The Relationship of Lack of Access to Affordable and Healthy Foods and Obesity Rates in Tennessee Adults and Children

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ABSTRACT

This research explores how obesity rates correspond to the percentage of a county's population living in food deserts. Archival data were used from the Food Desert Locator of United States Department of Agriculture's Economic Research Service, the 2010 CDC's data of obesity rates per Tennessee county, the U.S. Census Bureau 2010 population data, and the Tennessee Coordinated School Health Childhood Obesity Rates by County Data of 2008-2009. Results indicated that the sample with 61 counties was best suited to test the hypotheses as the data were similar for theses counties and would not drastically skew the results. The percentages of the populations living in food deserts were significantly correlated to obesity rates. There was no moderation, but percentages of households without a vehicle and population with at least a bachelor's degree were significant predictors of adult and childhood obesity rates. The percentage of non-Hispanic white population was a significant predictor of adult obesity. Meanwhile, population living in urban food deserts and childhood poverty rate were significant predictors of childhood obesity. These findings suggest that at the county level, the resources available to the population may influence obesity rates.

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CHAPTER I: INTRODUCTION AND REVIEW OF THE LITERATURE

In 1948, the World Health Organization (WHO) defined health as a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity. For many years, there have been a multitude of publications describing ways to improve health, become stronger, and decrease the prevalence of diseases. As the world population is living longer than past generations, people are interested in how to at least maintain their overall health and quality of life throughout their lifespan.

Many of the diseases that diminish overall health quality are those that are non-communicable (non-transmittable and non-infectious) diseases, which can possibly be prevented when risk factors are lowered (Alleyne, Hancock, & Hughes, 2011). One risk factor for many non-communicable diseases is obesity (WHO, 2011). Although debated by many health organizations, the WHO stated obesity is chronic disease (2001). Obesity has become an epidemic- affecting large portions in industrialized and developing countries' populations. Obesity is complex in nature as it has genetic, biological, behavioral, social, cultural, and environmental influences (U.S. Department of Health and Human Services, 2001).

Recently, research has started to explore environmental effects on the rapid increase in obesity rates. A major environmental topic being studied is the so-called "food desert"— a physical space lacking healthy and affordable food. Little research has been done on obesity rates impacted by food deserts as defined by the United States Department of Agriculture (USDA) Food Desert Locator. The research that has been conducted has had mixed results.

In this literature review, I will first discuss the prevalence of obesity and the research on obesity's impact on health. Second, I will examine causes and consequences of obesity by presenting relevant research. Third, I will define the concept of food deserts and analyze the impact of food deserts on obesity rates in some areas of the United States. Lastly, I will discuss the possible relationship between food deserts and obesity rates of Tennessee children and adults.

Prevalence of Obesity

Obesity is defined as having a body mass index (BMI) of 30 (kg/m^2 or (lbs x 703)/in^2) or more for adults (CDC, 2010). Because girls and boys have different amounts of body fat and the amount changes with age, the BMI for children is calculated and then plotted on the CDC BMI for age and sex to determine the percentile. A child is considered overweight if the percentile is between 85 to 94 and obese when the percentile is 95 or higher (CDC, 2011). Obesity also has several categories based on BMI as follows: class I obesity 30 – 34.9, class II obesity 35 – 39.9, and class III obesity $\geq$ 40 (WHO, 2006). BMI correlates to the degree of body fat, but should not be taken into account for muscular people (CDC, 2010). Also, waist measurements should be no more than 40 inches for men and no more than 35 inches for women. Those with more fat accumulation around the mid-section are at higher risk for other diseases such as type 2 diabetes and heart disease than those carrying more fat around the hips and thighs (National Heart Lung and Blood Institute, 2011).

The WHO (2015) provides several sobering statistics with regard to obesity. For example, there are at least 600 million adults ages 18 years or older (13%) who are obese worldwide. Approximately 15% of women and 11% of men in the world are obese. It is estimated that worldwide 42 million children ages 5 and under are at least overweight and the number is rising. It is extremely likely that these children will become obese adults and add to the statistics of early death, illnesses, and disabilities. Overweight and obesity, the fifth leading risk of death globally, is linked to at least 3.4 million adult deaths a year (Lim et al., 2012). Most industrialized nations have seen a huge rate of increase in obesity with the fastest rate of increase being in the developing countries. Obesity has a global impact of about $2 trillion. Between two and seven percent of total health care costs in most developed countries goes towards obesity. The value rises to approximately twenty percent when adding in the treatments of associated diseases (Dobbs et al., 2014).

As of 2012, the United States leads the world in the adult population being obese. All genders, ages, racial, and ethnic groups have seen significant increase in obesity over the past 20 years (Minnesota Department of Health, 2002). Middle-aged adults had a higher prevalence of obesity than their older and younger counterparts. Prevalence of obesity was higher in middle-aged men than older men and younger men. Younger women had lower prevalence of obesity than middle-aged women and older women. Non-Hispanic Asian adults had the lowest prevalence of obesity compared to non-Hispanic white, Hispanic, and non-Hispanic black adults. Non-Hispanic black women had the highest prevalence of obesity compared to Hispanic, non-Hispanic white, and non-Hispanic Asian women. Hispanic men had the highest prevalence of obesity compared to non-Hispanic Asian and non-Hispanic white men, but did not significantly differ from non-Hispanic black men. The only difference in race by sex was found among non-Hispanic black women and non-Hispanic black men (Ogden, Carroll, Kit, & Flegal, 2013). As with adults, there is a racial disparity in the obesity prevalence in children.

Hispanic and non-Hispanic black children had significantly higher prevalence of obesity than non-Hispanic white and non-Hispanic Asian children. Youth ages 2-5 had a significantly lower prevalence of obesity compared to the 6-11 and 12-19 year olds (Ogden, Carroll, Kit, & Flegal, 2014). United States obesity percentages by age, sex, and race can be found in Table 1.

Table 1

United States Obesity Percentages by Age, Sex, and Race

	Adult	Men	Women	Child	Boys	Girls
Overall	34.9	33.5	36.1	16.9	18.6	15.0
Young (2-5 / 20-39 years)	30.3	29.0	31.8	8.4		
Middle (6-11 / 40-59 years)	39.5	39.4	39.5	17.7		
Older (12-19 / 60+ years)	35.4	32.0	38.1	20.5		
Non-Hispanic Asian	10.8	10.0	11.4	8.6		
Non-Hispanic white	32.6	32.4	32.8	14.1		
Hispanic	42.5	40.1	44.4	22.4		
Non-Hispanic black	47.8	37.1	56.6	20.2		

Note. Weights and heights from National Health and Nutrition Examination Survey (NHANES) 2011-2012. N =9120 (5181 adults). Adapted from “Prevalence of childhood and adult obesity in the United States, 2011-2012,” by C. Ogden, M. Carroll, B. Kit, and K. Flegal, 2014, *The Journal of the American Medical Association, 311*(8), 806-814. Copyright 2014 by American Medical Association.

A recent estimate places the overall economic cost at about $147 billion annually that goes towards medical care cost of obesity in the U. S. (Finkelstein, Trogdon, Cohen, & Dietz, 2009). One study estimated 111,909 excess deaths per year in the U. S.

associated with obesity and 82,066 of those deaths occurring in people with a BMI of at least 35 (Flegal, Graubard, Williamson, & Gail, 2005).

Within the United States, Tennessee ranks number 4 of states in adult obesity rate and number 6 in childhood obesity rate (Trust for America's Health, 2011). Overall and per grade, the students in rural schools had higher obesity and overweight prevalence than the students in metropolitan schools. Boys had a higher prevalence of obesity and overweight than girls in rural schools, but boys had a lower rate of obesity than girls in metropolitan schools (Tennessee Coordinated School Health, 2012-2013). Some analysts report that the cost of obesity for Tennessee is over $2.5 billion per year (Get Fit Tennessee, 2012). Tennessee obesity percentages in adults by race and children by race or area classification can be found in Table 2.

In summary, obesity is a significant health problem internationally, nationally, and in the state of Tennessee. Obesity affects millions of people of all ages throughout the world and is associated with diminished health to the point of death. Economically, billions of dollars are spent every year in the U.S. on healthcare costs related to obesity.

Causes and Consequences of Obesity

One of the major causes of obesity is that more calories are consumed than used by the body during the day. Most people develop overeating in childhood, often learning from others near them. Eating habits are learned behaviors from caregivers, family, and friends (Savage, Fisher, & Birch, 2007). Researchers also have shown that, when there is a stressful situation within the social realm, people turn to food and eat large portions of very unhealthy food (Zellner et al., 2006).

Table 2

Tennessee Obesity Percentages in Adults by Race and Children by Area Classification

	Adult	Men	Women	Child	Boys	Girls
Obese	33.7	30.5	32.0	21.5	22.4	20.4
Overweight				17.1	16.4	17.8
Rural				39.7	40.5	38.9
Metropolitan				36.1	35.3	36.9
Non-Hispanic white	30.2					
Hispanic	25.6					
Non-Hispanic black	40.4					

Note. Adapted from "A Summary of Weight Status Data Tennessee Public Schools, 2012-2013 School Year," by Tennessee Department of Education Office of Coordinated School Health, 2014. Adapted from "F as in Fat: How Obesity Threatens America's Future 2011," by Trust for America's Health, 2011.

Within the past century, United States society has changed its daily diet to more highly processed foods, meats, and refined grains of corn, soy, and wheat, while fruits, vegetables, and whole grains are less likely to be consumed (Pollan, 2008). The fat, sodium, sugar, and low nutrient and high energy contents of these former foods can cause weight gain, particularly when consumed in large quantities. Matthews, Wien, and Sebate (2011) compared food frequency from the late 1980 Child-Adolescent Blood Pressure Study of 1764 students enrolled either at a Seventh-Day Adventist or a public school. Results from the regression models showed that as more grains, nuts, vegetables, and low nutrient-dense foods were consumed, the risk of being overweight decreased. The risk of being overweight increased as dairy consumption increased. In a more recent study, as the total consumption of whole-fat dairy increased, the likelihood of being obese was significantly decreased (Crichton & Alkerwi, 2014).

As noted earlier, obesity refers to having an excess amount of body fat that endangers one's health by putting a person at risk for many diseases. A 26-year follow-up study of 5209 men and women who were free of any cardiovascular disease but were considerably overweight at their initial examination were selected from the Framingham Heart Study's original cohort to examine the relationship between obesity and cardiovascular disease (Hubert, Feinleib, McNamara, & Castelli, 1983). Results showed that obesity was a significant independent predictor of coronary disease, coronary death, and congestive heart failure in men. For women, obesity was a significant and independent predictor of coronary disease, stroke, congestive heart failure, coronary death, and cardiovascular death. An increased risk of cardiovascular disease was also seen in women and men when weight was gained after the young adult years.

In addition to being a risk factor for cardiovascular disease, obesity is associated with an increased risk for many other health problems. Mokdad et al. (2003) used data from the 2001 Behavioral Risk Factor Surveillance System (BRFSS). The Centers for Disease Control and Prevention and state health departments conduct the yearly BRFSS cross-sectional telephone survey to ask people 18 years and older about personal health issues. Results showed obesity was significantly related to diabetes, high blood pressure, high cholesterol, asthma, and arthritis.

Excess body weight also increases the risk of many cancers. Bergstrom, Pisani, Tenet, Wolk, and Adami (2001) conducted a meta-analysis of research done in the European Union to estimate the proportion of cancer cases associated with excess weight and cancer within different bodily sites. An estimated 34,800 new cases per year were attributed to obesity and another 37,000 were related to being overweight. Compared to a normal weight person, the risk of kidney cancer is 36% higher for an overweight person and 84% higher for an obese person. For gallbladder cancer, an estimated association predicted 34% and 78% increases in risk for overweight and obese people. Endometrial cancer risk increased by 59% for overweight women and 152% for obese women when compared to normal weight women. The risk of prostate cancer increases 6% for an overweight man and 12% for an obese man when compared to a normal weight man. Finally, in menopausal women, estimates of breast cancer predict that the excess risk is 12% for overweight and 25% for obese women.

Obesity is also a significant independent risk factor for gallbladder disease. Stampfer et al. (1992) evaluated 90,302 women ranging in age from 34 to 54 years from the Nurses' Health Study cohort for eight years. Compared to women with a BMI less than 24, those with a BMI over 30 had a gallstone incidence of greater than 1% per year. Women with BMI greater than or equal to 45 had a gallstone incidence of about 2% per year. Results also showed women with a BMI of 45 or more had a sevenfold increase risk for gallstones than women with a BMI less than 24.

