ABSTRACT

PIONTAK, JOY RAYANNE. Childhood Obesity and Place: Poverty, Race, and Food Access. (Under the direction of Dr. Michael D. Schulman).

Rates of childhood obesity have tripled in America in the last 30 years, making it one of the nation’s most pressing public health concerns and leaving researchers with important questions about how this has happened and how to change the direction of weight among children. However, while there is a great deal of research examining how diet, exercise, and type and frequency of food outlets impact individual weight status, the impact of social structural and community-level inequalities, particularly in rural areas, remain largely unexamined. Similarly, while persistent residential and educational segregation by race and socioeconomic status are commonly accepted as key aspects of understanding spatial inequality, little has been written about their effect on rates of childhood obesity across urban and rural spaces. Further, while one’s individual characteristics are known to be important parts of weight status, less is known regarding how their individual characteristics interact with their environment. My research seeks to fill this void by examining the effect of social place and interaction between individuals and their social place on rates of childhood obesity in North Carolina.

Using multilevel logistic regression I examine Body Mass Index (BMI) data collected from a sample of 74,822 public school students in grades 3-5 along with school- and county-level variables. The empirical chapters examine the effect of racial segregation and economic segregation at the school and community levels and the effect of food access, respectively. The results indicate that school poverty and minority-segregated schools have a statistically
significant and positive effect on the likelihood of a child being obese. The effect of the individual student’s race varied based on the racial composition of their school. Moreover, students in rural counties had an increased likelihood of being obese compared to their urban counterparts, net the effect of other variables in the model. The results for food access were less clear as the models did not indicate any statistically significant results, net the effect of the racial and economic segregation variables. The implications of this research, as well as directions for future research, are discussed.
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Childhood Obesity and Place: Poverty, Race, and Food Access

by
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DEDICATION

Dedicated with love to the (not so little) Aidan Piontak: for your kind heart, your curiosity, your creativity, your announcements and parties, and your jokes. You are the best kid and I am so grateful that I get to be your parent.
BIOGRAPHY

Joy Piontak was born in Chicago, IL and later moved to Catoosa, Oklahoma where she spent the majority of her childhood. Joy grew up with her parents, Cindy and Gary Piontak, and three siblings, Corrie, Nathan, and Rachel (Reggie).

Joy graduated high school from Claremore Alternative Learning Center in 1996 and began taking classes at Tulsa Community College the following fall. In 2000, Joy earned an Associates in Arts and transferred to the University of Tulsa. She graduated Cum Laude in May of 2003 with a Bachelor’s of Arts in Sociology, a Minor in Political Science and a Certificate in Women’s Studies. Thanks to the tremendous support and encouragement of Dr. Jean Blocker, Dr. Susan Chase, and Dr. Lara Foley at the University of Tulsa, Joy enrolled in the Sociology graduate program at North Carolina State University where she went on to earn a Master of Science in Sociology in 2008.

Joy currently resides in Raleigh with her partner, Zachary Gillan, and nine year old son, Aidan.
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CHAPTER ONE: INTRODUCTION

In a speech in 2010, First Lady Michelle Obama proclaimed obesity to be “an epidemic and one of the greatest threats to America’s health and economy” (Hellmich 2010). Her voice is one of many calling for increased attention to the staggering rise in rates of obesity in America. Of particular concern is the rate of childhood obesity, which has tripled among American children since 1980 (Ogden et al. 2002). Recent national estimates suggest that the percentage of obese school-aged children (BMI≥95\textsuperscript{th} percentile) is now around 17 percent. If overweight children (BMI≥85\textsuperscript{th} percentile) are also included, this proportion leaps to around one-third. (Ogden et al. 2010a).

With approximately one in three children currently overweight or obese, experts warn that the health implications for future generations are alarming. Obese children are not only much more likely to suffer from other childhood health problems such as high blood pressure than non-obese children, but are also more likely to be obese as adults (Freedman et al. 2007). As obese adults they are at higher risk for many chronic conditions including cardiovascular disease, diabetes, and certain cancers (Freedman et al. 2007; National Institutes of Health 1998; Nguyen et al. 2011). Based on the current rates of childhood obesity, researchers have even argued that the average life expectancy may be two to five years shorter for this generation, reversing a long-term trend of increases in average life expectancy (Olshansky et al. 2005).

While rates of childhood obesity have increased throughout the population in the past 30 years, reports indicate that race, poverty, and geographic location significantly affect variations in obesity rates (Centers for Disease Control and Prevention 2009; Ogden et al.
Poor and minority children experience higher rates of obesity and overweight than their wealthier, whiter counterparts (Ogden and Carroll 2010). Given that the rates of childhood obesity are not randomly distributed throughout America, investigating and understanding the social basis of obesity is imperative to understanding these recent trends.

Despite the uneven distribution of childhood obesity rates, the research and interventions surrounding the issue of childhood obesity largely rely on an individualist discourse centered on personal responsibility. For example, both the Centers for Disease Control and the “Let’s Move” program established by the First Lady encourage parents and students to make healthier food choices and to reduce children’s screen time (Li and Hooker 2010; Thompson 2010). To the extent that environmental factors are discussed, they tend to focus on physical aspects of place (e.g. number of stores, fast food restaurants, parks, etc.) and exclude discussions of social inequality across place, such as racial and economic segregation (Burdette and Whitaker 2004; Williams et al. 2012).

This research provides an examination of the social structural context, such as racial and economic segregation, to understand the social basis of childhood obesity. To do so, I bring together sociological literature on inequality across place and public health literature on childhood obesity to add to both bodies of literature. Similarly, while there is some literature on environmental causes and a great deal on the role that individual-level characteristics play, they are often examined separately. Disagreements over the relative importance of structure or individual characteristics are a longstanding point of discussion in the sociological conversation (Mayhew 1980). This research uniquely contributes to and furthers this discussion through the use of a multilevel modeling technique to examine individual-level,
school-level, and community-level characteristics together and in concert with how they interact to effect a child’s likelihood of obesity.

Placing Blame

Given that obesity is most prevalent among the poor, it is essential to examine how the problems of the poor have historically been conceptualized. Research on poverty, as well as other inequalities, has a long history of pointing the finger at individual deficiencies (Murray 1994). While manifestations of this argument range from the biological inferiority of the poor to unwise choices on their part, the cause of poverty was always the individual. This is also evident in the focus on healthier eating habits and increasing exercise (Hawkins and Linvill 2010).

Individualistic approaches to poverty are often expanded into the cultural approach. The “culture of poverty” approach argues that rather than flawed individuals, a poverty-enforcing culture lies at the root of the social problem (Katz 1990). When applied to childhood obesity, this approach points to a culture of junk food consumption that perpetuates the problem of obesity (Boutelle et al. 2007). The prominence of this approach is evident in the most recent USDA Dietary Guidelines for Americans which places “Social and Cultural Norms and Values” as the outermost ring of their figure depicting the social ecological framework in which decisions regarding nutrition and physical activity are made (U.S. Department of Agriculture and U.S. Department of Health and Human Services 2010, p. 56). What’s missing is a structural layer which acknowledges that individuals and their cultures are affected by the social structure.
The structural approach examines how stratification, economic systems and spatial segregation create and maintain unequal access to resources. This is the approach I will be adopting in this research. Despite the fact that obesity is highly correlated with race, class, gender, and geographic location (Ogden et al. 2010a), very little is known about the effects of the social environment or place. To begin to fill this gap, this research project examines the role of place through an analysis of the effects of racial segregation, poverty, urban/rural location, and food deserts on childhood obesity.

In the following, I explore the historical context through which current structures of inequality across place have evolved. This serves as a background for the issues that will be addressed in this research.

**Historical Context**

Awareness of the historical contexts of racial segregation, poverty, and food access are important for understanding how Americans have come to be organized across place. Residential segregation by race has a long history in the United States. Prior to the 1900s African-Americans and Whites did not have the type of segregated living arrangements that we see today. During the civil war, there is little evidence that skin color was a basis for exclusion from neighborhoods in northern cities (Massey and Denton 1993). However, the same authors argue that over the last 90 years racial segregation has been actively maintained by whites. Through explicit laws and later individual contracts, racial segregation was enforced well into the 1970s. Despite the 1988 Fair Housing Amendments aimed at decreasing institutional discrimination in housing, Massey and Denton (1993) point out that
segregation patterns continue to be “maintained today by a set of institutions, attitudes, and practices that are deeply embedded in the structure of American life” (p. 217).

Today residential segregation remains a very real part of the American landscape. Preliminary results from the 2010 Census show that the Dissimilarity Indices\(^1\) for the top 50 most segregated cities range from indices of 81.5 to 56.2 for African-Americans and Whites and 63.4 to 43.3 for Latinos and Whites. While these estimates are lower than prior years and thus indicate that metropolitan segregation may be slowing declining, new macro patterns of segregation may be emerging. As increased numbers of African American families are leaving the inner cities, there is evidence that new patterns of segregated suburban communities and rural areas may be emerging to replace old patterns of segregation (Parisi, Lichter, and Taquino 2011). Research shows that not only is race a persistent factor, but poverty is concentrated in particular communities and that these patterns remain consistent over time (Wimberley and Morris 2003). Moreover, there is evidence that affluent families are distancing themselves from both middle- and lower-income Americans (Reardon and Bischoff 2011).

Racial segregation involves both housing and schooling. While the 1954 Supreme Court decision \textit{Brown vs. Board of Education} has a prominent place in our collective imaginations as the end of educational segregation in America, in reality it created a brief period of integration followed by a less visible re-segregation (Kozol 2005). Even within integrated schools there is evidence that resources are not allocated evenly between white

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\(^1\) The dissimilarity index is a commonly accepted measure of separation between two groups within a county and it ranges from 0 to 100 with 0 indicating perfect integration and 100 complete segregation. Scores of 60 and above considered high.
and non-white students (Lewis 2011). This inequality has implications not only for academic resources, but also for the resources necessary for maintaining good student health such as food and physical education.

Historically, schools have been a very significant site for the politics of poverty and food access. While school meals were initiated through local efforts in the Progressive Era around the turn of the century, it was not until the 1930s that the government became involved. The initial program was born out of an embarrassing incident in which the then Secretary of Agriculture ordered the slaughter and disposal of a massive number of young pigs in order to stabilize the hog market. Public outcry over the waste of food when so many were in need led to the establishment of relief channels by which surplus agricultural items could go to the needy. The program has changed significantly over the years as political and public priorities have shifted. During the War on Poverty in the 1960s, the program expanded greatly, with spending increasing from $201.8 million in 1967 to $2.3 billion in 1975, in an effort to end hunger and malnutrition among American children. While meal quality was a part of the discussion, the focus was on the urgent need to end hunger in the 1960s and ‘70s (Poppendieck 2010).

The 1980s brought a new political focus on lowering government spending and a new war on the poor themselves. In the face of budget cuts and increasingly limited resources, competitive food sales (private companies selling food products within schools) were given a boost in public schools. The Dietary Guidelines for Americans, first published in 1980, increased concerns about the American diet at the same time that schools were receiving a great deal of dairy and beef subsidies. As Poppendieck (2010:77) articulates in her historical
account: “The old worries about vitamin and mineral deficiencies had given way to mounting anxiety about heart disease and diabetes, with overweight and diets high in saturated fats identified as the underlying cause.” In 1994, legislation was passed to require school meals to comply with Dietary Guidelines as part of the Healthy Meals for Healthy Americans Act (Poppendieck 2010). Some feared that these regulations would result in junk food that was fortified with the required nutrients and offered in lieu of fruits and vegetables (Pannell 1995).

In addition to issues of spatial segregation with regard to housing, schools, and food programs for children, recent decades have also seen a significant change in American food and food access. With the introduction of high fructose corn syrup (HFCS) in the 1980s, the cost of manufacturing processed foods was lowered significantly. HFCS’ ability to act as an inexpensive filler, sweetener, and preservative has made it a staple ingredient in inexpensive and highly processed foods. While there has been debate about the role that HFCS has played in the increase in rates of obesity, there is little doubt that it has made highly processed and high caloric foods more easily available and cheaper than before (Duffey and Popkin 2008). Even as processed foods became more readily available to lower income Americans, the 1990s also saw the beginning of the organic farming and whole foods movement, bringing high quality and high cost foods to those Americans who could afford them (Miller 2010). Recent data show that the price of fresh fruits has experienced higher inflation than that of processed foods (Drewnowski 2004; Drewnowski and Barratt-Fornell 2005; Parker-Pope 2007). In a New York Times article, Dr. Adam Drewnowski, a professor of Epidemiology at the University of Washington, went so far as to say that “Not only are the empty calories
cheaper, but the healthy foods are becoming more and more expensive. Vegetables and fruits are rapidly becoming luxury goods” (Parker-Pope 2007:1). In addition to price changes, we have seen a consolidation of larger grocery stores resulting in the creation of food deserts which have limited many marginalized peoples’ ability to access fresh foods (Blanchard and Matthews 2007).

Within this historical context, Americans experienced a significant increase in obesity, particularly among children. Racial and economic segregation persist, leaving poorer and non-white communities with fewer resources in their schools and communities. Food store consolidation, changing school food program priorities, and price increases significantly affect the ability of marginalized people to access the healthy foods that more privileged Americans enjoy. Given what we know about inequality and how it structures the lives of Americans, it is imperative to understand the role of place in matters of public health.

This rise in childhood obesity has taken place in the context of larger structural changes that remain largely unexamined. When social conditions are discussed, they often lack a critical, sociological examination of how resources are distributed among groups of people across place. Childhood obesity has become a serious public health concern at the same time that structural inequalities among racial and class groups have become muted in contemporary discourse (Bonilla-Silva 2010). This research seeks to bring together what we know about systematic inequality and childhood obesity to gain a fuller understanding of how structural inequality affects this serious public health issue.

Summary of Chapters
This research examines the effects of poverty, race, and food access on childhood obesity. In chapter 2, I begin with a review of the perspectives surrounding individual and structural approaches to social problems. Next, I provide a summary of the literature on childhood obesity and a review of the research on how poverty, race and food access affect health. I also discuss how this research fills critical gaps in these literatures and how it contributes to the scholarly debate on childhood obesity. I end the chapter by discussing how this work will address those gaps.

Chapter 3 discusses the methodological approach of the research. I begin by setting forth the research questions that I developed based on my review of the current literature. In this chapter, I provide a detailed overview of the data sources, data access, and database construction. I also include detailed descriptions of key variables, descriptive statistics, and multicollinearity diagnostic results. Additionally, given the structural nature of this research project, I articulate the statistical approach and rationale behind the analyses.

In chapter 4, I examine the effect of school- and community- level poverty on childhood obesity. I begin with an examination of the covariance among students in schools and schools in counties and find that there is statistically significant covariation that justifies the use of a multilevel model. Next, I discuss the correlation between high poverty and high racial segregation at the school level. I then present the results of the nested multilevel models. I find that school-level poverty does impact the likelihood of obesity among children in the sample. Finally, I discuss the implications of the findings and how they relate to prior research on poverty and obesity.
Chapter 5 examines the effect of school- and community-level racial segregation on rates of childhood obesity, as well as the interaction between individual race and the racial composition of the school. I find that school racial segregation does have a statistically significant effect on the likelihood of obesity for students in the sample. Second, I find that there is an interaction between the student’s race and the racial composition of their school. Finally, I discuss the implications of this finding and how it relates to the current literature.

In chapter 6, I examine the effect of food deserts on the likelihood of obesity. I begin by examining the differences between urban and rural food environments in North Carolina. Next, I test the effect of several food environment variables on the likelihood of obesity. My findings indicate that children who lived in food desert counties did not have a different likelihood of obesity compared to children who did not live in food desert counties. I then explore the implications of this finding and suggestions for future research.

Finally, chapter 7 provides a summary of this research and the findings. It details why this research is important, the strengths and weakness of this research and the implications for the direction of future research on childhood obesity as well as policy implications.
CHAPTER TWO: LITERATURE REVIEW

This chapter provides a review of the relevant literatures for this research. It begins with an overview of perspectives about the individual and structural approaches to sociological issues and how this project fits into this discussion. Next, I review the relevant research on childhood obesity. The literature on childhood obesity is large and growing at a rapid pace; as such, the review concentrates less on individual epidemiological and public health studies and more on overall trends, general assumptions and findings. I also review the literature on health and structural inequality as it relates to poverty, racial segregation, and food access. Finally, I conclude this chapter by providing a summary of the literature and a discussion of how this research contributes to sociological approaches to childhood obesity.

Theoretical Approaches

Della Fave argues that “Stratified social orders are maintained through a wide variety of mechanisms, one being broad-based legitimating ideology of the notion of unequal distribution of primary resources” (1980:955). It is this ideology that leads to the presumption that those who do not have enough resources are somehow personally deficient, leading researchers, policy makers, and activists alike to look for the answer to social ills in the actions and qualities of the individuals themselves instead of the social structure. It is often only when the legitimating ideologies can no longer explain away inequality that we begin to look for blame outside of the victims themselves (Della Fave 1980). In the same way that the Great Depression brought demands for assistance from the government for those oppressed by capitalism (Piven and Cloward 1993), perhaps the mass increases in obesity rates will encourage a look beyond the individual to the social context.
Placing the blame for inequality on those who are the victims of unequal social structures is a well-established phenomenon in sociological theory. There are several ways in which this process of victim blaming takes place in order to maintain, justify, and reproduce inequalities. Part of this process involves the defining of one group as intellectually and/or morally superior to another (Schwalbe et al. 2000). Differences are seen as defects and are used to justify the poor treatment of those in the subordinate group. This process, known as “oppressive othering,” serves to legitimate inequality and a common understanding that subordination is deserved.

The difficult task of attempting to understand individual behavior without losing sight of the role that social conditions play, is a matter of much discussion among sociologists (Jepperson and Meyer 2011; Melamed and North 2010). Arguing that 95 percent of the interesting sociological variation happens at what he calls the structural level, Mayhew’s scathing review of American sociologists’ focus on individuals started a discussion that has continued in the sociological literature (Mayhew 1980; Mayhew 1981). Jepperson and North, in a similar fashion, caution against assuming that social conditions are accounted for in the characteristics of individuals (2011). Others have stressed the importance of understanding that individual actions make up what we know as social structures (Fenstermaker and West 2002; Schwalbe et al. 2000). In sum, while individualistic approaches may still dominate American sociology, there is a continued discussion about how to incorporate the larger social context more fully into research about social actors.

In the review that follows, I argue that limiting the scope of analysis to individuals often results in making invisible those processes that work to create and maintain unequal
access to resources. Further, if we do not understand the context in which choices are made, we run the risk of misrepresenting behaviors that are a reflection of social standing. We are also in danger of blaming the victims, those in subordinate social positions, for problems that have largely to do with the context in which they live and the unequal distribution of primary resources. Further, without an examination of the structure, we cannot fully understand the sociological processes at work.

Children Obesity

A recent qualitative study aimed at understanding how the public views and understands the problem of obesity found that respondents overwhelmingly blamed individuals for their obesity (Niederdeppe, Robert, and Kindig 2011). The most frequently cited reasons for obesity were “1) intrinsic individual dispositions (e.g., lazy, unmotivated); 2) lack of knowledge and skills; and 3) genetic, medical, or biological causes” (Niederdeppe et al. 2011: 3). Moreover, the article found that respondents were more reluctant to support policies addressing structural barriers to decrease childhood obesity than adult obesity. They were more likely to blame poor parenting and less likely to be sympathetic or think external changes would address the problem for children. Research on the framing of obesity in media also indicates that individual behavioral changes were the most often cited solution to obesity (Barry et al. 2011). We see a parallel in the academic research on childhood obesity with regard to explaining the recent increases in childhood obesity.

Research on childhood obesity, consistent with popular opinions, often focuses on individual-level factors as the root cause of increased rates (Barlow 2007; Birch and Ventura 2009). A search of this body of literature, which primarily comes from the fields of public
health and medicine, reveals a broad range of potential contributors (genetic, behavioral, cultural preferences, food environment), but beyond an accounting of food stores or gyms, there is a distinct lack of research on social structural causes. Even characteristics known to be grouped spatially (such as low-income or minority status) are cast as individual traits (Clarke et al. 2009; Neumark-Sztainer et al. 2003; Ogden et al. 2010b). Moreover, despite the plethora of research, there remains a real lack of progress in terms of finding ways to effectively prevent or treat childhood obesity (Barlow 2007; Birch and Ventura 2009; Reinehr and Wabitsch 2011). In the following, I provide an overview of the current literature on the individual, cultural, and environmental causes of childhood obesity, followed by a discussion of what is missing from this literature.

Epidemiological research has made significant attempts to uncover a genetic basis for obesity; however, to date even the most promising findings are only applicable to a very small proportion of the population (Han et al. 2008; Han, Lawlor, and Kimm 2010; Strauss 2002). Twin and adoption studies are often the source for examining genetic differences, and a recent systematic review shows that they are focused almost exclusively on white children (Silventoinen et al. 2010). This review also finds that presumed genetic effects explain less variation than family environment in early childhood. While there have been some isolations of genetic abnormalities that effect obesity (Han et al. 2010), these do not explain the large increase in the proportion of children who are obese or overweight over such a short period of time. Moreover, genetic predispositions are known to be affected (i.e., of more or less importance) by the child’s home environment and behaviors (Barlow 2007; Bouchard 2009). Other research has shown that less than 5 percent of obese people have an identified genetic
abnormality (Power and Schulkin 2009). Considering the limitations of genetic research, an examination of inequalities across place and available resources within communities is necessary in order to fully understand this important public health issue.

Individual behaviors among children have also been extensively researched and some patterns have been found at the individual level. Increases in the portion size of meals and decreases in physical activity in favor of television or video games have been cited as factors that have contributed to higher obesity rates (Fisher, Rolls, and Birch 2003; Flood, Roe, and Rolls 2006; McConahy et al. 2002; Nielsen and Popkin 2004; Nielsen, Siega-Riz, and Popkin 2002; Nielsen and Popkin 2003; Piernas and Popkin 2011). Longitudinal studies indicate that these lifestyle trends persist into adulthood (Gordon-Larsen, Nelson, and Popkin 2004a). As such, a great deal of research has focused on the measurement and modification of these behaviors through attempts to educate and motivate (essentially re-train) children to eat different foods (Barlow 2007; Bean et al. 2011; Collins et al. 2006; Collins, Watson, and Burrows 2010; Fisher et al. 2003; Kelly et al. 2011; Mushser-Eizenman et al. 2010; Tripp et al. 2011) These studies, as with the ones focused on parental behavior, assume that it is poor choices or a lack of individual knowledge that fuels obesity among children.

Some research on television viewing has found that while there are statistically significant relationships between television viewing and weight with regard to white children, it is not always so with non-white children (Henderson 2007). Another longitudinal study suggests that children may become inactive due to obesity and not the other way around (Metcalf et al. 2011). With such ambiguity around the relationships between individual behaviors and their relationship to obesity in certain groups of children, we must
look to the context in which these children live to understand these relationships. In sum, relatively little is known about the context in which children and families are making behavioral choices in this literature.

