GEOGRAPHIC IMPACTS OF FEDERALLY FUNDED STATE-BASED OBESITY PROGRAMS ON ADULT OBESITY PREVALENCE IN THE UNITED STATES

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ABSTRACT

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Approximately one-third of adults in the United States are obese. Following a moderate increase in obesity during the 1970s, obesity prevalence in the U.S. has more than doubled since the 1980s. There are also large black and white disparities in obesity prevalence. Obesity is an important public health problem because it is related to many comorbidities, including heart disease and cancer that cause premature mortality.

Since 2000, the Centers for Disease Control and Prevention (CDC) Division of Nutrition, Physical Activity, and Obesity (DNPAO) has funded 37 state health departments to reduce the rising obesity in populations within their states. Importantly to-date there have not been any national studies evaluating the impacts of these CDC-DNPAO funded programs on changing obesity prevalence within and across funded and non-funded states. This dissertation research therefore, investigated the impacts of CDC-DNPAO state-specific obesity intervention programs on the geography of adult obesity in the United States at the county level. The Behavioral Risk Factor Surveillance System (BRFSS) and census data comprised the data used for this research. Theoretical frameworks and techniques were applied from the fields of health geography, population geography and economics. This dissertation research included three independent and interrelated studies described below.

The first study utilized a spatial microsimulation approach to indirectly estimate

obesity prevalence at the county level. Obtaining a comprehensive obesity dataset across all counties is challenging because the BRFSS is designed to estimate obesity prevalence only at the national or state levels. There is a need therefore to apply spatial microsimulation modeling to virtually replicate the demographic characteristics of BRFSS survey respondents and allocate their BMI status at the county level. Obesity prevalence estimates—i.e., the number of obese cases/ population at risk from the spatial microsimulation modeling were mapped to visualize and explore the spatial patterns and detect obesity clusters. Counties in Southern states, especially along the Mississippi River and the Appalachian Mountains, and counties containing or in proximity to American Indian reservation sites had elevated obesity prevalence rates across time, 2000 to 2010. The output from the spatial microsimulation is also used in the subsequent two studies in this dissertation research. The second study evaluated the impact of the CDC-DNPAO programs on obesity prevalence in states with and without funding using an interrupt time series modeling technique to identify where state CDC-DNPAO programs were more or less protective of adult obesity and where to target future interventions. The third study partitioned the variance in obesity prevalence between blacks and whites into explainable and unexplainable portions of obesity using a reweighting decomposition technique to further understand these disparities.

The findings from this research identified where programs have been successful in controlling obesity and where to target future interventions to reduce obesity, reduce racial disparities in obesity and improve population health. The translation of this knowledge will also be helpful to reduce obesity in other countries, particularly those countries experiencing a transition toward obesity in their populations.

TABLE OF CONTENTS

LIST OF TABLES……………………………………………………………………………..vi

LIST OF FIGURES…………………………………………………………………...…..viii

1. INTRODUCTION: OBESITY WORLDWIDE AND IN THE UNITED STATES…………..1
1.1. Geography of Obesity Worldwide……………………………………………………….1
1.1.1. The Global Obesity Epidemic……………………..…………………………….1
1.2. Geography of Obesity in the United States…………………………………………….5
1.2.1. Measurement of Obesity……………………………………………………………5
1.2.2. Monitoring Obesity..……………..…………………………………………………6
1.3. Disease Ecology of Obesity in the United States……………………………………..10
1.3.1. The Population Base………………………………..…………………………11
1.3.2. The Behavioral Base……………………………………………………………....12
1.3.3. The Environment Base…..…………………………………………………......14
1.4. Interventions to Reduce Obesity in the United States………………………………..15
1.5. The Need of This Study……………………………………………………………………19
1.6. Goal and Objectives of this Research…………………………………………………….21
1.6.1. Study Hypotheses…..……………………………………………………………22
1.6.2. Study Design……………………………………………………………………...22

2. STUDY I: SPATIAL AND SPATIO-TEMPORAL PREVALENCE OF ADULT OBESITY AT THE COUNTY LEVEL IN THE UNITED STATES: A SPATIAL MICROSIMULATION APPROACH……………………..…………………………………………………………..25
ABSTRACT…………………………………………………………………………….…25
2.1. Background…..…………………………………………………………………………27
2.1.1. United States: Challenges in Monitoring Obesity at the Local Level…………..28
2.1.2. Spatial Microsimulation: the Geographic Approaches of Small Area Estimation...……………………………………………29
2.2. Methods……………………………………………………………………………………31
2.2.1. Study Area…..…………………………………………………………………....31
2.2.2. Data…………………………………………………………………………………….31
2.2.3. Spatial Microsimulation…..………………………………………………...…32
2.3. Results……………………………………………………………………………………..36
2.3.1. Temporal and State-level Analyses.……………..…………………………….…36
2.3.2. Validity Test…..……………………………………………………………...…40
2.3.3. County-level Analyses…..………………………………………………………41
2.4. Discussion & Limitation……………………………………………………………..51
2.5. Conclusions……………………………………………………………………………54

3. STUDY II: IMPACTS OF FEDERALLY FUNDED STATE OBESITY PROGRAMS ON ADULT OBESITY PREVALENCE IN THE UNITED STATES, 1998-2010………………..56
ABSTRACT…………………………………………………………………………………56
3.1. Introduction…………………………………………………………………………………57

3.2. Methods…..……………………………………………………………………………..61
3.2.1. Study Area..……………………………………………………………………61
3.2.2. Data......…………………………………………………………………………61
3.2.3. Analysis…………………………………………………………………………..62
3.3. Results..……………………………………………………………………………64
3.3.1. Logistic Regression Analysis...…………………………………………………64
3.3.2. Quasi-experimental Analysis..…………………………………………………..68
3.4. Discussion & Limitation….……………………………………………………………70
3.5. Conclusion………………………………………………………………………………72

4. STUDY III: EXPLAINED AND UNEXPLAINED RACIAL AND REGIONAL INEQUALITY IN OBESITY PREVALENCE IN THE UNITED STATES……………………..…………..74
ABSTRACT……………………………………………………………………………..74
4.1. Introduction……………………………………………………………………......76
4.2. Methods…………………………………………………………………………………81
4.2.1. Study Area...……………………………………………………………………81
4.2.2. Data..……………………………………………………………………………...81
4.2.3. Analysis……..……………………………………………………………………84
4.3. Results…...………………………………………………………………………..88
4.4. Discussion & Limitation……..……………………………………………………94
4.5. Conclusion………………………………………………………………………………96

5. CONCLUSIONS………………………………………………………………………97
5.1. Overall contribution…..…………………………………………………………...97
5.2. Future Studies…..……………………………………………………………….100

BIBLIOGRAPHY……………………………………………………………………………...103

LIST OF TABLES

Table 1.1. States with Highest and Lowest Obesity Prevalence Rates in 2010……..……..9