Fertility in men and women is also affected by obesity. Magnusdottir et al. (2005) selected men who had contacted the Department of Assisted Reproduction at the Landspitali University Hospital of Iceland between March 1999 and May 2001 that fit into one of the study groups based on sperm concentration and motility in previous analysis. Poor semen quality was three times more likely to be found in obese men than normal weight men. In addition, semen quality and BMI had a significant negative correlation. Another study examined 3029 sub-fertile couples that included men with normal semen and women who were ovulatory during January 2002 and February 2004. For every increment of a woman's BMI over 29, she had a 4% decrease in the likelihood of possible spontaneous pregnancy (van der Steeg et al., 2008).

People living with obesity suffer physically, emotionally, and socially during normal day-to-day routines. In a meta-analysis conducted by Shiri and colleagues (2010), the prevalence of low back pain was highest in obese people, followed by overweight and normal weight, respectively. An increased incidence of back pain more than once during a 12-month period was only seen in obese people. Some obese individuals are more susceptible to binge eating. Binge eating is associated with symptoms of depression, low self-esteem, borderline personality disorder symptoms, and a greater possibility of being diagnosed with Axis I mental disorder (Yanovski, Nelson, Dubbert, & Spitzer, 1993). In one study, moderate to extreme dissatisfaction with overall appearance was reported by 68% of obese people seeking weight reduction (Sarwer et al., 1998).

Using a cross-sectional analysis of the 1996 National Longitudinal Study of Adolescent Health, Swallen, Reither, Haas, and Meier (2005) divided BMI into 5 categories: Underweight, normal, at risk for overweight, overweight, and obese. There was a significant relationship between BMI and general and physical health. Overweight and obese adolescents had significantly worse self-reported health and more functional limitations than normal weight adolescents. Younger obese and overweight adolescents had an increased risk of depression, low self-esteem, and school or social functioning problems.

Obesity can have a negative social impact including employment discrimination, discrimination from health care professionals, and educational barriers and problems with interpersonal relationships. Employment discrimination starts as early as when one applies for a job. Giel et al. (2012) had 127 volunteer human resource (HR) professionals view standardized photographs of 6 people that differed in gender, ethnicity, and BMI and complete the following tasks: match the person to a profession; eliminate one of the 6 from being hired; and select 3 of the 6 candidates to supervisor positions. Obese men and women were more often paired with lower prestige jobs than high and medium prestige jobs. When eliminating an applicant, the obese female was disqualified by 42% of the HR professionals. Obese men and ethnic normal weight females were also significantly more likely to be eliminated. The supervisor positions were 4.6 times more likely to go to a normal weight candidate than an obese candidate.

Once the job is obtained, women and men are viewed differently depending on their weight within the workplace (Judge & Cable, 2011). When height, age, marital status, school-age children in household, overall health, smoking behavior, drinking behavior, hours worked, educational attainment, organizational tenure, necessary training, intrinsic job characteristics, self-esteem, industry, and civil service position are controlled, men and women are paid differently based on weight. As women weighed more, their salaries significantly decreased. Conversely, men had a significant increase in pay as their weight went up (Judge & Cable, 2011).

Health care professionals also show discrimination towards obese patients. Hoppe and Ogden (1997) conducted a study about the perceptions of nurses toward obese patients. The majority of the nurses believed that the patients were not able to lose weight because of noncompliance. If weight loss was not obtained, nurses thought it did not have anything to do with an ineffective program or the lack of counseling.

Even health care professionals specializing in obesity show strong weight bias. Schwartz et al. (2003) gave 389 professionals attending a conference for the study of obesity the Implicit Association Test (IAT) and a self-report questionnaire. The results of the IAT showed that the health care professionals have an anti-fat implicit bias and share the stereotypes of lazy, stupid, and worthless associated with the obese. Using the self-report questionnaires, those healthcare professionals who had more obese friends, weighed more, understood the obesity experience, and were male, older, and emotionally positive about life were less likely to have implicit anti-fat bias.

When obese patients either sense or know that health care providers have an anti-fat bias, the likelihood of seeking preventive medical care is lessened. Fontaine, Faith, Allison, and Cheskin (1998) used data from the 1992 Cancer Control and Health Insurance Supplements, self-reported sociodemographic information, and the use of medical services to see if there was a relationship between BMI and women using healthcare services. When all other covariates were adjusted, obese women were more likely to delay getting clinical breast exams, gynecological exams, and Pap smears. BMI did not delay getting mammograms nor lessen the amount of physician visits.

Obesity can be a barrier in the educational environment and affect relationships with others. In one study (Durante, Fasolo, Mari & Mazzola, 2014), young children, ages 6 to 11, had more negative attitudes towards their overweight peers than their normal weight and thin peers. Overweight female peers were judged less favorably, overall. Fortunately, there was an increase in the social acceptance by their peers as the children aged. The majority of a sample of high school students reported seeing overweight or obese peers being teased, ignored, threatened verbally, physically harassed, and having bad rumors spread about them (Puhl, Luedicke, & Heuer, 2011). Not only are overweight or obese students judged by their peers, obesity is negatively viewed by school personnel. At least 20% of the school staff from an urban junior and senior high school that took the survey agreed that obese people are not tidy, very emotional, have more family problems, and unsuccessful at work compared to their non-obese peers (Neumark-Sztainer, Story, & Harris, 1999). Weight bias is also found in institutes of higher education. Burmeister, Kiefner, Carels, and Musher-Eisenman (2013) found that the applicants for graduate psychology programs were less likely to receive an offer of admission after an interview if the person had a higher BMI.

In summary, obesity is associated with many diseases, some of which can cause serious deterioration to a person's health and even cause death. Along with being a risk factor for several diseases, obesity can cause harm to someone's physical, emotional, and social well-being, as both self and others perceive and react to the burden of extra weight. Most of the ill effects of obesity have significantly increased within the past century as the human diet has changed from wholesome foods to highly processed foods.

Access to Affordable and Healthy Foods: The Concept of Food Deserts

There is extensive evidence that behavior and environment play large roles in determining who becomes obese (U.S. Department of Health and Human Services, 2001). Among the environmental factors that contribute to the obesity epidemic are economic growth, modernization, urbanization, and globalization of food markets, as well as the easy availability of fast foods with high fat, sugar, calories, and large portions

(Popkin, 2006). In addition, people may have more commitments to family such as a child's extracurricular activities or taking care of an ailing family member; work to be seen as a valuable employee for possible promotion; and possible community involvement which leaves less time for food preparation (Devine et al., 2006). Due to these situations, people opt for fast-food restaurants or other unhealthy foods that are quick and easy to obtain. People of low socioeconomic status tend to buy cheaper foods that are less nutritious. These unhealthy food choices are a key contributor to the rise in obesity (Bader, Purciel, Yousefzadeh, & Neckerman, 2010).

In many communities, the most available food is high in sugar, fat, calories, and low-nutrients, while vegetables, fruits, lean meats, legumes, whole grains, and dairy are less readily available. These communities are known as low-access food deserts. Researchers in Northern Ireland coined the phrase "food desert" to describe areas with limited access to affordable food for residents (Furey, Strugnell, & McIlveen, 2001). A food desert is an area where affordable fresh fruits, vegetables, and other whole foods are not readily available due to a lack of grocery stores and farmers' markets (United States, 2008). Food deserts are usually found in either urban or rural low income areas. The Healthy Food Financing Initiative (HFFI) Working Group, a partnership between the U.S. Departments of Treasury, Agriculture, and Health and Human Services, defines a food desert as a low-income census tract where many of the residents have low-access to a large grocery store or supermarket (U.S. Health and Human Services, 2010).

Instead of having access to supermarkets or other outlets to buy healthy foods, those living in food deserts have more ready access to small convenience stores and fast food restaurants where they can buy less healthy food-like substances. Some researchers have speculated that higher rates of obesity could be explained by the lack of access to supermarkets in low-income neighborhoods in the United States (Cummins & Macintyre, 2006). A cross-sectional study of 10,763 participants in Mississippi, North Carolina, Maryland, and Minnesota (Morland, Diez Roux, & Wing, 2006) revealed that the prevalence of obesity was 24% lower and the prevalence of overweight was 9% lower when there was a supermarket located within the census tract. Also, the prevalence of obesity was higher in areas where a convenience store was located. Obesity rates were highest in the areas where there was an absence of a supermarket and lowest when only supermarkets and no convenience stores nor fast-food restaurants were located within the census. Those census tracts with a mix of food stores had a prevalence of obesity between the other two conditions.

People may be more likely to adopt a diet high in energy-dense foods when there are limited places to buy food. In return, these people are more at risk of becoming overweight or obese. Morland, Wing, Diez Roux, and Poole (2002) found that wealthier neighborhoods had significantly more supermarkets and gas stations with convenience stores, but less places to consume alcohol than the poorest neighborhoods. When comparing racial inequality among the neighborhoods, there were four times more supermarkets in white neighborhoods compared to black neighborhoods. Caraher, Dixon, Lang, and Carr-Hill (1998) discovered those of low socioeconomic status were less likely to have access to a car which makes it more difficult to obtain healthy food from distant supermarkets and transport large amounts of food at once.

Researcher have estimated the association between BMI and grocery stores locations. For example, Inagami, Cohen, Finch, and Asch (2006) used data from the Los

Angeles Family and Neighborhood Study (L.A. FANS) and data from the 2000 U.S. census. The L.A. FANS survey data included height, weight, income, transportation, and most relied upon grocery store location of 2144 adults from 65 neighborhoods. After the grocery store data were adjusted for individual and neighborhood characteristics, the results for a high BMI were positively associated with owning a car, being black or Latino, age, living in a very low socioeconomic status (SES) area, going to grocery stores in more disadvantaged areas than the residential area, and traveling more than 1.76 miles to the preferred grocery store. Meanwhile, a lower BMI was seen in those with a college education. A follow-up study by Ingami, Cohen, Brown, and Asch (2013) found those without a car who live in a high density of fast food restaurants have a higher BMI than those without a car who live in an area without fast food restaurants.

Overweight and obesity have also been associated with the prevalence of food deserts. For example, Schafft, Jensen, and Hinrichs (2009) located food deserts in rural Pennsylvania by using Geographic Information System (GIS) and gathered BMI data of the school districts’ student population residing in rural Pennsylvania food deserts. The analyses indicated that there was an increase in the rates of overweight children as the percentages of the students living in food deserts increased.

Ghosh-Dastidar et al. (2014) found that distance to stores and prices were positively associated with obesity in one research model when analyzing data of residents in two predominantly African American Pittsburgh neighborhoods without a supermarket. In another model, prices only were significantly correlated to obesity. People who shopped at the higher priced stores were less likely to be obese. The authors suggested that marketing plays a role in the choices the consumers make as the higher price stores are more likely to put healthy options in the store than the lower price stores. All models showed a positive correlation between age, kids in the household, female, people with less than a college education, and obesity.

Reed et al. (2013) studied the eating habits of a small group of African American preteen girls and their mothers' who lived in Chicago food deserts. Two-thirds of the girls and over 90% of the mothers were overweight or obese. Poor nutrient intake was seen for both groups. There was a higher prevalence of overweight and obese girls when the mothers received financial assistance. Most of the mothers had an education less than a bachelor's degree, low income, were single, received financial assistance, and many were unemployed.

Some researchers have examined why unhealthy food purchases are made in urban food deserts. For example, Zachary, Palmer, Beckham, and Surkan (2013) recruited participants from a southwest Baltimore, Maryland, census tract that only had one supermarket and a few corner stores. The majority of the participants were African American and the average household income was significantly less that the average household income of the city. Although low-income shoppers had the knowledge and preference for healthy foods, their decisions to buy unhealthy foods were due to being cost-effective to feed the family and the store's layout, pricing and perceived quality of the products, and overall perceived quality of the supermarket.