As noted above, the importance of parental behavior and home environment have emerged as key issues in childhood obesity research. These concepts, however, are rarely conceptualized as much more than individual or family preferences with no discussion of context or structural limitations (Kelly et al. 2011). A recent review of the childhood obesity literature (Tabacchi et al. 2007) found extensive research on the behavioral practices of pregnant mothers, such as undernutrition, hyper caloric nutrition, excessive protein intake, smoking, pre- and post- pregnancy weight and dietary toxic substances. There is also an extensive literature on the practices of the parents of young children, such as breastfeeding and weaning behaviors, the introduction of food, variations in food type presentations, and attitudes towards feeding (Baranowski et al. 1990; Bergmann et al. 2003; Birch and Ventura 2009; Catalano et al. 2003; Gregory, Paxton, and Brozovic 2011; Han et al. 2010; Hetherington et al. 2011; Tabacchi et al. 2007). Family routines and practices for school-aged children have also received attention in an attempt to understand the household practices associated with lower weight in children (Anderson and Whitaker 2010; Chan and Sobal 2011; Hall et al. 2011; Neumark-Sztainer et al. 2003). Some research has even gone so far as to suggest that a mother’s marital status contributes to obesity among children (Huffman, Kanikireddy, and Patel 2010).

Despite this volume of research on maternal and familial behaviors, there is very little literature on the context in which these choices are made. The underlying assumption is that
these choices stem from cultural practices and must simply be unlearned. One study that examined family meals and weight among adults revealed that the frequency of eating meals at home was associated with being married and not working full-time (Sobal and Hanson 2011). This research suggests that meals at home may be correlated with other very important differences among families and resources that are in fact the cause of difference and not the practices themselves (Sobal and Hanson 2011). Another study found that despite respondents’ insistence that the cost of healthy foods was a major barrier and evidence that they already had a basic knowledge of healthy foods, the recommended intervention for these low-income, primarily Latina, mothers was still nutritional education (Slusser et al. 2011). As evidenced above, these studies do not account for the scope of food choices available to families. Further they tend to favor the promotion of a particular educational curriculum or the establishment of particular family routines over addressing the context in which food choices and family routines are created. Some argue that this focus on behaviors rather than structure is similar to the misguided attempts to convince single mothers to get married in order to curb poverty (Kirkland 2011). In actuality, all of these behaviors and choices are affected by structural inequality and place, and without an understanding of how these barriers affect obesity, it is problematic to assume that the obese are simply culturally deficient.

Researchers have oftentimes attributed racial differences to different cultural values regarding health. There is support for this in the literature regarding body image. A survey asking adults to rank child health concerns as “big problems” found that while “childhood obesity” was cited number one overall, results by race revealed that for African American
and Hispanic respondents “drug abuse” was ranked higher (C.S. Mott Children's Hospital National Poll on Children's Health 2011). Studies find that compared to White women and girls, African American women and girls report greater satisfaction with their bodies, diet less, and are less likely to overestimate their weight (Abrams, Allen, and Gray 1993; Hudson 2008; Story et al. 1995; Wildes, Emery, and Simons 2001). Recently, some scholars have questioned the validity of survey instruments based on White middle class culture to measure body image among other ethnic and racial groups (Cole and Sabik 2009; Nichter 2000). They argue that history and social context effect how one interprets and answers questions about one’s own body. It may not be that non-white, non-middle class women are less concerned about weight or health, but that discussions around weight and body image are different in communities in which the characteristics of one’s bodies are a reflection of their marginalized racial/ethnic group. For example, many African-American parents attempt to instill a sense of pride in their children by teaching them to resist negative messages about their bodies by repeating messages about being proud of who they are (Stevenson et al. 2002). Youth who recall receiving such messages report higher self-esteem (Constantine and Blackmon 2002). In this context, asking non-White women about their bodies may be indistinguishable from questions about racial pride (Cole and Sabik 2009). Alternately, “fat talk” is often a culturally accepted ritual that White mothers engage in with their daughters (Cole and Sabik 2009), but which may have little to do with health. In other words, it is important to understand the context in which these choices and discussions are carried out.

Differences in bone density and muscle versus fat weight may also unfairly bias Body Mass Index measurements in favor of White respondents (Flegal et al. 2010). An in-depth
review of these and other limitations of BMI and its implications for obesity research are addressed later in the methodological section.

In addition to the research mentioned above, there is some evidence that there is an increasing awareness of the importance of environment, as illustrated by some promising work examining obesity using a social ecological framework. The most recent Dietary Guidelines for Americans, issued by the CDC, contains a section devoted to this model (p. 55, 2010). Unfortunately, the model presented still cites “Social and Cultural Norms and Values” as the outermost ring in their model, indicating that it is the context in which other ecological factors (such as industry and government) occur. While there is no doubt that cultural norms affect eating and obesity, it is also clear that culture is shaped by conditions of oppression and structural inequality. Furthermore, demographic characteristics such as race/ethnicity and socioeconomic status are only included at the level of the individual. This is problematic given what we know about how race and socioeconomic status make a profound difference in where one will reside, go to school, and work. If the framework does not incorporate the structural inequality that we know to exist for certain groups of people, we cannot accurately address the problem of childhood obesity. Furthermore, without a comprehensive understanding of how race and class segregation come about and are maintained, we may run the risk of simply gentrifying “problem areas” and reshaping special patterns of segregation (Guthman 2011; Quastel 2009).

The Body Mass Index literature overall has paid relatively little attention to structural explanations and the role of place in the rise of obesity, but there remain some notable exceptions. Cross-national studies find relationships between development and changes in
obesity indicating that as social patterns of inequality in other countries begin to mirror those of the United States, so do their obesity rates (Popkin 2010; Popkin 2009). There has also been obesity research that examines the physical and social environments in conjunction with individual behavioral choices. These studies show that environmental variables have a significant impact on health (Singh, Siahpush, and Kogan 2010). One study found that individual measures often masked the important effects of neighborhood on health (Nelson et al. 2006). A growing body of literature of urban neighborhoods also shows that neighborhood characteristics have an impact on obesity among children (Black and Macinko 2008; Black et al. 2010; Rahman, Cushing, and Jackson 2011). However, they acknowledge that residence does not account for other variations in “place,” such as school and work environments.

All of these findings suggest that understanding structural inequality and the role of place in the study of childhood obesity is an important direction for new research. Research on childhood obesity has largely focused on genetic and behavioral characteristics of individuals, and to the extent that it measures environment, it rarely looks beyond the family of origin or food characteristics of the built environment. This research fails to consider the structural barriers that limit access to the tools needed to maintain a healthy body weight and ignores structural limitations that constrain individual choices. While individual factors do certainly play a role in obesity, the recent abrupt rise in obesity rates and their unequal patterns point to a combination of factors including individual, family, and community (Schafft, Jensen, and Hinrichs 2009). Moreover, research on environment examines it separately from individual-level characteristics, so we do not know how attributes of the
individual interact with the social structural composition of their schools and communities. In the following section I will review the literature on structural inequality as it relates to poverty, racial segregation, urban/rural residence, and food access.

*Structural Inequality*

Lobao and colleagues argue that, “Inequality—the study of who gets what and why—has been at the heart of sociology since the inception. However, this simple formula fails to acknowledge that *where* is also a fundamental component of resource distribution” (2007:1). In this context, the use of the term *place* refers not only to a geographic location but also the material resources and meanings and values associated with it (Gieryn 2000). How researchers conceptualize the scale and boundaries of place can vary greatly across studies. Cross-national research has examined the role of uneven development (or underdevelopment) among countries and how this has led to differences across space. However, less is known about how these global expansions impact intra-national resource distribution (Lobao et al. 2007; Schafft et al. 2009).

Rural sociologists have been in the forefront of research examining the sub-national scale, looking for comparisons and drawing connections between places usually examined separately (Lobao 2004a). Roscigno and colleagues (2006) provide a particularly helpful example of this in their examination of education inequalities across place. They find that both rural and urban students experienced resource deficiencies that translated into lower school performance (Roscigno, Tomaskovic-Devey, and Crowley 2006). Research on the South has shown us how uneven development across place occurs, given particular characteristics of regions (Tomaskovic-Devey and Roscigno 1997; Wimberley and Morris
2003). Recent research on the working poor indicates that the working poor in non-metropolitan areas benefit less from residence and family labor supply relative to their metropolitan counterparts (Slack 2010a). These studies provide evidence that the role of space, particularly as it relates to poverty, race, urban vs. rural, and access to resources, is of particular importance.

**Poverty**

Childhood obesity is not evenly distributed across different socioeconomic statuses. While the association of poverty and obesity may seem counterintuitive, poor children have higher rates of obesity in the United States (Clarke et al. 2009; Jyoti, Frongillo, and Jones 2005; Ogden et al. 2010b; Vieweg et al. 2007). However, a majority of the research previously discussed explores individual and cultural reasons for these differences. In this section, I review the literature that has examined the role of place. I begin with cross-national research regarding links between poverty and obesity, followed by research on residential segregation by socioeconomic status, and school poverty. I draw on literature that has directly examined childhood obesity when available, and incorporate the broader literature on the effect of structural poverty when unavailable. Finally, I address how this research will uniquely contribute to the issue of structural poverty and obesity.

While historically malnutrition has been associated with being underfed, researchers find that in developed countries, poverty and food insecurity may result in a population with food that meets or exceeds the number of kilocalories they need (Tanumihardjo et al. 2007). However, the low dietary quality of the available food leads to obesity and does not provide the body with enough nutrients to promote good health (Tanumihardjo et al. 2007; Usfar et
Many have argued that this uneven distribution of healthy food results in poor children having access only to high calorie/low nutrition food (Dietz 1995; Drewnowski et al. 2009). In the United States research has shown that food insecurity is indeed correlated with obesity (Eisenmann et al. 2011; Jyoti et al. 2005; Larson and Story 2011a). An exploratory study examining the role of stunted growth as an explanation for higher BMI, found that for Mexican-American children there is evidence of malnutrition (stunted growth) among overweight/obese children (Iriart et al. 2011). Despite the established connections between obesity, international development, and uneven access to resources (Caballero 2005; Monteiro et al. 2004; Tanumihardjo et al. 2007), relatively little is known about how the spatial distributions of inequalities within the United States have affected childhood obesity.

Poverty is often included in research as a characteristic of the individual or the household; however, residential segregation often occurs along income levels and thus results in environments that are resource poor and others that are not. Income segregation, the concentration of people in neighborhoods based on income and/or wealth, is a persistent feature of the American landscape (Swanstrom et al. 2004). The nature of housing market practices keeps low-income families relegated to certain neighborhoods in which real estate is more affordable, thus creating what is referred to as the “segregation of poverty” (Reardon and Bischoff 2011). However, as income inequality has increased greatly over the last several decades, the process of “segregation of affluence” has been stronger than the “segregation of poverty,” meaning that segregation has occurred because those at the very high end of the socioeconomic status have moved further away from everyone else. Reardon and Bischoff argue that this is potentially very problematic as it means that disadvantaged
families may not experience any “local spillover of public goods” in terms of access to the same schools, parks, or services (2011). While there is limited research on how community poverty is related to obesity in children in the United States, one study of neighborhood disadvantage finds that neighborhood SES is positively associated with adolescent obesity in Canada (Janssen et al. 2006) and a second found evidence that for adult women neighborhood SES may impact BMI (Robert and Reither 2004).

Due, in part, to residential patterns of economic segregation, schools are also an important way in which children’s environments are organized by socioeconomic status in the United States. As seen in the review of the obesity literature, there is a presumption that the poor have less knowledge about healthy eating behaviors (Birch and Ventura 2009). However, a study examining the dietary intake of 3rd graders who received an in-school food education intervention found no significant differences between their pre- and post-intervention behavior. Their answers did not significantly differ from those in the control group, either, indicating that perhaps an education focusing on individual food choices, while ignoring the structural constraints of what is available to eat at school and at home, fails to capture the context of their choices. The only difference found among the children in the study was between the nutritional intake of students from low socioeconomic status schools and those in high socioeconomic status schools, in that the former received more of their calories from fats, oils, and sweets. The authors note that this could be due to the low cost of these energy-dense foods, but they offer no structural-level examination (Hovland et al. 2010). The study also contained no measure of the student’s BMI. This study is consistent with a systematic review of school-level interventions that found similarly inconsistent/not
significant results from diet and physical education interventions, but the studies they examined did not control for SES (Brown and Summerbell 2009). However, of the three dietary interventions they reviewed, only one showed a statistically significant improvement in BMI relative to the control group. The study was unique in that while it provided dietary information to all students, only students in the intervention group received a healthy breakfast at school (Ask et al. 2006). These studies lend further support to the idea that lack of access to resources is key to obesity among children.

Another school-level study examined the effect of select school characteristics on the BMI of high school students (O'Malley et al. 2007). While they found that students in schools with lower SES had higher rates of obesity, net the effect of other measures including student socioeconomic status, this work had several limitations. First, SES was measured by student reports of their parents’ level of education and did not include any measures of poverty either at the school or individual level. They also found that school SES had an effect net of individual student’s SES. The BMI itself was gathered from student reports and not direct measurement. Additionally, the study did not analyze the data using a multilevel modeling technique, but only provided descriptive information on how the schools varied on particular characteristics. A second study that employed a more complex model found that regardless of household SES, more students in public schools were overweight than those at private schools (Li and Hooker 2010), suggesting that school resources matter over and above family resources. Similarly, a study of Canadian students found that school nutrition programs mediated the detrimental academic effects of food-insecure households on children.
(Roustit et al. 2010). Therefore, the school remains a highly important site for either minimizing or exacerbating inequality among children.

My research contributes to the literature on poverty and obesity in several key ways. Research on SES and obesity has generally focused on adults, so this research fills an important gap by focusing on children. Further, research that finds a relationship between neighborhood SES and obesity has focused on urban areas. However we know that key differences can be found regarding the effects of poverty between urban and rural areas. Thus by incorporating both urban and rural counties in this research I am able to examine the effects of county-level SES. Additionally, the focus on SES and obesity has largely concentrated on poor environments, but given what we know about the “segregation of affluence” with regard to income segregation, I will examine the contextual impacts of poor as well as affluent counties and schools on childhood obesity.

Studies of county-level poverty have historically excluded other sites of deprivation such as school or work and likewise for school-level studies. My research examines both the county and the school levels to gain a more complex understanding of how these various environments affect weight status among children. Moreover, studies of the built environment have tended to gloss over or ignore the role of class or poverty segregation that may be the cause of these patterns. By including several structural components, such as spatial inequality through racial and socioeconomic segregation, in a multilevel model, I am able to clarify these relations in a way that has not previously been done in the literature.

Research on the relationships among poverty, childhood obesity and race has not produced consistent results. A recent data brief published by the National Center for Health
Statistics finds that while there is a significant and inverse relationship between childhood obesity and family poverty status for non-Hispanic white children, there is not a statistically significant relationship for Hispanic or African-American children (Ogden et al. 2010b). I discuss the unique role of racial spatial segregation below.

*Racial Segregation*

Racial minorities in the United States are more likely than White children to be overweight or obese (Ogden et al. 2010b). The previously discussed literature on childhood obesity has examined both individual and cultural reasons for these disparities. In this section, I review the literature on racial segregation as it relates to differences in residential segregation and school segregation. Finally, I discuss how this research will add to the literature on race and childhood obesity.

Residential segregation by race has a long and persistent history in the United States and is a key part of understanding spatial inequality. Particularly for African Americans, residential segregation is associated with increased poverty, housing deterioration, unemployment, inferior public services, and lower quality schools, among other things (Massey and Denton 1993). Segregated neighborhoods have less access to safe recreational facilities (Centers for Disease Control and Prevention 1999) and have higher costs of living (Williams and Collins 2001). These structural constraints cannot be accounted for simply by controlling for individual-level racial identity but are characteristics of place. This gives residents of these areas a social context different from African Americans who are not residing in racially segregated spaces (Robert 1999; Williams and Collins 2001; Williams and Collins 1995).
Although decreased social and economic well-being among residentially isolated minorities is well established, few studies examine the health impacts of these relationships. One exception is the 2006 study by Chang, which examines the relationship between adult weight status (as measured by BMI) and racial residential segregation. The study finds that African Americans living in segregated metropolitan neighborhoods were more likely to be obese (Chang 2006). Although it relied on self-reports of height and weight, the study is an important one, as it highlights the importance of looking at spatial factors and moving beyond individual-level race variables. However, the study does not include measures of the social environment, and thus the researchers could not be sure about the causal mechanisms. Another study of adults in Philadelphia also found that BMI was higher for African American women (but not men) in racially isolated neighborhoods and that this effect was somewhat mediated by the physical disorder of the neighborhood (Chang, Hillier, and Mehta 2009).

While these studies point to the relationship between segregation and BMI, research has been limited to adults living in urban neighborhoods. Consistent evidence shows that obesity among children could result in serious adverse effects as they reach adulthood (Reilly and Kelly 2011). Therefore, understanding the relationship between segregation and obesity among children is of particular importance. Minority concentration in nonmetropolitan areas is an important part of spatial inequality. Researchers find it to be associated with increases in socioeconomic inequality between white and minority populations (Albrecht, Albrecht, and Murguia 2005). Recent analyses also find that racial segregation in the inner city may be lessening while segregation in suburban areas is increasing, stressing the importance of
looking beyond inner cities for sites of segregation (Frey 2011). Many of these studies do not account for anything other than residence, leaving out important institutional components of segregation such as school or work environments.

In addition to residential segregation, public schools have, after a period of modest integration, become increasingly re-segregated over the last 20 years (Kozol 2005). Much in the same way that residential segregation by race restricts the amount of resources available in communities, students in high minority schools are likely to have fewer available resources (Condron 2009; Kozol 2005). While some studies point to the widening of academic achievement gaps between white and minority students as segregation increases (Condron 2009; Lleras 2008), little is known how this isolation affects students’ health. However, we can expect, based on what we know about academic achievement, that as school segregation increases, the health gap between white and minority students would increase as well. One study of food options in American schools found that schools with high concentrations of minority or low-SES students had less-healthy food options than other schools (Delva, O'Malley, and Johnston 2007). Another study found that minority girls in predominately white schools had lower BMIs than those who attended predominately nonwhite schools (Bernell, Mijanovich, and Weitzman 2009). However, the authors attributed these differences to social norms and the influence of white children on minority children without including any measure of poverty at the school level. Given what we know about the resource disparities that exist between predominately white and nonwhite schools, and without controlling for school or community level measures of inequality, this conclusion seems premature at best. Moreover, a study of New York schools found a higher
clustering of fast food restaurants around predominately African American schools relative to whites (Kwate and Loh 2010), and one of secondary schools nationally showed clustering around low-income schools (Zenk and Powell 2008). An examination of differences in children’s BMI must therefore control for both school-level SES and racial segregation in order to fully understand the impact of schools on childhood obesity.

My research uniquely contributes to this body of literature by looking at the health effects of racial segregation at the county and school level for public school children. The focus on urban residential segregation and adults has left out children and variations in segregated places. Prior research on school segregation has focused on achievement, but as public education resources dwindle and low-income schools must focus their attention on student achievement required by “No Child Left Behind” policies, physical education and health will likely be pushed aside. By examining this relationship in conjunction with school-level poverty, I will examine the effects of various intersections of inequality known to impact health.

Urban / Rural

Not only does the racial makeup of communities affect obesity, but so does rural residence. Duncan’s 1999 study of rural poverty provides a vivid picture of the meaning of race, place, and poverty in the United States (Duncan and Coles 1999). Several other quantitative researchers have supported her qualitative descriptions in the area of health outcomes and childhood obesity. Data collected from the National Survey of Children’s Health directly examined the likelihood for obesity and overweight among children in rural and metropolitan areas. The researchers found that children living in rural areas are more
likely to be overweight or obese as compared to children in metropolitan areas. While some of the differences were explained by increased screen time (i.e., television, video games, and computers), less physical activity, an increased likelihood of being uninsured, and not having had any preventative medical care in the last year, differences between rural and urban residents existed even when other factors were controlled. The authors suggest that perhaps the built environment (lack of parks, limited transportation, and stores) accounts for these differences but that further research is needed (Lutfiyya et al. 2007). A recent study of a sample of high school students in Ontario finds that rural students had the highest level of overweight and obesity, followed by urban and suburban youths, respectively (Ismailov and Leatherdale 2010). Another study that looked at several aspects of the physical environment showed that youth in working class, rural, low socioeconomic status, or inner city urban neighborhoods were more likely to be overweight relative to their new suburban counterparts (Nelson et al. 2006). However, despite several studies showing an increase in obesity in rural children, they appear to be slightly more physically active than their urban counterparts (Liu et al. 2008).

State and regional disparities are also important predictors of childhood obesity. Given that the “Deep South” has been associated with the poorest child health relative to other regions, it is not surprising that this region also suffers from higher rates of obesity (Goldhagen et al. 2005). Studies show that North Carolina has especially high rates of childhood obesity (Singh, Kogan, and van Dyck 2008) and recent national estimates have ranked it as having the 11th highest rate of childhood obesity (about 19 percent) among all states (Trust for America's Health 2010). Research using the National Survey of Children’s
Health found that, while controlling for individual and state level predictors, the South had the highest percent of children with “no days of rigorous physical activity” (Singh et al. 2009). The South remains a very segregated region as well. However, these studies did not account for racial segregation among rural and urban children.

Despite the variations in experiences for youth in urban vs. rural areas, and the consequences of these differences for youth, these sites have traditionally been examined separately in the literature. By including students from both urban and rural schools in my research, I am able to uniquely examine the different ways in which unequal distributions of resources may affect students in each environment. By controlling for urban and rural differences while examining the role of concentrations of poverty and racial segregation, I allow for a fuller understanding of how these processes work.

Food Deserts

Globalization and corporate consolidation have had significant effects on food access, particularly for poor and rural communities. Access to enough nutritious food depends on a great number of factors affected by one’s place, but few researchers have attempted to situate the variations in obese and overweight status within the larger geographic context of food access.

In order to fully understand the current state of spatial access to affordable food, one must understand the recent changes in the grocery industry. Over the last 30 years in the United States, the power over grocery sales of a small handful of corporations has increased while the number of small-scale local grocers has decreased (Lyson and Raymer 2000). Studies repeatedly show that these larger stores, such as Wal-Mart and Albertson’s, are often
able to drive out smaller local businesses by purchasing large quantities of food at decreased prices. As a result, in 2001, the Census reported that discount superstores and large chain supermarkets accounted for 89.8 percent of all grocery sales in the United States (U.S. Bureau of the Census 2001). This has resulted in an overall decrease in the total number of stores since the 1980s (Blanchard and Matthews 2007).

