Locally undesirable land uses in minority neighborhoods: disproportionate siting or market dynamics? *Yale Law Journal*. 103(6):1383-1422.

Brajer, V., & Hall, J. V. (2005). Changes in the Distribution of Air Pollution Exposure in the Los Angeles Basin from 1990 to 1999. *Contemporary Economic Policy*, *23*(1), 50–58. doi:10.1093/cep/byi005

Brodkin, Karen. (1998). *How Jews Became White Folks*. NJ, USA: Rutgers University Press.

Bullard, R., Mohai, P., Saha, R., & Wright, B. (2007). *Toxic Wastes and Race at Twenty A Report Prepared for the United Church of Christ*. Retrieved from http://www.ucc.org/assets/pdfs/toxic20.pdf

Bullard, Robert (1990*). Dumping in Dixie: Race, Class, and Environmental Quality*, 3rd ed. Boulder, CO: Westview Press.

Census 2001. *1999 Metropolitan Areas Cartographic Boundary Files*. U.S. Census Bureau, Geography Division, Cartographic Products Management Branch. Available at: http://www.census.gov/geo/www/cob/ma1999.html

Census 2010. Metropolitan and Micropolitan Statistical Areas, Annual Estimates of the Population. Available at: http://www.census.gov/popest/data/metro/totals/2012/index.html

Census 2012. Census 2000 Geographic Definitions. U.S. Census Bureau. Available at: http://www.census.gov/geo/www/geo_defn.html#MA.

Census 2013. "Measures of Residential Segregation" Available at: http://www.census.gov/hhes/www/housing/housing_patterns/pdf/app_b.pdf

Chakraborty, J., and M. P. Armstrong. 1997. ''Exploring the Use of Buffer Analysis for the Identification of Impacted Areas in Environmental Equity Assessment.'' Cartography and Geographic Information Systems 24(3):145–57.

Charles, Zubrinsky Camille. 2003. "The Dynamics of Racial Residential Segregation." Annual Review of Sociology, Vol. 29: 167-207

Cole, Luke W. and Sheila R. Foster. (2001). "From the Ground Up: Environmental Racism and the Rise of the Environmental Justice Movement." New York: New York University Press.

Crowder, K., & Downey, L. (2010). Interneighborhood Migration, Race, and Environmental Hazards : Modeling Microlevel Processes of Environmental. *American Journal of Sociology*, *115*(4).

Downey, L. (2005). The Unintended Significance of Race: Environmental Racial Inequality in Detroit. *Social Forces*, *83*(3), 971–1007.

Downey, L. (2007). US Metropolitan-area Variation in Environmental Inequality Outcomes. *Urban Studies*, *44*(5), 953–977.

Downey, L., Dubois, S., Hawkins, B., & Walker, M. (2008). Environmental Inequality in Metropolitan America. *Organization & environment*, *21*(3), 270–294.

DuBois, W.E.B. 1996 (1899). The Philadelphia Negro: A Social Study. Philadelphia: University of Pennsylvania Press.

Environmental Integrity Project (EIP). (2004). Who's Counting? The Systematic Underreporting of Toxic Air Emissions. Environmental Integrity Project and the Galveston-Houston Association for Smog Prevention. Available at: http://environmentalintegrity.org/pdf/publications/TRIFINALJune_22.pdf

Environmental Protection Agency (2005). National-Sclae Air Toxics Assessmnt for 2005 Fact Sheet. 4 United States Environmental Protection Agency. Office of Air Toxics. Washington, DC. Available at: http://www.epa.gov/airtoxics/nata2005/05pdf/nata2005_factsheet.pdf

Environmental Protection Agency (2007). EPA's Risk-Screening Environmental Indicators (RSEI) Methodology. RSEI Version 2.1.5 United States Environmental Protection Agency. Office of Pollution Prevention and Toxics. Washington, DC. Available at: http://www.epa.gov/opptintr/rsei/pubs/method_oct2007.pdf

Environmental Protection Agency (2012a). Our Nation's Air: Status and Trends through 2010. U.S. Environmental Protection Agency Office of Air Quality Planning and Standards EPA-454/R-12-001. Research Triangle Park, North Carolina.