Table 2.1. Spaital Microsimulation Modeling of BRFSS and County Demographic Characteristics and their Subcategories……………………………………………..……33

Table 2.2. Simulated State-level Obesity Prevalence Rates, United States 2000-2010…………………………………………………………………………………….38

Table 2.3. Top 5 States with Highest or Lowest Obesity Prevalence Rates, United States 2000-2010………………………………………………………...……………..…..40

Table 2.4. Differences in this Study's Simulation and the CDC's Statistical Estimation of Obesity Prevalence Rates…………………………………………...……..……….. 41

Table 2.5a. Top 15 Lowest Obesity Prevalence Counties, United States 2000-2010.......46

Table 2.5b. Top 15 Highest Obesity Prevalence Counties, United States 2000-2010………………………………………………………………………..……......47

Table 3.1. CDC-DNPAO and Non-DNPAO States, United States from 2000 to 2010……………………………………………………………………….………....59

Table 3.2. States with DNPAO Programs and their Duration, United States 1999 to 2010………………………………………………………………………..……......60

Table 3.3. The Effects of DNPAO and its Duration on the Odds of Being Obese..………..66

Table 3.4. The Effects of DNPAO and its Duration (categorized) on the Odds of Being Obese……………………………………………………………………………..…… 67

Table 3.5a. Results from a Quasi-experimental Analysis 1: between Massachusetts (Treatment State) and Connecticut (Control State)………………………………..... 69

Table 3.5b. Results from a Quasi-experimental Analysis 2: between North Carolina (Treatment State) and Delaware and Virginia (Control States)…………………………. 69

Table 3.5c. Results from a Quasi-experimental Analysis 3: between Texas (Treatment State) and Alabama, Louisiana, and Mississippi (Control States)………………..….… 69

Table 4.1. Estimated Mean BMI and Obesity Using Ordinary Least Squares and Logit Regression and Explanatory Risk Factors, United States, 2010…………………………..83

Table 4.2. Proportions of Black and White Racial Groups and Other Descriptive Statistics, United States, 2010…………………………………………………………………………....87

Table 4.3. Differences in Mean BMI and Obesity Prevalence for Blacks and Whites, United States, 2010…………………………………………………………………………....89

Table 4.4. Mean BMI Gaps between Blacks and Whites, United States, 2010…………..91

Table 4.5. Gaps in Mean Obesity Prevalence Rates per 100 Population (%) between the Blacks and the Whites, 2010…………………………………………………………….…93

LIST OF FIGURES

Figure 1.1. Adult Obesity Prevalence Rates by Country Worldwide in 2008……………..3

Figure 1.2. Temporal Trends in Percent Overweight and Obesity among Adults in the U.S. 1962-2010………………………………………………………………………………..8

Figure 1.3. Obesity Prevalence by States, United States 1990-2010………..……………..9

Figure 1.4. Theoretical and Conceptual Framework to Study Obesity……………..….... 24

Figure 2.1. Temporal Change in State-level Obesity Prevalence Rates in the United States, 2000-2010……………………………………………………………………….… 37

Figure 2.2. Estimated Obesity Prevalence Rates at the County Level, United States 2000-2010……………………………………………………………………………………… 43

Figure 2.3. Estimated Obesity Prevalence Rates County-Clusters and Outliers Using Anselin Local Moran's I, United States 2000-2010……………………..…………………. 49

1. INTRODUCTION: OBESITY WORLDWIDE AND IN THE UNITED STATES

1.1. Geography of Obesity Worldwide

1.1.1. The Global Obesity Epidemic

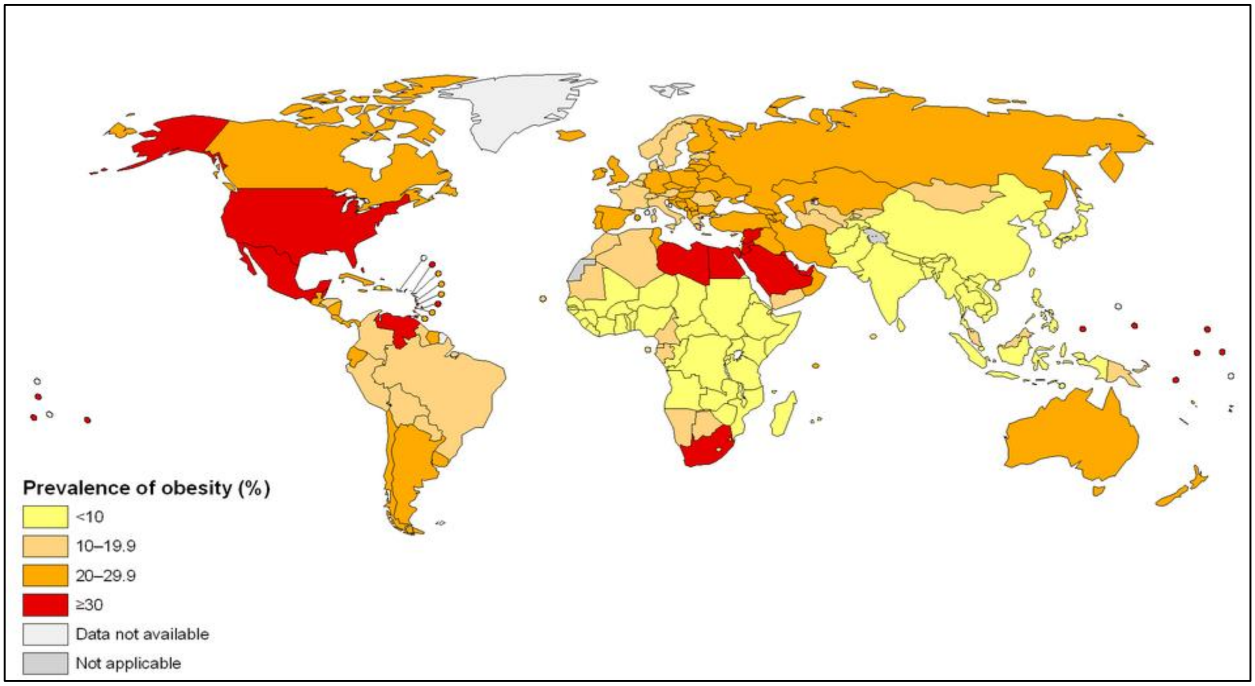
Obesity is one of the most challenging public health problems facing the United States and other countries in the world today. Obesity is described as abnormal or excessive body fat accumulation that may cause negative health outcomes. The 10th revision of International Statistical Classification of Diseases and Related Health Problems (ICD-10) published by the World Health Organization (WHO), the directing and coordinating authority for health within the United Nation's system, classifies obesity as a severe medical condition—one of the "Endocrine, Nutritional and Metabolic" diseases (E65-E68) (WHO, 2010). Body Mass Index or BMI is the quantitative measure used to calculate obesity using the height and weight of individuals—i.e., the individual's weight in kilogram divided by the square of one's height in meters (Centers for Disease Control and Prevention (CDC), 2012). An adult is considered obese if his/her BMI is 30 (kg/m^2) or greater. Adults with a BMI between 25.0 and 29.9 are considered "overweight". The normal BMI for adults is 18.5-24.9 (kg/m^2).