Along with children, there has been a link between environment and the BMI of older adults. A stratified random sample of adults between 50-75 years old from the metropolitan area of Portland, Oregon's 120 neighborhoods resulted in 1221 participants for the study (Fuzhong et al., 2009). Interviewers collected data on each participant's height, weight, diet, physical activities, sociodemographic information, and perception of the neighborhood. Results indicated as neighborhood fast-food density increased, there was an increase in the rate of obesity among residents who frequented fast-food restaurants, did not meet recommended levels of physical activity, and who had lower self-efficacy in eating fruits and vegetables. Non-Hispanic black residents' prevalence of obesity increased when there was a high-density of fast-food outlets in the neighborhood.

Although several studies support the negative effects of living in a food desert, other studies have not found a link between high BMI and food environment. An and Sturm (2012) studied food environments with consumption and BMI of Californian youth by using data from the California Health Interview Survey (CHIS). CHIS data included daily servings of fruits, vegetables, juice, milk, soda, high-sugar foods, and fast foods and linked consumption to the neighborhood food environment. Analysis of the data from 8226 children and 5236 adolescents showed no evidence for a relationship between food environment on dietary intake or body weight of California children and adolescents.

Recently, Lee (2012) conducted a study to determine if children's obesity disparities could be explained by the lack of access to healthy food and/or the excessive availability of unhealthy foods. Lee merged data from the early childhood longitudinal study-kindergarten cohort and the National Establishment Time Series data to code for places to obtain food. The results indicated that BMI increased more for poor children than non-poor children and that black and Hispanic children had higher BMI than white children. Also, the children living in poor, minority neighborhoods have greater access to fast-food, convenience stores, full-service restaurants, and large grocery stores. The affluent, white majority neighborhoods had more fast food chains within the retail food sector. There were no significant findings when change in BMI and change in exposure of food outlets were examined. Therefore, exposure to food outlets may not be an independent factor in the rise of childhood obesity rates. Mothers with the highest level of education was a significant protective factor over children gaining weight over time. Children in non-rural areas, or who were black or Hispanic had significantly lower BMI shifts when there was a greater access to corner markets. When the self-reported parental health was poor, television viewing hours were high, or physical activity level was low, there was a significant increase in BMI over time.

Alviola, Nayga, and Thomsen (2013) used childhood obesity rates in the Arkansas school districts from 2007 to 2009 and data from the USDA food desert locator to see if the rates correlated with school district in a food desert. They found no significant correlation between obesity rates and school district in a food desert, the percentage of students eligible for free and reduced lunches, or the accessibility of food stores. Aggregating the data to school district level instead of the population block level might have caused a difference in the results from other studies. This study also used the earlier 1-mile distance used by the USDA food desert locator rather than the updated half mile distance.

In summary, researchers have been examining environmental factors to explain the rise in obesity over the past few decades. One of the environmental factors is the change in types of food consumed as consumer exposure has gone from fresh food to convenience and fast-food. Several studies have found a link between rising BMI and food environment. However, other studies have failed to find a link between BMI and the types of food exposure people have in their neighborhoods.

Statement of the Problem and Hypotheses

Obesity is a major health problem that affects millions of people worldwide and that is associated with diminished health. Along with being a risk factor for several diseases, obesity can cause harm to people's physical, emotional, and social well-being. Most of the ill effects of obesity have significantly increased within the past century as the human diet has changed from wholesome foods to highly processed foods. The change in diet has been brought on by an increased exposure to highly processed foods and decreased availability of wholesome foods within the shopping environment. The term *food desert* refers to low income areas with low access to healthy and affordable foods. Several studies have found a link between rising BMI and food environment, while other studies have failed to find a link between BMI and the types of food exposure people have in their neighborhoods.

There is very little research on obesity and food deserts that are outlined by the Food Desert Locator of United States Department of Agriculture's Economic Research Service. By using the locator, researchers can use a standard operational definition of a food desert. This study focuses on the obesity rates in Tennessee food deserts, since Tennessee is ranked very high in adult and childhood obesity. It examines how several demographic variables are related to obesity rates in adults and children and the frequency of food deserts. Findings from this study may help clarify how the food environment plays a role in weight for Tennessee children and adults.

Hypothesis 1: Populations in Food Deserts

If food deserts limit the access of residents to healthy food options, then the rate of adult and childhood obesity should be higher in those Tennessee counties with a larger percentage of the population living in food deserts than in those counties with a smaller percentage living in food deserts.

Hypothesis 2: Car Ownership

Car ownership is believed to be a moderating variable between adult and childhood obesity rates and food deserts. A stronger obesity/food desert relationship is expected as counties' percentage of households without a car goes up.

Hypothesis 3: Urban and Rural Food Deserts

Type of food desert is believed to be a moderating variable between adult and childhood obesity rates and food deserts. Counties with a higher percentage of the food desert population living in urban food deserts will have a lower obesity rate and a stronger obesity/food desert relationship is expected. This would be expected due to the distance and time needed to travel to obtain food, as some studies found that driving distance was an independent predictor of BMI in the participants being studied (Ghosh-Dastidar et al., 2014; Schafft et al., 2009).

Hypothesis 4: Ethnicity/Race

Ethnicity is believed to be a moderating variable between adult and childhood obesity rates and food deserts. Counties with higher percentage of non-Caucasian population will show a stronger obesity/food desert relationship. Often times there is a racial inequality in number of supermarkets among neighborhoods. Predominantly Caucasian neighborhoods have more supermarkets leading to more food deserts for non-Caucasian neighborhoods (Morland et al, 2002). Additionally, many studies show the non-Caucasian population suffers from more diseases and has a higher BMI than their Caucasian counterparts (Barder et al, 2010; Fuzhong, et al, 2000; Inagami et al, 2006; Lee, 2012).

Hypothesis 5: Socioeconomic Status

Socioeconomic status is believed to be a moderating variable between adult and childhood obesity rates and food deserts. Counties with high poverty rates will have a stronger food desert/obesity relationship than counties with lower poverty rates. Often times, supermarkets and large grocery stores are not located in low income areas because the business cannot be supported. Without the supermarkets or large grocery stores, people are reliant on small stores that usually have higher food prices (Cummins & Macintyre, 2006; Morland et al., 2006). Those with lower incomes are often trying to get cheaper food that lasts for an extended period of time (Weinfield et al., 2014). The foods with longer shelf lives are usually not very healthy and filled with chemical preservatives (Pollan, 2008). A diet consisting mainly of unhealthy foods is a key component to obesity (Bader et al., 2010; Inagami et al., 2006).

Hypothesis 6: Education

Education is believed to be a moderating variable between adult and childhood obesity and food deserts. For those counties with a greater percentage of higher education degrees, the food desert/obesity relationship will be weaker than those counties with a smaller percentage of higher education degrees. A few studies have shown that people living in food deserts with higher education have a lower prevalence of obesity

(Ghosh-Dastidar et al., 2014; Inagami et al. 2006). Other researchers have shown children with mothers with higher education degrees have a lower prevalence of obesity (Lee, 2012).

CHAPTER II: METHOD

Databases

I used data from four archival sources to test the hypotheses: the data from the Food Desert Locator of United States Department of Agriculture's Economic Research Service (http://www.ers.usda.gov/data-products/food-access-research-atlas/go-to-the-atlas.aspx#.U_rfiICwK-c), the 2010 CDC's data of obesity rates per Tennessee county (http://www.cdc.gov/diabetes/atlas/countydata/atlas.html), the U.S. Census Bureau 2010 population data (http://www.census.gov/2010census/popmap/), and the Tennessee Coordinated School Health Childhood Obesity Rates by County Data of 2009. These data sources were selected because the year of record was approximately the same and are described in greater detail in the following sections.

*Food Desert Locator***.** Food desert rates and locations in the U.S. are available from the online Food Desert Locator from the Economic Research Services (ERS/USDA) interactive map. Residents are not counted who live within a food desert census tract but are close to a large grocery store supermarket of another census tract (Breneman &Ver Ploeg, 2011b; Ver Ploeg et al., 2012). Within Tennessee, there are 420 food deserts in 65 of the 95 counties throughout the state.

The ERS originally used 1-kilometer square grids to analyze the number of people with limited access to food and the number of people living in low-income, limited access areas (Breneman & Ver Ploeg, 2011a). In the latest data analysis, square grids of 1/2-kilometer were used for population data as well as the locations of stores. According to the HFFI Working Group (U.S. Department of Health and Human Services, 2010), a community qualifies to be *low access* when at least 500 people or at least 33% of the census tract's population resides more than 1/2 mile from a supermarket or large grocery store in an urban area, or more than 10 miles from a supermarket or large grocery story in a rural area. The 0.5/10-mile distance is measured between the geographic center and the nearest supermarkets or large grocery stores within the 1/2-kilometer square. Then, the estimated populations or housing units more than 1/2 mile (urban) or 10 miles (rural) from a large grocery store or supermarket are aggregated to census tract level. In order for the community to be designated a *low-income* community, the census tract must either have at least 20 percent or higher poverty rate or for tracts not in the metropolitan area, the median family income is 80 percent or lower than the statewide median family income, or for a tract in a metropolitan area, the median family income is 80 percent or lower than the statewide median family income or the metropolitan area median family income. An urban area has a population of at least 2500 people in the centroid of the 1/2 kilometer square, while anything less is defined as a rural area (Breneman & Ver Ploeg, 2011b; Ver Ploeg et al., 2012).

The 2010 Census of Population and Housing contained the population and income data. From 2010, a list of stores authorized to receive Supplemental Nutritional Assistance Program (SNAP) benefits and data from Trade Dimensions TDLinx were used to make a directory of supermarket and large grocery store locations. A large grocery store has all major food departments and annual sales of at least $2 million (Ver Ploeg et al., 2012). Environmental Systems Research Inc. built the Food Desert Locator by using the ArcGIS Server technology, topographic maps, satellite maps, and address locator service (Breneman & Ver Ploeg, 2011a). The data included in the Food Desert Locator site and the definitions of these data can be found in Table 3.

Table 3

Definition of Variables Included in the Food Desert Locator

Variable	Definition
number of low-income people with low access to a supermarket or large grocery store	estimation of people with an annual household income less than or equal to 200 percent of the Federal poverty thresholds for family size that live more than 1/2 mile (urban tract) or 10 miles (rural tract) from the nearest supermarket or large grocery store
percentage of total population that is low-income and has low access to a supermarket or large grocery store	people with an annual household income less than or equal to 200 percent of the Federal poverty thresholds for family size that live more than 1/2 mile (urban tract) or 10 miles (rural tract) from the nearest supermarket or large grocery store divided by the total population of the census tract
number of people age 0-17 with low access to a supermarket of large grocery store	estimation of people 0-17 years living more than 1/2 mile (urban tract) or 10 miles (rural tract) from the nearest supermarket or large grocery store
percentage of total population that is age 0-17 and has low access to a supermarket or a large grocery store	people 0-17 years living more than 1/2 mile (urban tract) or 10 miles (rural tract) from the nearest supermarket or large grocery store divided by the total population of children for the census tract

Note. Definitions adapted from the USDA Food Desert Locator.

2010 CDC's Age-Adjusted County Level Estimates of the Percentage of Adults who are Obese in Tennessee. Data from CDC's Behavioral Risk Factor Surveillance System and U.S. Census Bureau's Population Estimates Program were used to estimate the prevalence of adult obesity by county from self-reported heights and weights. County level estimates are averaged based upon three years of data which include the year of estimate, the year before, and the year after. Obesity rates were calculated for 3 age groups, 20-44, 45-64, and 65+, and the overall rate was adjusted by age with weights of 0.52, 0.31, and 0.17, respectively. CDC's Behavioral Risk Factor Surveillance System (BRFSS) is a state-based telephone survey for the adult population that is ongoing and monthly. During the survey, participants answered questions about behavioral risk factors and preventive health practices. Census Bureau's Population Estimates Program (PEP) is population estimation of the United States, states, counties, cities, towns, and territories.

U.S. Census Bureau State and County QuickFacts 2010 Population Data. The U.S. Census Bureau State and County 2010 Population Data contain basic population information, race, household information, business information, and geographical information of each county in Tennessee and combined total for the state of Tennessee.

*Tennessee Coordinated School Health Childhood Obesity Rates by County Data of 2009***.** During 2008-2009 school year, Body Mass Index (BMI) was calculated from students in grades K, 2, 4, 6, 8, and one year in high school by Tennessee Coordinated School Health Coordinators in every district. Heights and weights collected from 225,461 students were used to categorize each age and sex-specific BMI as underweight, healthy weight, overweight, or obese as defined by the CDC. Westat, Inc., of Rockville, MD, consulted in the preliminary data analysis to ensure the overall student population of Tennessee was represented by the collected information (Tennessee Department of Education Office of Coordinated School Health, 2014). These data were obtained from the director of the Nutrition, Physical Activity, and Obesity program of Tennessee Department of Health.