This concentration has resulted in the proliferation of what are increasingly known as “food deserts” or places “where people do not have easy access to healthy, fresh foods, particularly if they are poor and have limited mobility” (Elliott 1997). These places have become a topic of concern and interest among policy makers and researchers (Whitacre et al. 2009). The widespread use of the term has been credited in part to First Lady Obama’s campaign to increase access to healthy foods and recreational facilities. In 2011, the US Department of Agriculture released an interactive map allowing people to search for food deserts in their area (US Department of Agriculture: Agricultural Marketing Service 2012). In addition, their website informs readers that the USDA is at the forefront of identifying and eliminating food deserts as one of their “High Priority Performance Goals” (US Department of Agriculture: Agricultural Marketing Service 2012). All this attention has prompted debates about the exact role of food deserts in obesity trends, particularly the increasing rate of obesity among the poor (Kolata 2012).

Early studies on food deserts were primarily done in the United Kingdom, and many focused on qualitative analyses (Schafft et al. 2009). In addition, many of the early studies in the United States examined only urban environments (Paez et al. 2010). Some recent studies concentrate on the issues of quantitatively identifying food deserts in rural areas (McEntee
and Agyeman 2010; Schafft et al. 2009). To this end, McEntee and Agyeman attempted to standardize the measurement of rural food deserts using GIS mapping of Vermont. They found that many food deserts overlapped with high-poverty areas (2010). A similar nationwide study in 2007 found that food deserts were concentrated in areas that were primarily poor and that lacked access to reliable transportation (Blanchard and Matthews 2007). Given the lack of public transportation in rural areas, food deserts are a very significant problem for the rural poor. Food deserts often leave the poor reliant on convenience stores or gas stations which specialize in high calorie foods and offer a severely limited stock of fresh fruits and vegetables, if any are available at all (Schafft et al. 2009).

Blanchard and Matthews found that regionally the South had higher levels of poverty, lower median incomes (both within and outside of food deserts) and less access to transportation relative to other regions (2007).

Research on food access also finds that neighborhoods with high minority populations have different food environments than predominately White neighborhoods. Studies of urban areas have consistently found that predominately Black and Hispanic neighborhoods have fewer supermarkets than predominately non-Hispanic White neighborhoods (Block and Kouba 2006; Block, Scribner, and DeSalvo 2004; Morland et al. 2002; Morland and Filomena 2007; Powell et al. 2007; Raja, Ma, and Yadav 2008). Other studies that have examined distance have found that African Americans travel the farthest to get to a grocery store (Zenk et al. 2005) While non-White neighborhoods are more likely to have grocers (smaller retailers), the quality of food tends to be poorer and provide fewer
healthy food options (Block and Kouba 2006; Lewis et al. 2005; Morland and Filomena 2007).

Poverty is also an important characteristic of food deserts. Poor residents travel farther to grocers and tend to have less access to chain stores with lower prices (Alwitt and Donley 1997; Chung and Myers 1999). However, it is important to note that even among low-socioeconomic areas, White neighborhoods had higher numbers of supermarkets than predominately Black neighborhoods (Morland et al. 2002). These studies primarily rely on urban and occasionally suburban areas and little is known about rural food deserts in the United States.

Research on the association between obesity and food environments has mixed results in the literature. Further a majority of this research has focused on adults and not children (Boone-Heinonen et al. 2011). However, a recent cross-sectional study finds an association between low BMI and access to chain supermarkets, particularly for African American children (Powell et al. 2007). A longitudinal study of school-aged children found that the food environment did not have an independent effect on weight status and cautioned researchers to take a nuanced approach to understanding food environments (Lee 2012).

Studies of rural food deserts in the United States are relatively recent and the examination of their effect on children’s health is still relatively sparse in the sociological literature. One notable exception, Schafft et al, examined the effect of food deserts on the BMI of Pennsylvania school children (2009). They found that, consistent with other studies, food deserts were most likely to be in communities that were structurally and economically disadvantaged. However, net of these effects, they found that food deserts were associated
with increases in child obesity. The data in this particular study used only aggregate-level BMI measures and aggregate measures of inequality and therefore could not control for individual-level or school-level characteristics. Moreover, the study did not incorporate any measures of race or racial segregation in their analysis.

An increased interest in food deserts has led to the creation of a “food desert locator” by the U.S. Department of Agriculture, which provides comprehensive food access data by census tracts. The data define food deserts as tracts in which a grocery store is a significant distance away (>10 miles for rural counties and >1 mile for urban) for 33 percent or more of the residents within a census tract. This helps to standardize the measurement of food access in the United States and provide researchers with a helpful overview of the spatial distribution of these resources.

My research contributes to these burgeoning bodies of literature by combining rich, new food desert data with measurements of childhood obesity across North Carolina. This is unique in that it will combine individual-level variables and nest them in their environments in the same model, which allows me to greatly expand on the findings in Pennsylvania. Moreover, as noted previously, most work has neglected to include rural environments in discussions of food deserts, which has been a significant hole in the literature.

Summary and Potential Contributions

Traditional research on childhood obesity concentrates primarily on characteristics of the individual or on cultural beliefs and practices in order to understand variations in obesity rates. However, sociologists have much to offer this literature, given their discipline’s rich history of examining the social context, or place, in which individuals exist. By drawing from
these rich bodies of literature, my research provides a much needed addition to a scant body of literature regarding the effects of structural inequality in schools and communities, as well as individual characteristics, on rates of childhood obesity.

Past research that has examined structural inequality and the role of place has its limitations in that it has often neglected to examine both urban and rural sites, children, and contexts such as schools, residence, and food environments. Further, it has not addressed how characteristics of individuals and characteristics of their social environment interact. Below I address each of these limitations and how my work can uniquely contribute to our understanding of childhood obesity.

First, research that has examined obesity and place has largely focused on adults rather than children. This is highly significant given that obese children face increased health risks and premature death as adults (Reilly and Kelly 2011). Much research has also noted that eating patterns, physical fitness, and sedentary behaviors are often established early in life and therefore interventions during childhood may be of particular importance (Gordon-Larsen, Nelson, and Popkin 2004b). Additionally, one of the consistent limitations in adult health and segregation literature is that it cannot account for work environments and is limited to residential segregation. By examining children, I am afforded the unique opportunity to control for their county environment in addition to their school environment.

Second, while it is clear that one’s individual race and the race of one’s neighborhood are correlated with many health outcomes, there is little research on their interaction. My research will fill that gap by examining the effects of individual, school, and community inequality on the rate of childhood obesity and their interaction. Prior research is also
generally lacking in terms of its exploration of both urban and rural poverty, despite the known differences that place has on how poverty translates into individual disadvantages. Moreover, research on resource-rich environments and concentrations of affluence is essentially non-existent. I will not only examine the effect of minority-segregated and high-poverty schools and counties, but also the effect of White-segregated and high-affluence areas and interactions with individual racial identity for both.

Third, research that examines childhood obesity from a structural perspective has often only examined one aspect of place while ignoring other major characteristics known to impact resources. For example, studies on race differences and health outcomes typically focus on urban areas. This research project is unique in that it looks at both urban and rural counties and examines the role of segregation among children in both of them. Further, research on the physical environment often neglects the social inequality that gives rise to such disparities between communities and schools. By using multilevel modeling techniques, I will be able to examine the effects of individual-level variables at two additional layers of segregation and inequality—both at school and county levels. With this technique I am also able to test for interactions between individual characteristics and their social context.

One consistent drawback of a majority of prior BMI research is that it has primarily been calculated using self-reported height and weight from respondents, or their parents. However, self-reports tend to lead to an under-estimation of obesity and overweight (Field, Aneja, and Rosner 2007). This study is unique in that the data were gathered by physical education teachers from students during the course of their classes. Not only does this
provide an accurate measure of the students’ height and weight, but we also have data on the date of the test, which allows me to control for the time of year that the student was assessed.

Finally, only one sociological study of rural food deserts and childhood obesity currently exists, and as with many other studies on inequality and inequality in resource distributions, it does not account for anything other than county-level variables and aggregate-level BMI data. This study builds on that work by allowing for an examination of school variables and individual-level variables for a much more complex analysis of the context in which these children live. It draws on advances in food desert measurement and combines it with rich school and student data, providing a holistic examination of the issue of food access and obesity among public school children.

This research is important because without an understanding of the larger structural constraints affecting the health and wellbeing of children we are unable to address their needs in a satisfactory way. By continuing to concentrate on individual eating habits, we cannot understand the context of choices and cannot fully address the real barriers to health among children. Further, research that examines the physical environment has often neglected to examine the social basis of the environment such as racial and poverty segregation at both the school and community levels. It has also been limited by not examining the interaction of individual characteristics and one’s environment. By using multilevel modeling and pulling together several bodies of literature on spatial segregation, I will be able to uniquely contribute to this discussion and recommend avenues for future research and interventions.

Conclusion
As this review has shown, the literature examining childhood obesity is growing, and there remain many unanswered questions about the social basis of trends in childhood obesity. Sociological theorists have long debated how to best study sociological phenomena, but it is clear that this social problem requires an examination of the social context to further our understanding. By filling gaps in the current body of literature, I hope to further the discourse surrounding the issue of childhood obesity in America. The next chapter will detail both the research questions that were borne out of this review of the literature and exactly how I will answer those questions with the available data.
CHAPTER THREE: DATA AND METHODS

Research Questions

Given what we know about trends in childhood obesity and inequality across place, the following research questions seek to fill the gaps in the current bodies of literature and expand our understanding of both of these social problems. First, are children in minority segregated schools and communities more likely to be overweight or obese compared to children in white segregated schools and communities? Prior research demonstrates that such segregation increases the achievement gap between minority and white students (Condron 2009); this project extends the question to the problem of obesity. Based on the prior literature, I expect that students in white segregated schools will have lower rates of obesity than students both in minority segregated schools or racially integrated schools.

My second research question deals with economic distress in communities and its effect on rates of childhood obesity. The question guiding this research is: Are students more likely to be obese or overweight in poor communities and schools compared to more affluent ones? I anticipate that economic segregation will affect the likelihood of being obese, with students from more affluent schools and communities having lower rates of obesity compared to students in high poverty schools and neighborhoods.

Finally, what effect does living in a food desert have on the likelihood of being overweight or obese? I examine the effect of living in a food desert, as well as both individual- as well as school- level characteristics, in order to clarify our understanding of the causal relationship between food deserts and childhood obesity. Further I include both food desert variables and social inequality (race and class) in the same model. This replicates and
expands on prior research on obesity and food deserts (Schafft et al. 2009) and based on this prior research, I anticipate that students in both urban and rural food deserts will be more likely to be obese than those that do not live in a food desert.

All of these questions will be examined net of the effects of other mediating demographic and economic factors, which have been drawn from the existing literature. As such each question will include individual-level demographic control variables that measure the respondent’s race, grade, and gender, and the county’s unemployment rate, median income, rural/urban status, racial segregation, and the poverty rate by racial group.

Given the research questions, I require data on individual students, their school, and their county. Next, I detail how I acquired the three levels of data used for this project.

Data Sources /Preparation

Student Data

In 2006, through a grant from the Health and Wellness Trust Fund, the North Carolina Alliance for Athletics, Health, Physical Education, Recreation, and Dance (NCAAHPERD) began collecting data on students in six low-income North Carolina school districts with high health disparities. Physical Education teachers in these districts received training in a new curriculum designed to get students to be physically active for the whole class period. Later in the grant, training on the FitnessGram™ software was added. In 2008 NCAAHPERD was awarded a second grant from Kate B. Reynolds Charitable Trust (KBR) that allowed them to greatly expand the program. The program, known as the In-school Prevention of Obesity and Disease (IsPOD), facilitated, among other things, the purchase of FitnessGram™ software for all North Carolina public schools that chose to participate in the
IsPOD program. This software provides Physical Education teachers with a database to record their students’ fitness scores on a variety of measures. One of the measures includes the students’ height and weight, which can then be used to calculate their Body Mass Index (BMI). Over the course of the three year grant period training and software was eventually offered to all teachers of 3rd-8th grade students in the 115 school districts, known as Local Education Areas (LEAs), in North Carolina. The most recent data available at the start of the present study are from the 2009-10 school year and do not include data from all districts. Figure 1 reports the county locations of the reporting schools, which highlights this spatial diversity. Please note that while there are 40 LEAs included, two of them are within the same county and therefore there are 38 counties in the sample.

An analyst from the State Center for Health Statistics was the first to receive and process the data for the 2009-10 school year. They were responsible for verifying that each student was a registered North Carolina public school student by merging the data with official records on a combination of variables (see Appendix 1 for data handling procedures at SCHS). As part of the process of matching student reports with DPI, SCHS staff also added information about their race, gender, grade, school and LEA information.\(^2\) Data were stripped of identifiers during processing.

As an employee of ETR Services, LLC, I have been working on evaluating the IsPOD project since the fall of 2009. In July of 2010, I sent an email to the then-director of NCAAHPERD, Ron Morrow, requesting use of the data for my dissertation project. My request was granted, and following my signing and returning a “Data Use Agreement” a

\(^2\) This information is also asked of the physical education teacher submitting the data, however DPI data was used for this analysis given that it is their official record which is provided by the child’s legal guardian.
month later, I was given permission to use the data for my own project. On October 4, 2010 I submitted the required “Request for IRB Exemption” form to the Internal Review Board at North Carolina State University. On October 11, 2010 I received a letter stating that an administrative review had determined that the study is exempt from the federal regulations outlined in 45 CFR part 46, and that the IRB had therefore approved the study.

The datafile I received included 72,547 Fitnessgram™ reports submitted in the fall of 2009 and 102,752 reports from the following spring. For this research the analysis is limited to students in grades 3-5 who were assessed in the 2009-10 school year (after June 30, 2009 but before July 1, 2010). The reason for limiting the sample to those grades was two-fold: First, the response rate for teachers of students in grades 6-8 was considerably lower than those who taught younger students. Later focus group analyses indicated that teachers in middle school had more complex schedules (often only seeing students for one semester or quarter a year, etc.), and therefore collecting data on each student was often challenging.³ The second reason was substantive, in that research shows that BMI among children going through puberty may be less reliable than those who are not (Sugiura and Murata 2011). Therefore, students who did not meet the grade or date criterion were purged from the sample (25,395 fall records and 27,849 spring records). Next I conducted a list-wise deletion of students whose reports were missing data for their height and/or weight measurement: 5,286 in the fall and 16,052 in the spring. Large amounts of missing data were expected as new teachers were added to the program each year and therefore many teachers were still becoming familiar with the software and number and types of assessments needed – for

³ Personal communications with Lois MacGillivray (ETR Services, LLC) and Judy Martino (Assistant Executive Director of NCAAHPERD)
example, many tested various PE skill levels with the software (strength, flexibility, etc.) but did not record height and weight. Data were also missing due to teachers entering incorrect student ID numbers. Because these students are elementary school age, student compliance was generally not an issue according to teacher reports.

Some students had duplicate records due to teacher or software errors or in some cases because the student had more than one PE teacher. Six hundred ninety-seven (697) fall records and 214 spring records were identical duplicates and purged from the database. For students with more than one record (identified by their id number) within the same semester their most recent assessment was kept and all prior records were deleted (67 records deleted from the fall and 1,331 from the spring). The cleaned fall 2009 data and spring 2010 data consisted of 41,169 and 57,317 records, respectively. These cleaned files were then merged using the identification number to create a file of 75,596 distinct student records with at least one BMI measure from the 2009-10 school year.\(^4\) Seven additional records were deleted after the merge for having invalid data leaving a total of 75,589 student records from 394 different schools, and 54 counties (58 Local Education Areas).

**RESPONSE RATES**

The use of FitnessGram™ software was adopted at the district level first, and in most cases teachers were not mandated to participate. Conversely, if district administrators did not opt to participate in the *IsPOD* program, teachers could still attend trainings and receive access to the software and submit data if they so chose. Consequently, not all schools in the 58 LEAs are represented in the data, and a varying number of students within each school

\(^4\) 22,890 students had both a fall and a spring record and in those cases the spring assessment was kept
might be missing (for example, if only one teacher chose to participate then only their
students would be included). As indicated previously, since this is an ongoing study and data
for this research came from one of the earlier years of the project, data have not been
received from all LEAs in the state. Given this, after merging in the school and county data, I
took some additional steps to exclude cases in which a teacher had only submitted data on a
few students in the LEA.

By merging in the Average Daily Membership (ADM) for each school by grade for
the 2009-10 school year (North Carolina Department of Public Instruction 2010c), I created a
response rate variable in order to determine the response rate for the 3rd-5th graders at each
school. I took the total number of 3rd-5th grade students for which I had BMI reports at each
school and divided it by the total ADM for grades 3-5 at the school. Table 1 indicates the
distribution of response rates for each school in North Carolina that had one or more of those
grades (N=1395). A modal response rate category is 90-99 percent followed by less than 10
percent and 100 percent. Schools that had less than 10 percent of students responding (208
students from 75 different schools and 18 LEAs) were eliminated from the analysis file,
given that the teachers at the school were not systematically collecting data on all of their
students. It also seems likely that these 208 students were transferred at some point in the
2009-10 school year (as the school is based on their end of the year assignment in the DPI
database and not necessarily the reporting teacher’s school), or that the information was
simply entered incorrectly. The majority of the schools that reported less than 10 percent of
students also came from LEAs in which no other schools submitted data, suggesting that one
of those errors in reporting had occurred. Once students from these schools were eliminated,
the sample contained 75,381 students from 319 different schools in 40 different LEAs (38 counties). The mean response rate for the remaining schools was 87.6 with a standard deviation of .14.

The majority of studies on the BMI of youth rely on parental reports of their child(ren)’s weight and height. This study, however, relies on direct measurement of height and weight of school children as part of their physical education course by a physical educator. In order to translate the height and weight into a meaningful statistic, I downloaded and merged the “Body Mass Index for Age Tables, Children Ages 2-20 Years” (Centers for Disease Control and Prevention 2010) with the student data to plot students based on their weight, height and age.

These data also include demographic information on students, such as their race/ethnicity, grade, and gender, which allows for an added level of analysis not available in the prior BMI study involving school children (Schafft et al. 2009). These data not only allow for individual-level analysis of the students, but also provide information on their school, thus providing a second level of analysis in addition to the third level of data on the county.

School Data

Variables on schools were taken from data available to the public through the Department of Public Instruction of North Carolina (North Carolina Department of Public Instruction 2010a; North Carolina Department of Public Instruction 2010b; North Carolina Department of Public Instruction 2010c). These include the percentage of children that receive a free or reduced lunch, a normative measure for school economic disadvantage, and
the racial/ethnic makeup of the student population (accounted at the end of the first month of school). Excel files were downloaded from the DPI website, then uploaded into SAS and merged with student data using the school and LEA identification numbers.

COUNTY DATA

Finally, schools in the dataset are nested within their counties. Using data downloaded in Excel from the National Center for Education Statistics, I merged them into SAS and linked each LEA to the county in which it was located. An Excel file downloaded from the U.S. Department of Agriculture “food desert locator,” on the number of census tracts in each county without sufficient access to grocery stores (Economic Research Service 2011a), was used to measure food access. Additional information on North Carolina counties, including urban/rural status, median income by race, crime index, and housing information, was downloaded from the North Carolina Rural Economic Development Center and originally provided by the American Community Survey 2006-2009 summary and the 2010 U.S. Census. The dissimilarity index for racial segregation was calculated with census tract data for North Carolina that I downloaded directly from the U.S. Census FactFinder (U.S. Census Bureau 2011).

After being cleaned and processed for the 2009-2010 school year, which the data involved in this study are from, the analyzable sample included data from 40 out of the 115 (about 35 percent) Local Education Areas (LEAs) in North Carolina, which consisted of 38 counties, 319 schools, and 75,318 students. Despite the unique nature of these data, the final sample for the empirical analyses matches the state student population on key demographic variables and contains counties with a diverse range of socioeconomic, racial, and rural/urban
attributes. Appendix C displays the demographic data on individuals in the sample as well as the total population of 3rd-5th graders enrolled in North Carolina public schools in that school year. At the school level, the data represent both ends of the poverty and segregation spectrum as well as both urban and rural counties spread out in all regions of the state. The implications of the non-random nature of the sample will be discussed later as the specific research questions and methodologies are developed in more detail. However, given the large scale of the IsPOD project (which aims to eventually provide this software to all PE teachers) the sample provides a very diverse group of schools and populations from which to examine these issues.

This unique collection of data provides the appropriate information needed to address the research questions in this project. Next, I will detail specifically how I constructed the key variables for this analysis and the specific statistical technique that is used.

**Key Variables**

**DEPENDENT VARIABLE: OBESITY**

The dependent variable for this research is whether or not a child is obese. To operationalize the variable, each respondent’s height and weight was transformed into a measure that is meaningful and able to be compared with children of different ages. First, the Body Mass Index was calculated by dividing the respondent’s weight in kilograms by their height in meters squared: \( \text{BMI} = \text{Weight (kg)} / (\text{Height (m)} \times \text{Height (m)}) \). However, unlike adults, BMI cannot be compared directly between children of various ages; instead their BMI is plotted on a CDC growth chart to determine the child’s percentile for their age at the time of the test and their gender. I constructed a variable to measure the respondent’s age at test
using the date of their test as well as their date of birth. Using the child’s age in months,
gender, and BMI, I created a variable for what percentile their BMI fell into. The percentile
was then used to place children in one of four weight categories: underweight, normal,
overweight, and obese. Children are considered overweight if they are at or above the 85th
percentile for their age and gender, up until the 95th percentile, at which point the child is
considered obese (Ogden et al. 2010a). I then created a dichotomous variable in which
students were coded with “1” if they were obese and “0” if they were not obese. This
measure of obesity will serve as the dependent variable for all of the research questions.

There has been some criticism of using BMI as a measure of health (Guthman and
DuPuis 2006). Because BMI is unable to access how much of one’s weight is due to fat and
how much is due to muscle, since it does not measure the adipose tissue, it can be
problematic as a diagnostic measure of individual health.\(^5\) However, despite these criticisms
BMI remains the most common clinical assessment of weight (Mullen and Shield 2004) and
an appropriate tool for assessing obesity differences between groups. Below is a detailed
description of all of the independent variables included in this research. Table 2 provides a
brief overview of the sources of these variables.

**STUDENT VARIABLES: CONTROLS**

Grade, race, and gender measures are derived from the Department of Public
Instruction (DPI) NCWISE database by the North Carolina State Health Statistics department
that processes the data that has been submitted by PE teachers. Grade is included as a
continuous variable in the analysis. Gender, which has also been shown to be associated with

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\(^5\) Athletes are likely to be considered “obese” due to muscle weight and differences in bone density could
account for higher BMI among African-Americans.
obesity (Sweeting 2008), will be included as a dummy variable, using “male” as the omitted reference category. Race was recoded to limit the number of categories: children who were not White, African American, and Hispanic, were recoded as “other.” These categories were then recoded as dummy variables in which “White” was the omitted reference category.