Environmental Protection Agency (2012b).Basics of TRI Reporting. U.S. Environmental Protection Agency. Toxic Release Inventory (TRI) Program. Available at: http://www.epa.gov/tri/triprogram/bussinesscycle/index.html

Environmental Protection Agency (2013). "How did the 2009 Omnibus Appropriations Act change the TRI Form A reporting requirements?" Available at: tri.supportportal.com/ics/support/KBAnswer.asp?questionID=16564&hitOffset=128 &docID=1453

Farley, Reynolds, Sheldon Danziger, and Harry Holzer. (2000). "The Evolution of Racial Segregation." IN Detroit Divided. New York: Russell Sage Foundation

Farrell, C.R. 2008. "Bifurcation, Fragmentation, or Integration? The Racial and Geographic Structure of Metropolitan Segregation, 1990-2000." *Urban Studies* 45(3): 467-499.

Frey, W. (2003). Revival. *American Demographics*,. October: 26–31.

Frey, W. and R. Farley. 1996. "Latino, Asian and Black Segregation in U.S. Metropolitan Areas: Are Multiethnic Metros Different?" Demography 33(1): 35-50.

Frey, William H. and Dowell Myers. (2005) "Racial Segregation in U.S. Metropolitan Areas and Cities, 1990-2000: Patterns, Trends and Explanations." Research Report 05-573. Ann Arbor: University of Michigan Population Studies Center.

Garrard (1994) Fear and Loathing in the Siting of Hazardous and Radioactive Waste Facilities- A Comprehensive Approach to a Misperceived Crisis. *Tulane Law Review*.

Gee, G.C., Payne-Sturges, D.C., 2004. Environmental health disparities: a framework integrating psychosocial and environmental concepts. Environ. Health Perspectives. 112 (17), 1645–1653.

Geer, Laura A., Jeremy Weedon, Michelle L. Bell (2012). Ambient air pollution and term birth weight in Texas from 1998 to 2004. Journal of the Air and Waste Management Association. 62(11): 1285–1295.

Grant, D., Trautner, M. N., Downey, L., & Thiebaud, L. (2010). Bringing the Polluters Back In: Environmental Inequality and the Organization of Chemical Production. *American Sociological Review*, *75*(4), 479–504.

Grineski, Sara (2007). Incorporating health outcomes into environmental justice research : The case of children ' s asthma and air pollution in Phoenix , Arizona. *Environmental hazard 7: 360 -371.*

Guzmán. (2001). The Hispanic Population. Census 2000 Brief. U.S. Department of Commerce. Economics and Statistics Administration. C2kBR/01-3.

Hamilton, James T. (1995). Testing for Environmental Racism: Prejudice, Profits, Political Power? *Journal of Policy Analysis and Management*, 14(1).

Hawley, Amos. (1971) Urban Society: An Ecological Approach. 2nd ed. New York

Hayanga, Awori J., Steve B. Zeliadt, and Leah M. Backhus (2013). Residential Segregation and Lung Cancer Mortality in the United States. 148(1):37-42.

Helper, Susan, Timothy Krueger, and Howard Wial. (2012). Locating American Manufacturing: Trends in the Geography of Production. Brookings Institute. Metropolitan Policy Program. Advanced Industries Series no(2). Available at: http://www.brookings.edu/~/media/research/files/reports/2012/5/09%20locating%20 american%20manufacturing%20wialh/0509_locating_american_manufacturing_rep ort.pdf

Iceland, John and Kyle Anne Nelson. 2008. "Hispanic Segregation in Metropolitan America: Exploring the Multiple Forms of Spatial Assimilation." *American Sociological Review*. 73, 5: 741-765.

Iceland, John, Luis Sanchez, and Gregory Sharp. (2010), "Racial and Ethnic Residential Segregation in the United States: Comparisons Across Racial and Ethnic Groups, 1970-2009." Changing American Neighborhoods and Communities Report Series no 3. Penn State Population Research Institute.

Iceland, John. 2004. "Beyond Black and White: Residential Segregation in Multiethnic America." *Social Science Research*. 33, 2: 248-271.

Kahn, M. E. (1997). Particulate pollution trends in the United States. *Regional Science and Urban Economics*, *8*(1), 86–107.

Kahn, M. E. (1999). The Silver Lining of Rust Belt Manufacturing Decline. *Journal of Urban Economics*, *46*(3), 360–376.

Kain, John. (1968) Housing Segregation, Negro Employment, and Metropolitan Decentralization. *Quarterly Journal of Economics*. 82(2): 175-197.

Kandel,William and JohnCromartie. 2004.New Pattern of Hispanic Settlement in Rural America. Rural Development Research Report No. 99.Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Kasarda, John. (1972). The Theory of Ecological Expansion: An Empirical Test. Social Forces. 51(2): 1655-175.