Procedure

Each county's child population can be found by subtracting the over 18 years of age population from the total county population found in the U.S. Census Bureau data. To find the percentage of each county's child population living within a food desert, the number of children in all the food deserts per county is totaled from the Food Desert Locator data and then divided by the county child population. This percentage is correlated to the corresponding county childhood obesity rate from the Tennessee Coordinated School Health Childhood Obesity Rates by County Data of 2009.

The adult population of each county can be found in the U.S. Census Bureau data for each county as the over 18 years of age population. To find the percentage of each county's adult population living within a food desert, the number of adults in all the food deserts per county is totaled from the Food Desert Locator data and then divided by the county 18 years and over population. The percentage of the adult population living in a food desert is correlated to the corresponding county adult obesity rate from the 2010 CDC's Age-Adjusted County Level Estimates of the Percentage of Adults who are Obese in Tennessee.

To compare percentage of housing units without a vehicle with each county's obesity rates, the total number of housing units without a vehicle is then divided by total number of housing units in the county, which is found in the U.S. Census Bureau State and County QuickFacts 2010 Population Data. The percentage of housing units without a vehicle with low access to a supermarket or large grocery store of each county is compared to the corresponding county adult obesity rate from the 2010 CDC's Age-Adjusted County Level Estimates of the Percentage of Adults who are Obese in Tennessee and childhood obesity rates from the Tennessee Coordinated School Health Childhood Obesity Rates by County Data of 2009.

Each county's poverty rate and percentage of adults 25 years old or older with at least a bachelor's degree can be found in the US Census State and County QuickFacts 2010 Population Data. Table 4 contains an overview of the calculations used for the major measures.

Table 4

Calculations for Major Measures

Variable	Equation
County child population (0-17yrs) (U.S. Census Bureau)	Total county population - 18 & over county population
Percentage of county's child population living in a food desert (Food Desert Locator)	(Number of children living in all the county's food deserts / county child population) X 100
County adult population (U.S. Census Bureau)	18 & over county population
Percentage of county's adult population living in a food desert (Food Desert Locator)	(Number of adults living in all the county's food deserts / county adult population) x 100
Percentage of county's housing units without a vehicle	(Number of housing units without a vehicle / number of county's occupied housing units) x 100
Percentage of county's adult population in urban food desert	(Number of adults living in an urban food desert / total number of adults living in food desert) x 100
Percentage of county's child population in urban food desert	(Number of children living in an urban food desert / total number of children living in food desert) x 100

CHAPTER III: RESULTS

Descriptive Statistics

There were 420 food deserts, 393 urban and 27 rural, in the state of Tennessee. Sixty-five of the 95 counties had at least one food desert. The four counties with the major metropolitan areas, (Nashville-Davidson 73, Chattanooga-Hamilton 29, Knoxville-Knox 32, and Memphis-Shelby 112), accounted for 246 food deserts. First, data from all 95 counties in Tennessee were analyzed. To further investigate the data for each hypothesis, the main data set was partitioned to just include the 65 counties with at least 1 food desert. Then, the data were subdivided to the 61 counties with at least 1 food desert, excluding the 4 counties with the major metropolitan areas in Tennessee. Dividing the data allowed for analyzing variables that could change in significance for predicting adult and childhood obesity by eliminating data that could skew the results. It also examined if including all the counties' data could be used to generate a general model. Descriptive statistics and intercorrelations for each data set (95, 65, and 61 counties) can be found in Tables 5, 6, and 7, respectively.

Hypothesis 1: Populations in Food Deserts

Hypothesis 1 proposed that as the percentage of the adult and child populations living in food deserts increased, the adult and childhood obesity rates per county should increase. There were no significant correlations to support percentages of the populations living in food deserts and obesity rates per county when all 95 counties were tested (see Table 5). There was a significant correlation between childhood obesity rates and adult

Table 5

Descriptive Statistics and Intercorrelations for all 95 Counties

Variable	AO	CO	AP	CP	Bach	NHW	CFD	AFD	HNV	AU	CU
AO	-										
CO	.31*	-									
AP	.22*	.54**	-								
CP	.23*	.58**	.94**	-							
Bach	-.35**	-.65**	-.58**	-.65**	-						
NHW	-.33**	.15	.03	.15	-.35**	-					
CFD	.16	.02	.17	.16	.16	-.36**	-				
AFD	.17	.02	.16	.15	.17	-.37**	.99**	-			
HNV	.28*	.22*	.51**	.46**	-.22*	-.41**	.29*	.29*	-		
AU	-.07	-.24*	-.21*	-.25*	.46**	-.25*	.66**	.67**	-.07	-	
CU	-.07	-.24*	-.21*	-.25*	.46**	-.25*	.66**	.67**	-.07	1.00**	-
M	32.79	24.53	19.75	29.51	15.52	87.78	12.20	10.38	5.74	56.16	55.91
SD	2.41	3.98	4.93	6.81	7.07	11.60	12.99	11.05	1.78	47.86	47.80

Note. N = 95. AO = adult obesity rate; CO = childhood obesity rate; AP = adult poverty rate; CP = childhood poverty rate; Bach = percentage of county population with at least a bachelor's degree; NHW = percentage of non-Hispanic white population; CFD = percentage of children living in food deserts; AFD = percentage of adults living in food deserts; HNV = percentage of housing units without a car; AU = percentage of adults living in urban food deserts; CU = percentage of children living in urban food deserts. *p < .05, **p < .001.

Table 6

Descriptive Statistics and Intercorrelations for 65 Counties with a Food Desert

Variable	AO	CO	AP	CP	Bach	NHW	CFD	AFD	HNV	AU	CU
AO	-										
CO	.39**	-									
AP	.31*	.56**	-								
CP	.32*	.58**	.95**	-							
Bach	-.43**	-.69**	-.63**	-.67**	-						
NHW	-.36*	.14	.07	.14	-.30*	-					
CFD	.24	.20	.37*	.42**	-.08	-.26*	-				
AFD	.25*	.20	.36*	.40**	-.08	-.27*	.98**	-			
HNV	.43**	.22	.51**	.49**	-.24	-.47**	.46**	.46**	-		
AU	-.12	-.20	-.28*	-.22	.34*	-.05	.32*	.34*	-.12	-	
CU	-.12	-.19	-.27*	-.21	.33*	-.05	.32*	.34*	-.11	1.00**	-
M	32.78	24.05	19.42	28.70	17.16	85.57	17.83	15.17	5.73	82.08	81.72
SD	2.67	4.14	4.80	7.02	7.89	12.89	12.07	10.27	1.80	34.70	34.85

Note. *N* = 65. AO = adult obesity rate; CO = childhood obesity rate; AP = adult poverty rate; CP = childhood poverty rate; Bach = percentage of county population with at least a bachelor's degree; NHW = percentage of non-Hispanic white population; CFD = percentage of children living in food deserts; AFD = percentage of adults living in food deserts; HNV = percentage of housing units without a car; AU = percentage of adults living in urban food deserts; CU = percentage of children living in urban food deserts. *$p < .05$, **$p < .001$.

Table 7

Descriptive Statistics and Intercorrelations for 61 Counties with a Food Desert, Excluding the 4 Major Metropolitan Areas

Variable	AO	CO	AP	CP	Bach	NHW	CFD	AFD	HNV	AU	CU
AO	-										
CO	.40*	-									
AP	.28*	.58**	-								
CP	.30*	.60**	.95**	-							
Bach	-.41**	-.67**	-.67**	-.72**	-						
NHW	-.48**	-.05	.09	.16	-.13	-					
CFD	.27*	.30*	.39*	.45**	-.21	-.16	-				
AFD	.28*	.30*	.39*	.43**	-.20	-.19	.98**	-			
HNV	.48**	.37*	.56**	.54**	-.43**	-.37*	.42**	.43**	-		
AU	-.10	-.17	-.27*	-.21	.32*	.01	.31*	.32*	-.17	-	
CU	-.10	-.16	-.26*	-.20	.31*	.01	.31*	.32*	-.16	1.00**	-
M	32.89	24.40	19.56	28.91	16.21	87.06	17.23	14.66	5.60	80.90	80.52
SD	2.68	4.01	4.86	7.07	7.12	11.05	12.08	10.34	1.75	35.52	35.66

Note. $N = 61$. AO = adult obesity rate; CO = childhood obesity rate; AP = adult poverty rate; CP = childhood poverty rate; Bach = percentage of county population with at least a bachelor's degree; NHW = percentage of non-Hispanic white population; CFD = percentage of children living in food deserts; AFD = percentage of adults living in food deserts; HNV = percentage of housing units without a car; AU = percentage of adults living in urban food deserts; CU = percentage of children living in food deserts. *$p < .05$, **$p < .001$.

obesity rates. The percentage of adults living in food deserts was also strongly and positively correlated to the percentage of children living in food deserts.

For the data from only the counties with at least one food desert, a significant correlation partially supported the hypothesis (see Table 6). Adult obesity rates were positively correlated with the percentage of adults living in food deserts. As with the total county sample, adult and childhood obesity rates were positively correlated, and percentages of adults and children living in food deserts were strongly and positively correlated.

When the 4 major metropolitan counties with 29 or more food deserts were eliminated as outliers, the hypothesis was supported (see Table 7). Adult obesity rates were positively correlated with the percentage of adults living in food deserts and childhood obesity rates were positively correlated with the percentage of children living in food deserts. Correlations between childhood obesity rates and adult obesity rates, percentage of adults living in food deserts and percentage of children living in food deserts, percentage of adults living in food deserts and childhood obesity rates, and percentage of children living in food deserts and adult obesity rates were also significant.

Hypothesis 2: Car Ownership

According to hypothesis 2, I expected that car ownership would moderate the relationship between obesity rates and percentage of each population living in food deserts. To test this prediction, I conducted multiple regression analyses using the data from all 95 counties. In the first step, two variables were included: food desert adult or child percent and percentage of households without a car per county. These variables accounted for a significant amount of variance in adult obesity rate, $R^2 = .09$, $F(2,92) =$

4.28, p = .017, but not with childhood obesity rate, R^2 = .05, $F(2,92)$ = 2.53, p = .085. To avoid potentially problematic high multicollinearity with the interaction term, the variables were centered and interaction terms between percentage of population (adult or child) in food deserts and car ownership were created (Aiken & West, 1991). As shown in Tables 8 and 9, results indicated that only the greater percentage of households without a car was associated with higher adult and childhood obesity rates. The interactions between percentage of the populations in food deserts and car ownership were not significant, ΔR^2 = .02, $\Delta F(1, 91)$ = 2.24, $t(91)$ = 1.50, p = .138, and ΔR^2 = .00, $\Delta F(1, 91)$ = 0.19, $t(91)$ = -0.44, p = .661, respectively, indicating car ownership was not a moderating variable.

When only the data from the 65 counties with food deserts were analyzed, these variables accounted for a significant amount of variance in adult obesity rates, R^2 = .19, $F(2,62)$ = 7.14, p = .002, but not in childhood obesity rates, R^2 = .06, $F(2,62)$ = 2.01, p = .143. After centering the variables and computing the interaction terms, results indicated that only the greater amount of households without a car was associated with higher adult obesity rates, as shown in Table 8. The interactions between car ownership and the percentage of the populations living in food deserts were not significant for adults and children, ΔR^2= .00, $\Delta F(1, 61)$ = 0.01, $t(61)$ = -0.07, p = .944, and ΔR^2 = .01, $\Delta F(1, 61)$ = 0.56, $t(61)$ = -0.75, p = .455, respectively, suggesting car ownership was not a moderating variable.