**School Level Variables**

The second set of variables includes characteristics at the school level. As noted, poverty is an important part of understanding childhood obesity; therefore the percentage of students who receive a free or reduced lunch will be used to measure economic disadvantage at the school level. This variable is constructed using data from the “North Carolina Department of Public Instruction, Child Nutrition Services, Free and Reduced Application Data by Site for 2009-10” (North Carolina Department of Public Instruction 2010a), which uses the number of students who receive a free and reduced lunch divided by the Average Daily Membership\(^6\) for that school year to determine the “percent needy” at each school. This is the same measure that the state uses to assess economic disadvantage in schools. Of the 319 schools in the sample, two were missing poverty data for their site and were eliminated from the sample.

Next, I created a measure of racial segregation for each school using data from the North Carolina Department of Public Instruction “Grade, Race, Sex 2009-10” report. The report is divided by school. Within each school it provides the gender and race breakdown for students on the last day of the first month of school. Because these data are produced at

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\(^6\) The sum of the “number of days in membership” for all students divided by the number of school days in the term yields ADM. The final average daily membership is the total days in membership for all students over the school year divided by the number of days school was in session. Average daily membership is a more accurate count of the number of students in school than enrollment.
the end of the first month of the school year, the number of students may differ from the Average Daily Membership (ADM) (a more accurate accounting of the total number of students in that school year) which was used as the denominator for determining the response rates for each school and for the percent needy at each school. The US Department of Education Federal guidelines (see FR Doc E7-20613) regarding the collecting and reporting of racial categories has undergone changes recently that were partially in effect at the time of this study. While DPI had begun using the same racial categories as the US Census, as mandated, for students in the 2009-10 school year the aggregate reporting of those new categories did not begin until the following year (2010-11). As such, individual students have a larger scope of racial categories than the school reports indicate. For, example, students can be categorized as “Multi-racial,” while the school level reporting only allows students to be included in one racial category. This discrepancy could cause the slightly higher percentage of students who are listed as “Other” in the sample, as it is possible that they would have been listed as “Multi-racial” individually but counted as either “White” or “Black” in the aggregate school-level data. However, given the nature of the study and the interest in minority vs. white-segregated schools, the school-level accounting does not impede my ability to measure segregation. Racial makeup of schools was calculated by setting the number of students of a particular racial category over the sum of students in all racial categories. As is the standard in prior literature on racial segregation (see Condron 2009) I coded white segregated schools as those in which 75 percent or more of the students are white. Likewise, minority segregated schools are those in which at least 75 percent of the
students are non-white. If the school does not meet either of the aforementioned criteria it is considered an integrated school.

COUNTY LEVEL VARIABLES

The third level of the model incorporates aggregate-level county data obtained from the 2010 census, the 2006-2009 summary data from the American Communities Survey, the North Carolina Rural Economic Development Center, and the US Department of Agriculture. First, I constructed a variable to control for the urban or rural character of the county, as studies have shown different effects of segregation for urban and rural communities (Ismailov and Leatherdale 2010; Liu et al. 2008). Using data provided through the North Carolina Rural Economic Development Center, I constructed a dummy variable that indicated whether the county is rural (urban is the omitted baseline category). Using data downloaded from the U.S. Department of Agriculture, I created a dummy variable for counties that had one or more census tract that is considered a food desert. Counties that do not have any census tracts that are food deserts are the omitted baseline category.

To assess the racial segregation in a county, I used the dissimilarity index which measures the evenness of the distribution of two groups among small geographic units (i.e. census tracts) within a larger geographic unit (i.e. county). This is the most widely used measure of residential segregation (Massey and Denton 1988). After downloading tract-level demographic data from the 2010 census (U.S. Census Bureau 2011) I calculated the segregation of White people and African American people in each county using the following formula:
I also created a measure of segregation between Hispanic people and White people and between American Indian and White.

Another important aspect of place with regard to child health is county-level poverty. As such, I included the percentage of people in poverty, one for each racial category, from the 2005-2009 American Communities Survey. The percentage of households receiving Supplemental Nutrition Assistance (SNAP) and the unemployment rate were also taken from the ACS. Studies have also shown that being uninsured has an impact on health, so a measure of the percentage of the population that is uninsured, taken from the 2010 Census, was also included. Social disorganization, as measured by the crime rate, is another variable used to measure spatial inequality and was also included from the 2010 census.

**Sample and State Population Comparisons**

Since the data were not drawn using a simple random sample, Appendix C provides a comparison between the sample that was collected and the state population of 3rd-5th grade public school students. The distributions follow the same patterns as the state distributions, although the sample has a slightly lower proportion of African American students and slightly more students considered “Other”. This could be due to the aforementioned changes in racial categories. The grade level distributions and gender mirror that of the total population of youth in NC. Appendix C shows the descriptive statistics for students’ weight category within the sample. It is similar to the distribution of weight among children in the US at large, with slightly over one third of the students categorized as overweight or obese.
Appendix C also provides descriptive statistics of all North Carolina schools that provide instruction for at least one of the 3rd-5th grades as well as the sample of schools used for this study. As is evident from the table, the sample has a similar distribution to the state on the key variables. The sample has a slightly higher percentage of minority segregated schools and a slightly lower percentage of integrated schools than does the state overall. This is not surprising given that the original counties in the IsPOD initiative were selected because of their race-based health disparities. The schools in the sample have a slightly lower average with regard to economic disadvantage, but the same range as the state. These tables also show the county variables for both the state and the distribution for the counties used in the sample. The sample has a slightly higher proportion of urban counties and a slightly higher percentage of food desert counties. Otherwise the sample counties are very similar to the other counties in North Carolina.

*Descriptive Statistics*

Table 3 shows the descriptive statistics for key variables used in this study. Twenty percent of the students in the sample are overweight. The sample is comprised of approximately half girls and half boys, and evenly distributed between grades 3-5. As anticipated, the majority of the students are White, followed by Black, and Hispanic.

Approximately half of the schools are not racially segregated, followed numerically by white segregated and minority segregated, respectively. The majority of schools are medium poverty, followed by high poverty and low poverty, respectively. Finally, a majority of the counties are rural with a great deal of variation in their food environments.
Correlation matrices were then run to check for multicollinearity among the variables in the final sample. Results of these tests are presented in Appendix B. All correlations were less than .70 in the data. The highest correlations were among school-level poverty and school-level racial segregation. This is consistent with literature on school segregation and is discussed in detail in Chapter 4. Unfortunately, there are not any clear multicollinearity diagnostics for multilevel modeling so in order to further investigate this issue I ran a series of bivariate models in order to examine the relationship closely. My results confirm the relationship between the percentage of minority students and the percent of economically disadvantaged students; however, this relationship is minimized by making them dummy variables instead of leaving them as interval/ratio level variables (see Chapter 4).

Estimation Technique

Consistent with prior literature (Schafft et al. 2009), Body Mass Index will be measured using a dichotomous variable of this analysis. In other words, I will model the likelihood of a child being “obese” as opposed to “not obese.” The limited range of this type of dependent variables violates the assumptions of Ordinary Least Squares (OLS) regression and therefore it is not appropriate for this research (Pampel 2000). Alternately, logistic regression models the log likelihood of an event occurring. Therefore, the model is not limited by the binary outcome variable but instead models a full range of possible likelihood outcomes. As each predictive variable is added to the model, I can assess its impact of the log likelihood that a particular event will occur (in this case the event is obesity). As such, I will use logistic regression models for these data.

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7 Personal communication with Dr. Shevaun Neupert, Associate Professor of Psychology, North Carolina State University
Given the structural nature of the research questions as well as the clustered nature of the data, it is important to use a statistical technique that allows for the analysis of the individual- as well as the aggregate-level data. Since I anticipate that there will be some variation between schools and counties, I cannot use a standard regression model, as I cannot assume that errors between individuals are random (Luke 2004a). Therefore, it is important to use a measure that allows me to examine the effects of these levels separately. Given that I anticipate the differences between groups will be meaningful, a model that does not account for the magnitude of differences between levels is insufficient (e.g. GEE models which control for clustering but do not allow for variables at the school or county levels). As such, I will be using hierarchical logistic regression to address these research questions. By conducting a multilevel analysis in which I nest students within their schools and then their counties, this study presents the unique opportunity of examining childhood obesity while utilizing both structural- and individual- level variables.

Conclusion

These data have several strengths that make them appropriate for this project. First, other efforts to collect BMI data on North Carolina youth collect only a few youth per county (North Carolina Nutrition and Physical Activity Surveillance System 2010) or are only intended to produce state level estimates (Miles, Herrick, and Ford 2010). While those studies provide very important and necessary data for monitoring the health of all North Carolina children, they do not allow for this sort of in-depth county- and school-level analysis. One of the strengths of the data used in this particular study is that it provides height and weight information from a large number of children within each county and school that
were included in the *IsPOD* initiative at the time. Additionally, unlike the North Carolina Nutrition and Physical Activity Surveillance System (NC-PASS) study which collects data only on children who have visited North Carolina Public Health sponsored WIC and Child Health Clinics, these data include all students attending public schools—allowing for a broader range of SES among respondents. Moreover, unlike other state data such as the Child Health Assessment and Monitoring Program (CHAMPS) survey of North Carolina children, these data were gathered by PE teachers and not parents, who have a tendency to underestimate weight (Field et al. 2007).

By combining the student data with school- and county-level data, the final dataset is well suited to answering the research questions. However, despite these strengths there are several limitations. While these students match the state on several key variables, the data do not constitute a random sample. These are instead a convenience sample gathered only on students who had PE teachers that were trained under the *IsPOD* initiative and provided access to FitnessGram™ software. Therefore, students included in this study may differ from those in the state on unmeasured variables. Nonrandom samples are most commonly used in situations in which the researcher is asking about information that is difficult to gather through a random sample and cannot be generalized to all North Carolina students. This is not an uncommon issue when examining biological or culturally sensitive information (McCullagh 2008). Other exploratory studies may also rely on nonrandom samples to explore new issues (Mackie and Lips 2010). Similar studies that relied on convenience samples have also compared the collected data to other populated and weighted data when appropriate (Austin and Irwin 2010). Finally, while these data allow for an in depth
examination of characteristics of place in North Carolina, and these patterns of racial and economic segregation are part of all regions of the US (Kawachi 2002; Parisi et al. 2011), these data cannot be generalized to the United States. They provide an initial examination at the role of place within one state, which I hope will lead to additional research on these larger issues of segregation and the role of place in other regions.

Data for this project (both population and sample) only represent students that were enrolled in a public school for the 2009-10 school year. This excludes an estimated 21,744 children aged 8-10 reported by a parent/guardian to be homeschooled in that year (State of North Carolina Department of Administration 2010a), as well as 22,975 3rd - 5th graders enrolled in a private schools (State of North Carolina Department of Administration 2010b). Moreover, while charter schools were allowed to participate in the IsPOD initiative and record student data, the data was excluded from the analysis, representing about 8,583 students in grades 3-5 enrolled in charter schools (North Carolina Department of Public Instruction 2009). Despite this, almost 90 percent of children in North Carolina attend non-charter public schools and therefore offer a useful population to consider these research questions. By focusing on public education I am also able to explore how place and public education, a site intended to equalize opportunities, can mitigate or reinforce inequalities.

Finally, these data do not include family variables and therefore I cannot control for characteristics of the family such as family size, income, networks, voluntary organization membership, church affiliation, or neighborhood residence. The effect of this limitation will be discussed in greater depth within the empirical chapters.
With this unique set of data, I am able to answer the important questions posed at the beginning of this chapter and better understand the role of place in rates of childhood obesity. In the next three chapters, I examine each of the research questions in sequence.
CHAPTER FOUR: EMPIRICAL ANALYSIS: POVERTY AND CHILDHOOD OBESITY

As evidenced in Chapter 2, the existing research on poverty and childhood obesity tends to omit a comprehensive analysis of place. This chapter seeks to fill that gap in this literature by examining the relationships among childhood obesity and poverty at the school and county levels. The research question guiding this analysis is as follows: are students more likely to be obese in poor communities and schools compared to students in affluent communities and schools?

To answer this question, I use a logistic regression multilevel model that incorporates individual-level, school-level, and county-level variables. Whether or not a student is obese will be the predicted, or dependent, variable. For details on the source and measurement of variables, refer to Table 2. Unfortunately, the North Carolina data do not provide the poverty status of individual students, so I am only able to control for race, gender and grade at the individual level. The implications of this limitation will be discussed at length in the latter part of this chapter. Poverty information at the school level is measured by the percentage of students that receive free or reduced lunches. At the county level, economic distress is measured using a variable for the percentage of households receiving funds through the Supplemental Nutrition Assistance Program (SNAP) and a variable controlling for the percentage of people in the county who are uninsured.8

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8 Two additional analyses were run using the 2009 poverty rate and then the ACS 2005-2009 child poverty rate as alternative measures for county level economic distress. The results for all of the poverty measure variables produced similar results and therefore only the results of the SNAP measure are reported.
I anticipate that students attending affluent schools (i.e. those with lower percentages of students who receive free or reduced lunch) will have lower predicted odds of being obese compared to students in less affluent schools, net the other variables in the model. At the county level, I anticipate finding that the higher the levels of disadvantage in the county, the higher the odds of students being overweight when compared to students in less economically depressed counties, net of the other variables in the model.

**Correlations: Poverty and Racial Segregation**

Correlation matrices revealed some potentially problematic relationships among some of the measures of school and community disadvantage. In order to address the issue of poverty, I will first discuss issues of correlation between poverty and race at the school level. According to previous studies, racial segregation for minority children is often accompanied by high levels of school-level poverty and, conversely, white segregated schools are often associated with low school-level poverty (Roscigno 1999; van Ewijk and Sleegers 2010). The North Carolina data for this project are consistent with this finding. The percentage of economically disadvantaged students at a school is positively correlated with the percent of minority students \( r = .73393 \) and is statistically significant at the .0001 alpha level. This is consistent with other studies examining race and poverty at the school level (Konstantopoulos and Chung 2011; Roscigno 1999; Roscigno and Ainsworth-Darnell 1999; Thompson 2004). While these findings speak to the interconnectedness of race and disadvantage, I will rely on methods used in prior studies to resolve the statistical problems of high intercorrelation among the race and poverty measures to gain a greater understanding of each variable’s relative effects (Condron 2009; Konstantopoulos and Chung 2011).
In order to investigate the school-level race and poverty separately and to resolve the issues of multicollinearity associated with these inter-correlations, I created a categorical variable for both racial segregation and poverty segregation. Unfortunately, there is no standard measure for assessing the impact of multicollinearity in multilevel modeling, however by examining bivariate models I was able to determine that by creating dummy variables I was able to minimize the strength of the relationships. Drawing from prior segregation literature (Condron 2009), schools with 75 percent or more of its students receiving a free or reduced lunch were considered “high poverty,” those with 25 percent or less were considered “low poverty” and those with 26-74 percent were considered “moderate poverty.” The recoding of school poverty into categories has a basis in prior research on schools (Condron 2009; Konstantopoulos and Chung 2011). The categories were constructed with the goal of evenly distributing schools into the three relatively balanced categories.

Table 4 shows the relationship between minority segregation and poverty concentration for the students in the North Carolina sample. Students attending schools with high minority populations are the most likely to be in high poverty schools and those students in schools with low minority populations are most likely to be in low poverty schools. These findings closely resemble the distribution of all schools in the state (see Appendix C). An examination of the 614 students in schools that are both high poverty and white segregated reveals that 100 percent of them are located in rural counties. This is important as it reveals how the relationship between rural and urban environments interacts with the measures of

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9 Personal communication with Dr. Shevaun Neupert, Associate Professor of Psychology, North Carolina State University
segregation and exclusion. This highlights the need for research on school environments that extends beyond an exclusive examination of urban racial and economic segregation.

The recoding into a categorical variable resolves the issues of multicollinearity. The correlation remains highest among the minority segregated and high poverty schools (.69), but this is lower than the correlation prior to recoding and the other correlations are no longer problematic (see Appendix B).

At the county level, the crime rate and living in a rural county were negatively correlated (-.7). There is literature indicating that the difference between urban and rural counties makes an important difference with regard to the effect of poverty and racial segregation (Slack 2010b). Additionally, in this project I am specifically interested in the differences between urban and rural places and their impact on childhood obesity, therefore the crime rate variable was dropped from the analysis. Additionally several measures of poverty were available in the dataset, but issues of multicollinearity result from including more than one, and therefore, could not all be included in the models. Given the relationship between food insecurity and obesity (Eisenmann et al. 2011), I included the percent of households participating in the Supplemental Nutrition Assistance Program (SNAP) as the county level measure of economic distress. This particular variable was used because it is a more recent measure (2010) than the measures of the percent poor (ACS 2005-09). Moreover, it represents those who have net incomes of less than 100 percent of the poverty level coupled with very limited economic resources at their disposal (United States Department of Agriculture 2012) and those who have specifically sought assistance with
buying food. This variable thus serves as an estimate of economic distress as related to food insecurity within the county.

The dependent variable used in the models for this analysis is the individual-level measure of whether or not a child is obese. The models predict the likelihood of a child being obese net the other variables in the model. The level one (student) independent variables for these models are race, gender, and grade. Level two (school) independent variables will include the measures of school poverty and racial segregation discussed above. Finally, level three (county) independent variables are rural residence, the presence of a food desert in the county as measured with the 2000 Census, dissimilarity indices for Black/White and Hispanic/White segregation from the 2010 Census, the percentage of households receiving SNAP in 2010, and the percentage of uninsured persons from the American Communities Survey (ACS) 2008-09. See Table 2 for detailed information on the variables.

Method

MULTILEVEL EQUATION AND VARIANCE

To effectively model these data and address the research question regarding the role of school and community poverty on obesity, I use a multilevel logistic regression model. To confirm that there was a statistical need for multilevel analysis, I used a chi-square statistic to determine if there was a statistically significant difference in obesity rates by schools and by counties, respectively, in the sample (Snijders and Bosker 2012). Both tables were statistically significant at the .05 alpha level and confirm the need for a multilevel model. Because the dependent variable is binary, a logic function is used to model the log odds of the event (Pampel 2000). Similar to the standard logistic regression equation, the multilevel
The logistic regression model calculates the likelihood of an event (in this case, a child being obese) as the dependent variable:

$$\text{logit}(p) = \ln \left( \frac{p}{1-p} \right)$$

The standard logistic regression model then calculates the effects of predictor variables on the odds of the event occurring with the following equation:

$$\text{logit}(p) = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + \ldots + b_k X_k$$

The multilevel model has the additional ability to allow for intercepts to vary at the student, school, and county level; also known as “random intercepts.” The equations below depict the equations for a base 3-level model (Guo and Zhao 2000). These equations include both fixed and random effects with one predictor variable ($x$), with $i$, $j$, and $k$ representing students, schools, and counties, respectively:

$$\log \left( \frac{p_{ijk}}{1 - p_{ijk}} \right) = \beta_{0jk} + \beta_{1j} x_{ij} \quad \text{(level one)}$$

$$\beta_{0jk} = \beta_{0k} + u_{0kj} \quad \text{(level two)}$$

$$\beta_{1j} = \beta_{1} + u_{1j} \quad \text{(level two)}$$

$$\beta_{0k} = \beta_{0} + v_{0k} \quad \text{(level three)}$$

The combined equation is:

$$\log \left( \frac{p_{ijk}}{1 - p_{ijk}} \right) = \beta_0 + \beta_1 x_{ijk} + u_{ijk} x_{ijk} + v_{0k} + u_{0kj}$$

Estimation of these models was done using the PROC GLIMMIX procedure in base SAS software (version 9.2). Studies have shown that this procedure, particularly when used with large datasets, provides similar results to other software packages and estimation procedures (Li et al. 2011).
Unlike traditional logistic regression models that have one random error term to capture all of the unexplained variance in the outcome variable of the model, a multilevel model is able to divide this variance among the three levels in the model. Relying on the work of Goldstein and colleagues (2002), I estimate the total variance by adding the school-level (level 2) and county-level (level 3) variance to the estimated individual level variance (level 1). The level one variance is calculated using a standard logistic distribution:

$$\pi^2/3 = 3.29$$

The residual variance amounts for level two and three that are obtained by the covariance parameter estimates generated by the SAS GLIMMIX procedure for which I also requested a WALD measure of statistical significance and the confidence intervals for each (Goldstein et al. 2002; Snijders and Bosker 1999). These estimates serve as a measure of residual intraclass correlation, and the technique of standardizing the level one variance is known as the “latent variable approach” (Snijders and Bosker 1999). Pursuant of the suggestion of Guo and Zhao, (2000) the variance at levels two and three will be reported in the multilevel analysis tables.

To obtain the variance at both the school and county levels, I first ran a base multilevel model. In this case that means an empty 3-level model without predictor variables at any level. Table 5 shows the results for five nested multilevel models predicting the likelihood of obesity for children in the dataset. Model 1 is the base model and does not contain predictor variables at any level. The school and county level random effects are both statistically significant at the .05 alpha level indicating that there is a significant covariance within and between schools as well as within and between counties. In order to calculate the total variance for all three levels, the standard level one variance is added to level two and
level three variance provided by the SAS output. To then calculate the percentage of total variance at each level (individual, school, and county), I divide the variance at each level by the total variance. Using this latent variable approach to estimate the total variance, the equations are as follows:

\[ \text{.1735 (school level)} + .02461 (county level variance) + 3.29 (level one variance) = 3.48811 \text{ total} \]

Percentage of total variance at the school level:

\[ .1735 / 3.48811 = 4.97\% \]

Percentage of total variance at the county level:

\[ .02461 / 3.48811 = 1\% \]

These equations tell the researcher how much unexplained variance is attributed to each level of the model. According to the results above, the greatest amount of variation is attributed to differences among individual students, followed by differences among schools, and then among counties. For example, 4.97 percent of the unexplained variance in the model is attributed to differences among schools. These results demonstrate that there is significant covariance at the school and county levels, meaning that these are important sites of variation in rates of obesity among children. Further, according to the latent variable approach, there is more unexplained variance at the school level than at the county level. Although this is to be expected in multilevel models, with each higher level in the model we expect there to be less unexplained residual variance than in the previous level, particularly with regard to health outcomes (Sacker, Wiggins, and Bartley 2006).

Given the results of these tests, and the statistically significant variation among schools and counties in the sample, it is important to model these data in a way that accounts
for that variation and allows one to test the significance of these variables at each level. The following section provides the results for nested models that control for variables at each level of analysis.

Results

Individual Level Predictors

Model 2 in Table 5 adds the individual-level predictors (student variables) in the three-level base model. Consistent with prior research, race, age, and gender all have statistically significant (p<.05) effects on the likelihood of a child being obese. While statistically significant, the effect of gender is very small. The odds ratios are calculated by taking the exponential function of the regression coefficient ($e^b$) which is then interpreted as the ratio of the odds of being obese between two categories or for each one unit increase for interval/ratio variables (Pampel 2000). According to the model, the odds of girls being obese is .85 times the odds of boys being obese, net the other factors in Model 2. Conversely, race has a larger effect on the likelihood of obesity: The odds of obesity for Black children in the model are about 1.7 times the odds for Whites, and Hispanic youth’s odds are 1.99 times that of White children. Children of “other” races had odds that were 1.3 times the odds of White children in the model. Year in school also has a statistically significant effect on the likelihood of obesity. With each grade increase, the odds that a student would be obese increased by about .06, net the other variables in the model.