Kim, Yeni, Bung-Nyun Kim, Yun-Chul Hong, Min-Sup Shin, Hee-Jeong Yoo, Jae-Won Kim, Soo-Young Bhang, Soo-Churl Cho (2009). Co-exposure to environmental lead and manganese affects the intelligence of school-aged children. NeuroToxicology. 30(4): 564–571.

Konisky and Schario (2010). Examining Environmental Justice in Facility-Level Regulatory Enforcement. Social Science Quarterly. 91(3): 835-855.

Kurtz, H. E. (2003). Scale frames and counter-scale frames: constructing the problem of environmental injustice. Political Geography, 22(8), 887–916.

Lee, S., and Leigh, N. G. (2007). Intrametropolitan Spatial Differentiation and Decline of Inner-Ring Suburbs: A Comparison of Four U.S. Metropolitan Areas. *Journal of Planning Education and Research*, *27*(2), 146–164.

Lee, Sungyun, Paul Mohai and Byoung-suk Kweon (2010). Comparing TRI Emission Estimates with the National Air Toxics Assessment and Air Quality Monitoring Data. Presented at the National Training Conference on the Toxics Release Inventory (TRI) and Environmental Conditions in Communities. November 2, Washington, D.C.

Lichter, D. T., Parisi, D., & Taquino, M. C. (2013). The Geography of Exclusion : Race , Segregation , and Concentrated Poverty. Social Problems. *59*(3), 364–388.

Lieberson, Stanley, 1980. *A Piece of the Pie: Black and White Immigrants Since 1880*. Berkeley, CA: University of California Press.

Logan, John and Brian Stults (2011). "The Persistence of Segregation in the Metropolis: New Findings from the 2010 Census." Census Brief prepared for Project US2010.

Lopez, R. (2002). Segregation and black/white differences in exposure to air toxics in 1990. *Environmental Health Perspectives*, *110 Suppl* , 289–95.

Lynch, Michael J., Paul B. Stretesky and Ronald G. Burns. (2004) Determinants of environmental law violation fines against petroleum refineries: Race, ethnicity, income, and aggregation effects. Society and Natural Resources , 17 (4) : 343 – 5

Maantay, J. (2002). Mapping environmental injustices: pitfalls and potential of geographic information systems in assessing environmental health and equity. *Environmental health perspectives*, *110 Suppl* , 161–71.

Maasoumi, E., & Millimet, D. L. (2005). Robust inference concerning recent trends in US environmental quality. *Journal of Applied Econometrics*, *20*(1), 55–77. doi:10.1002/jae.759

Marsh, K., W. Darity, Jr., P. Cohen, L. Casper, and D. Salters. 2007. "The Emerging Black Middle Class: Single and Live Alone." Social Forces. 86(2): 1-28.

Massey, Douglas and Nancy Denton. 1993. *American Apartheid.* Cambridge, MA: Harvard University Press.

Massey, Douglas S., The Dimensions of Residential Segregation , Social Forces, 67:2 (1988:Dec.) p.281. (1988)., *2*.

Mather, Mark, Kelvin Pollard, and Li. J. (2011). *Reports on America: First Results from the U.S. Census*. Population Reference Bureau.

Mitchell, J.T., D.S.K. Thomas, and S.L. Cutter, 1999. "Dumping in Dixie Revisited: The Evolution of Environmental Injustices in South Carolina", *Social Sciences Quarterly* 80 (2): 229-243

Mohai, Paul and Robin Saha. (2006) . Reassessing Racial and Socioeconomic Disparities in Environmental Justice Research. Demography. 43(2): 383-399.

Morello-Frosch, R., & Jesdale, B. M. (2006). Separate and Unequal: Residential Segregation and Estimated Cancer Risks Associated with Ambient Air Toxics in U.S. Metropolitan Areas. *Environmental Health Perspectives*, *114*(3), 386–393.

Morello-Frosch, R., & Lopez, R. (2006). The riskscape and the color line: examining the role of segregation in environmental health disparities. *Environmental research*, *102*(2), 181–96.

Mouw, T. (2000). Job Relocation and the Racial Gap in Unemployment in Detroit and Chicago, 1980 to 1990. *American Sociological Review*, *65*(5), 730.

National Cancer Institute. Asbestos Exposure and Cancer Risk Fact Sheet. Available at: http://www.cancer.gov/cancertopics/factsheet/Risk/asbestos.

Oakes, J., Anderton, D. L., & Anderson, A. B. (1996). A Longitudinal Analysis of Environmental Equity in Communities with Hazardous Waste Facilities. *Social Science Research*, *25*(2), 125–148.