After removing the 4 major metropolitan counties from the data set with the counties with at least 1 food desert, the percentage of adult or child populations living in

Table 8

Regression Models for Predicting Adult Obesity Rates from the Percentage of Adult Population Living in Food Deserts and the Percentage of the Counties' Housing Units Without a Car

	All 95 Counties			65 Counties with Food Deserts			Counties with at least one Food Desert, Excluding 4 Urban Areas		
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2	
Predictor	*B*	*B*	95% CI	*B*	*B*	95% CI	*B*	*B*	95% CI
Constant	32.79	32.71	[32.23, 33.20]	32.78	32.78	[32.14, 33.42]	32.89	32.90	[32.27, 33.54]
% in Food Desert	0.02	0.01	[-0.04, 0.06]	0.02	0.02	[-0.05, 0.09]	0.02	0.02	[-0.05, 0.10]
% without Car	0.34*	0.31*	[0.03, 0.59]	0.59*	0.60*	[0.20, 0.99]	0.68*	0.69*	[0.29, 1.09]
Interaction		0.01	[0.00, 0.03]		0.00	[-0.02, 0.02]		0.00	[-0.02, 0.02]

Note. *B* = unstandardized coefficient. CI = confidence interval. *p < .05.

Table 9

Regression Models for Predicting Childhood Obesity Rates from the Percentage of Childhood Population Living in Food Deserts and the Percentage of the Counties' Housing Units Without a Car

	All 95 Counties			65 Counties with Food Deserts			Counties with at least one Food Desert, Excluding 4 Urban Areas		
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2	
Predictor	*B*	*B*	95% CI	*B*	*B*	95% CI	*B*	*B*	95% CI
Constant	24.53	24.57	[23.75, 25.39]	24.05	24.18	[23.11, 25.25]	24.40	24.48	[23.48, 25.48]
% in Food Desert	-0.02	-0.01	[-0.08, 0.06]	0.04	0.05	[-0.05, 0.15]	0.06	0.06	[-0.03, 0.16]
% without Car	0.53*	0.54*	[0.07, 1.02]	0.38	0.42	[-0.23, 1.07]	0.69*	0.72*	[0.11, 1.34]
Interaction		-0.01	[-0.03, 0.02]		-0.01	[-0.05, 0.02]		-0.01	[-0.04, 0.02]

Note. *B* = unstandardized coefficient. CI = confidence interval. *$p < .05$

food deserts and car ownership accounted for significant amounts of variances in adult and childhood obesity rates, $R^2 = .24$, $F(2,58) = 9.14$, $p < .001$, and $R^2 = .16$, $F(2,58) = 5.65$, $p = .006$, respectively. Once the variables were centered and the interaction terms were entered into the models, results indicated that only the greater amount of households without a car was associated with higher adult and childhood obesity rates, as shown in Tables 8 and 9. The interaction between car ownership and the percentage of the populations living in food deserts were insignificant for adults and children, $\Delta R^2 = .00$, $\Delta F(1, 57) = 0.04$, $t(57) = -0.21$, $p = .837$, and $\Delta R^2 = .01$, $\Delta F(1, 57) = 0.37$, $t(57) = -0.61$, $p = .547$, respectively, indicating car ownership was not a moderating variable. Thus, there was no support for hypothesis 2.

Hypothesis 3: Urban and Rural Food Deserts

To test hypothesis 3, that the type of food desert moderates the relationship between obesity rates and percentage of each population living in food deserts, I conducted multiple regression analyses using the data from all 95 counties. In the first step, two variables were included: food desert adult or child percent and percentage of food desert population living in urban food deserts per county. These variables accounted for a significant amount of variance in adult and childhood obesity rate, $R^2 = .09$, $F(2,92) = 4.53$, $p = .013$, and $R^2 = .11$, $F(2,92) = 5.90$, $p = .004$, respectively. After variables were centered and the interaction terms were computed to put in the second models, the only significant variable was the percentage of children in urban food deserts (see Tables 10 and 11). The results indicated that as the percentage of children living in urban food deserts increased, childhood obesity rates decreased, as shown in Table 11. Food desert type did not moderate the relationship between the percentage of the populations living in

Table 10

Regression Models for Predicting Adult Obesity Rates from the Percentage of Adult Population Living in Food Deserts and the Percentage of those Adults Living in Urban Food Deserts

	All 95 Counties			65 Counties with Food Deserts			Counties with at least one Food Desert, Excluding 4 Urban Areas		
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2	
Predictor	*B*	*B*	95% CI	*B*	*B*	95% CI	*B*	*B*	95% CI
Constant	32.79	32.60	[31.69, 33.51]	32.78	32.58	[31.80, 33.37]	32.89	32.65	[31.85, 33.45]
% Food Desert	0.09*	0.07	[-0.02, 0.16]	0.08*	0.07	[-0.01, 0.14]	0.09*	0.07	[-0.01, 0.15]
% Urban	-0.02*	-0.01	[-0.03, 0.01]	-0.02	0.00	[-0.04, 0.03]	-0.02	0.00	[-0.04, 0.04]
Interaction		0.00	[0.00, 0.00]		0.00	[0.00, 0.01]		0.00	[0.00, 0.01]

Note. *B* = unstandardized coefficient. CI = confidence interval. **p* < .05.

Table 11

Regression Models for Predicting Childhood Obesity Rates from the Percentage of Childhood Population Living in Food Deserts and the Percentage of those Children Living in Urban Food Deserts

	All 95 Counties			65 Counties with Food Deserts			Counties with at least one Food Desert, Excluding 4 Urban Areas		
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2	
Predictor	*B*	*B*	95% CI	*B*	*B*	95% CI	*B*	*B*	95% CI
Constant	24.53	24.79	[23.40, 26.18]	24.05	24.38	[23.22, 25.55]	24.40	24.59	[23.46, 25.72]
% Food Desert	0.10*	0.12	[.00, .23]	0.10*	0.12*	[0.03, 0.22]	0.13*	0.14*	[0.05, 0.24]
% Urban	-0.04*	-0.04*	[-0.07, -0.01]	-0.03*	-0.06*	[-0.11, -0.01]	-0.03*	-0.04	[-0.09, 0.00]
Interaction		0.00	[0.00, 0.00]		0.00	[-0.01, 0.00]		0.00	[-0.01, 0.00]

Note. *B* = unstandardized coefficient. CI = confidence interval. **p* < .05.

food deserts and the prevalences of obesity for adults and children, $\Delta R^2 = .00$, $\Delta F(1, 91) = 0.23$, $t(91) = 0.48$, $p = .630$, and $\Delta R^2 = .00$, $\Delta F(1, 91) = 0.20$, $t(91) = -0.45$, $p = .655$, respectively.

When only the data from the 65 counties with food deserts were analyzed with the same variables, these variables accounted for a significant amount of variance in adult and child obesity rates, $R^2 = .11$, $F(2,62) = 3.74$, $p = .029$, and $R^2 = .11$, $F(2,62) = 4.00$, $p = .023$, respectively. After variables were centered and the interaction terms were computed to put in the second models, the percentage of children living in food deserts and the percentage of children in urban food deserts were significant. The results indicated that as the percentage of children living in food deserts increased, childhood obesity rates increased. Also, results indicated that as the percentage of children living in urban food deserts increased, childhood obesity rates decreased, as shown in Table 11. However, type of food desert did not moderate the relationship between the percentage of the populations living in food deserts and the prevalences of obesity for adults and children, $\Delta R^2 = .01$, $\Delta F(1, 61) = 0.71$, $t(61) = 0.84$, $p = .402$, and $\Delta R^2 = .02$, $\Delta F(1, 61) = 1.12$, $t(61) = -1.06$, $p = .294$, respectively.

After removing the 4 major metropolitan counties from the data set with the counties with at least 1 food desert, the percentage of adult or child populations living in food deserts and the type of food desert accounted for significant amounts of variances in adult and childhood obesity rates, $R^2 = .12$, $F(2,58) = 3.85$, $p = .027$, and $R^2 = .16$, $F(2,58) = 5.49$, $p = .007$, respectively. After variables were centered and the interaction terms were computed to put in the second models, the percentage of children living in food deserts was significant. The results indicated that as the percentage of children living in food deserts increased, childhood obesity rates increased, as shown in Table 11. Food desert type did not moderate the relationship between the percentage of the populations living in food deserts and the prevalences of obesity for adults and children, $\Delta R^2 = .02$, $\Delta F(1, 57) = 1.08$, $t(57) = 1.04$, $p = .303$, and $\Delta R^2 = .01$, $\Delta F(1, 57) = .43$, $t(57) = -0.65$, $p = .517$, respectively. Thus, there was no support for hypothesis 3.

Hypothesis 4: Ethnicity/Race

According to hypothesis 4, I expected that ethnicity would moderate the relationship between obesity rates and percentage of each population living in food deserts. To test this prediction, I conducted a multiple regression analyses using the data from all 95 counties. In the first step, two variables were included: food desert adult or child percent and percentage of non-Hispanic whites per county. These variables accounted for a significant amount of variance in adult obesity rate, $R^2 = .11$, $F(2,92) = 5.90$, $p = .004$, but not with childhood obesity rate, $R^2 = .03$, $F(2,92) = 1.26$, $p = .288$. The variables were centered and interaction terms between percentage of population (adult or child) in food deserts and ethnicity were created and entered into a new model for each (adult or child). Only the percentage of non-Hispanic whites was significant for adult obesity. Results indicated that as the percentage of non-Hispanic white population increased, the adult obesity rate decreased, as shown in Table 12. Ethnicity did not moderate the relationship between the percentage of the populations living in food deserts and the prevalences of obesity for adults nor children, $\Delta R^2 = .00$, $\Delta F(1, 91) = 0.14$, $t(91) = -0.37$, $p = .714$, and $\Delta R^2 = .01$, $\Delta F(1, 91) = 1.17$, $t(91) = -1.08$, $p = .283$, respectively.

When only the data from the 65 counties with food deserts were analyzed with the same variables, these variables again accounted for a significant amount of variance in

Table 12

Regression Models for Predicting Adult Obesity Rates from the Percentage of Adult Population Living in Food Deserts and the Percentage of the Counties' non-Hispanic white Population

	All 95 Counties			65 Counties with Food Deserts			Counties with at least one Food Desert, Excluding 4 Urban Areas		
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2	
Predictor	*B*	*B*	95% CI	*B*	*B*	95% CI	*B*	*B*	95% CI
Constant	32.79	32.77	[32.28, 33.25]	32.78	32.79	[32.16, 33.42]	32.89	32.89	[32.29, 33.50]
% Food Desert	0.01	0.01	[-0.04, 0.06]	0.04	0.04	[-0.02, 0.11]	0.05	0.05	[-0.01, 0.12]
% NHW	-0.07*	-0.06*	[-0.11, -0.01]	-0.07*	-0.07*	[-0.13, -0.01]	-0.11*	-0.11*	[-0.17, -0.05]
Interaction		0.00	[0.00, 0.00]		0.00	[0.00, 0.00]		0.00	[0.00, 0.00]

Note. *B* = unstandardized coefficient. CI = confidence interval. **p* < .05.

adult obesity rates, $R^2 = .16$, $F(2,62) = 5.75$, $p = .005$, but not in childhood obesity rates, $R^2 = .08$, $F(2,62) = 2.64$, $p = .080$. The variables were centered and interaction terms were created and entered into the new models. Only the percentage of non-Hispanic whites was significant for adult obesity. Once again, results indicated that as the percentage of non-Hispanic white population increased, the adult obesity rate decreased, as shown in Table 12. Ethnicity did not moderate the relationship between the percentage of the populations living in food deserts and the prevalences of obesity for adults and children, $\Delta R^2 = .00$, $\Delta F(1, 61) = 0.05$, $t(61) = 0.22$, $p = .827$, and $\Delta R^2 = .01$, $\Delta F(1, 61) = .63$, $t(61) = -0.79$, $p = .431$, respectively.

After removing the 4 major metropolitan counties from the data set with the counties with at least 1 food desert, the percentage of adult or child populations living in food deserts and the ethnicity accounted for significant amounts of variances in adult obesity rates, $R^2 = .27$, $F(2,58) = 10.52$, $p < .001$, but not for childhood obesity, $R^2 = .09$, $F(2,58) = 2.79$, $p = .070$. The variables were centered and interaction terms were created and entered into the new models. The percentage of non-Hispanic whites was significant for adult obesity rates, and the percentage of children in food deserts was significant for childhood obesity rates. Results indicated that as the percentage of non-Hispanic white population increased, the adult obesity rate decreased, as shown in Table 12. In addition, as the percentage of children living in food deserts increased, the childhood obesity rate increased. Ethnicity did not moderate the relationship between the percentage of the populations living in food deserts and the prevalences of obesity for adults and children, $\Delta R^2 = .00$, $\Delta F(1, 57) = 0.06$, $t(57) = 0.24$, $p = .808$, and $\Delta R^2 = .02$, $\Delta F(1, 57) = 1.21$,

$t(57) = -1.10$, $p = .276$, respectively (see Table 13). Thus, there was no support for hypothesis 4.