School Level Predictors

Models 3, 4, and 5 present the results for the addition of school-level variables in the three-level model. Model 3 is a multilevel model that includes the same individual-level
variables discussed above and adds two dummy variables for racial segregation at the school level (see Table 2 for detailed variable information). Model 4 introduces the variables for poverty segregation at the school level to the model with individual-level controls. Model 5 combines both the racial and poverty school-level segregation variables in the same model with the individual-level control variables.

All of the individual-level variables from Model 2 remained statistically significant and in the same direction. However, the effects of these individual-level variables slightly decreased. For example, in Model 4, the odds for Black youth being obese in the sample is only 1.6 compared to the odds of Whites in the sample, which is down from 1.7 in the prior model. The odds of obesity for Hispanic children decreased by a little less than .01 relative to Whites as well, net of the other variables in the model. The effect of grade remained consistent in both Model 2 and Model 4.

The two dummy variables that measure poverty segregation at the school level are statistically significant at the .05 alpha level in Model 4. High poverty schools had a statistically significant and positive effect on the likelihood of obesity, net the other factors in Model 4. Model 4 shows that the odds of a student in a high poverty schools being obese is about 1.15 times that of children in moderate poverty schools. Conversely, students in low poverty schools have lower odds of being obese compared to students in schools with moderate poverty. The model predicts that the odds of obesity for students in low poverty schools are .63 times that of students in moderate poverty schools, net the other variables in the model.
Model 5 contains all of the school level variables for both racial and poverty composition, as well as the control variables at the individual level. Once racial segregation at the school level is introduced into the model, the difference between high poverty and poverty integrated schools is no longer statistically significant, net the other factors in the Model 5. Conversely, the predicted difference between low poverty and poverty integrated schools remains statistically significant and negative. Net the other variables in the model, the odds of students in low poverty schools being obese are about .65 times students in schools with moderate poverty in the Model 5. Additionally, by using the latent variable approach, the percentage of unexplained variance at the school level has decreased significantly from about 5 percent in the base model to about 2 percent of the total variance in Model 5. This indicates that the variables in the school-level model account for a substantial proportion of the unexplained variance.

**COUNTY LEVEL PREDICTORS**

Model 6 is the full model and includes the county-level variables. Of the individual-level variables, gender is no longer statistically significant in the final model. However, race and grade at the individual level remain statistically significant and in the same direction as when they were introduced in Model 2 of Table 5.

School-level predictors in the final model (6) also remain consistent with the prior model (5). School-level racial segregation is not statistically significant controlling for other variables in the model. School-level poverty concentration is statistically significant, but only between students in very low poverty schools compared to those at moderate poverty schools. As with the prior model, net the other variables in the model, the odds of being
obese for students in low poverty schools is 0.66 times that of students at schools with moderate poverty. The variable that measures the difference between medium poverty and high poverty is no longer statistically significant.

Model 6 also includes variables that capture the place variations in county environments. The model predicts that there is a statistically significant relationship between place (being in a rural or urban county) and the likelihood of childhood obesity. The odds of students within rural counties being obese is 1.25 times the odds of students in urban counties, net the other variables in the model. Moreover, the measure of economic distress, the percent of families in the county receiving food stamps, has a statistically significant and positive effect on the likelihood that a child will be obese in the model. For each one percent increase in the percent of households receiving food stamps, the odds that a student will be obese increases by 7.9, net the other variables in the model.

Several of the variables added in Model 6 were not statistically significant. The county-level variables to measure the residential segregation of Whites and African-Americans and Whites and Hispanics, respectively, were not statistically significant in Model 6, net the effect of the other variables. Similarly, the percentage of people uninsured in the county did not have a statistically significant effect on the likelihood of obesity, net the other variables in Model 6. Finally, the dummy variable to measure whether or not a county contained one or more census tracts considered a food desert, was not statistically significant at the .05 alpha level in Model 6. It is important to note that these results are all net the effects of individual- and school-level variables already controlled in the model. These results are discussed in the next section of this paper.
INTERACTION EFFECTS

Since race and economic segregation both had independent effects when added to the model separately, the final model includes a test for interaction effects at the school level. The first interaction model is the full model presented in Model 6 of Table 5, with the addition of three interaction variables. Each of the new variables is a product of two dummy variables: one for school poverty and one for racial segregation (with the exception of racial segregation and low poverty since there were no low poverty, minority segregated schools). In other words, the following variables were added: 1) minority segregated*high poverty 2) white segregated*high poverty 3) white segregated*low poverty. The interaction terms for race and poverty at the school level were not statistically significant and so the results were not reported in Table 5. Interaction terms are then added to test for a three way relationship between a student’s race, racial segregation at the school level, and poverty segregation at the school level. In order to test for a three way interaction, all possible two level interactions were also included in the model (Gossett et al. 2011). The three-variable interaction coefficients for Black, White and Hispanic students with school level poverty were not significantly significant. However, it is important to note that in a complex model with 3-way multilevel categorical variables it is possible that multicollinearity is causing the effects to be non-significant (Carmines and Zeller 1979).

SUMMARY

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10 The model was first run without the county level variables and there was a significant interaction between white segregation and low poverty. However, this relationship was no longer statistically significant when the county level variables were included.
11 The two-level interaction between student level race and school level poverty interaction was statistically significant, but without the ability to control for student level poverty status I could not be confident about this relationship and did not include it as a finding.
Multilevel logistic regression models permits one to examine the effects of both individual characteristics and context on the likelihood of a child being obese. The initial tests run on the North Carolina data reveal that there are statistically significant variations among schools and among counties. These results demonstrate the importance of using the multilevel model to examine the predictor variables in a way that accounts for the structure of the data and the independent influence of context. Model 2 reveals that race, gender, and grade are important predictors of childhood obesity. Models 3, 4, and 5 include school-level variables for the poverty and race context of the school that the child attends. These models indicate that school-level race and poverty variables are statistically significant, net the individual-level controls. However, when all school-level variables are combined in Model 5, the effect of race is no longer statistically significant. Only schools that were low poverty have a statistically significant and negative effect on the likelihood of obesity relative to medium poverty schools.

A majority of the county-level variables are not statistically significant in the full model. Rural residence and the percentage of people receiving SNAP benefits have a statistically significant and positive effect on the likelihood of obesity in Model 6. However, other variables measuring economic distress and food access, such as the presence of food deserts in the county, the percentage of individuals without health insurance, are not statistically significant, net the other variables in the model. None of the variables measuring residential racial segregation are not statistically significant, net the other variables in Model 6. In the next section I discuss the implications of these statistical results.

Discussion and Conclusion
The findings in this chapter reveal that while student demographics are an important part of childhood obesity, there are also important structural effects. Consistent with prior research on childhood obesity (Ogden et al. 2010a), I find that the race, gender, and grade of individual students have statistically significant effects on the likelihood of obesity. However, while student characteristics are important, using this model also revealed that there are important similarities among students at the same school, and schools in the same counties. The multilevel logistic regression models are able to allow for random effects at the school and county and level. By using these models, I find that there are statistically significant inter-class correlations among students at schools, and also among schools within the same counties. Allowing the intercepts to vary at both the school and county level in the models revealed that there are statistically significant variation at these levels and that I could not assume random variation between individual students. Thus, I conclude that there are important effects of place that are persistent even when individual-level characteristics are controlled, as is evident in Model 2. This is an important addition to existing research on childhood obesity that tends to examine mainly individual-level characteristics and behaviors (Birch and Ventura 2009; Flegal et al. 2010; Ogden et al. 2010b).

Both county- and school-level variables are statistically significant. This result adds to the body of literature that examines the effect of school-level variables on obesity (Li and Hooker 2010; O'Malley et al. 2007). Conversely, studies of county- or neighborhood-level deprivation have historically excluded other sites of deprivation such as school or work (Chang et al. 2009; Robert and Reither 2004). This research adds to our knowledge by
examining both sites and finding that school environment, as well as the county environment, have statistically significant effects on the likelihood of obesity among children.

The research question guiding this chapter is whether or not students are more likely to be obese in poor communities and schools as compared to affluent communities and schools. The results indicate that while students in poor schools are significantly more likely to be obese relative to children in schools with moderate poverty, the effect disappears when school-level racial segregation is included in the analyses. So while poverty at the school level is an important predictor of obesity, net of the effects of the individual student’s race, racial segregation at the school level appears to largely account for differences between moderate and high poverty schools.

The difference between low poverty schools and moderate poverty schools remains strong and negative, even when racial segregation is controlled. In all the models, students in low poverty (affluent) schools were less likely to be obese compared to all other students, net of the other variables in the model. This remained true even when county context was controlled. These results add to our understanding of socio-economic segregation. A great deal of research examines poverty at the structural level and focuses on residential segregation (Kawachi 2002; Mayer 2002; Williams and Collins 2001), leaving out other important sites of inequality such as schools.

While these findings replicate prior research on childhood obesity and school-level SES (Li and Hooker 2010; O'Malley et al. 2007), they also expand this literature in important ways. First, these analyses combine both racial segregation and poverty segregation at the school level. This is important given that race and poverty segregation are often correlated at
the school level. I find that contrary to the assumptions of prior research, the concentration of poverty may be less important than the concentration of affluence in some schools. While this study did not measure affluence directly, the impact of very low poverty schools had on the likelihood of obesity was statistically significant and negative in all the models, net all the other variables. The results of this study indicate that the largest difference exists between those schools with very little poverty and middle to high poverty schools, instead of an isolation of the very poor from everyone else. This is consistent with recent findings on patterns of residential segregation that show an isolation of affluence to a greater degree than the segregation of the poor (Albrecht et al. 2005).

The results for community-level measures of poverty were less clear. Consistent with the random effects at the school level, I also find that there are statistically significant covariances within and between counties, which supports a place-oriented approach to studying childhood obesity. The measure of economic distress and food assistance within the county, operationalized by the percentage receiving SNAP, does have a statistically significant and large positive effect on the likelihood of childhood obesity, even when other student-, school-, and county-level variables are controlled. This is consistent with studies that indicate that economic distress and food insecurity can lead to increases in obesity (Dietz 1995) and lends support to the hypothesis that students within food insecure counties have different rates of obesity. However, the percentage of uninsured persons in the county was not statistically significant. Overall, I conclude that children in high poverty communities and schools show an increased likelihood of obesity relative to those in low poverty schools and
communities, while noting that further research is needed to replicate and expand our understanding of different measures of economic distress at the county level.

Working in the tradition of rural sociologists, who have been at the forefront of research that examines the effect of place at the sub-national scale (Lobao 2004b; Roscigno and Ainsworth-Darnell 1999), this research furthers our understanding of how county environments affect childhood obesity. Residing in a rural county has a statistically significant effect on childhood obesity. Research that examines the role of obesity and economic segregation has often focused on adults in urban settings (Chang et al. 2009; Robert and Reither 2004). However rural sociologists, in examining other social phenomena, have noted the importance of examining the effect of rural and urban sites when examining the role of place (Lobao and Saenz 2002). This research adds to this body of literature in that it examines the role of county-level economic distress in both urban and rural areas in childhood obesity rates and reveals that urban/rural is an important component of place that deserves additional attention in future research. Consistent with similar studies that have examined the obesity rate of children in rural areas (Liu et al. 2008; Shriver et al. 2011), I find that children in rural counties have a higher likelihood of obesity compared to their urban counterparts. This study replicates that important finding and adds to our understanding by showing that this finding remains even when poverty and racial segregation at the school- and county-levels are held constant. This study’s examination of elementary school children broadens our understanding of the role of place for children.

In addition to the above findings, there are several variables at the county-level that did not have statistically significant effects on childhood obesity in the North Carolina
sample. Racial residential segregation did not have a statistically significant effect. School- and community-level racial segregation is discussed in detail in Chapter 4. The variable for food deserts did not have a statistically significant effect in Model 6. While these results will be discussed in Chapter 6, it is important to note here that new research shows that poverty and food access may be more complex than can be accounted for with the variables in the model. Research by Han et al (2012), for example, reveals a complex relationship between the BMI of adults and a number of contextual factors such as household poverty, SNAP receipt, number of food stores, and food prices. While a control for food deserts is sufficient to examine the relationships between county and school poverty in this analysis, the next chapter examines alternate ways to measure food access within counties.

This research also adds to the literature by using a multilevel logistic model to examine the role of context in the study of childhood obesity. Using this modeling strategy has allowed the examination of both individual- and structural-level variables. The multi-level models allowed for the examination of the specific variance at each level of analysis separately and likewise adding explanatory variables at each of those levels. In other words, I was able to explain some of the differences that exist between schools in a way that traditional logistic regression modeling does not allow. While discussions of the relative importance of individuals and structure have been a persistent feature in sociological research for some time (Mayhew 1980; Mayhew 1981), this approach allows a new way of examining both in statistical models. In this way, it provides a framework for future studies interested in the role of both school- and county- level environments on childhood obesity.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH
While this study provides important information on the effects of place there are several limitations. First, these data do not provide an individual level measure of poverty. Therefore, I am unable to control any measure of poverty or income at the student level of the model. Without such a control, I cannot be entirely confident that these results are strictly a school-level effect. Another limitation is that while I use a well-vetted measure of school-level poverty (percent of students receiving a free or reduced lunch) this study cannot measure affluence at the school level. Not including a measure of wealth or affluence is a common limitation in studies of inequality (Condron 2009), however it would be helpful in order to fully examine the relationship between economic resources at the school level and obesity. I was similarly unable to measure affluence at the county level. The robust finding for the receipt of food stamps variable must also be explored in depth to find out exactly what causal mechanisms are at play. It is important to note that using the SNAP variable to measure economic distress may underestimate those in need. Not all immigrants are eligible to receive benefits and studies show that not all families eligible for benefits apply and/or are approved to receive them (Purtell, Gershoff, and Aber 2012).

Finally, while this study is an appropriate starting point for understanding the relationship between structural inequality and its effect on individual child obesity, additional research should be conducted to explore the exact avenues by which poverty at the school negatively impacts students. Research shows that nationally, variations in the regulation of food in schools has an impact on weight status (Taber et al. 2012). There is literature on the underfunding, poor nutrition, and lack of educational programs at poor schools, and these factors need to be understood at the community level in order to minimize health inequalities.
The empirical results are an important first step in understanding how structural poverty impacts students. Minimizing health inequalities should involve not only low poverty schools and communities, but socioeconomic segregation that separates wealthy students and communities from everyone else. Attentiveness to these issues could help prevent further increases in childhood obesity in North Carolina by allowing stakeholders to focus efforts on ensuring socioeconomic diversity in all schools and not a singular focus on poor children. As residential neighborhoods stratify in such a way that children of middle and low socioeconomic status are isolated from wealthier families, health and school officials will need to re-evaluate efforts that focus exclusively on integrating the poor with non-poor students. Public education has a unique and important role in the lives of Americans and provides an opportunity to minimize some of the devastating health effects of family and individual poverty. However, if schools remain socioeconomically segregated, the ability of education to foster equality is greatly diminished.
CHAPTER FIVE: EMPIRICAL ANALYSIS: RACIAL SEGREGATION AND CHILDHOOD OBESITY

Educational and residential segregation by race have a long and persistent history in the United States (Massey and Denton 1993). The research questions guiding this chapter examine the impacts of racial segregation on rates of childhood obesity: Are children in minority segregated schools and communities more likely to be obese compared to children in racially integrated schools and communities? And, are children in white segregated schools and communities less likely to be obese than children in racially integrated schools and communities? Does the effect of the individual racial identity of the student on the likelihood of obesity vary based on the racial composition of their school? The research question is broken into several parts since prior research demonstrates that children in minority segregated schools and neighborhoods experience a decrease in opportunities (Roscigno 1999), and that children in white segregated schools and communities are able to hoard privileges (Rury and Saatcioglu 2011).

Research demonstrates that segregation increases the achievement gap between minority and white students (Condron 2009). This chapter expands the investigation of the effects of segregation to the problem of obesity. Sociologists are also searching for ways to understand the interplay between characteristics of individuals and their environment (Jepperson and Meyer 2011; Mayhew 1980). This research attempts to understand the interactions among individuals and characteristics of their environment as it pertains to race at the individual, school and places/community levels.
Based on previous research, I expect that students in white segregated schools will have lower rates of obesity than students in racially integrated schools and, conversely, students in minority segregated schools will have higher rates of obesity compared to those in racially integrated schools. Since one’s individual race, gender, and grade are known to affect the likelihood of being obese, I controlled for these at the individual level.

Methods

Estimation Technique

To effectively analyze these data and address the research questions, I use a multilevel logistic regression model. Because the dependent variable is binary, it violates the basic assumptions of linear OLS regression. Therefore, a logic function to model the probability of the event is the appropriate statistical approach (Pampel 2000). Similar to the standard logistic regression equation, the multilevel equation calculates the likelihood of an event (in this case: a child’s being obese) as the dependent variable. Given that the data and research questions involve the use of clustered data, I cannot assume that errors are random and therefore the multilevel model, which accounts for co-variation of students within schools and counties, is preferred over a standard logistic regression model (Luke 2004b). Detailed information on this type of modeling and the equation used are available in Chapter 4. Estimation of these models was done using the PROC GLIMMIX procedure in base SAS software (version 9.2). Studies show that this procedure, particularly when used with large datasets, provides similar results to other software packages and estimation procedures (Li et al. 2011).
To answer these questions, I am using data from a sample on North Carolina students, their schools, and their counties. Individual variables are included at level one of the empirical model. The second level of the model includes characteristics of the school. I assess the degree to which aggregate school-level variables account for racial differences among individual students. I anticipate that students in highly segregated schools will be more likely to be obese regardless of their individual race. Finally, level three of the model will incorporate variables to control for the residential racial segregation of the county.

Table 5, Model 1, shows the results for an empty (no predictor variables) 3-level model predicting the likelihood of obesity for children in the North Carolina dataset. The school- and county-level variation at the bottom of each model indicates that for each of the levels there is statistically significant co-variation. In other words, there is significant variation in obesity among schools and among counties. This is important because it demonstrates that examining social context is an important aspect of understanding childhood obesity, and without it the models would be misspecified. In the next section, I review each of the remaining nested models in Table 5.

Results

Individual Level Predictors

Model 2 of Table 5 provides the results of the multilevel model with the individual-level control variables. Consistent with prior literature, race has a statistically significant effect on the likelihood of obesity net the other variables in the model. The odds ratio of Black children in the model were about 1.7 times that of Whites, and the odds of obesity for Hispanic youth were 1.99 times that of White children. Children whose race was categorized
as “Other” had odds of obesity that were 1.3 times that of White children in the model. However, as discussed in Chapter 3, racial segregation impacts health in a way that individual racial identity cannot completely account for (Williams and Collins 2001). Model 3 adds school-level variables to account for school-level racial segregation.

**SCHOOL LEVEL PREDICTORS**

In Table 5, Model 3 shows the results of the addition of school-level variables to the multilevel model. This is still a three-level model, meaning that the intercepts for schools and counties are random and still show statistically significant variation among schools and among counties. The control variables for the individual-level variables of race, gender, and grade remain statistically significant and in the same direction as in Model 2.

Two additional variables in Model 3 measure the effect of minority segregated schools and white segregated schools, respectively, relative to integrated schools.12 Model 3 shows that being in a minority segregated school had a statistically significant effect on the likelihood of obesity compared to integrated schools, net the other variables in Model 3. The odds of obesity for students in minority segregated schools are 1.3 times that of students in integrated schools. Conversely, the odds of obesity for students in white segregated schools are about .11 times less compared to students in integrated schools. This coefficient was also statistically significant at the .05 alpha level.

Model 4 introduces two variables that measure poverty segregation to the model with individual-level controls. The variable for high poverty schools has a statistically significant and positive effect on the likelihood of obesity, net the other variables in Model 4. Model 4

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12 See Table 2 for information on variable construction and data sources
shows that the odds of obesity for students in high poverty schools are about 1.15 times children in moderate poverty schools. Conversely, students in low poverty schools had lower odds of being obese compared to students in schools with moderate poverty. The model predicts that the odds of obesity for students in low poverty schools are .63 times the odds of students in moderate poverty schools, net the other variables in the model.

Model 5 shows results from the addition of both school racial and poverty segregation variables to the multilevel model. Once the school level poverty variables are added to Model 5, the variables for racial segregation are no longer statistically significant. This remains true for the final model (Model 6) as well, which include the addition of the county-level variables. The results indicate that while students in segregated schools do have different rates of obesity, net the other factors in Model 5, this relationship is due largely to the socio-economic differences between minority and white segregated schools.

**COUNTY LEVEL PREDICTORS**

Model 6 is the full model and includes variables measuring place by using county-level variables. There is still statistically significant variation at the county level, indicating that it is important to control for differences among places. However, Model 6 shows that none of the racial segregation variables are statistically significant. Neither the dissimilarity index for Black and White residents nor the index for White and Hispanic residents is statistically significant at the .05 alpha level net the other factors in Model 6.

Overall, racial characteristics have statistically significant impacts at the individual and school levels. To further explore the relationship between individual-level racial identity
and school-level racial segregation, the next Section will test for statistically significant interactions between these two variables.

**INTERACTION EFFECTS**

The literature suggests that racial context matters over and above individual racial identity (Williams and Collins 1995). Therefore, I ran an analysis to check for interaction effects between individual level race and the racial composition of the school. This is also known as a cross-level interaction, as it is testing to see if the racial context of the school (level 2 variable) mediates the relationship between individual level race (level 1) and the dependent variable. To test for the presence of an interaction between individual race and school racial segregation, six interaction terms were added to the full model (see Model 6 in Table 5). Each variable was a product of an individual racial/ethnic category and a school racial segregation category. By comparing the -2 log likelihood from the interaction model and the full model\(^\text{13}\), I found there is a statistically significant difference at the .05 alpha level:

\[
\text{-2} \log \text{likelihood of Full Model} - \text{-2} \log \text{likelihood of Full Model with Interaction Effects} = 34.01
\]

\[\text{DF} = 6\]

Therefore, I concluded that the relationship between individual racial identity and obesity is mediated by the level of school racial segregation. In other words, the magnitude of the relationship between race and obesity depends on the racial segregation of the school.

\(^{13}\) The LAPLACE method was specified in the PROC GLIMMIX procedure in order to produce AIC and -2 log likelihood estimates for comparing across models. Variables coefficients were similar to the models in Table 5 which used the default pseudo-likelihood (PL) methods- for more information see: Schabenberger, Oliver. 2007. "Growing Up Fast: SAS 9.2 Enhancements to the GLIMMIX Procedure." in *SAS Global Forum 2007: Statistics and Data Analysis*. Cary, NC: SAS Institute Inc.,.
The interaction terms and the calculated odds ratios are included in Table 6. The control variables produced results consistent with those presented in Table 5 and were therefore not included in Table 6 for the sake of brevity. Table 6 shows that the Black children in minority segregated schools are somewhat less likely to be obese compared to White students in minority segregated schools. To easily interpret the interaction effect on the odds of a child being obese, I ran a separate model for each type of school (minority segregated, not racially segregated, and white segregated). Figure 1 shows the odds ratio of Black, Hispanic, and Other students compared to White students at each type of school. In White segregated schools, the odds of Black students being obese are about 1.8 times the odds of obesity for white students. They are slightly less likely to be obese in schools with no racial segregation. Finally in schools that are minority segregated, the odds of a Black student being obese are 1.3 times the odds of obesity for White students. For Hispanic and White children the trend is less clear. The odds of obesity for Hispanic students in White segregated schools are about 1.5 times the odds of White students. The odds of obesity for Hispanic students decreases slightly relative to the odds of White students in Minority segregated schools (1.7) and is highest in racially integrated schools (1.8).