Obesity is a global pandemic because a large proportion of populations in most middle and high-income countries have similar public health (chronic diseases) problems caused by overweight and obesity (Brug and Crawford, 2009; WHO 2013). The WHO estimated that worldwide more than one out of three adults aged 20 years and older (35%, 1.4 billions) were overweight in 2008 (WHO, 2013). In addition, one third of those overweight—approximately 11% of the world's adult population (about 200 million men and 300 million women) were reported obese (WHO, 2013). Kelly et al. (2008) estimated that approximately 60% of the world's population (3.3 billions) will be overweight (2.2 billion) or obese (1.1 billion) by 2030 if the current trends in overweight and obesity prevalence persists.

Since obesity is an underlying cause of many chronic diseases, including but not limited to cardiovascular disease, Type-II diabetes, osteoarthritis, stroke and certain types of cancers, the increasing trends in obesity are contributing to the "chronic disease burden" in countries around the world (Vandegrift and Yoked, 2004; WHO, 2013). Lim et al. (2012) estimated that premature death caused by high BMI increased 72% from 1990 (1.96 millions) to 2010 (3.37 millions) worldwide. Murray et al. (2012) found that overweight and obesity reduced healthy life expectancy by 94 million years worldwide by calculating Disability-Adjusted Life Years (DALYs) in 2010.

The spatial patterns of adult obesity prevalence across the world differ by countries and regions. Figure 1 shows the prevalence of adult obesity by country worldwide in 2008. Among the six WHO regions (African Region, Region of the Americas, Eastern Mediterranean Region, European Region, South-East Asia Region and Western Pacific Region), the Americas (mean 26.7, range: 40.9 (Saint Kitts and Nevis) to 8.4 (Haiti)) and European Regions (21.9, range: 29.3 (Turkey) to 9.9 (Tajikistan)) have the highest obesity prevalence rates, whereas South and East Asian countries have the lowest obesity prevalence (2.7, range 16.1 (Maldives) to 1.1 (Bangladesh)) on average. Eastern Mediterranean, African, and the Western Pacific Regions have a prevalence of 18.7, 8.3, and 5.9, respectively.

Figure 1.1. Adult[1] Obesity Prevalence Rates[2] by Country Worldwide in 2008.



Source: WHO (2011) with permission to use.
[1] Adults aged 20 years and older.
[2] Prevalence rates are sex and age standardized.

When only focusing on the obesity prevalence among middle and high income countries using the statistics from the Organization for Economic Cooperation and Development (OECD), a frequently cited international organization for developed economies, the overall obesity prevalence for 34 member countries was 16.9 in 2009 (OECD, 2012). While the United States (33.8) and Mexico (30.0) are among the highest, South Korea (3.8) and Japan (3.9) are among the lowest prevalence nations. Active daily walking with the use of the public transportation, more mixed land use practice in urban areas, and well balanced food intake traditions—i.e. less processed grain based diet with vegetable, fruits, and fish but less meat, animal fat, and sweets—are major explanation for the lower obesity prevalence in these two East Asian countries (Senauer and Gemma, 2006).

Interestingly some the Western Pacific Island counties have the highest prevalence of obesity in the world today despite their relatively small populations: Nauru (71.1), Cook Islands (64.1), Tonga (59.6), Samoa (55.5) and Palau (50.7). The trends in obesity prevalence in these top five countries began in the 1960s and have risen continuously since then (Ulijaszek, 2005). The most important factors underlying the high prevalence of obesity in these countries is the limited arable land and importation of Western processed food, sedentary life styles and cultures that perceives obese bodies as attractive, healthy and a product of wealth (Ulijaszek, 2005; Cassels, 2006).

One notable phenomenon of the global obesity epidemic is that many low and middle income countries have the “paradoxical dual burden” of obesity and malnutrition: widely pervasive malnutrition in young children and high obesity prevalence in older children, adolescents and adults (Kelly et al., 2008; WHO, 2013). For example, in 2008 29% of Egyptian (Per Capita Gross Domestic Product (GDP) in 2012: $3,214) children less than five years of age were critically malnourished while 34.6% of adults were obese (Egypt Ministry of Health and Population, 2012). Rapid demographic shifts of increasing median age as a result of rising life expectancy and/or declining birth rates is one of the causes of the paradoxical nutritional dual burden in developing countries. Other contributing factors that explain the paradoxical dual burden include unsanitary waste discharge systems that cause diarrheal and infectious diseases leading to malnutrition and rapid urbanization and changes in lifestyles that contribute to obesity (i.e. increased consumption in more processed and westernized foods and declining levels of physical activity). Underdeveloped public health systems in these countries are also unable to prevent or manage these opposing nutritional deficiencies (Food and Agriculture Organization of the United States, 2006).

1.2. Geography of Obesity in the United States

1.2.1. Measurement of Obesity

The definition and measurement of obesity has changed over time. Before the body mass index (BMI) was widely used in the field the Metropolitan Life Insurance Company (MLIC) tables, tabulated sex-specific standard heights and weights, were widely used to measure obesity in the United States since the 1940s. However the use of the MLIC tables were limited because (1) the measurements were developed from persons of 25-29 years old and did not include other age groups; (2) non-standardized protocols and equipment were used to develop the measures; and (3) there was a substantial time difference between the development of the measures and their implementation (e.g. the MLIC tables used in the 1980s were actually based on measurements from the 1950s to the 1970s) (Kuczmarski and Flegal, 2000).

The measurement of body mass index (BMI) as a measure of overweight and obesity was initiated in the 1970s, for use by the medical and academic fields (Keys et al., 1972); however, the BMI thresholds for overweight and obesity varied by time. For example, the U.S. governments used the thresholds overweight (27.8 for men and 27.3 for women) and obesity (31.1 for men and 32.3 for women) when initiating many health interventions and promotions like “Healthy People 2000s” (U.S. Department of Health and Human Services 1990). Since that time through today, the National Institutes of Health (NIH) adopted the current BMI guidelines which were recommended by the WHO in 1998 (obese = BMI > 30.0; overweight = BMI 25.0-29.9; normal weight = BMI 18.5-24.9; and underweight = BMI ≤ 18.4) to monitor and evaluate population overweight and obesity prevalence. Using these common thresholds for overweight and obesity has also been useful to compare prevalence rates across nations and populations over time (past to present).

1.2.2. Monitoring Obesity

The Centers for Disease Control and Preventions (CDC) monitors the prevalence of obesity in the United States using the Behavioral Risk Factor Surveillance System (BRFSS) and the National Health and Nutrition Examination Survey (NHANES). This study will focus on the BRFSS.