Park, Robert. 1915. "The City: Suggestions for the Investigation of Human Behavior in the City." American Journal of Sociology. 20: 577-612.

Pastor, M., Sadd, J. im, & Hipp, J. (2001). Which Came First? Toxic Facilities, Minority Move-In, and Environmental Justice. *Journal of Urban Affairs*, *23*(1): 1–21.

Pastor, Manuel. (2008). *Second Narrative Report for Data Analysis for Change: Research Consortium for Environmental Justice. Center* for Justice, Tolerance and Community. University of California, Santa Cruz, CA.

Political Economy Research Institute (PERI). How Accurate are the RSEI Data on Toxic Air Pollution? University of Massachusetts Amherst, MA. Available at: http://www.peri.umass.edu/accurate/

Pulido, L. (2000). Rethinking Environmental Racism : White Privilege and Urban Development in Southern California. *Annual of the Association of American Geographers*, *90*(1), 12 –40.

Quillian, Lincoln. 1999. "Migration Patterns and the Growth of High-Poverty Neighborhoods, 1970-1990." American Journal of Sociology 105: 1-37.

Reardon, S. F., & O'Sullivan, D. (2004). Measures of Spatial Segregation. *Sociological Methodology*. (650): 121–162.

Right to Know Network. (2013). TRI Facilities for Miami, Florida in 2001. Available at: http://www.rtknet.org/db/tri/tri.php?city=miami&state=fl&dbtype=C&rsei=y&sortp=D&detail=-1&datype=T&reptype=f&reporting_year=2001&submit=GO&sum_expand=H

Robertson, H. (1995). "If your grandfather could pollute so can you." *Catholic University Law Review*.

Smith, C. L. (2009). Economic deprivation and racial segregation: Comparing Superfund sites in Portland , Oregon and Detroit, Michigan. *Social Science Research*, *38*(3), 681–692.

Stretesky, P., & Hogan, M. J. (1998). Environmental Justice: An Analysis of Superfund Sites in Florida. *Social Problems*, *45*(2), 268–287.

Sugrue, Thomas. (1996). *The Origins of the Urban Crisis: Race and Inequality in Postwar Detroit*. Princeton, NJ: Princeton University Press.

Taylor, Dorceta. (2000). The Rise of the Environmental Justice Paradigm Injustice Framing and the Social Construction of Environmental Discourses. American Behavioral Scientist. 43(4): 508-580.

Taylor, Dorceta. (2009). *The Environment and the People in American Cities, 1600's - 1900's: Disorder, Inequality and Social Change.* Durham, NC: Duke University Press.

Timberlake, J. M., and Iceland, J. (2007). Change in Racial and Ethnic Residential Inequality in American Cities, 1970–2000. *City & Community*, *6*(4), 335–365.

United Church of Christ (1987). Toxic Wastes and Race in the United States. A National Report on the Racial and Socio-Economics Characteristics of Communities with Hazardous Waster Sites. New York, NY: Commission for Racial Justice.

Venkatesh, Sudhir. 2000. *American Project: The Rise and Fall of a Modern Ghetto*. Cambridge, Mass: Harvard University Press.

Watson, Tara (2009). "Inequality and the Measurement of Residential Segregation by Income." *Review of Income and Wealth* 55: 820-844.

Weber, Alfred. (1909) Uber den Standort der Industrien (translated by Friedrich C. J. (1929) Alfred Weber's Theory of the Location of Industries, University of Chicago Press, Chicago.

Weinberg, Daniel. (2011). U.S. Neighborhood Income Inequality in the 2005–2009 Period. American Community Survey Reports. US Census. Available at: http://www.census.gov/prod/2011pubs/acs-16.pdf

Wheeler, C. H., & La Jeunesse, E. a. (2008). Trends in Neighborhood Income Inequality in the U.S.: 1980-2000. *Journal of Regional Science*, *48*(5), 879–891.

Wial, Howard and Alec Friedhoff. (2006). "Bearing the Brunt: Manufacturing Job Loss in the Great Lakes Region, 1995–2005." Brookings Institute. Metropolitan Policy Program.

Williams, D. R., & Sternthal, M. (2010). Understanding Racial-ethnic Disparities in Health: Sociological Contributions. Journal of Health and Social Behavior, 51(1 Suppl), S15–S27. doi:10.1177/0022146510383838

Wilson, William Julius. (1987) The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy. Chicago: University of Chicago Press.

Wilson, William Julius. (1996). When Work Disappears: The World of the New Urban Poor. New York: Alfred A. Knopf.