It is important to note that these are the interaction effects between students within school types. There are also differences in the likelihood of obesity at each school. In other words, while Black students are less likely to be obese relative to Whites students, when combined with the average odds of being obese (the intercept for each model) I find that all students at Minority segregated schools have an increased likelihood of obesity relative to Black students at White Segregated schools. This is due to the fact that the odds of being
obese in the White segregated schools, net the other variables in the model, are only 0.11 compared to 0.24 at Minority segregated schools and 0.30 at racially integrated schools.

**SUMMARY**

The multilevel logistic regression models allow one to examine the effects of both individual characteristics and context on the likelihood of a child’s being obese. The initial tests run on these data reveal that there is statistically significant variation among schools and between counties. This highlights the importance of using the multilevel model to examine the predictor variable in a way that accounts for the structure of the data and the independent influence of context (which is not possible in traditional logistic regression).

Model 2 reveals that race, gender, and grade are all significant predictors of childhood obesity. Model 3 includes school-level racial segregation variables to Model 2. Students attending minority segregated school have an increased likelihood of being obese, compared to children in racially integrated schools. Conversely, students attending white segregated schools are less likely to be obese than students in racially integrated schools. These findings are net the effect of individual level controls for race, gender, and grade. Model 4 reveals that school-level poverty has a statistically significant effect on obesity, net the individual-level control variables. These models indicate that school-level race and poverty variables are statistically significant, net the individual-level controls, when added to the model separately. However, when all school-level variables were combined in Model 5, the effect of race was no longer statistically significant and only schools that were very low poverty had a statistically significant and negative effect on the likelihood of obesity relative to medium poverty schools.
A majority of the county-level variables were not statistically significant in the full model. Rural residence and the percentage of people receiving SNAP benefits had a statistically significant and positive effect on the likelihood of obesity in Model 6. However, other variables measuring economic disadvantage and food access, such as the presence of food deserts in the county, the percentage of individuals without health insurance, were not statistically significant, net the other variables in Model 6. The implications of these inconsistent county-level economic distress results are addressed in Chapter 4. The county-level race variables tested the significance of a dissimilarity index for racial residential segregation between Whites and African Americans and a second index to test the significance of racial segregation between Whites and Hispanics. Neither of these variables are statistically significant, net the other variables in Model 6. This could be due to the fact that residential segregation often results in school segregation. Therefore, it could be that the addition of the residential segregation variables did have a statistically significant effect once school-level segregation was controlled.

Individual racial identity and school-level racial segregation are both important predictors of childhood obesity. However, prior research has found that the effects of individual identity can vary based on the racial context (Bernell et al. 2009; Williams and Collins 2001). By including interaction terms for both individual-level race and school-level racial segregation, for the North Carolina sample I find that there are statistically significant interactions. In other words, the effect of attending a minority segregated or white segregated school on the likelihood of obesity varies according to the individual racial identity of the student.
By calculating the odds ratios for the interaction effects term coefficients, I was able to interpret the direction and magnitude of the interactions for students. I find that while black students are more likely to be obese, the magnitude of this difference is smaller in minority-segregated schools. White students are similarly less likely to be obese in white segregated schools compared to black students in white segregated schools. The results for Hispanic students are less clear. The difference between white students and Hispanic students in minority segregated schools in not statistically significant. However, the magnitude of the difference between Hispanic children and White children in white segregated schools decreased in White segregated schools. The practical implications of these results, in the context of the current literature, will be discussed in the next section.

Discussion and Conclusion

The analysis in this chapter addressed the question of whether racial segregation impacts rates of childhood obesity. The data were analyzed using a multilevel logistic regression model which is an appropriate approach for data that are clustered within groups. In this case, students are clustered within schools and their schools are then clustered within counties. Multilevel logistic regression accounts for the co-variation within these groups in a way that individual level modeling cannot determine. Moreover, this modeling strategy allows me to measure the variation at each level, and to add variables at each level of analysis. This strategy improves upon earlier work that provided only descriptive information on differences between schools (O'Malley et al. 2007). Further, by using a three-level model, I am able to examine the effects of both community- and school- level variables, two sites often examined separately (Janssen et al. 2006; Li and Hooker 2010). By using this technique
to examine the issues of childhood obesity, I was able to uniquely contribute to our understanding of childhood obesity by examining both the role of social context and the individual.

Consistent with prior research (Ogden et al. 2010a; Ogden et al. 2010b), individual-level race, gender, and grade all had statistically significant effects on the likelihood of a child’s being obese. Holding those variables constant, I then addressed the research questions about school and place. The results indicate that, net of the effects of the individual level characteristics, minority racial segregation at the school level did have a statistically significant effect on the likelihood of obesity among students in the North Carolina dataset. Students attending minority segregated schools were more likely to be obese than students in integrated schools. However, as discussed in Chapter 4, minority segregated schools are also disproportionately likely to be in high poverty schools. Therefore, controlling for poverty at the school level is an important part of understanding this relationship. Once variables for school level poverty were added to the model, the effects of school level racial segregation were no longer statistically significant. Therefore, while racial segregation at the school level is associated with increases in the likelihood of obesity, net individual level racial identity, the relationship appears to be due to the effect of high poverty rather than racial composition per se.

The findings at the school level are consistent with studies that show students in minority-segregated schools have poorer academic outcomes compared to students in white segregated or integrated schools (Lleras 2008; Roscigno and Ainsworth-Darnell 1999). Other research shows that schools with high minority populations have poorer quality food (Delva
et al. 2007). However, as noted previously, there has been less research examining the health effects of students in minority segregated schools, and existing studies tend to focus on either race or poverty (Bernell et al. 2009; O'Malley et al. 2007). This research examines the role of both racial and economic segregation at the school-level and finds that the effect of race is no longer statistically significant once poverty is controlled.

The research questions also address the issue of racial residential segregation at the county level. There is great deal of literature correlating residential segregation by race with poor health among adults, including an increased risk for obesity among women (Chang 2006; Williams and Collins 2001; Williams and Sternthal 2010). However, prior studies were unable to incorporate other sites of segregation such as school or work. Several studies examine racial segregation in the context of isolation within inner-cities (Massey and Denton 1993). New research shows that places outside the city may be increasingly segregated by race (Frey 2011). Therefore this research adds an important component to the discussion of racial segregation and health, by examining this relationship in both urban and non-urban schools.

Racial segregation within the county, as measured by two dissimilarity indexes, was examined in the full model. The results indicate that county-level racial residential segregation did not have a statistically significant effect on the likelihood of obesity for children in the North Carolina sample, net the other factors in the model. There are several possible reasons this measurement was not statistically significant. First, it is important to remember that according to the model and interpretation of the random intercepts (see Chapter 4), there is greater variation at the school level than the county level. Therefore, one
would anticipate that the school variables have stronger effects on student outcomes. This is supported by the fact that very few of the county-level variables were statistically significant in the full model. Moreover, in a multilevel model, the degrees of freedom are fewer for each of the successive levels of analysis. Therefore, it is difficult to get statistically significant results for the higher levels of analysis. This is an issue with the results in the other chapters as well. Second, since school segregation is caused in part by residential segregation patterns, it could be that racial segregation was accounted for at the school level and therefore, the county variables are not significant. A replication of this study using a larger sample of counties would be helpful in determining if these effects are a result of the particular nature of this North Carolina sample or if they are non-significant when racial segregation is controlled at the school level.

The second research question in this chapter asks whether or not children in white segregated schools and communities are less likely to be obese than children in racially integrated schools and communities. According to the model, attending a white segregated school decreased the likelihood that a child would be obese compared to children who attended racially integrated schools, net the other factors in the model. This demonstrates the importance of looking not only at disadvantages but also at the importance of understanding how these relationships affect privileges and can lead to hoarding opportunities. This finding is consistent with research on rural communities that shows that high levels of racial segregation negatively affect minorities, but may also increase opportunities for whites (Albrecht et al. 2005). Similar to the results for minority segregated schools, when school level poverty was added to the model, the effects of white segregation at the school level
become non-significant (p=.46). Therefore, the benefits and costs associated with both types of racial segregation may reflect differences in school-level socioeconomic status. As noted above, county-level variables for racial segregation were also not statistically significant.

Finally, the third research question in this chapter asks if the effects of individual racial identity on the likelihood of obesity vary based on the racial composition of the students’ school. According to the analysis, there is a statistically significant interaction between individual racial identity and the racial segregation of the school. This is a notable finding because it demonstrates the importance of the interplay of individuals and their environments. It is not enough to look only at schools or only at individual identities - it is their interaction that can produce different outcomes.

As seen in the empirical analysis, the difference in the likelihood of obesity between White and Black students in minority segregated schools decreases significantly, net the other factors in the model. White children in minority segregated schools are more likely to be obese than in any other type of school and Black children in White segregated schools do not experience the same decrease in the odds of being obese that White children experience. This finding, while inconsistent with some research (Bernell et al. 2009; Chang et al. 2009), is consistent with a study that examined women’s weight status and urban neighborhood racial composition (Ruel et al. 2010). It is possible, and indeed Ruel et al. suggest this as well, that while there are certain economic disadvantages associated with minority segregated schools (or in their case neighborhoods) they are hard to disentangle from racial segregation. Researchers may not be able to parse out the effects of economic deprivation from those of racial segregation. Moreover, research may miss ways in which places with minimal
interpersonal racism may affect wellbeing. Other studies find that racism and discrimination can have a detrimental effect on health (Saffron and Nazroo 2004). Therefore, it is possible that while there are certain economic disadvantages associated with minority segregated schools (or in their case neighborhoods), limited interactions with White students may provide some protection from racism, and the threat of racism. This protection from racism for Black students may provide positive effects on their health status. This is contrary to prior research by Bernell et al. (2009) that presumed that decreased rates of obesity among minority girls were due to the influence of white girls and their increased likelihood to state that they value thinness (Story et al. 1995). However, their study did not include any school-level poverty measures. The results of this research show that poverty has a greater influence than racial segregation and the interactions reveal that students in White-segregated schools benefit the most if they are White.

Overall, while there are significant effects of racial segregation, they seem to be due to differences in poverty rather than racial segregation per se. Moreover, while individual race and school racial composition play important roles in childhood obesity rates, this research highlights the need to examine these two levels in conjunction with place-level variables. It adds to both the literature on race and childhood obesity by finding that in addition to individual racial identity, context has a significant effect on the rate of childhood obesity and how much students’ racial identity increases or decreases the chance of being obese. This study adds to the literature of both community segregation and school segregation and health by including both school- and county- level racial composition for a large group of North Carolina students. While additional research is needed to tease out the
exact mechanisms at play, it is clear that research on childhood obesity should not ignore the racial context, and the interactions among individuals and their schools and communities.

Adding to our understanding of race and place, this research also raises important questions about how we provide adequate resources for all students and the social basis of increases in childhood obesity.

Sociologists have long been interested in how individuals affect, and are affected, by their social worlds (Mayhew 1980). This research finds that not only can individual traits (much as being a racial minority) affect health, but also one’s environment can either minimize or exacerbate that affect.

While this study provides important information on the effects of place, in particular schools and communities and their role in childhood obesity, there are several limitations. As noted previously, the data used were not a random sample of students in North Carolina or the United States. While the students closely matched the North Carolina student population on key demographic characteristics, a true stratified random sample is needed for these findings to be generalizable to students in the state or the United States at large. Further, these data only provide a cross-sectional look at students in grades 3-5. To better understand the causal link between social context and childhood obesity, a longitudinal analysis would be an appropriate next step. Additionally, studies (Tabacchi et al. 2007; Thompson 2010) have shown that obesity may begin prior to school age and therefore studies examining younger children may provide a better picture of how students are affected by these social contexts.
These findings are an important first step to understanding how structural factors, such as racial segregation, impact students. It demonstrates the importance of addressing not only how racial identity effects obesity, but how the racial makeup of the school can mediate that effect on a students’ health. This is important information for stakeholders interested in effective obesity prevention and intervention programs in elementary schools. Advocates for student health must not only focus their efforts on targeted interventions for individual students, but to the overall racial- and economic composition of the school and target interventions to the school environment. Public education has a unique and important role in the lives of Americans and provides an opportunity to exacerbate or minimize some of the effects of both individual prejudice and institutionalized racism. Ensuring that students are free from discriminating acts and are given access to all the resources they need are both essential parts of minimizing racial inequality among American children.
CHAPTER SIX: EMPIRICAL ANALYSIS: FOOD DESERTS AND CHILDHOOD OBESITY

Food deserts have become a topic of concern among researchers and policy makers in recent years. While a great deal of research has examined the effect of urban food environments, research on rural areas remains scarce. In this chapter, I examine issues of food access across both urban and rural counties in North Carolina and examine its effect on childhood obesity. This chapter will begin by examining the new ways that food deserts are being conceptualized by reviewing the food environment variables that will be added to the models in this chapter. Next, I will examine the differences between rural and urban food deserts in North Carolina. And finally, this chapter addresses the effect of food deserts on childhood obesity by asking the research question: what effect does living in a food desert have on the likelihood of a child being obese? Based on prior studies of childhood obesity and food deserts (Schafft et al. 2009), I anticipate that living in a food desert county will increase the likelihood of obesity.

Measuring Food Deserts

New Variables

The increased interest in food deserts and their relationship to obesity coincides with new large-scale datasets about food accessibility in the United States being made available from the US Department of Agriculture (Economic Research Service 2011a). In the USDA Food Desert Locator, a food desert is defined as a census tract characterized as both “low-income” and “low food access”. A tract is considered “low income” if “(1) the poverty rate for that tract is at least 20 percent, or (2) for tracts not located within a metropolitan area, the
median family income for the tract does not exceed 80 percent of statewide median family income; or for tracts located within a metropolitan area, the median family income for the tract does not exceed 80 percent of the greater of statewide median family income or the metropolitan area median family income.” (Economic Research Service 2011b:1). A rural census tract is classified as having low food access if 500 people or at least 33 percent of the population lives 10 or more miles from a supermarket or large grocery store. An urban census tract is classified as having low food access if 500 people or at least 33 percent of the population lives 1 or more miles from a supermarket or large grocery store.\textsuperscript{14}

The USDA method of measuring food deserts is consistent with some previous studies of food deserts in the United States. However, it is important to note that a great deal of work has been done by geographers and others who have approached the issue in alternative ways (Blanchard and Matthews 2007; Schafft et al. 2009; Walker, Keane, and Burke 2010). Unfortunately, since the data used in this project does not provide information about students’ residence or neighborhoods, I am unable to replicate some of the more interesting, and nuanced, approaches. However, alternative variables were added to this research in lieu of geographic variables of neighborhood or residence and the implications for this approach will be discussed later.

Using the USDA census tract data, I created a variable to control for the presence of a food desert within the county. I created a dummy variable in which counties with one or

more food desert census tracts were coded “1.” They were coded “0” if the county had no food desert tracts. Since I was unable to determine where each student lived, I also created a second variable to control for the proportion of the county that was considered a food desert. To this end, I created a variable using the number of food desert tracts as a percentage of the total number of census tracts in the county. In other words, the variable was a fraction that was calculated by dividing the total number of food desert tracts by the total number of census tracts within the county according to the 2000 census.

Researchers are exploring new ways to conceptualize and measure food access (An and Sturm 2012). Some researchers have criticized the singular focus on large grocers as the only source of healthy foods, while ignoring local sources of good food such as farmers markets and farm to school programs (Short, Guthman, and Raskin 2007). Moreover, the focus of much research has been on urban rather than rural areas. Given that rural areas often do not have the same public transportation infrastructure as urban areas, families’ access to reliable transportation might be key to having a complete picture of who does and who does not have access to fresh foods. In response to these issues, I included additional measures of food access in order to have a more nuanced approach to food deserts. The additional variables are from the “Food Environment Atlas” public dataset provided by the USDA. These data provide a method to examine food environments aggregated at the county, rather than at the census tract, level. While census tract data provides a sub-county examination of neighborhoods, it is difficult to obtain such rich detail at this level. Further, for the purposes of this study in which I am examining the county context in which students go to school, and
not their particular neighborhoods, the county level variables are appropriate for the empirical models.

Two variables are added to measure the local foods environment. One variable measured the number of farmers markets per 1,000 people in the county. The USDA defines a farmers market as “a retail outlet in which two or more vendors sell agricultural products directly to customers through a common marketing channel. At least 51 percent of retail sales are direct to consumers” (US Department of Agriculture 2012). The second variable is a dummy variable for whether or not the county has a “Farm to School” program. Farm to School programs grew out of a partnership between the Department of Defense and the Markets and Food Distribution Division of the North Carolina Department of Agriculture and Consumer Services in 1997 and seek to use local foods in schools. While programs are tailored to specific communities, they include school gardens, nutrition education, local purchasing programs, and/or farm tours (The National Farm to School Network 2012; US Department of Agriculture 2012).

To address the issue of transportation and proximity to stores that is a subject of concern among food desert researchers (see: Walker et al. 2010), I include a new variable that incorporates both distance and household access to cars. The variable measures the percentage of households that live more than one mile from a large grocery store or supermarket in which no one in the household owns a vehicle. Because this accounts for transportation, the measure is the same for both rural and urban counties. Additionally, the average amount of SNAP funds per month is included to control for variations in purchasing power among poor families. This data from 2010 is measured by “The average monthly
dollar amount of SNAP…benefits in a county divided by the county population” (US Department of Agriculture 2012). Finally, the Food Environment Atlas has the additional advantage of being slightly more up to date than the Food Desert Locator in that it includes data from as recently as 2009. Table 3 displays the univariate distributions for the North Carolina counties where the sampled students attend school.

**Urban and Rural Differences**

Given the limited amount of work on rural food desert areas, particularly with regard to the USGA Food Environment data, I will examine the differences between urban and rural counties before proceeding to the multilevel analysis. Based on the definitions and standards used to measure urban and rural food deserts (33 percent of the county living 1 mile or more from a grocer in urban tracts and 10 miles or more for rural tracts), an estimated 75 percent of food deserts in the continental United States are in urban census tracts and the remaining 25 percent are in rural census tracts. Similarly, in North Carolina, all 15 urban counties have at least one food desert census tract while forty-two, or about half, of North Carolina rural counties have at least one food desert. The USDA contends that the 10 mile marker definition of a food desert is appropriate in rural counties because the population is sparsely distributed and “vehicle ownership is high” (US Department of Agriculture: Agricultural Marketing Service 2012). However, other research shows that particularly in the South, low rates of vehicle ownership can be a significant issue for food access (Blanchard and Matthews 2007). To parse out the relationships between urban and rural in North Carolina counties with regard for measures of food access, I conducted a series of bivariate *t* tests (see: Yoshida et al. 2011) to determine if there are statistically significant differences between urban and rural counties.
using the standard USDA food desert categorization (1 mile or more for urban areas and 10 miles or more for rural) and a measure that includes the percent of households without a vehicle and live 1 mile or more from a grocer.

I examined the differences in means between urban and rural counties for the variable measuring the percentage of the county census tracts that are food deserts and the measure of the percentage of households without cars living a mile or more from a large grocery store. The entire population of counties (N=100) in North Carolina was used for these analyses. By conducting t-tests to examine relationships, I find that for the first measure (percent of county that is a food desert), the mean for urban counties (.15) is higher than that of rural counties (.09) and the difference is statistically significant at the .05 alpha level. In other words, the mean percentage of food desert census tracts in urban counties is higher (.06 higher) than the mean percentage of food desert census tracts in rural counties in North Carolina. A greater percentage of urban counties have food desert tracts as compared to rural counties. This North Carolina finding is consistent with food deserts in the rest of the continental United States as well, in that a majority of them are in urban counties (Ver Ploeg et al. 2009).

Next, I examined mean differences for the percentage of households without a vehicle living over one mile from a store. A t-test between urban and rural counties using the variable for the percentage of households that are without a vehicle and live over one mile from a store produced the opposite result. The mean for rural counties is 5.7 and the mean for urban counties is 2.8. The 2.95 point difference is statistically significant at the .0001 alpha level. In other words, the rural counties have a higher percentage of households without a car that live more than one mile from a store. Therefore, when accounting for vehicle ownership
and the households that are not within walking distance of a grocer, North Carolina households in rural counties seem to be more disadvantaged in terms of food access than households in urban areas. Given the decreased access to public transportation and infrastructure in rural areas (Blanchard and Matthews 2007), it is also possible that food access in rural areas is even more difficult than even these numbers suggest.

These results highlight the difficulty of investigating food access in rural areas. If researchers continue to make assumptions about vehicle access in rural areas, they may overestimate the population’s access to large grocers. While these findings may not be particularly surprising given the lower concentration of households in rural areas, it is important because it highlights the need to critically examine food desert measures in light of urban and rural differences. Further, it suggests that perhaps food deserts in rural areas may be especially troubling given the high percentage of residents who do not have access to vehicles.

Next, I will examine the effect of both food desert variables on the likelihood of obesity using the North Carolina data. I will include the second measure of food access (vehicle ownership and household distance), as well as controls for local foods, such as farmers markets and farm to school programs, as well as the average amount of SNAP allotments within the county.

Methods

Estimation Technique

To effectively model these data and address this chapter’s research question, I use a multilevel logistic regression model. As in previous analyses, because the dependent variable
is binary, it violates the basic assumptions of linear OLS regression. Therefore, a logic function to model the probability of the event is the appropriate statistical approach (Pampel 2000). Similar to the standard logistic regression equation, the multilevel equation calculates the likelihood of an event (in this case: a child being obese) as the dependent variable. Given that the data and research questions involve the use of clustered data, I cannot assume that errors are random. Therefore, the multilevel model which accounts for co-variation of students within schools and counties is preferred over a standard logistic regression model (Luke 2004b). Detailed information on this type of modeling and the equation used are available in Chapter 4. Estimation of the models in this chapter were done using the PROC GLIMMIX procedure in base SAS software (version 9.2) (Li et al. 2011).

Model 1 of Table 5 is the null, or the base, model. This model tests for statistically significant variation at the school and county levels. Both covariance estimates are statistically significant at the .05 alpha level. Therefore, the multilevel model is an appropriate approach to modeling these nested data.