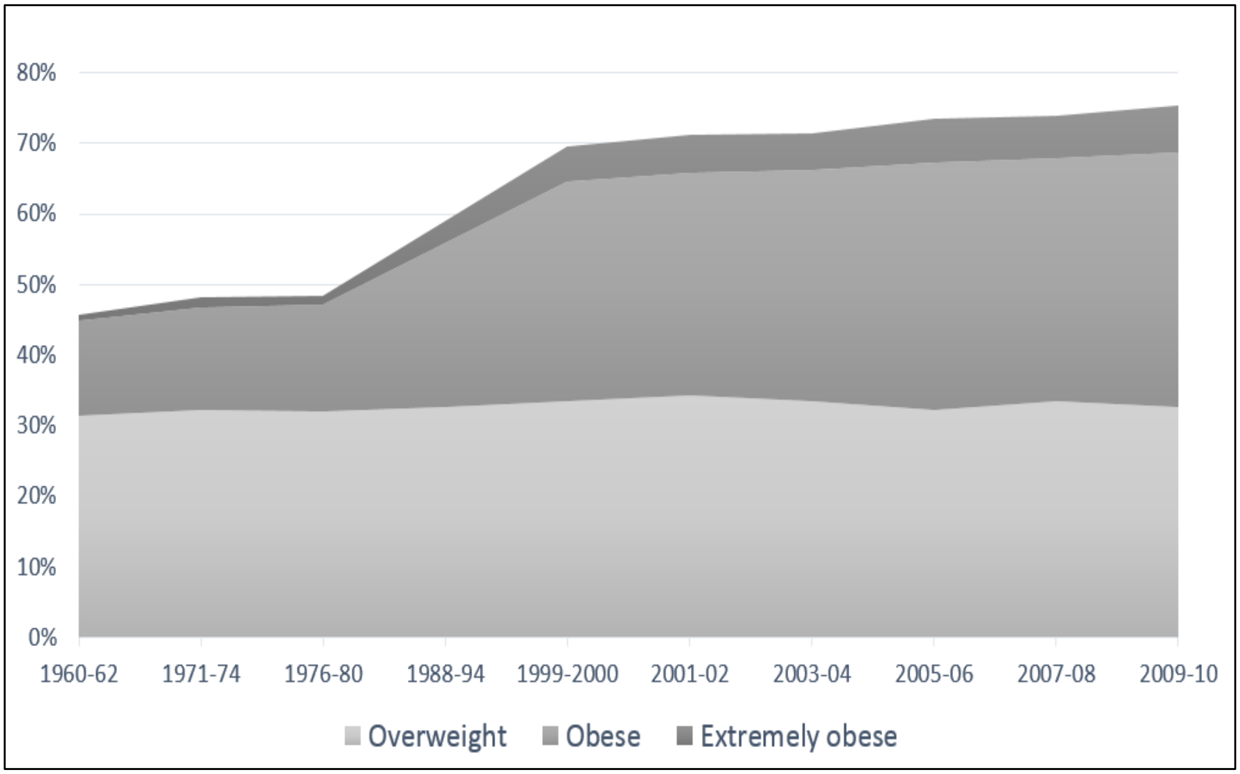
The BRFSS is known as the largest public health survey in the world. The BRFSS was first implemented in 1984. It is a state-based, self-reported health survey system for gathering information on adult disease outcomes, health risk behaviors, preventive health practices, and health care access (CDC, 2013). These data are collected via telephone interviews conducted by each state health department on an annual basis. These data are processed and weights are assigned to demographic and health characteristics and the geography of the interviewees to appropriately reflect the U.S. population (CDC, 2013). Although BRFSS reveals important information on health-related demographic, socioeconomic, and behavioral characteristics it has some limitations: (1) since it uses land-line telephones (1998-2010) and/or cell phones (after 2011) to conduct interviews, people without a land-line phone and people rejecting to answer their telephone could be under-sampled, in particular if they live in a rural and remote area; (2) low income and/or minority racial/ethnic groups also tend to be under-sampled due to low availability of landline phones; (3) there may be self-reporting bias—i.e. several studies have found that women were likely to underreport their weight while men over-reported their height (Ezzati et al., 2006; Yun et al., 2006; North Carolina State Center for Health Statistics, 2012).

Since 2011 the BRFSS has been implemented cell-phone uses to have more young or minor populations in its survey sample.

The NHANES, first conducted in 1971, is also a public health survey and research program to assess the health and nutritional status of adults and children in the United States. The sample size of each year's survey is about 5,000 persons nationwide. The survey combines in-depth personal interviews that collect data on the demographic, socioeconomic, dietary, and health-related behaviors of respondents and physical examinations (medical, dental, physiological measurements, and laboratory tests) which are collected by trained public health personnel.

Following the current BMI classification and the early versions of NHANES, approximately 14% of adult Americans were obese in the early 1970s. In the late 1970s the percentage of obese adults began to rise and continued to rise through the 1980s and 1990s (Cutler et al., 2003). Between 1988 and 1994 (the NHANES III), 23% of adult Americans were reported obese (Ogden and Carroll et al., 2010). By 2000, the obesity prevalence rate among adults from the BRFSS reached to 31 per 100 population (Chou et al., 2004). In the 2010 BRFSS, 36% of adults were reported as obese and another one third of U.S. adults (33%) were reported to be overweight (Fryar et al., 2012). Figure 1.2 shows the temporal trends in adult obesity prevalence in the United States. A research based on linear time trend forecasts expects that the half of U.S. adults (51%) will be obese by 2030 (Finkelstein et al., 2012).

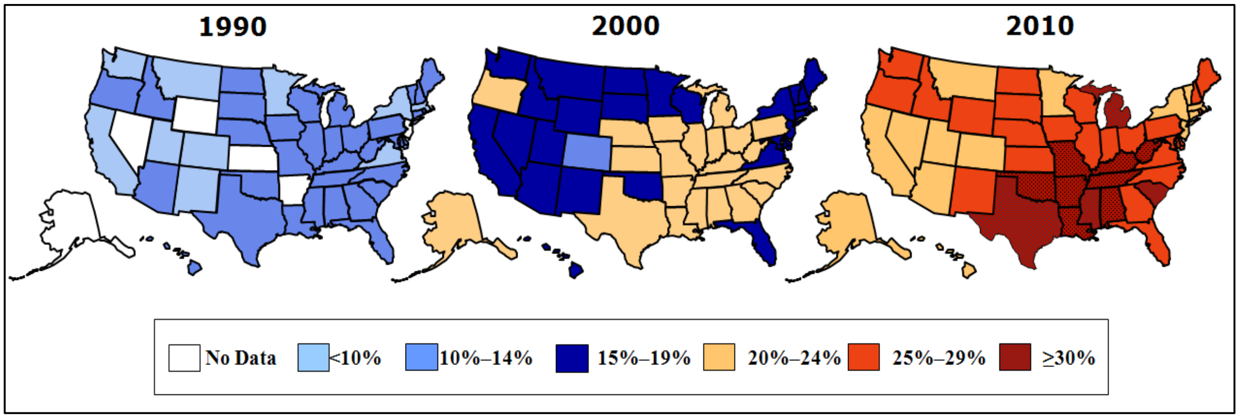
Figure 1.2. Temporal Trends in Percent Overweight and Obesity among Adults in the U.S. 1962-2010.