Hypothesis 5: Socioeconomic Status

To test hypothesis 5, that poverty rates would moderate the relationship between obesity rates and percentage of each population living in food deserts, I conducted multiple regression analyses using the data from all 95 counties. In the first step, two variables were included: food desert adult or child percent and poverty rates for either population per county. These variables accounted for a significant amount of variance in adult and child obesity rates, $R^2 = .07$ $F(2,92) = 3.32$, $p = .040$, and $R^2 = .34$, $F(2,92) = 23.63$, $p < .001$, respectively. Next, the variables were centered and interaction terms were calculated for adults and children to put into new models. As shown in Tables 14 and 15, poverty rates were significant for adult and childhood obesity rates. Results indicated that adult and obesity rates increased as poverty rates increased. However, poverty rates did not moderate the relationship between the percentage of the population in food deserts and the prevalence of obesity for adults or children, $\Delta R^2 = .01$, $\Delta F(1, 91) = 0.85$, $t(91) = 0.92$, $p = .360$, and $\Delta R^2 = .00$, $\Delta F(1, 91) = 0.32$, $t(91) = 0.57$, $p = .573$, respectively.

When only the data from the 65 counties with food deserts were analyzed with the same variables, these variables accounted for significant amounts of variance in adult and childhood obesity rates, $R^2 = .12$, $F(2,62) = 4.03$, $p = .023$, and $R^2 = .34$, $F(2,62) = 16.14$, $p < .001$, respectively. After the variables were centered and interaction terms were computed for the new equation, only poverty rate was significant for childhood obesity,

Table 13

Regression Models for Predicting Childhood Obesity Rates from the Percentage of Childhood Population Living in Food Deserts and the Percentage of the Counties' non-Hispanic white Population

	All 95 Counties			65 Counties with Food Deserts			Counties with at least one Food Desert, Excluding 4 Urban Areas		
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2	
Predictor	*B*	*B*	95% CI	*B*	*B*	95% CI	*B*	*B*	95% CI
Constant	24.53	24.41	[23.58, 25.25]	24.05	23.98	[22.96, 25.00]	24.40	24.35	[23.34, 25.35]
% Food Desert	0.02	0.02	[-0.05, 0.09]	0.09	0.08	[-0.01, 0.17]	0.10*	0.09*	[0.00, 0.17]
% NHW	0.06	0.09	[0.00, 0.18]	0.07	0.08	[-0.01, 0.18]	0.00	0.02	[-0.08, 0.12]
Interaction		0.00	[-0.01, 0.00]		0.00	[-0.01, 0.00]		0.00	[-0.01, 0.00]

Note. *B* = unstandardized coefficient. CI = confidence interval. *p < .05.

Table 14

Regression Models for Predicting Adult Obesity Rates from the Percentage of Adult Population Living in Food Deserts and the Counties' Percentage of Adult Poverty

	All 95 Counties			65 Counties with Food Deserts			Counties with at least one Food Desert, Excluding 4 Urban Areas		
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2	
Predictor	*B*	*B*	95% CI	*B*	*B*	95% CI	*B*	*B*	95% CI
Constant	32.79	32.74	[32.25, 33.23]	32.78	32.79	[32.07, 33.50]	32.89	33.02	[32.26, 33.78]
% Food Desert	0.03	0.02	[-0.03, 0.07]	0.04	0.04	[-0.03, 0.12]	0.05	0.07	[-0.02, 0.15]
% Poverty	0.10	0.12*	[0.01, 0.23]	0.14	0.14	[-0.03, 0.30]	0.11	0.08	[-0.10, 0.26]
Interaction		0.01	[-0.01, 0.02]		0.00	[-0.02, 0.02]		-0.01	[-0.03, 0.01]

Note. *B* = unstandardized coefficient. CI = confidence interval. **p* < .05.

Table 15

Regression Models for Predicting Childhood Obesity Rates from the Percentage of Childhood Population Living in Food Deserts and the Counties' Percentage of Childhood Poverty

	All 95 Counties			65 Counties with Food Deserts			Counties with at least one Food Desert, Excluding 4 Urban Areas		
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2	
Predictor	*B*	*B*	95% CI	*B*	*B*	95% CI	*B*	*B*	95% CI
Constant	24.53	24.49	[23.80, 25.17]	24.05	24.00	[23.02, 24.98]	24.40	24.56	[23.57, 25.55]
% Food Desert	-0.02	-0.03	[-0.10, 0.03]	-0.02	-0.03	[-0.12, 0.07]	0.01	0.03	[-0.07, 0.12]
% Poverty	0.35*	0.35*	[0.25, 0.46]	0.36*	0.37*	[0.21, 0.52]	0.33*	0.31*	[0.16, 0.46]
Interaction		0.00	[-0.01, 0.01]		0.00	[-0.01, 0.02]		0.00	[-0.02, 0.01]

Note. *B* = unstandardized coefficient. CI = confidence interval. *p < .05.

as shown in Table 15. Again, as the childhood poverty rate increased, the childhood obesity rates increased. However, poverty rates did not moderate the relationship between the percentage of populations in food deserts and prevalence of obesity for adults and children, $\Delta R^2 = .00$, $\Delta F(1, 61) = 0.00$, $t(61) = -0.07$, $p = .946$, and $\Delta R^2 = .00$, $\Delta F(1, 61) = 0.06$, $t(61) = 0.24$, $p = .811$, respectively.

After removing the 4 major metropolitan counties from the data set, the percentage of adult or child populations living in food deserts and the poverty rates accounted for significant amounts of variances in adult and childhood obesity rates, $R^2 = .11$, $F(2,58) = 3.68$, $p = .031$, and $R^2 = .37$, $F(2,58) = 16.68$, $p < .001$, respectively. Once the variables were centered and interaction terms were computed, results indicated that childhood poverty rate was the only significant variable, suggesting that as childhood poverty rate increased, then the childhood obesity rate increased. There was no evidence that poverty rates moderated the relationship between the percentage of populations in food deserts and the prevalence of obesity for adults and children, $\Delta R^2 = .01$, $\Delta F(1, 57) = 0.50$, $t(57) = -0.71$, $p = .483$, and $\Delta R^2 = .00$, $\Delta F(1, 57) = 0.39$, $t(57) = -0.62$, $p = .536$, respectively. Thus, there was no support for hypothesis 5.

Hypothesis 6: Education

According to hypothesis 6, the percentage of county population with an education level of bachelors' degrees or higher was expected to moderate the relationship between obesity rates and percentage of each population living in food deserts. To test this prediction, I conducted multiple regression analyses using the data from all 95 counties. In the first step, two variables were included: food desert adult (or child) percent and percent of bachelors' degrees per county. These variables accounted for a significant amount of variance in adult and child obesity rates, $R^2 = .18$, $F(2,92) = 9.97$, $p < .001$, and $R^2 = .43$, $F(2,92) = 35.20$, $p < .001$, respectively. The two variables were centered and the interaction terms were computed for adults and children. When the new variables were entered into the new equations, the percentage of adults living in food deserts and percentage of the population with at least a bachelor's degree or higher were significant predictors of adult obesity rates. The percentage of the population with a bachelors' degrees or higher was a significant predictor of childhood obesity rates. As shown in Tables 16 and 17, the results indicated adult obesity rates increased when the percentage of the adult population living in food deserts increased and/or when the percentage of the population with at least a bachelor's degree decreased. Childhood obesity rates were higher when the percentage of the population with at least a bachelor's degree was lower. However, education did not moderate the relationship between percentage of the populations living in food deserts and the prevalences of obesity for adults and children, $\Delta R^2 = .00$, $\Delta F(1, 91) = 0.03$, $t(91) = -0.18$, $p = .861$, and $\Delta R^2 = .00$, $\Delta F(1, 91) = 0.13$, $t(91) = 0.37$, $p = .715$, respectively.

When only the data from the 65 counties with food deserts were analyzed with the same variables, these variables again accounted for significant amounts of variance in adult and childhood obesity rates, $R^2 = .23$, $F(2,62) = 9.36$, $p < .001$, and $R^2 = .50$, $F(2,62) = 30.79$, $p < .001$, respectively. The two variables were centered and the interaction terms were computed for adults and children. When the new variables were entered into the new equations, the percentage of the population with at least a bachelor's degree or higher was a significant predictor of adult and childhood obesity rates. As shown in Tables 16 and 17, the results indicated adult and childhood obesity rates

Table 16

Regression Models for Predicting Adult Obesity Rates from the Percentage of Adult Population Living in Food Deserts and the Percentage of the Counties' Population with at least a Bachelor's Degree

	All 95 Counties			65 Counties with Food Deserts			Counties with at least 1 Food Desert, Excluding 4 Urban Areas		
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2	
Predictor	*B*	*B*	95% CI	*B*	*B*	95% CI	*B*	*B*	95% CI
Constant	32.79	32.80	[32.34, 33.26]	32.78	32.78	[32.18, 33.38]	32.89	32.88	[32.23, 33.53]
% Food Desert	0.05*	0.05*	[0.01, 0.09]	0.06	0.06	[0.00, 0.12]	0.05	0.05	[-0.01, 0.12]
% Bachelors	-0.13*	-0.13*	[-0.20, -0.07]	-0.14*	-0.14*	[-0.22, -0.06]	-0.14*	-0.14*	[-0.25, -0.02]
Interaction		0.00	[-0.01, 0.01]		0.00	[-0.01, 0.01]		0.00	[-0.01, 0.01]

Note. *B* = unstandardized coefficient. CI = confidence interval. **p* < .05.

Table 17

Regression Models for Predicting Childhood Obesity Rates from the Percentage of Childhood Population Living in Food Deserts and the Percentage of the Counties' Population with at least a Bachelor's Degree

	All 95 Counties			65 Counties with Food Deserts			Counties with at least 1 Food Desert, Excluding 4 Urban Areas		
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2	
Predictor	*B*	*B*	95% CI	*B*	*B*	95% CI	*B*	*B*	95% CI
Constant	24.53	24.51	[23.88, 25.14]	24.05	24.05	[23.30, 24.80]	24.40	24.42	[23.62, 25.22]
% Food Desert	0.04	0.04	[-0.01, 0.09]	0.05	0.05	[-0.02, 0.11]	0.05	0.06	[-0.01, 0.13]
% Bachelors	-0.38*	-0.38*	[-0.47, -0.29]	-0.36*	-0.36*	[-0.46, -0.26]	-0.36*	-0.35*	[-0.49, -0.21]
Interaction		0.00	[-0.01, 0.01]		0.00	[-0.01, 0.01]		0.00	[-0.01, 0.01]

Note. *B* = unstandardized coefficient. CI = confidence interval. **p* < .05.

increased when the percentage of the population with at least a bachelor's degree was lower. However, once again, education did not moderate the relationship between the percentage of the populations living in food deserts and the prevalences of obesity for adults and children, $\Delta R^2 = .00$, $\Delta F(1, 61) = 0.01$, $t(61) = 0.09$, $p = .926$, and $\Delta R^2 = .00$, $\Delta F(1, 61) = 0.01$, $t(61) = -0.09$, $p = .931$, respectively.

After removing the 4 major metropolitan counties from the data set, the percentage of adult or child populations living in food deserts and the percentage of the population with a bachelor's degree accounted for significant amounts of variances in adult and childhood obesity rates, $R^2 = .20$, $F(2,58) = 7.46$, $p = .001$, and $R^2 = .47$, $F(2,58) = 25.86$, $p < .001$, respectively. The two variables were centered and the interaction terms were computed for adults and children. When the new variables were entered into the new equations, the percentage of the population with at least a bachelor's degree or higher was again a significant predictor of adult and childhood obesity rates. As shown in Tables 16 and 17, the results indicated adult and childhood obesity rates increased when the percentage of the population with at least a bachelor's degree was lower. However, education did not moderate the relationship between the populations living in food deserts and the prevalences of obesity for adults and children, $\Delta R^2 = .00$, $\Delta F(1, 57) = 0.00$, $t(57) = -0.05$, $p = .957$, and $\Delta R^2 = .00$, $\Delta F(1, 57) = 0.04$, $t(57) = 0.20$, $p = .843$, respectively. Thus, hypothesis 6 received no support.