Results

Individual and School Level Predictors

Table 5 provides the results of the nested multilevel model with individual-level control variables. Consistent with prior studies, race, grade and gender have statistically significant effects on the odds of obesity net the other variables in the model. Being male and white are both associated with a lower likelihood of obesity relative to females and racial minorities. At the school level, students at low poverty schools have a decreased likelihood of obesity compared to students in medium poverty schools. When school poverty is
controlled, the effect of racial segregation at the school-level is no longer statistically significant in the model.

COUNTY LEVEL RESULTS

At the county level, rural residence and percentage of households receiving SNAP benefits have statistically significant and positive effects on the likelihood of obesity. It is important to note that a recent review of the literature found that participating in food assistance programs does not cause obesity among children (DeBono, Ross, and Berrang-Ford 2012; Larson and Story 2011b). As such, this variable is used to measure economic distress and receiving food assistance is not assumed to be a cause of obesity. Model 6 also includes a dummy variable measuring whether or not the county contains one or more food deserts. According to the model, there is not a statistically significant difference between food desert counties and non-food desert counties on the likelihood of obesity, net the other variables in the model.

Model 7 in Table 8 includes the alternative measures of a food desert at the county level. The dummy variable for food deserts in the county was replaced with four new variables. The first is intended to replace the food desert variable in the last model, and the others provide additional controls for the food environment. These variables are as follows: percentage households without a car living one or more miles from a large grocer, the average monthly SNAP amount, the number of farmer’s markets per 1,000 people, and a dummy variable controlling for the presence of farm to schools program(s). The variable controlling for the percentage uninsured was dropped from this model as it is not a statistically significant variable in any of the nested models. Consistent with Model 6 in
Table 5, I find that the individual-level and school-level variables remain statistically significant and in the same direction. The odds of a girl being obese are 0.85 times the odds of boys. The odds of obesity for Black children in the model is about 1.7 times the odds for Whites, and the odds for Hispanic youth is 1.92 times the odds of White children. Children whose race was categorized as “Other” had odds 1.3 times that the odds of White children in the model. However, the effects of the county-level variables change when the new food desert environment variables are added.

Rural residence, according to Model 7, has a statistically significant and positive effect on the likelihood of obesity. The odds of being obese for children in rural counties is 1.24 times the odds for students in urban counties, net the other variables in the model. The variable for the percentage of households receiving SNAP is no longer statistically significant when the food access variables are added to the model. This lends support to arguments that SNAP reflects inequalities across places and is not a cause of obesity (Larson and Story 2011b). However, while the coefficients indicate that the percentage of the county households without a vehicle and living far from a grocer is associated with an increased likelihood of obesity, none of the other food access variables are statistically significant at the .05 alpha level, net the other variables.

The food desert variables in Model 5 are explaining a much smaller percentage of the variation within the model (see county-level covariation in Table 8) than the model with the four food desert measures. Model 5 also indicates that the covariance parameter for the county-level is not statistically significant in this final food access model, indicating that there is no longer a statistically significant amount of covariation at the county level once the
variables in the model are controlled. In other words, while there are few statistically significant findings for the county-level food desert variables, a great deal of the previously unexplained variation among counties is accounted for in the final model that uses the new variables.

Models were also run testing for interaction effects between the food desert variables and rural residence at the county level. These tests indicate that there was not a statistically interaction between these two measures. The results were not included in the tables.

**SUMMARY**

Before beginning the multilevel models, I examined differences across counties in North Carolina. My *t*-test results indicate that the standard USDA food desert measurement may not be appropriate for rural counties because it does not account for all the variation in the local foods environment, particularly in rural areas. I added new variables to measure food access. I then proceeded with the multilevel modeling of the food access variables.

Next, using multilevel logistic regression models, I examine the effects of both individual characteristics and context on the likelihood of a child’s being obese. The initial tests run on the North Carolina data reveal that there is statistically significant variation among schools and between urban and rural counties. These results validate the use of the multilevel model to examine the predictor variable in a way that accounts for the structure of the data and the independent influence of context. The results for race at the individual level, and race and poverty at the school level were significant.

The traditional USDA measure of food deserts did not have a statistically significant impact on the likelihood of obesity among children. A second food desert variable and three
additional food environment variables were similarly non-significant at the .05 alpha level. It is important to note that in the multilevel (or hierarchical) model the degrees of freedom vary depending on which level of analysis the variable is from. For example, for county-level variables, the number of degrees of freedom are based on the number of counties in the sample, while the individual-level variables have degrees of freedom based on the total number of students. Therefore, with each increase in the model hierarchy, the bar for statistical significance is increased. In this analysis, the sample of counties is quite small (n=38) making statistically significant findings at this level more difficult relative to the school or individual levels. Therefore, the lack of statistically significant findings at the county level could be attributed to the particular characteristics of this dataset. It is important to note that despite the statistical challenges noted, rural residence did have a statistically significant impact on obesity in all of the models. More research is needed to understand the relationships among space, place, and childhood obesity.

Discussion and Conclusion

This chapter addresses the research question: what effect does living in a food desert have on the likelihood of being overweight or obese? Since research on food deserts is relatively new and since previous studies concern urban areas, it was necessary to examine how the standard measures of food deserts and of food access vary across urban and rural counties. The standard quantitative measure used by the USDA of “1 or more mile” urban area criteria has been modified to make it applicable to rural environments. Researchers use a 10 mile standard for rural areas, assuming that households are more likely to have a vehicle, assuming that driving 10 miles takes a comparable amount of time and effort as walking a
mile in an urban area (Blanchard and Matthews 2007). However, as the results of this chapter show, using a 10 mile standard for rural areas without accounting for vehicle access may be overestimating food access in rural areas. When using this measurement, rural counties in North Carolina, and the continental United States as a whole, are much less likely to be identified as a food desert than urban counties (about 1:4). However, when using a variable that measures the percentage of households without a vehicle and also over one mile from a large grocery store, I find that rural counties in North Carolina have a higher percentage of households with low food access than households in urban counties. This research demonstrates that a more nuanced approach to rural areas is needed in order to avoid underestimating the number of food deserts in rural places. It also requires additional research on rural areas to better understand issues of transportation and infrastructure and how that impacts food access.

Other researchers criticize how food deserts are quantified because existing measures do not account for small local vendors (Short et al. 2007). In response to these concerns, I added two variables (for farmers markets and farm to school programs) as controls in the multilevel models. While this does not control for all small grocers, farmers markets and farm to schools programs can be important ways to bring local foods to schools and local populations. Understanding how food sources outside of large corporate chains affect obesity can also provide important information for stakeholders interested in providing sustainable healthy food access.

Following the bivariate examination of all 100 urban and rural counties in North Carolina, I used the sample of students from the 38 counties represented in that sample to test
the effects of the two different approaches to measuring food deserts on the likelihood of obesity. I ran two full multilevel models, one using the standard food desert measure and a second in which I added a variable accounting for vehicle ownership to the model and included controls for local food (farmers markets and farm to schools programs) and SNAP amounts. Consistent with prior research, individual-level race, gender, and grade all have statistically significant effects on the likelihood of a child being obese. Holding those variables constant, I then addressed the specific research question for this chapter using a multilevel model. The results indicate that, net the effects of the individual- and school-level characteristics, none of the food desert variables have statistically significant effects on the likelihood of obesity among students in the dataset. This is consistent with recent research on youth in California showing there were not significant associations between food deserts and obesity (An and Sturm 2012).

Going to school in a rural county has a statistically significant effect in the models, indicating that differences between rural and urban counties remain important. As such there is a continued need to investigate the exact ways in which the characteristics of rural places affect childhood obesity. Despite the fact that none of the food desert variables had statistically significant effects in the full multilevel model, the results of the urban and rural county comparisons are important. They show that there are unique obstacles to accessing that food in rural counties. Exploring these differences and the role of local foods can help to better address childhood obesity in rural areas.

While this study provides important information on the effects of place, particularly regarding schools and communities and their role in childhood obesity, there are several
limitations. First, the North Carolina data do not provide information on the student’s home addresses, or even their neighborhood. Therefore, I am not able to control for the particular food environment in which they live, only the general conditions of the county in which their school is located. Understanding that food environments are an important part of the context in which people make food decisions, more detailed information matching students to their homes and census tracts would be helpful. The way food deserts are conceptualized in this project includes it as a county level variable and that may not be a small or precise enough indication of where parents and children live and go to school. Future research that was more attuned to commuter patterns used in labor market literature may be helpful in framing food consumption patterns (Tolbert and Sizer 1996). The replication of complex conceptualizations of food deserts in rural areas done by Schafft et. al. (2009) would also add to our understanding of food access in rural areas.

Rural food deserts have received much less attention than urban food deserts both in academic research and the media. While this project begins to explore new methods of measuring and examining rural food environments, more research, perhaps beginning with qualitative research of families in rural counties, is needed to understand what issues are unique to these places. Particularly in the South, where rural poverty is high and vehicle ownership is low, research examining the infrastructure available to poor families is an important area of research. Further, this project did not control for other aspects of food access, such as fast food restaurants, which are also important aspects of place and weight status (Boone-Heinonen et al. 2011). Future research should examine the role of prepared food outlets in urban and rural places.
It is also important to consider that the lack of a statistically significant food desert finding could be due to deficiencies in the built environment that are reflections of the longstanding neglect racially and economically segregated neighborhood have historically experiences. In other words, the segregation itself could be the root cause of health differences. Other researchers have also suggested this with regard to differences in weight status (Guthman 2011). Guthman (2011) argues that segregation might simply be correlated with other deficiencies in the built environment, such as a lack of stores. It is possible, given that racial and economic segregation were controlled in the model at the school- and county-levels, that they accounted for all of the variation that could otherwise have been attributed to a lack of grocers. In other words, while a lack of grocers may be associated with childhood obesity, the relationship may be spurious in that they both result from a history of segregation and oppression that result in very distinct characteristics of place. It is therefore possible that the effect of the built environment does not add any additional explanatory value in models that already account for segregation along racial and income lines.

Finally, while obesity has become a very important and well-documented measure of health among children, other measures of child health are important. Research that examines the effect of limited food access on sufficient nutrient consumption among children should also be conducted to better understand the relationship between place and child health.

Further examination of the role of racial and economic segregation is needed to fully understand the social basis of obesity. And while the impact that food environments have on obesity in this study is unclear, the differences between urban and rural places are ripe for further research. Using new and expanded measures of food deserts that are specific to the
particular characteristics of place is important to understanding and treating childhood obesity. New measures need to be sensitive to the particular historical characteristics of place and how these characteristics work in rural places, in particular. We cannot assume that the challenges and barriers to healthy affordable foods for children are the same across all spaces. Responses to these challenges require an understanding of and respect for the effects of context in order to be effective and respectful.
CHAPTER SEVEN: SUMMARY AND CONCLUSION

In the first part of this chapter, I will review the research questions and the findings from the empirical analyses. I will discuss where I am able to use the data to draw firm conclusions and where the answers to the questions are somewhat tentative. In the second part of the chapter, I will summarize the results in terms of the larger issues involving the study of social organization. Finally, I will draw policy implications from the results.

Research question 1 was addressed in chapter 4 and asked: are students more likely to be obese in poor communities and schools compared to students in affluent communities and schools? I used a multilevel logistic regression model to address this question. The empirical results from the North Carolina data show that children attending high poverty schools were more likely to be obese than children at medium or low poverty schools. Further, children in very low poverty schools were less likely to be obese than other children. Even when racial segregation was accounted for, children attending low poverty schools were still less likely to be obese relative to other children. It is clear from these analyses that the proportion of poor students at the schools impacts rates of childhood obesity, even when individual level characteristics are controlled. These results also suggest that the concentration of wealth (and not just poverty) may play a role in the rates of differences among schools; however I was not able to test this directly with these data. Further, economic disadvantage at the community level was associated with higher rates of obesity, net the school level effects. Again, a measure of wealth at the community level would strengthen the analysis as would additional data on the poverty of the households in which students live. However, these
findings suggest that this methodological approach using multilevel models is an important way to examine childhood obesity in its socioeconomic context.

The second research question was addressed in chapter 5 and asks if children in minority segregated schools and communities were more likely to be obese compared to children in white segregated schools and communities. I also used a multilevel logistic regression model to develop an empirical analysis to address this question. The empirical results from the North Carolina data show that students in minority segregated schools were more likely to be obese than children in schools with no racial segregation. Further, students in white segregated schools were less likely to be obese than those without racial segregation. These results were net of the individual students’ race. While the relationship between school racial segregation and obesity was no longer statistically significant when school poverty was controlled, it is nonetheless an important part of understanding the interaction between individual race and the racial context of the school. The empirical analyses also found that there was a statistically significant interaction between a student’s race and the racial makeup of their school. White students in minority segregated schools were more likely to be obese than Whites in white segregated schools. Alternately the difference between White and Black students was minimized in minority-segregated schools and increased in white-segregated schools. From these analyses I conclude that the racial context of the school can mitigate how one’s racial identity will affect their likelihood of obesity. The results at the county level were not as clear-cut. I found no statistically significant effects for the measures of residential racial segregation in the county. Unfortunately, the data do not indicate the
residence or neighborhood of the students, but this approach would be appropriate for further investigating these relationships.

The final research question was addressed in chapter 6 and asks what effect living in a food desert has on the likelihood of being obesity. To address this research question I developed an empirical analysis using a multilevel logistic regression model. The empirical analyses from the North Carolina data show that living in a county with a food desert did not significant affect the likelihood of obesity. Because the findings were not significant in the multilevel model, there were no definitive conclusions to this research question. However, based on the results from the racial and economic segregation variables, these findings suggest that food deserts may be a reflection of existing social inequalities and exclusions across places and not the cause of differences in obesity. Further, a series of *t*-tests examining all North Carolina counties indicated that food access and consumption differences between rural and urban counties may not be accounted for in current USDA food desert definitions. Unfortunately, these data do not allow me to examine or control for the students’ neighborhood or residence. Future work could use a multilevel approach that accounts for whether or not the student resides in a food desert. Next, I examine how the results of the empirical models assist us in understanding the larger context of research on childhood obesity and on studying individuals and their social contexts.

The rate of childhood obesity in the United States has tripled since the 1980s, drawing a great deal of attention from health researchers, Surgeon Generals past and present, sociologists and parents (C.S. Mott Children's Hospital National Poll on Children's Health 2011; Hawkins and Linvill 2010; Ogden and Carroll 2010). Prompted by this discussion,
researchers have examined the behaviors and culture surrounding food and exercise practices among parents and children (Tabacchi et al. 2007). Practitioners calling for action rely heavily on solutions focused on the reeducation of children, parents and physicians (Silberman 2012). Researchers have also examined the role that a child’s race and household income plays in their likelihood of obesity (Ogden et al. 2010b). However, despite the fact that obesity rates vary by race and social class, and that people are likely to be grouped spatially along race and class lines, little is known about the effects of structural inequality at the subnational level on rates of childhood obesity. This research has sought to unite these bodies of literature and increase our understanding of the role of place on childhood obesity. In the following, I will detail the ways in which this research has added to our understanding of the impact of economic segregation, racial segregation, and food access on childhood obesity in a sample of North Carolina children.

Sociologists have a history of debate regarding how best to study individuals and social context (Mayhew 1980). Mayhew’s seminal pieces in the 1980s provide a sharp critique of American sociology and its focus on the study of individuals as a way to understand social structures (Mayhew 1980; Mayhew 1981). The study of childhood obesity, primarily found in public health, has similarly focused on the individual behaviors to explain increased rates of obesity (Tabacchi et al. 2007). This research has added considerably to our knowledge of healthy behaviors and genetic abnormalities at the individual level, but has fallen short of explaining the rapid increases since the 1980s. We also know that race, class, gender, and geographic location affect the likelihood that one will be obese (Ogden et al. 2010b). This research highlights some of the concerns that Mayhew and others have
articulated. It demonstrates that there is a unique effect of environment that cannot be accounted for by examining individual characteristics. Chapter 4 showed that there is statistically significant co-variation at the school and county levels, meaning that there are spatial correlations that need to be accounted for when studying childhood obesity. Further, as highlighted in Chapter 5, the impact of one’s racial identity on his or her likelihood of obesity is contingent on the racial composition of their school. This is consistent with other studies of adults and health that have also found that racial differences in health cannot be fully understood outside of the context in which they live (Williams and Sternthal 2010). This research adds to the discussion by showing the importance of place in the study of childhood obesity and echoes other sociologists’ concerns that an exclusive focus on individual characteristics to explain social phenomena is often insufficient.

Methodologically, this work provides an understanding of individuals and place by using the hierarchical logistic regression model instead of standard logistic regression (Guo and Zhao 2000). The hierarchical method allowed for the examination of individual, school, and county characteristics simultaneously, thus assessing the impact of variables at each level. I was also able to examine co-variations at each level to see if there were differences between schools and counties. Another advantage of this statistical technique is its ability to test cross-level interactions that allowed me to examine the interaction between an individual and their environment. This is an important approach for researchers who would like to understand students in the context of their daily lives. Moreover, the use of a statistical method that does not control for the co-variation of students within schools and communities’ may produce misleading results (Ruel et al. 2010).
While there is prior work that has examined structural inequality and the role of place in rates of childhood obesity, it has neglected to examine both urban and rural sites, lacked research on children, and failed to examine various contexts such as schools, residence, and food environments. This research examined both urban and rural sites, as well as school and county environments. I found that rural residence did increase the likelihood of obesity, net the effect of the other variables. This points to the importance of further research on rural areas and the unique challenges that they face that are not currently accounted for in the literature. Chapter 6 in particular reveals that there may be important differences in the specific nature and obstacles to food access between urban and rural counties that are not accounted for in traditional measures of food deserts. Moreover, by examining children nested in both schools and communities this research expands on existing research that has focused on adults and neighborhoods (Chang et al. 2009).

While school and residential segregation shapes the context in which children are raised, the nature of this segregation has changed in recent years (Parisi et al. 2011; Reardon and Bischoff 2011). Chapter 4 examines the role of income segregation at the school and community level and finds that there are differences in obesity between very low-poverty schools and middle- and high-poverty schools. This finding is consistent with research that shows the “segregation of affluence” as a new persistent thread in the United States, which has a drastic impact on rates of childhood obesity. In Chapter 5 I find that racial segregation in schools not only affects the likelihood of obesity, but that it also mediates the effect of a child’s racial identity. And finally Chapter 6 found that the built environment, in this case the presence of grocers, did not impact childhood obesity over and above the effect of racial and
poverty segregation. This is important as it echoes and supports the contention of other researchers that deficiencies in the built environment are reflections of a history of persistent racial and economic segregation and that this history has resulted in differential outcomes (Guthman 2011).

Strengths and Limitations

This research adds to our current understanding of childhood obesity by providing an examination of the role of structural inequality. While prior research has established correlations between a child’s SES and racial identity and obesity, I find that characteristics of the environment matter as well. This adds an important social basis to a body of literature that has explored changes in individual health behaviors (Gordon-Larsen et al. 2004b). Understanding the social basis is important because, as established in this research, it has an additional effect on the likelihood that a child will be obese.

Research that has examined aspects of either school or neighborhood effects on obesity has often not examined multiple aspects of place simultaneously (Li and Hooker 2010; O’Malley et al. 2007). This research examines both race and poverty together to provide a more complete picture of how multiple aspects of the environment can affect obesity.

Despite these contributions to the body of literature, there are some limitations to this project. First, these data are not a random sample of the state of North Carolina or the United States and therefore are not generalizable to those populations. While this project is an important step in beginning to model these types of relationships and in beginning to understand how these structural inequalities affect obesity, more research is needed to see if
these findings remain true for other populations of students elsewhere in the United States. Moreover, these data did not include any family or household variables, meaning that I was unable to control for family income or family behaviors. Future research that controlled for family characteristics would strengthen these research findings. Similarly, I did not have information on the poverty status of individual students, which would have strengthened the analysis related to school level poverty. Finally, while this research suggests that segregation of affluence may be critical for understanding how context affects the likelihood of obesity, I did not have a way to control for the amount of wealth at the school or community level. While this is a common issue in income inequality research, particularly at the school level (Condron 2009), my findings suggest that research on differences between wealthy- and middle- and low-income places is needed to be able to fully understand the how inequalities of place affect childhood obesity.

As childhood obesity continues to be a concern of American parents, policy-makers, and researchers, this research adds to our understanding of how place matters for understanding and intervening in this important public health issue. Further research is needed to understand what aspects of place impact childhood obesity.

Policy Implications

While this research is not an evaluation of any particular childhood obesity program or intervention, the results are relevant to larger policy debates about how to deal with childhood obesity. Many policies designed to prevent or decrease obesity are directed at the individual level. These include advocating more exercise, eating less fast food, and reducing screen time among children. This research adds to this conversation by showing the
importance of structural issues that complement individual- or family-level interventions. This research has shown that the school and community context are important for both identifying children who are at risk and for understanding the contexts that can minimize or exacerbate those risks.

Racially and economically integrating schools has been a topic of much debate in the United States and this research adds to this discussion. The Supreme Court, in recent years, has examined affirmative action policies at the college level and caused policy makers and education administrators at all levels to reassess their diversity policies. While it is well established that integrated schools can help to lower the achievement gap among students, there are also health implications for segregating students based on race and socioeconomic status. Because neighborhoods tend to be segregated along these lines, school boards must be willing to enact policies to counteract this spatial separation through school assignments. Further, this research suggests that perhaps diversity training and active support of minority students in majority white schools might be helpful in decreasing the obesity gap between them and other students.

The No Child Left Behind Act has shifted the focus in many schools to testing and academic performance and away from elective courses such as physical education. This could be particularly problematic for high poverty schools that may struggle to maintain acceptable test scores and must divert energy and scarce resources to improving test scores in favor of classes such as art, music, or physical education. Moreover, the focus should not only be on high poverty schools, but on a holistic approach that minimizes differences between high income schools and everyone else. This research highlights the need to ensure
that physical activity and health education are equally accessible to all students. Schools have a unique opportunity to minimize inequalities that exist between students. In the case of child health, schools have the potential to impact their long-term health and to even improve educational outcomes.

Finally, policy makers have become increasingly interested in the issue of food deserts in recent years and this research speaks to that as well. While my findings are limited, they do point to the need to be conscious of the economic and racial segregation as well as the rural or urban nature of a community when discussing food deserts. Food deserts are not created in a vacuum and, as such, careful attention needs to be paid to the specific needs of the community in order to avoid exacerbating other inequalities. For example, we know that minority communities are more likely to have small grocers with limited health food selections compared to large scale supermarkets (Block et al. 2004). However, the introduction of large corporate grocers could have consequences for the local community and its economy that might not be understood without a careful consideration of the needs of that community. Therefore, policies aimed at strengthening local food sources and providing incentives for increasing healthy foods to local retailers who currently exist could address both issues of food access and the social structural issues, such as limited resources in minority communities that likely resulted in the food desert.

Similarly, rural areas have higher rates of childhood obesity and this is persistent even when economic and racial segregation are controlled. There is little research on the unique challenges that rural areas face in terms of access to healthy foods and lack of infrastructure. Moving forward, policy makers and other stakeholders must be conscious of the unique
challenges faced in different communities and places. Working with rural communities to strengthen their access to healthy foods and physical education is important to addressing the needs and remaining respectful of their particular challenges.