Source: Fryar et al. (2012).

In addition to the epidemic levels of overall obesity there are distinct geographic inequalities by states and counties within the United States (Figure 1.3). In 1990 all states had less than 15% of obesity prevalence. In 2000 most Southern and Midwestern states experienced rapid increases in obesity prevalence (i.e., up to 25 per 100 population) (Flegal et al., 2002). In 2010 all states had an obesity prevalence of 20 or higher with many Southern states including Alabama, Arkansas, Kentucky, Louisiana, Mississippi, Missouri, Oklahoma, Tennessee, and West Virginia having an obesity prevalence ≥ 30 (CDC, 2013b). Table 1.1 lists five top states with the highest and lowest obesity prevalence in 2010.

Figure 1.3. Obesity Prevalence[1] by States, United States 1990-2010.



Source: CDC (2013b) with permission to use.

[1] Rates per 100 population

Table 1.1. States with Highest and Lowest Obesity Prevalence Rates[1] in 2010.

Rank	Highest	Rates	Lowest	Rates
1	Mississippi	34.0	Colorado	21.0
2	West Virginia	32.5	Nevada	22.4
3	Alabama	32.2	Connecticut	22.5
4	South Carolina	31.5	Utah	22.5
5	Kentucky	31.3	Hawaii	22.7

Source: CDC (2012).

[1] Rates per 100 population

Since most obesity comorbidities are the leading causes of preventable death obesity has enormously influenced mortality in the U.S: Mokdad et al (2004) found that obesity caused approximately 400,000 premature deaths, more than 16% of deaths in the United States, which was second to tobacco-related causes of mortality in 2000. Masters et al (2013) found that approximately 18% of the deaths for adults aged 40 to 85 years in the United States were associated with obesity in 1986 to 2006. These studies demonstrate the urgency to reduce obesity as a major public health problem in the United States.

Obesity also poses a heavy financial burden on public health spending in the United States. The costs of obesity and comorbidities include (1) direct health services costs such as physician fees, laboratory and drug therapy, and (2) indirect costs such as health insurance premiums, decreased compensation of workers, and disability (Trogdon et al., 2008). Colditz (1992) estimated that obesity was responsible for $39 billion or 5.5% of total medical costs in the U.S. in 1986. Finkelstein et al. (2009) reported that the obesity-related spending in 1998 reached $42 billion or about 6% of the U.S. medical spending. The medical costs associated with obesity increased two-fold in 2006 to $86 billion or 10% of medical costs. Recent obesity studies argue that the total cost of obesity and its related illnesses were much higher than documented in previous studies. Cawley and Meyerhoefer (2012) argued that the adults' obesity-related medical costs were more than $209 billion or 21% of the national medical care costs in 2005. The American Public Health Association (2012) estimated that $300 billion annually was spent on obesity and related problems. Yang et al (2011) estimated the additional cost of obesity could increase from $48 to $66 billion each year if the current obesity prevalence trend continues. Importantly, if obesity prevalence remains the same and does not increase over the next two decades an estimated $549.5 billion could be saved in the U.S. economy (Finkelstein et al., 2012).

1.3. Disease Ecology of Obesity in the United States

Since the onset of the obesity epidemic health and social science scholars have investigated individual and population-based risk factors for obesity. The major factors that have been found to contribute to obesity are grouped below into those relating to populations, behaviors, and environments.

1.3.1. The Population Base

Population-based hypotheses for increasing obesity prevalence include genetics and demographics differences in populations. Bouchard et al. (2003) reported more than 300 human genes or gene markers are involved in the causal pathway of obesity. Some single-genes as well as a combination of genetic factors have been shown to significantly increase or decrease obesity in individuals. For example, a deficiency in Leptin, a hormone secreted by adipocytes is known to be associated with obesity (Atkinson, 2005; Racette et al., 2003). Bouchard et al. (2003) also reported that identical twins are likely to have similar metabolism in the amount of body weight and fat gained even though they developed apart. However the influence of genetics does not appear to be a predominant factor contributing to the rapid increase in obesity prevalence in the United States worldwide (Racette et al., 2003).

The increase in obesity prevalence is observed by demographic characteristics. By analyzing age-adjusted obesity prevalence for 5,555 adults aged 20 years or older from 2007-2008 NHANES surveys, Flegal et al. (2010) found that the likelihood of obesity peaked among women aged 40 to 59 years (38.2 per 100 population, 95% CI: 33.8-42.6) compared to women aged 20 to 39 years (34.0, 95% CI: 29.0-39.1) and aged 60 years or older (33.6, 95% CI: 30.2-36.9); for men, the oldest group had the highest obesity prevalence (37.1, 95% CI: 33.1-41.0) than the youngest group (27.5, 95% CI: 23.8-31.2) and the middle-aged group (34.3, 95% CI: 29.8-38.8). Generally women have higher obesity prevalence rates compared to men possibly due to the differences in physiology and food consumption preferences (Kanter and Caballero, 2012). Non-Hispanic blacks and Latino have higher obesity prevalence than non-Hispanic whites for reasons still under investigation (Frank et al., 2004; Robert and Reither, 2004). The influence of changes in marital status on body weight varies differently for men and women: Sobal et al. (2003) conducting a longitudinal study using the 1970s-1980s US National Health and Nutrition Epidemiological Follow-up Survey (NHEFS) found that unmarried women who became married gained on average 4.7 lbs, married-to-divorced/separate men gained 2.5 lbs. These findings suggest that marital status and weight gain operate differently for women and men. Education is a very important individual and population-based characteristic that prevents obesity. Using 2005-2008 NHANES Ogden (2010) reported that college graduate males and females had lower obesity prevalence rates (27.4 per 100 population and 23.4 respectively) than high school graduates males (34.8) and females (39.8). Education reduces obesity by increasing incomes and food availability options—resources to purchase fruit and vegetables (Rundle et al., 2008). In contrast, lower incomes and living in poverty increases BMI because people with limited resources consume more processed foods than fresh produce (Lopez and Hynes, 2006).