Supplementary Analyses

After testing the hypotheses, I conducted multiple regressions to predict adult and childhood obesity in each of the 3 conditions (all 95 counties, 65 counties with at least 1 food desert, and 61 counties with at least 1 food desert, excluding the 4 major metropolitan areas) based on the available independent variables. The predictors included childhood (or adult) obesity rate, percentage of population with at least a bachelor's degree, adult poverty rate, child poverty rate, percentage of non-Hispanic white population, percentage of housing units without a car, percentage of children living in food deserts, percentage of adults living in food deserts, percentage the adults living in urban food deserts, and percentage of children living in urban food deserts. The overall models for adult and childhood obesity rates were significant, $R^2 = .39$, $F(10, 84) = 5.47$, $p < .001$, and $R^2 = .48$, $F(10, 84) = 7.63$, $p < .001$, respectively. The results indicated that the percentage of the population with at least a bachelor's degree and the percentage of non-Hispanic white population were significant negative predictors of adult obesity rate. Only the percentage of the population with at least a bachelor's degree was a significant negative predictor of childhood obesity (Table 18).

The models for adult and childhood obesity rates in the 65 counties in Tennessee with at least one food desert were significant, $R^2 = .48$, $F(10, 54) = 4.93$, $p < .001$, and $R^2 = .53$, $F(10, 54) = 6.01$, $p < .001$, respectively. The results indicated that percentage of population with at least a bachelor's degree and the percentage of non-Hispanic white population were significant negative predictors of adult obesity rate. Only the percentage of the population with at least a bachelor's degree was a significant negative predictor of childhood obesity (Table 19).

The models for adult and childhood obesity rates in the 61 counties with a food desert, excluding the major metropolitan areas in Tennessee were also significant, $R^2 =$

Table 18

Regression Models for Predicting Adult and Childhood Obesity in all 95 Tennessee Counties

	Adult				Child			
Predictor	*B*	SE	95% CI	*t*	*B*	SE	95% CI	*t*
Constant	46.32	3.62	[39.13, 53.51]	12.81	22.22	9.24	[3.85, 40.58]	2.41
AO(CO)	0.05	0.07	[-0.09, 0.19]	0.69	0.12	0.17	[-0.22, 0.45]	0.69
Bach	-0.20*	0.05	[-0.30, -0.10]	-4.06	-0.27*	0.08	[-0.43, -0.12]	-3.58
AP	0.13	0.13	[-0.40, 0.13]	-0.99	0.12	0.21	[-0.29, 0.53]	0.59
CP	0.05	0.11	[-0.16, 0.26]	0.48	0.08	0.16	[-0.24, 0.41]	0.50
NHW	-0.12*	0.02	[-0.16, -0.07]	-4.76	-0.01	0.04	[-0.10, 0.07]	-0.34
HNV	-0.09	0.16	[-0.41, 0.22]	-0.58	-0.17	0.25	[-0.66, 0.32]	-0.69
CFD	-0.05	0.11	[-0.28, 0.17]	-0.47	-0.08	0.18	[-0.43, 0.27]	-0.46
AFD	0.09	0.14	[-0.18, 0.36]	0.64	0.11	0.21	[-0.31, 0.53]	0.52
AU	-0.09	0.17	[-0.43, 0.26]	-0.50	-0.03	0.27	[-0.56, 0.50]	-0.11
CU	0.08	0.17	[-0.26, 0.43]	0.49	0.03	0.27	[-0.50, 0.56]	0.11

Note. $N = 95$. B = unstandardized coefficient. CI = confidence interval. AO = adult obesity rate; CO = childhood obesity rate; AP = adult poverty rate; CP = childhood poverty rate; NHW = percentage of non-Hispanic white population; Bach = percentage of county population with at least a bachelor’s degree; CFD = percentage of children living in food deserts; AFD = percentage of adults living in food deserts; HNV = housing units without a car; AU = percentage of adults living in urban food deserts; CU = percentage of children living in urban food deserts. *$p < .05$.

Table 19

Regression Models for Predicting Adult and Childhood Obesity in the 65 Tennessee Counties with a Food Desert

	Adult				Child			
Predictor	*B*	SE	95% CI	*t*	*B*	SE	95% CI	*t*
Constant	43.17	4.60	[33.95, 52.39]	9.39	21.61	10.59	[0.38, 42.83]	2.04
AO(CO)	0.08	0.09	[-0.10, 0.26]	0.86	0.20	0.20	[-0.23, 0.57]	0.86
Bach	-0.19*	0.06	[-0.30, -0.07]	-3.22	-0.28*	0.08	[-0.45, -0.11]	-3.29
AP	-0.16	0.20	[-0.56, 0.24]	-0.81	0.10	0.29	[-0.49, 0.69]	0.32
CP	0.07	0.15	[-0.23, 0.36]	0.45	0.07	0.22	[-0.37, 0.50]	0.31
NHW	-0.10*	0.03	[-0.16, -0.05]	-3.67	-0.01	0.05	[-0.10, 0.08]	-0.25
HNV	0.13	0.22	[-0.32, 0.57]	-0.58	-0.29	0.33	[-0.94, 0.36]	-0.90
CFD	-0.05	0.12	[-0.30, 0.20]	-0.43	-0.07	0.18	[-0.43, 0.30]	-0.38
AFD	0.07	0.15	[-0.22, 0.36]	0.48	0.12	0.22	[-0.32, 0.55]	0.54
AU	-0.04	0.19	[-0.43, 0.34]	-0.23	-0.07	0.28	[-0.64, 0.50]	-0.25
CU	0.05	0.19	[-0.34, 0.43]	0.24	0.07	0.28	[-0.49, 0.63]	0.25

Note. $N = 65$. B = unstandardized coefficient. CI = confidence interval. AO = adult obesity rate; CO = childhood obesity rate; AP = adult poverty rate; CP = childhood poverty rate; NHW = percentage of non-Hispanic white population; Bach = percentage of county population with at least a bachelor's degree; CFD = percentage of children living in food deserts; AFD = percentage of adults living in food deserts; HNV = housing units without a car; AU = percentage of adults living in urban food deserts; CU = percentage of children living in urban food deserts. $^{*}p < .05$.

.49, $F(10, 50) = 4.71$, $p < .001$, and $R^2 = .51$, $F(10, 50) = 5.29$, $p < .001$, respectively. Once again, the results indicated that percentage of population with at least a bachelor's degree and the percentage of non-Hispanic white population were significant negative predictors of adult obesity rate. Only the percentage of the population with at least a bachelor's degree was a significant negative predictor of childhood obesity (Table 20).

Table 20

Regression Models for Predicting Adult and Childhood Obesity in the 61 Tennessee Counties with a Food Desert, Excluding the 4 Major Metropolitan Areas

	Adult				Child			
Predictor	*B*	SE	95% CI	*t*	*B*	SE	95% CI	*t*
Constant	43.29	4.86	[33.52, 53.05]	8.90	25.76	10.75	[4.17, 47.36]	2.40
AO (CO)	0.06	0.10	[-0.14, 0.25]	0.59	0.12	0.20	[-0.29, 0.53]	0.59
Bach	-0.14*	0.07	[-0.27, -0.01]	-2.09	-0.28*	0.09	[-0.46, -0.10]	-3.07
AP	-0.23	0.20	[-0.64, 0.18]	-1.13	0.03	0.30	[-0.57, 0.63]	0.10
CP	0.15	0.16	[-0.16, 0.46]	0.96	0.14	0.23	[-0.32, 0.59]	0.61
NHW	-0.12*	0.03	[-0.19, -0.06]	-3.80	-0.05	0.05	[-0.16, 0.05]	-0.97
HNV	0.19	0.23	[-0.27, 0.65]	-0.84	-0.26	0.33	[-0.92, 0.41]	-0.77
CFD	-0.01	0.13	[-0.28, 0.25]	-0.11	0.09	0.23	[-0.37, 0.55]	0.38
AFD	0.02	0.16	[-0.30, 0.34]	0.14	-0.05	0.19	[-0.44, 0.33]	-0.27
AU	-0.03	0.19	[-0.42, 0.36]	-0.14	-0.05	0.28	[-0.62, 0.51]	-0.18
CU	0.03	0.19	[-0.36, 0.41]	0.15	0.05	0.28	[-0.51, 0.61]	0.19

Note. $N = 61$. B = unstandardized coefficient. CI = confidence interval. AO = adult obesity rate; CO = childhood obesity rate; AP = adult poverty rate; CP = childhood poverty rate; NHW = non-Hispanic white; Bach = percentage of county population with at least a bachelor's degree; CFD = percentage of children living in food deserts; AFD = percentage of adults living in food deserts; HNV = housing units without a car; AU = percentage of adults living in urban food deserts; CU = percentage of children living in urban food deserts. *$p < .05$.

CHAPTER IV: DISCUSSION

The objective to this study was to evaluate the possible link between obesity rates in Tennessee counties and percentages of the counties' population living in food deserts along with other possible moderating variables: car ownership, type of food desert, ethnicity, socioeconomic status, and education.

Hypothesis 1: Populations in Food Deserts

From the overall data set, the correlations between adult or childhood obesity rates and percentage of adult or childhood population living in food deserts were insignificant and trivial. These results may be due to the 30 of the 95 counties not having at least one food desert. This means those 30 counties have 0% of their adult and childhood populations living in food deserts, which would lower the averages of the percentages of the populations living in food deserts. By eliminating the data of 30 of the 95 counties as outliers that would negatively skew the results, one would expect the results would be more likely to show stronger correlations. Although the magnitude of the correlations did increase in comparison to the correlations using the data from all 95 counties, the magnitudes were small. As the percentage of adults living in food deserts increased, the counties' obesity rates significantly increased as hypothesized when analyzing data from the 65 counties with at least one food desert. The positive correlation between adults living in food deserts and obesity rates supports previous research (Cummins & Macintyre, 2006; Morland et al., 2006). Results that childhood obesity and food deserts were not significantly correlated supports some of the previous research (An & Sturm, 2012; Alviola, et al., 2013).

Childhood obesity and adult obesity were significantly and positively correlated to the percentages of children or adults living in food deserts when excluding the data from the four major metropolitan areas. These results support previous research for childhood obesity and food deserts (Schafft et al., 2009). The correlations between the percentages of the populations living in food deserts and obesity rates were highest in this dataset and the magnitudes of the correlations were moderate. Most of the major metropolitan areas have lower adult and childhood obesity rates and higher percentages of adults and children living in food deserts than the averages for the dataset of 65 counties. Eliminating the data from the four major metropolitan counties, which may have an inverse relationship, resulted in significant and stronger correlations between obesity rates and the percentages of the populations living in food deserts of the 61 counties.

Further testing was done to see if the relationship between obesity rates and the percentages of the populations living in food deserts were moderated by other variables including percentages of households without a vehicle, percentages of the populations living in food deserts, percentages of the populations living in urban food deserts, percentages of non-Hispanic white populations, percentages of the population living in poverty, and percentages of adult population with at least a bachelor’s degree.

Hypothesis 2: Car Ownership

The interactions between households without a vehicle and percentage of adults or children living in food deserts were not significant in predicting obesity rates in any of the models. Therefore, the percentage of the households without a vehicle does not moderate the relationship between the populations living in food deserts and obesity rates, which is inconsistent with the hypothesis. Also, the percentages of the populations living in food deserts were not significant in predicting obesity rates. However, the percentage of households without a vehicle was a significant predictor of adult and childhood obesity rates, except for childhood obesity when only analyzing the data from the 65 counties with at least one food desert. As the percentage of households without a vehicle increased, the obesity rates increased in those counties. This supports previous research on BMI and car ownership (Caraher, et al., 1998; Ingami et al., 2009), but does not support the other research (Ingami et al., 2006). Researchers have postulated that the lack of a personal vehicle is linked to higher BMI because it may be more difficult to obtain healthy food, especially in a large quantity at one time. Without a vehicle, people must coordinate their time with someone who does have a vehicle or take public transportation, if available, in order to go to a supermarket. Even if people live close to a supermarket and walk, they are limited on how much they can carry back to their households due to the weight of their groceries and their strength. All the extra effort and time to go to the supermarket does not appeal to most people when they can very easily get something to eat that is quick, convenient, portable, and often cheaper at fast food restaurants or convenience stores nearby. Usually the easier way of obtaining food without a vehicle is not as healthy and might lead to a higher BMI.