Childhood obesity has become an issue of great concern to parents, teachers, researchers, and policy makers alike. Understanding the way that place effects individuals and their health is key to ensuring that the next generation has access to the necessary resources to live healthy and productive lives.
Figure 1: North Carolina counties included in the analysis file
Table 1: Response Rates for all Public schools with 3-5th grade students (BMI reports received / ADM)

<table>
<thead>
<tr>
<th>Response Rate</th>
<th>Frequency</th>
<th>Percent</th>
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</thead>
<tbody>
<tr>
<td>00-09%</td>
<td>75</td>
<td>5.38</td>
</tr>
<tr>
<td>10-19%</td>
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</tr>
<tr>
<td>20-29%</td>
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<td>0.43</td>
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</tr>
<tr>
<td>70-79%</td>
<td>19</td>
<td>1.36</td>
</tr>
<tr>
<td>80-89%</td>
<td>47</td>
<td>3.37</td>
</tr>
<tr>
<td>90-99%</td>
<td>150</td>
<td>10.75</td>
</tr>
<tr>
<td>100%</td>
<td>60</td>
<td>4.30</td>
</tr>
<tr>
<td>no reports</td>
<td>1,001</td>
<td>71.76</td>
</tr>
<tr>
<td>TOTALS</td>
<td>1,395</td>
<td>100%</td>
</tr>
</tbody>
</table>
Table 2: Measurement of Independent Variables and Data Sources

<table>
<thead>
<tr>
<th><strong>Student variables:</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Student Race:</strong> Data from the Department of Public Instruction database for the 2009-10 school year. Students’ race was dummy coded. The dummy categories include: Black, Hispanic, and Other. Each of those categories are compared to the baseline (or omitted) category which is White.</td>
</tr>
<tr>
<td><strong>Student Grade:</strong> Data from the Department of Public Instruction database for the 2009-10 school year. The student’s grade for this year was included as a whole number (3,4, or 5).</td>
</tr>
<tr>
<td><strong>Student’s Sex:</strong> Data from the Department of Public Instruction database. Students were coded “1” if they were female and “0” if they were male.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>School variables:</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>School Economic Disadvantage:</strong> Data from the North Carolina Department of Public Instruction, Child Nutrition Services, Free and Reduced Application Data by Site for 2009-10. If 75% or more of the students receive a free or reduced lunch the school is high poverty. If 75% or more do not receive a free or reduced lunch the school is considered low poverty. This variable was then dummy coded. The dummy variables are: high poverty and low poverty. Each of the dummy variables is compared to the baseline (or omitted) category which is “medium poverty”.</td>
</tr>
<tr>
<td><strong>School Racial Segregation:</strong> Data from the Department of Public Instruction “Grade, Race, Sex 2009-10” report which reports the racial composition of schools at the end of the first month of the school year. Schools are considered minority segregated if 75% or more of the students are non-White. They are considered white segregated when 75% or more of the student body is White. Racial segregation was then dummy coded. The dummy categories include: minority segregated and white segregated. Each of the dummy variables is compared to the baseline (or omitted) category which is “no racial segregation”.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>County variables:</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Urban/Rural:</strong> Data from the North Carolina Rural Economic Development Center. A dummy variable was created for rural counties (rural=1) and compared to the baseline (or omitted) category urban (rural=0)</td>
</tr>
<tr>
<td><strong>County Residential Segregation:</strong> Data from the 2010 U.S. Census. A dissimilarity index calculates distribution of two groups among census tracts within a larger the county. The resulting score (ranging from 0-100) is interpreted as the percentage of people who would have to move to create an even distribution of the groups across the county.</td>
</tr>
<tr>
<td><strong>Economic Distress:</strong> Data from the from the 2005-2009 American Communities Survey. The variable is measured by the percentage (0-100) of households that are receiving</td>
</tr>
</tbody>
</table>
Table 2 Continued

<table>
<thead>
<tr>
<th>Supplemental Nutrition Assistance (SNAP).</th>
</tr>
</thead>
</table>

**Health Insurance:** Data from the 2010 Census. The variable is measured by the percentage of individuals (0-100) who do not have health insurance.

**Food Desert:** Data from the U.S. Department of Agriculture (using 2000 Census data). The dummy variable “food desert” is coded as “1” if there is one or more food deserts census tracts in the county. The baseline (or omitted) category (food desert=0) included counties without any food deserts.

**Farmers Market:** Data from the U.S. Department of Agriculture Food Environment Atlas. The number of farmers markets per 1,000 people in 2008.

**Farm to School:** Data from the U.S. Department of Agriculture Food Environment Atlas. Measured by a dummy variable indicating if there is a “farm to school” program in the county (farm=1). The omitted category (farm=0) includes counties without a program.

**SNAP Amount:** Data from the U.S. Department of Agriculture Food Environment Atlas. Measured by the average monthly dollar amount of SNAP benefits divided by the number of people in the county.
Table 3: Descriptive statistics for all key variables

<table>
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<tr>
<th>Variable</th>
<th>Sample Size</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
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<tbody>
<tr>
<td>Students (level 1)</td>
<td>74,822</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Obesity</strong></td>
<td>74,822</td>
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<tr>
<td>Obese</td>
<td></td>
<td>0.20</td>
<td>0.40</td>
<td>0</td>
<td>1.00</td>
</tr>
<tr>
<td>Not obese (omitted)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>74,822</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td></td>
<td>0.49</td>
<td>0.50</td>
<td>0</td>
<td>1.00</td>
</tr>
<tr>
<td>Male (omitted)</td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>Race</td>
<td>74,822</td>
<td></td>
<td></td>
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<td>Black</td>
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<td>0.25</td>
<td>0.44</td>
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<td>1.00</td>
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<td>Hispanic</td>
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<td>0.34</td>
<td>0</td>
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<td>Other</td>
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<td>0.08</td>
<td>0.27</td>
<td>0</td>
<td>1.00</td>
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<tr>
<td>White (omitted)</td>
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<td></td>
<td></td>
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<tr>
<td>Grade</td>
<td>74,822</td>
<td>3.99</td>
<td>0.81</td>
<td>3.00</td>
<td>5.00</td>
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<td>Schools (level 2)</td>
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</tr>
<tr>
<td><strong>Racial Segregation</strong></td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Minority segregated</td>
<td></td>
<td>0.27</td>
<td>0.45</td>
<td>0</td>
<td>1.00</td>
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<tr>
<td>White segregated</td>
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<td>0.24</td>
<td>0.43</td>
<td>0</td>
<td>1.00</td>
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<tr>
<td>No racial segregation (omitted)</td>
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<td></td>
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<tr>
<td>Poverty</td>
<td>317</td>
<td></td>
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</tr>
<tr>
<td>High poverty</td>
<td></td>
<td>0.29</td>
<td>0.46</td>
<td>0</td>
<td>1.00</td>
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<tr>
<td>Low poverty</td>
<td></td>
<td>0.14</td>
<td>0.35</td>
<td>0</td>
<td>1.00</td>
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<tr>
<td>Medium poverty (omitted)</td>
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<td></td>
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<tr>
<td>Counties (level 3)</td>
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<td></td>
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</tr>
<tr>
<td><strong>Urban/Rural</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural County</td>
<td></td>
<td>0.79</td>
<td>0.41</td>
<td>0</td>
<td>1.00</td>
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<tr>
<td>Urban County (omitted)</td>
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</tr>
<tr>
<td><strong>Residential Segregation</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black/White Dissimilarity Index</td>
<td></td>
<td>0.37</td>
<td>0.11</td>
<td>0.05</td>
<td>0.57</td>
</tr>
<tr>
<td>Hisp/White Dissimilarity Index</td>
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<td>0.27</td>
<td>0.11</td>
<td>0.08</td>
<td>0.48</td>
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<tr>
<td>Economic Disadvantage</td>
<td>38</td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>
Table 3 Continued

<table>
<thead>
<tr>
<th></th>
<th>% SNAP</th>
<th>% Uninsured</th>
<th>Food Desert</th>
<th>Food Environment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.14</td>
<td>0.05</td>
<td>0.06</td>
<td>0.27</td>
</tr>
<tr>
<td>% Uninsured</td>
<td>0.20</td>
<td>0.02</td>
<td>0.17</td>
<td>0.25</td>
</tr>
<tr>
<td>Food Desert</td>
<td>38</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Food desert tracts in county</td>
<td>0.63</td>
<td>0.49</td>
<td>0</td>
<td>1.00</td>
</tr>
<tr>
<td>No food desert tracts (omitted)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Food Environment</td>
<td>38</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average monthly SNAP amount ($)</td>
<td>38</td>
<td>88.24</td>
<td>9.81</td>
<td>66.00</td>
</tr>
<tr>
<td>% Households no car &amp; &gt; 1 mi to store</td>
<td>38</td>
<td>23.01</td>
<td>9.03</td>
<td>5.64</td>
</tr>
<tr>
<td>Farmers' markets/ 1,000 pop</td>
<td>38</td>
<td>0.02</td>
<td>0.03</td>
<td>0</td>
</tr>
<tr>
<td>Farm to school program</td>
<td>38</td>
<td>0.08</td>
<td>0.27</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 4: Bivariate relationship between school poverty and racial segregation among students (N=74,822)

<table>
<thead>
<tr>
<th></th>
<th>Poverty Segregated (=&gt;75%)</th>
<th>No income segregation (25%-74%)</th>
<th>Wealth Segregated (&lt;25%)</th>
<th>Totals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minority Segregated</td>
<td>74.53%</td>
<td>9.28%</td>
<td>0%</td>
<td>23.78%</td>
</tr>
<tr>
<td>Integrated (omitted)</td>
<td>22.2%</td>
<td>62.01%</td>
<td>45.23%</td>
<td>48.61%</td>
</tr>
<tr>
<td>White Segregated</td>
<td>3.27%</td>
<td>28.71%</td>
<td>54.77%</td>
<td>27.61%</td>
</tr>
<tr>
<td>Totals</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>
Table 5: Multilevel Logistic Regression Results Predicting Odds of Obesity (N=74,822 students, 317 schools, 38 counties)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Odds Ratio</td>
<td>Coeff. (SE)</td>
<td>Odds Ratio</td>
<td>Coeff. (SE)</td>
<td>Odds Ratio</td>
<td>Coeff. (SE)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.27</td>
<td>-1.31* (.04)</td>
<td>0.19</td>
<td>-1.67* (.07)</td>
<td>0.19</td>
<td>-1.64* (.08)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-2 Res Log</td>
<td>35335 2.1</td>
<td></td>
<td>35446 8.8</td>
<td></td>
<td>35450 9.9</td>
<td></td>
</tr>
<tr>
<td>Pseudo-Likelihood</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female (=1)</td>
<td>0.85</td>
<td>-0.162* (.07)</td>
<td>0.85</td>
<td>-0.162* (.07)</td>
<td>0.85</td>
<td>-0.162* (.07)</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black (=1)</td>
<td>1.71</td>
<td>.538* (.03)</td>
<td>1.66</td>
<td>.508* (.03)</td>
<td>1.65</td>
<td>.501* (.03)</td>
</tr>
<tr>
<td>Latino/a (=1)</td>
<td>1.99</td>
<td>.687* (.03)</td>
<td>1.93</td>
<td>.656* (.03)</td>
<td>1.91</td>
<td>.647* (.03)</td>
</tr>
<tr>
<td>Other (=1)</td>
<td>1.32</td>
<td>.274* (.04)</td>
<td>1.30</td>
<td>.259* (.04)</td>
<td>1.30</td>
<td>.258* (.04)</td>
</tr>
<tr>
<td>Grade</td>
<td>1.06</td>
<td>.059* (.01)</td>
<td>1.06</td>
<td>.059* (.01)</td>
<td>1.06</td>
<td>.060* (.01)</td>
</tr>
<tr>
<td>Segregation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minority Seg (=1)</td>
<td>1.35</td>
<td>.299* (.05)</td>
<td>1.09</td>
<td>.088* (.07)</td>
<td>1.13</td>
<td>.123* (.07)</td>
</tr>
</tbody>
</table>
Table 5 Continued

<p>| | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>White Seg (=1)</strong></td>
<td>0.90</td>
<td>-.108* (.06)</td>
<td>1.06</td>
<td>.054 (.06)</td>
<td>1.01</td>
<td>.012 (.06)</td>
</tr>
<tr>
<td><strong>Poverty</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>High Poverty</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.15</td>
<td>.140* (.05)</td>
<td>1.11</td>
<td>.101 (.06)</td>
<td>1.08</td>
<td>.080 (.06)</td>
</tr>
<tr>
<td><strong>Low Poverty</strong></td>
<td>0.63</td>
<td>-.461* (.06)</td>
<td>0.63</td>
<td>-.460* (.06)</td>
<td>0.66</td>
<td>-.423* (.06)</td>
</tr>
<tr>
<td><strong>Food Desert</strong></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.88</td>
<td>-.130 (.10)</td>
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<tr>
<td><strong>Rural County (=1)</strong></td>
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<td></td>
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</tr>
<tr>
<td></td>
<td>1.25</td>
<td>.225* (.10)</td>
<td></td>
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</tr>
<tr>
<td><strong>Black/White DI</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>1.34</td>
<td>.294 (.39)</td>
<td></td>
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</tr>
<tr>
<td><strong>Hispanic/White DI</strong></td>
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<td></td>
<td></td>
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</tr>
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<td></td>
<td>0.55</td>
<td>-.606 (.47)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>% Food stamps</strong></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>7.98</td>
<td>2.08* (.92)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>% Uninsured</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.05</td>
<td>-2.92 (1.95)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>School Level Covariance</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>.1735* (.018)</td>
<td>.1097* (.019)</td>
<td>.0882* (.011)</td>
<td>.0736* (.009)</td>
<td>.0732* (.009)</td>
<td>.0727* (.009)</td>
</tr>
<tr>
<td><strong>County Level Covariance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>.0246* (.015)</td>
<td>.0511* (.012)</td>
<td>.0796* (.026)</td>
<td>.0428* (.017)</td>
<td>.0449* (.018)</td>
<td>.0210* (.012)</td>
</tr>
</tbody>
</table>

*statistically significant at the .05 alpha level.
Table 6: Multilevel Logistic Regression Childhood Obesity Estimates and Odd Ratios for Individual Race and School Segregation Interactions Only (N=74,822 students, 317 schools, 38 counties)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimates</th>
<th>Odds Ratios</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black*Minority Segregated</td>
<td>-0.299* (.07)</td>
<td>0.741</td>
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<tr>
<td>Black*White Segregated</td>
<td>0.015 (.09)</td>
<td>1.015</td>
</tr>
<tr>
<td>Hispanic*Minority Segregated</td>
<td>-0.073 (.08)</td>
<td>0.930</td>
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<tr>
<td>Hispanic*White Segregated</td>
<td>-0.195* (.09)</td>
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</tr>
<tr>
<td>Other*White Segregated</td>
<td>-0.015 (.09)</td>
<td>0.986</td>
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<tr>
<td>Other*Minority Segregated</td>
<td>-0.279* (.10)</td>
<td>0.757</td>
</tr>
</tbody>
</table>

*statistically significant at the .05 alpha level
Figure 2: Odds of Obesity for Minority Students and White Student by School Segregation
Table 7: Descriptive Statistics for Food Access in North Carolina Counties and Sample

<table>
<thead>
<tr>
<th></th>
<th>All Counties (N=100)</th>
<th>Sample Counties (n=38)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (SD)</td>
<td>Range</td>
</tr>
<tr>
<td>% Households no car &amp; &gt; 1 mi to store (2006)</td>
<td>5.3 (2.4)</td>
<td>1.2-14.6</td>
</tr>
<tr>
<td>Farmers' markets/ 1,000 pop (2009)</td>
<td>.03 (.04)</td>
<td>0-.22</td>
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<tr>
<td>Average monthly SNAP $ benefits (2006)</td>
<td>88.40 (12.2)</td>
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<tr>
<td></td>
<td>All Counties (N=100)</td>
<td>Sample Counties (n=38)</td>
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<tr>
<td></td>
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<td>%</td>
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<tr>
<td>Farm to school program (2009)</td>
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<td>7%</td>
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</table>
Table 8: Multilevel Logistic Regression Coefficients for Full Model and Full Model with Food Access Variables (N=74,822 students, 317 schools, 38 counties)

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<th>Model 6: Full Model</th>
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<th>Model 7: Full Model with Food Access Variables</th>
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<td>Coeff. (SE)</td>
<td>Odds Ratio</td>
<td>Coeff. (SE)</td>
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<td>Constant</td>
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<td>-2 Res Log Pseudo-Likelihood</td>
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<td>354695.9</td>
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<td></td>
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<td>0.85</td>
<td>-.162* (.02)</td>
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<tr>
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<td>.501* (.50)</td>
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<td>.502* (.03)</td>
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<td>Latino/a</td>
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<td>.059* (.01)</td>
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<td>.133 (.07)</td>
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Table 8 Continued

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<th></th>
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<tr>
<td>% Food stamps</td>
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<td>Average monthly SNAP $ (2006)</td>
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<td>% Households no car &amp; &gt; 1 mi to store</td>
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<td>Farmers' markets/1,000 pop</td>
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<td>County-level Covariance</td>
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*statistically significant at the .05 alpha level.
Omitted/baseline categories: White, medium poverty schools, racially integrated schools, urban counties, and no farm to school program.
REFERENCES


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APPENDICES
### Appendix A: North Carolina State Health Statistics Processing Procedures

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<th>SAVE AS:</th>
<th>DELETE ALL TEST VALUES BUT:</th>
<th>OVERWRITE AND SAVE AS:</th>
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<td>EXPORT.JMP</td>
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### Pearson Correlation Coefficients, N = 74822

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### Pearson Correlation Coefficients, N = 317

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Pearson Correlation Coefficients, N = 38  
Prob > |r| under H0: Rho=0
APPENDIX C: Comparisons between total population of youth in North Carolina and youth in the sample

Comparing population of North Carolina students in grades 3-5 with North Carolina students in the sample on key demographic characteristics

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<tr>
<td>Female</td>
<td>166,917</td>
<td>36,720</td>
</tr>
<tr>
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<td>48.9%</td>
<td>49.1%</td>
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<tr>
<td><strong>Race</strong></td>
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<tr>
<td>White</td>
<td>180,100</td>
<td>39,731</td>
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<td>Hispanic</td>
<td>41,868</td>
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<td></td>
<td>12.3%</td>
<td>13.3%</td>
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<td>Other</td>
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</tr>
<tr>
<td></td>
<td>4.0%</td>
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<td>32.6%</td>
<td>32.7%</td>
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*data are from [http://www.ncpublicschools.org/fbs/accounting/data/](http://www.ncpublicschools.org/fbs/accounting/data/) “Grade, Race, Sex” counts and are limited to grades 3-5
Weight status distribution based on BMI, Sex, and Age (N=74,822)

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<td>Healthy weight (&gt; 5th percentile &lt; 85th percentile)</td>
<td>44,245</td>
<td>59.1%</td>
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<tr>
<td>Overweight (&gt;85th &gt; 95th percentile)</td>
<td>12,931</td>
<td>17.3%</td>
</tr>
<tr>
<td>Obese (= &gt; 95th percentile)</td>
<td>14,975</td>
<td>20%</td>
</tr>
</tbody>
</table>

*Charts obtained from: http://www.cdc.gov/growthcharts/percentile_data_files.htm

Comparing schools in the sample with all North Carolina public schools serving 3rd-5th graders

<table>
<thead>
<tr>
<th></th>
<th>Population (N=1,384*)</th>
<th>Sample (N=317)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>%</td>
</tr>
<tr>
<td><strong>Racial Segregation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minority Segregated</td>
<td>302</td>
<td>21.7%</td>
</tr>
<tr>
<td>White Segregated</td>
<td>380</td>
<td>27.2%</td>
</tr>
<tr>
<td>Integrated (omitted)</td>
<td>713</td>
<td>51.1%</td>
</tr>
<tr>
<td><strong>School % Economic-Disadvantaged</strong>*</td>
<td>Mean (SD)</td>
<td>Range</td>
</tr>
<tr>
<td></td>
<td>63.6% (.23)</td>
<td>2.2-100%</td>
</tr>
</tbody>
</table>

*Population missing=11
Comparing sample counties with all North Carolina counties on key variables

<table>
<thead>
<tr>
<th></th>
<th>Population (N=100)</th>
<th></th>
<th>Sample (N=38)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>%</td>
<td>N</td>
<td>%</td>
</tr>
<tr>
<td>Rural</td>
<td>85</td>
<td>85%</td>
<td>30</td>
<td>78.9%</td>
</tr>
<tr>
<td>Urban (omitted category)</td>
<td>15</td>
<td>15%</td>
<td>8</td>
<td>21.1%</td>
</tr>
<tr>
<td>Food Desert (omitted category is “No”)</td>
<td>57</td>
<td>57%</td>
<td>24</td>
<td>63.2%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Mean (SD)</th>
<th>Range</th>
<th>Mean (SD)</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black/White Dissimilarity Index</td>
<td>0.33 (.12)</td>
<td>0-.58</td>
<td>0.37 (.11)</td>
<td>.05-.57</td>
</tr>
<tr>
<td>Hispanic/White Dissimilarity Index</td>
<td>0.26 (.11)</td>
<td>0-.54</td>
<td>0.27 (.11)</td>
<td>.08-.48</td>
</tr>
<tr>
<td>American Indian/White Dissimilarity Index</td>
<td>0.26 (.15)</td>
<td>0-.82</td>
<td>0.25 (.13)</td>
<td>.08-.79</td>
</tr>
<tr>
<td>Black Poverty Rate</td>
<td>0.27 (.12)</td>
<td>0-.76</td>
<td>0.25 (.12)</td>
<td>0-.54</td>
</tr>
<tr>
<td>Hispanic Poverty Rate</td>
<td>0.35 (.15)</td>
<td>0-.87</td>
<td>0.35 (.15)</td>
<td>.15-.73</td>
</tr>
<tr>
<td>White Poverty Rate</td>
<td>0.12 (.03)</td>
<td>.05-.22</td>
<td>0.12 (.04)</td>
<td>.06-.22</td>
</tr>
<tr>
<td>% HH Receiving food stamps</td>
<td>0.15 (.05)</td>
<td>.06-.28</td>
<td>0.14 (.05)</td>
<td>.06-.27</td>
</tr>
<tr>
<td>% Substandard Housing</td>
<td>0.02 (.01)</td>
<td>0-.05</td>
<td>0.02 (.01)</td>
<td>.01-.05</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>0.11 (.02)</td>
<td>.06-.18</td>
<td>0.11 (.02)</td>
<td>.06-.17</td>
</tr>
<tr>
<td>Crime Rate</td>
<td>33.02 (18.4)</td>
<td>0-139.40</td>
<td>35.6 (15.36)</td>
<td>3.4-68.10</td>
</tr>
</tbody>
</table>