1.3.2. The Behavioral Base

Known risk factors for obesity relating to human behavior are sedentary lifestyle and poor dietary habits. Television (TV) watching, one of the favorite leisure time activities, is often cited as a major obesity risk factor. Hu et al. (2003) reported a strong association between the total hours spent watching TV and the higher risk of being obese among adult women in their multivariate analysis–i.e., for every two hours a day TV watching resulted in a 23% (95% CI: 17-30) increase in obesity among women after controlling for other demographic and socioeconomic risk factors. Tucker and Friedman (1989) also found that the odds of being obese for males who watched more than three hours of TV a day was twice as high (Odds Ratio (OR) = 2.1 (95% CI: 1.6-2.6)) as males with less than one hour of TV watching a day. TV habits in childhood and adolescence can also increase the likelihood of obesity in their adulthood and mid-life (Landhuis et al., 2008; Parsons et al., 2008). Watching TV not only makes people physically inactive and sedentary but also increases calorie intake seduced by food-related TV ads (Hu et al., 2003). Other sedentary behaviors including using the computer or playing video games is also attributed to obesity. In a study based on Los Angeles County, adults who participated in more than one hour of TV watching and/or computer using per day were OR = 1.2 (95% CI: 1.1-1.4) more likely to be obese compared to adults watching less than an hour of TV or computer use per day (Yancey et al., 2004). The odds of being obese was highest for adults who watched more than three hour of TV watching and/or computer using in this study (1.7, 95% CI: 1.4-2.1). Reducing the time spent watching TV and/or using computers is therefore, a critical behavior to maintaining normal weight. Furthermore, a recent survey found that a person who exercised at least 30 minutes once or twice a week had a 20% less chance of becoming obese than a person who did not exercise (Hendrick, 2009).

Dietary habits may be the most influencing behavior to increased risk of obesity. Consumptions in high-calorie food, highly processed food, fast-food, and oversized portions contribute to weight gain (Janssen et al., 2004; Boumtje et al., 2005). Eating fresh vegetable and fruits, on the contrary, is a healthy life-style choice that reduces the risk of obesity.

Finally, despite the long-term disadvantage to one’s health, smoking has been found to be associated with a lower obesity prevalence than non-smokers in adults, perhaps because smoking reduces appetite (Eid et al., 2008). Smoking however, is a major risk factor for a variety of diseases and is not recommended as a behavioral alternative to weight loss.

1.3.3. The Environment Base

Ewing et al. (2003) studied a sample of adult residents from 1998 to 2000 using those years of BRFSS datasets and found that residents of sprawling counties were more likely to have higher BMI compared to those who lived in densely populated counties because physical activity was diminished in suburbia. Adults living in a more compact county (i.e., one standard deviation above the mean county sprawl index) were less likely to be obese OR = 0.9 (95% CI: 0.86-0.95) than adults living in a more sprawling county. Another study by Frank et al. (2004) using a travel survey of 10,878 participants in Atlanta found that the likelihood of obesity could increase by 6% with one additional hour per day spent in vehicles. They also found that a quartile increase in mixed land-use index developed in terms of four different types of land use (residential, commercial, office, and institutional) was attributable to a 12.2% decrease in the likelihood of obesity. Mixed land-use planning and the promotion of public transit were also found to be good policy measures for decreasing individual's BMI in New York City (Rundle et al, 2008). However Vojnovic et al. (2013) recently found that the traditional relationship between higher densities, mixed land uses, higher connectivity, and greater accessibility do not guarantee higher pedestrian activity and lower BMI in declining inner-city neighborhoods in Lansing, Michigan. Neighborhood safety is an important risk factor that may impact BMI. Fish et al. (2010) found that Los Angeles residents who considered their neighborhoods unsafe in terms of crime victimization have OR = 2.81 (95% CI: 0.11-5.52) higher BMI than those who perceived their communities safe using the 2000-2001 Los Angeles Family and Neighborhood Survey.

Importantly, the characteristics of the environment and the processes by which individuals interact with their environment often determines healthy, since, individuals with lower socioeconomic status often live in poor neighborhoods, which are less favorable built environments for health (Darden et al., 2009). Especially in these poor environments there may be less access to high quality foods because of few to no grocery stores. The “food desert” hypothesis investigates the social conditions that economically and socially disadvantaged people suffer from higher food prices and the paucity of food stores in their neighborhoods (Zenk et al., 2005; Raja et al., 2010). However LeDoux and Vojnovic (2013) refuted the “food desert” hypothesis by showing that residents living in disadvantaged neighborhoods actually purchased their groceries from supermarkets in suburban locations outside of their neighborhoods due to the disproportionately with unhealthful food choices like convenience and party stores.

1.4. Interventions to Reduce Obesity in the United States

As the obesity epidemic has risen in the United States over the past few decades there has been the need for public health programs and policy implementation. There is no doubt that governments are important actors in curbing the obesity epidemic because they are responsible for enhancing public health by providing public goods and services (Gortmaket et al., 2011). All levels of government, i.e., federal, state and local have been involved in various programmatic and policy interventions to reverse the increasing trends of obesity prevalence in the United States (Khan et al., 2009). The U.S. federal government identified obesity as a key public health priority through the “2001 Surgeon

General’s Call to Action to Prevent and Decrease Overweight and Obesity” and the “2010 the Surgeon General’s Vision for A Healthy and Fit” (Office of the Surgeon General, 2012). One of the most notable public health interventions to address and understand the obesity epidemic in the U.S. was the establishment of the Division of Nutrition, Physical Activity, and Obesity (DNPAO) at the CDC with the approval of the U.S. Congress in 1999. The goal of the CDC-DNPAO program is “to prevent and control obesity and other chronic diseases through healthful eating and physical activity” (CDC, 2012b). The CDC-DNPAO program primarily aims to effectively influence individual’s behaviors and their environments because chronic energy imbalance involving both dietary intake and physical activity are recognized as major causes of obesity (Hamre et al., 2008; Gortmaker et. al, 2011). The CDC-DNPAO program is a competitive cooperative-agreement with participating state health departments applying for these grants to address the state’s obesity problem and concerns. State health departments can strengthen their ability to provide better health promotion, to implement effective nutrition and physical activity interventions, and to accumulate scientific evidence on obesity and its risk factors using the program funding (Hamre et al., 2008).