Hypothesis 3: Urban and Rural Food Deserts

The interactions between percentages of adults or children living in urban food deserts and percentage of adults or children living in food deserts were not significant in predicting obesity rates. Therefore, the percentages of the populations living in urban food deserts do not moderate the relationship between the populations living in food deserts and obesity rates as hypothesized. Since the percentage of the population of adults living in food deserts is positively and significantly related to obesity rates in all models, but the percentage of food desert population living in urban food deserts is significant and negatively related to adult obesity rates only when data from all 95 counties are examined, then a higher percentage of the food desert population living in rural food deserts may be strongly and positively related to and indicative of higher obesity rates in the models with 65 and 61 counties. For children, the percentage of the population living in food deserts is positively and significantly related to obesity rates, and the percentage of food desert population living in urban food deserts is significant and negatively related to obesity rates in all models. Thus, higher childhood obesity rates may be seen in counties that are significantly and positively related to a higher percentage of the food desert population in rural food deserts. These findings were expected partially due to those living in urban food deserts do not have as far to travel to obtain food compared to those in living in rural food deserts (Schafft et al., 2009; Ghosh-Dastidar et al., 2014).

Hypothesis 4: Ethnicity/Race

The interactions between percentage of non-Hispanic white population and percentage of adults or children living in food deserts were not significant in predicting obesity rates in any of the models. Therefore, the percentage of the non-Hispanic white population does not moderate the relationship between the populations living in food deserts and obesity rates as predicted. The percentage of the childhood population living in food deserts was only a significant predictor of childhood obesity in the model of 61 counties, but the percentage of the adult population living in food deserts was not a significant predictor for adult obesity in any of the models. However, the percentage of the population that is non-Hispanic white was a significant negative predictor of adult obesity in all the models, but not for childhood obesity. Childhood obesity cannot be predicted from the percentage of the non-Hispanic white population. This is consistent with previous research on adult obesity rates and ethnicity (Inagami et al., 2006; Ogden et al., 2009). Results indicating that the percentage of the population that is non-Hispanic white was a non-significant predictor of childhood obesity is inconsistent with previous research of ethnicity and childhood obesity (Morland et al., 2002; Lee, 2012; Ogden et al., 2014). These inconsistencies may be due to Tennessee counties having much higher percentages of their populations being non-Hispanic whites and higher childhood obesity rates than the US averages.

Hypothesis 5: Socioeconomic Status

The interactions between adult or childhood poverty rates and percentage of adults or children living in food deserts were not significant in predicting obesity rates. Therefore, the poverty rates do not moderate the relationship between the populations living in food deserts and obesity rates as hypothesized. The percentage of the adult or childhood population living in food deserts was a non-significant predictor of obesity rates in all models. However, childhood poverty rate was a significant predictor of childhood obesity rate in all models, but adult poverty rate was only a significant predictor for adult obesity rate when using the data from all 95 counties. These findings were moderately consistent with previous research (Inagami et al., 2006; Lee, 2012; Reed et al., 2013; Zachary et al., 2013). People of low socioeconomic status tend to buy cheaper foods that are less nutritious which is viewed as a key contributor to the rise in obesity (Bader et al., 2010). Previous research (Morland et al., 2002) also relates to these findings as more supermarkets were found in the wealthier neighborhoods which means that the poorest neighborhoods have less possible places to shop since the supermarkets and other stores cannot be monetarily supported.

Hypothesis 6: Education

The interactions between percentage of the population with at least a bachelor's degree or higher and percentage of adults or children living in food deserts were not significant in predicting obesity rates. Therefore, the percentage of the population with at least a bachelor's degree or higher does not moderate the relationship between the populations living in food deserts and obesity rates as the hypothesis predicted. The percentage of the population living in food deserts was a significant predictor of obesity only in the adult model with all 95 counties. However, the percentage of the population with at least a bachelor's degree or higher was a significant negative predictor for adult and childhood obesity rates in all models. The finding that having a bachelor's degree or higher is a significant predictor of having a lower obesity rate, which is consistent with previous research (Inagami et al., 2006; Reed et al., 2013; Ghosh-Dastidar et al., 2014). As seen in previous research by Lee (2012) and Reed et al. (2013), childhood obesity was lower if a mother had a bachelor's degree or higher. Having a degree is a significant protector from obesity possibly because of higher earning potential. Since those with a bachelor's degree may make more than those without a degree, they are less likely to live in poverty, may be able to afford a vehicle, have more expendable income for spending on healthy foods, and may be more knowledgeable about nutrition.

Best Data Sample for Hypotheses Testing

Having 3 data samples allows one to examine different viewpoints to answer the research questions by using the overall data for the state, then narrowing in on just the counties with at least one food desert, and finally zoning in on counties with at least one food desert, but excluding the four major metropolitan area. The sample of 61 counties with at least one food desert but excluding the four major metropolitan counties seems to be the best one to test the hypotheses. By eliminating the 30 counties without a food desert and the four major metropolitan counties with most of the state's food deserts, the remaining 61 counties are more alike to make comparisons than the samples with all 95 and 65 counties. More models are significant and coefficients of determination are slightly higher in most of the models in the 61 counties sample than the others. Overall, the percentages of the populations living in food deserts were correlated to obesity rates only in the sample of 61 counties. Also in the sample with 61 counties, the percentages of the populations living in food deserts were significant predictors of obesity rates in the models that include the percentages of the populations living in urban food deserts. Therefore, food deserts are not as important in predicting obesity rates in Tennessee as originally thought. Based on the results from this study, other social determinants are significantly related to obesity rates than the percentage of the populations living in food deserts. As for the other hypotheses, the variables that were predicted to be moderators between obesity rates and the percentages of the populations living in the food deserts were not supported in any model. However, percentage of households without a vehicle, percentage of county's non-Hispanic white population, and the percentage of the population with at least a bachelor's degree are significant predictors of adult obesity.

The percentage of households without a vehicle, the percentage of the population living in urban food deserts, childhood poverty rate, and the percentage of the population with at least a bachelor's degree were significant predictors of childhood obesity.

Implications for Reducing Obesity Rates

Because education was the most significant predictor of adult and childhood obesity in any of the three samples, local and state government officials could use studies like this to continue advocating ways to increase the readiness of students to score high enough on entrance exams to get into college and be able to pass the classes to obtain a bachelor's degree. Also, having the college scholarship programs and offering some free tuition for those going to school in state to lower the cost for potential students is another objective that officials have to strive to continue. The return of having a larger percentage of the population with at least a bachelor's degree should outweigh the initial investments of college preparation and scholarship programs. Economically for the state, a larger percentage of the population with at least a bachelor's degree is expected to attract businesses with better paying jobs. This often leads to more money generated for the state from the businesses and citizens having more expendable income. When there is more expendable income, the consumers can use this money on healthy food for their households. The healthier way of eating would mean a population with a lower BMI. Lowering BMI is correlated with decreasing the risk factor for many non-communicable diseases. If there are less people with non-communicable diseases, then the state would not have such a great expenditure on government assisted healthcare.

In addition to getting a bachelor's degree, states might consider implementing learning objectives to be taught about nutrition starting as young as pre-school and continuing throughout K-12 schooling. This in return may reinstate home economic and wellness classes to many schools that have cut these classes due to lack of funding (Martin, 2010). These classes would teach how to plan and prepare meals with healthy foods. Some of the objectives could be taught through joint programs from different state departments such as Department of Health, Department of Education, and Department of Agriculture. Education may be the major key factor to combat obesity for a healthier Tennessee population.

Implications for Future Research

Future research could include the obesity rates of the eighteen and nineteen-year-old populations. This is one of the limitations of the study since they are included neither in the child nor adult population. Obesity rates for children in the Tennessee state data include 0-17 year olds and the adult obesity rates in the CDC data are available for those 20 years old and older. Other factors for future research may include walkability and physical landscape of neighborhoods and physical activity of the citizens.

A possible approach would be to conduct a longitudinal study that would follow students from college preparation to obtaining a career. The study group could be compared to those who did not receive the treatment, such as those from other similar states or previous populations from Tennessee, to see if the education programs significantly affect the health and well-being of the population or if there are other potential factors to consider.

Conclusion

In conclusion, findings from this study do not support that the percentage of the population living in food deserts is a highly significant predictor of obesity rates in Tennessee counties. Variables that were hypothesized to be moderators between the percentages of the populations living in food deserts and obesity rates were not moderators in any of the models. In return, some of the social determinants were significant independent predictors of obesity rates. This study adds to the literature that food deserts may not be as an important part to the rise in obesity rates as once thought and future research should closely examine the percentages of households without a vehicle and percentages of population with at least a bachelor's degree as predictors of adult and childhood obesity rates. The percentage of the non-Hispanic white population may be analyzed in future studies as it was a significant predictor of adult obesity. Since childhood poverty rate was a significant predictor of childhood obesity, researchers may want to further investigate the relationship in other areas of the country.

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APPENDIX

APPENDIX A: INSTITUTIONAL REVIEW BOARD APPROVAL LETTER

IRB
INSTITUTIONAL REVIEW BOARD
Office of Research Compliance,
010A Sam Ingram Building,
2269 Middle Tennessee Blvd
Murfreesboro, TN 37129

MIDDLE TENNESSEE STATE UNIVERSITY

IRBN007 – EXEMPTION DETERMINATION NOTICE

Thursday, May 19, 2016

Investigator(s): Kristi Roberson; Tom Brinthaupt
Investigator(s') Email(s): kristilroberson@gmail.com
Department: Psychology

Study Title: The Relationship of Lack of Access to Affordable and Healthy Foods and Obesity Rates in Tennessee Adults and Children
Protocol ID: **16-1281**

Dear Investigator(s),

The above identified research proposal has been reviewed by the MTSU Institutional Review Board (IRB) through the **EXEMPT** review mechanism under 45 CFR 46.101(b)(2) within the research category *(4) Study involving existing data* A summary of the IRB action and other particulars in regard to this protocol application is tabulated as shown below:

IRB Action	EXEMPT from furhter IRB review***	
Date of expiration	**NOT APPLICABLE**	
Participant Size	Click here to enter text.	
Participant Pool	Click here to enter text.	
Mandatory Restrictions	Click here to enter text.	
Additional Restrictions	Click here to enter text.	
Comments	Click here to enter text.	
Amendments	**Date**	**Post-Approval Amendments** Click here to enter text.

***This exemption determination only allows above defined protocol from further IRB review such as continuing review. However, the following post-approval requirements still apply:

- Addition/removal of subject population should not be implemented without IRB approval
- Change in investigators must be notified and approved
- Modifications to procedures must be clearly articulated in an addendum request and the proposed changes must not be incorporated without an approval
- Be advised that the proposed change must comply within the requirements for exemption
- Changes to the research location must be approved – appropriate permission letter(s) from external institutions must accompany the addendum request form
- Changes to funding source must be notified via email (irb_submissions@mtsu.edu)
- The exemption does not expire as long as the protocol is in good standing

- Project completion must be reported via email (irb_submissions@mtsu.edu)
- Research-related injuries to the participants and other events must be reported within 48 hours of such events to compliance@mtsu.edu

The current MTSU IRB policies allow the investigators to make the following types of changes to this protocol without the need to report to the Office of Compliance, as long as the proposed changes do not result in the cancellation of the protocols eligibility for exemption:

- Editorial and minor administrative revisions to the consent form or other study documents
- Increasing/decreasing the participant size

The investigator(s) indicated in this notification should read and abide by all applicable post-approval conditions imposed with this approval. Refer to the post-approval guidelines posted in the MTSU IRB's website. Any unanticipated harms to participants or adverse events must be reported to the Office of Compliance at (615) 494-8918 within 48 hours of the incident.

All of the research-related records, which include signed consent forms, current & past investigator information, training certificates, survey instruments and other documents related to the study, must be retained by the PI or the faculty advisor (if the PI is a student) at the sacure location mentioned in the protocol application. The data storage must be maintained for at least three (3) years after study completion. Subsequently, the researcher may destroy the data in a manner that maintains confidentiality and anonymity. IRB reserves the right to modify, change or cancel the terms of this letter without prior notice. Be advised that IRB also reserves the right to inspect or audit your records if needed.

Sincerely,

Institutional Review Board
Middle Tennessee State University

Quick Links:

Click here for a detailed list of the post-approval responsibilities.
More information on exmpt procedures can be found here.