The theoretical framework within which CDC-DNPAO programs are designed is a five-level Social-Ecological Model (SEM), first proposed by McLeroy et al. (1988), which implies that human behavior can be influenced by distinct yet intertwined levels of society (Hamre et al., 2007; Brown, 2011). From the SEM perspective a society has five levels of interactions that include intrapersonal, interpersonal, organizational, community, and society levels (CDC, 2013c):

- Individual: Different food intake and physical activity habits by each person can determine one's weight. Obesity interventions should have an impact changes in one's cognitive and behavioral practices which have been formulated through one's knowledge, attitudes, experience, and beliefs.
- Interpersonal: Interpersonal interactions includes any social network and support system among people with a shared relationship in society. The common examples of interpersonal groups are families, friends, neighbors and work groups (McLerey et al., 1988). An interpersonal group is usually formed informally but sometimes it can be built through a formal organization such as a club or around a common interest. Individuals can expect physical and/or emotional support and reliance from informal members (Brown, 2011). Most norm and rules within interpersonal groups are naturally made and shared among members.
- Organizational: A society has various types of organizations generally formulated and governed by official rules and regulations. These organizations consist of individuals and interpersonal groups. For example people usually spend time in educational institutions (e.g. primary and secondary schools) and workplaces interacting with other members. While organizational characteristics and structures can significantly impact people's lives, they can also share unofficial and unconscious experiences among them (McLerey et al., 1988) which may lead to promotional or untoward personal behaviors and/or interpersonal interactions.
- Community: The concept of community can vary by definition and context. A community usually includes "families, informal social networks, neighborhoods, civic groups, and churches within which people formulate communities' norms and

values and individuals' beliefs and attitudes" (McLerey et al., 1988). In communities people share common values and experiences through social interactions. The CDC emphasizes the role of a community for obesity prevention because "like a large organization, it is able to make changes to policy and the environment to give residents the best possible access to healthful foods and places to be physically active" (CDC, 2007). Some frequently used ways for communities to address obesity include changes to zoning ordinances, improvements to parks and recreation facilities and creating ways to distribute free or inexpensive fruits and vegetables" (CDC, 2007).

- Societal: At the highest level societal or macro-level interventions can also be implemented to reduce obesity. Regulatory policies, interventions and laws implemented by local, state, or federal government may impact population-health outcomes or behaviors.

The five important evidence-based strategies for the CDC-DNPAO program include (1) balancing caloric intake and expenditure, (2) increasing physical activity, (3) increasing the consumption of fruits and vegetables, (4) decreasing television-viewing time, and (5) increasing breastfeeding (Yee et al., 2006).

Since obesity has a complex, multifaceted etiology, it is essential to have evidence-based strategies for implementing obesity prevention programs (Economos & Irish-Hauser, 2007). Obesity prevention and control interventions generally involve developing nutrition, physical activity, and environment plans to balance caloric intake and expenditure through public and private partnership (Hamre et al., 2008). In Michigan, for example, the Michigan Department of Community Health (MDCH) is working with county health departments and community coalitions through several obesity prevention programs such as opening more farmer's markets in disadvantaged neighborhoods, improving walking trails and bicycle facilities, and promoting healthy lifestyles through partnerships with non-profit organizations (CDC, 2012b). The national budget for the CDC-DNPAO program in 2010 was $90 million with the average annual state grant, approximately $756,000 (National Alliance for Nutrition and Activity, 2010).

After granting the programmatic funding CDC requests all funded states to submit performance reports on the effectiveness of the CDC-DNPAO program in their state. Based on these reports and new requests from other states, CDC-DNPAO will decide to continue the support for existing participants or provide new funding for current non-participating states (Yee et al., 2006; Hamre et al., 2008). Recent studies have also shown that CDC-DNPAO programs have provided funded states with momentums to develop statewide partnerships, establish health promotion infrastructures, implement policy interventions, and enacting obesity-related legislations (Hersey et al., 2011; Yee et al., 2006). Through these environmental interventions on obesity, CDC-DNPAO programs may contribute to control overall obesity prevalence in funded states. While these reports and studies provide important information on how well each state is performing, it is still unknown what the cumulative impacts are of state-based interventions on the geography of adult obesity and its racial inequalities in the United States.

1.5. The Need of This Study

Obesity is a major concern to public health worldwide. There are also regional variations in obesity prevalence. Obesity and many comorbidities contribute to a decrease in healthy life, premature mortality, and the increase in public health spending.

Western dietary habits and sedentary lifestyles and are major causes of obesity. Some developing countries are also experiencing the paradoxical dual burden of obesity and malnutrition under rapid westernization, demographic shifts, and underdeveloped public health system. Other micro- and macro- causes of obesity are still under investigation.

In the United States, obesity prevalence has more than doubled since the 1980s following a moderate increase in obesity during the 1970s. Currently two-thirds of U.S. adults are obese or overweight. Geographically Southern states have higher obesity prevalence than other states. In terms of race, blacks and American Indians are more likely to be obese compared to whites and other racial and ethnic groups. The CDC has been actively involved in monitoring obesity prevalence by conducting annual public health surveys –e.g., BRFFS and NHANES and implementing CDC-DNPAO programs. Researchers also have extensively investigated obesity risk factors in terms of population, behavior, and environmental perspectives. The most important individual and population-based risk factors for obesity are diet coupled with high fat and sugar and sedentary life styles. The effect of demographic characteristics, socioeconomic status and environments on obesity varies by population groups and regions.

This dissertation research addresses the obesity epidemic by focusing on three perspectives, studies that have not yet been addressed in the obesity literature and can broaden our understanding of the high obesity prevalence in the United States. The first study investigated the spatial and spatio-temporal prevalence of obesity at the county level. The obesity literature has been reporting obesity prevalence only at the national or state levels and there is an immediate need to investigate the prevalence at the county level to inform future obesity interventions. There are also no studies, to my knowledge, that use a spatial microsimulation methodology to calculate obesity prevalence across counties in the United States. The second study evaluated the impact of CDC-DNPAO programs on obesity prevalence at the county level within and across states over time using the output from the first study. To date no national study has been conducted to evaluate the CDC-DNPAO using simulated county-level obesity data. This study will indirectly evaluate the effectiveness of state-level obesity interventions on changing obesity prevalence. The third study focused on the racial inequalities in obesity prevalence. Partitioning the underlying causes of racial inequalities in obesity into known and unknown portions will be valuable to further understand why these disparities exist and how to implement future interventions to reduce the racial gaps.

1.6. Goal and Objectives of this Research

The purpose of this research is to investigate the impacts of CDC-DNPAO statewide intervention programs on the geography of adult obesity prevalence in the United States to identify where programs are successful and where to target future interventions to reduce obesity and improve population health.

The specific objectives of this research include:

- To visualize and explore the spatial and spatio-temporal patterns of obesity prevalence across counties in the United States (1998-2010) using the BRFSS datasets. A spatial micro-simulation approach will be implemented to calculate obesity prevalence estimates within and across counties.
- To evaluate the impacts of state-level CDC-DNPAO programs on county-level obesity prevalence (1998-2010) using a quasi-experimental modeling to identify

counties where state programs are more or less protective of obesity and to identify counties in need for future intervention; and

- To partition the variance in obesity prevalence between blacks and whites using a Blinder-Oaxaca Decomposition Technique into explainable and unexplainable causes of obesity to improve our understanding of racial disparities in obesity prevalence in the United States.

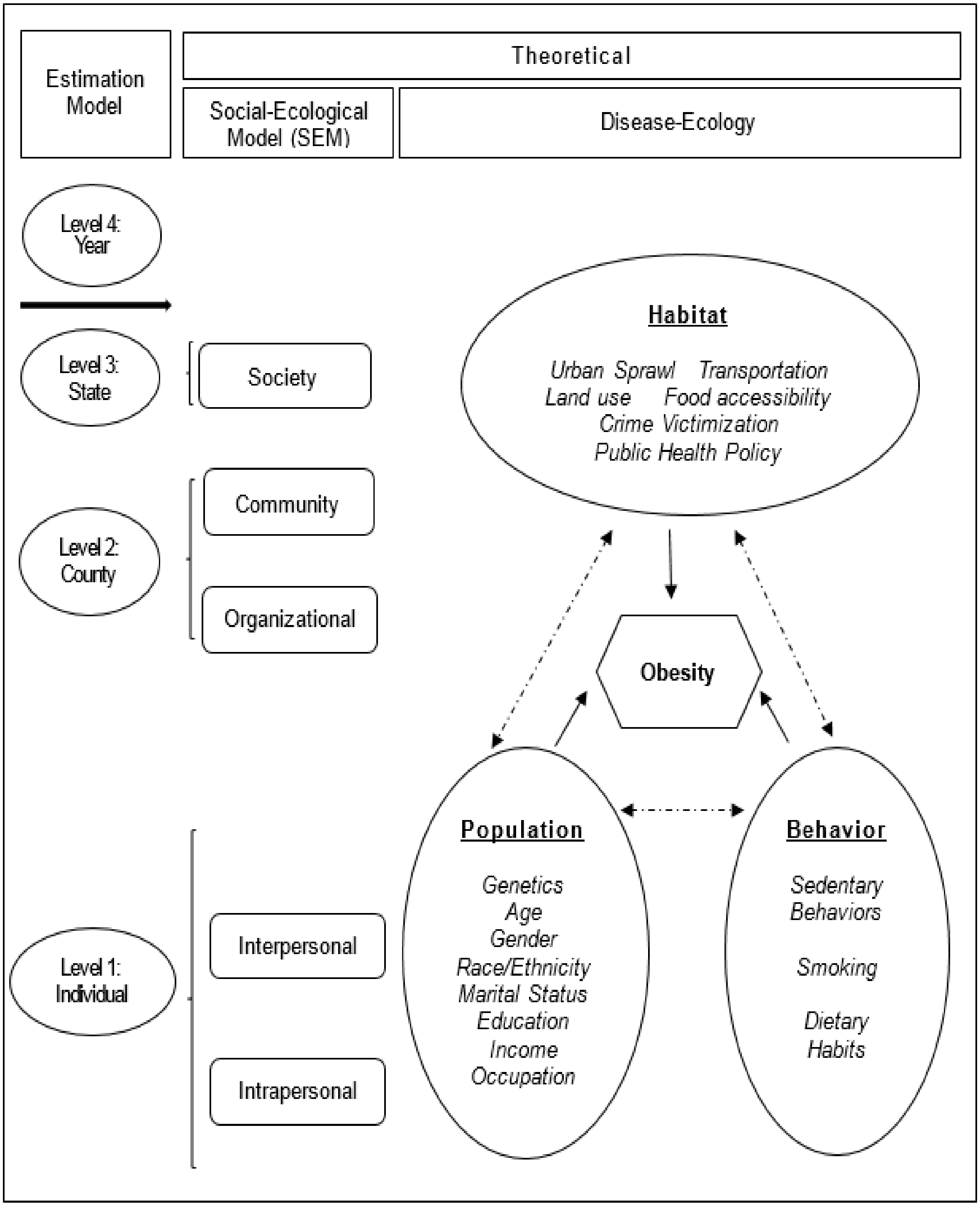
1.6.1. Study Hypotheses

- Hypothesis 1: The spatial and spatio-temporal patterns of obesity prevalence at *the county level* will be evenly distributed evenly across space and space-time in the United States between 1998 and 2010.
- Hypothesis 2: States that received CDC-DNPAO program funding will have lower obesity prevalence and have demonstrated a decrease in obesity prevalence over time compared to states without CDC-DNPAO programs.
- Hypothesis 3: The black-white gap in obesity prevalence in the United States will be largely unexplained by known risk factors for obesity.

1.6.2. Study Design

The three studies conducted will each use a retrospective cross-sectional study design. Figure 4 illustrates the theoretical and conceptual frameworks that will be utilized in this study. The ecology of obesity is imbedded within the social-ecological model used in the design of CDC-DNPAO programs. First this study applies a spatial microsimulation approach to estimate obesity prevalence rates for all counties in the United States. These maps will be visualized and explored for their spatial patterns and to detect clusters of high and low obesity prevalence. Second, an interrupted time-series model was implemented to estimate the effects of CDC-DNPAO programs on changing county-level obesity prevalence in the United States controlling for individual-, and state-level variations in risk factors across the study years. Finally, a Blinder-Oaxaca decomposition technique is applied to further understand the black-white disparities in obesity in the United States. While the disparities of other racial groups, such as American Indians are not investigated in this third study, the findings will be helpful for future research of these important groups. This dissertation utilized multiple study methods to achieve the goal and objectives and to examine the study hypotheses.

Figure 1.4. Theoretical and Conceptual Framework to Study Obesity.



Note. *Social-Ecological Model (SEM)* is the theoretical model for the CDC-DNPAO state interventions. *Disease-Ecology* summarizes the interactions between obesity and its risk factors from behavioral, population and environmental perspectives.

2. STUDY I: SPATIAL AND SPATIO-TEMPORAL PREVALENCE OF ADULT OBESITY AT THE COUNTY LEVEL IN THE UNITED STATES: A SPATIAL MICROSIMULATION APPROACH

ABSTRACT

Obesity is a growing public health concern in countries around the world, independent of income levels. There is a need to further monitor obesity prevalence at the local level within countries to intervene in appropriate ways. Public health surveys in the United States, including the Behavioral Risk Factor Surveillance System (BRFSS) are designed to calculate obesity prevalence at the national and state levels but not the county or local level. The purposes of this study are to implement a spatial microsimulation approach by which to estimate obesity prevalence rates at the county level in the United States and to observe the temporal, spatial and spatio-temporal changes in obesity prevalence from 2000 to 2010. Spatial microsimulation aims to iteratively replicate and allocate selected characteristics of sampled BRFSS respondents to county-level demographic characteristics of residents (sex, age, race/ethnicity, marital status, and education). Obesity counts and prevalence rates were then calculated at the county level and mapped to observe their spatial and spatio-temporal changes. The local Moran's I was also used to detect county-level obesity prevalence clusters and outliers. Obesity prevalence in the United States rose dramatically between 2000 and 2010 with substantial state variations. Spatially and spatio-temporally, counties in Midwestern states had higher obesity prevalence rates compared to Western and Northeastern states that had relatively more counties with lower obesity prevalence rates. Counties in Southern states, especially along the Mississippi River and the Appalachian Mountains, and counties containing or in

proximity to American Indian reservation sites had elevated obesity prevalence rates across time, 2000 to 2010. Counties within which future obesity-reduction interventions should be targeted to reduce obesity prevalence in the United States are highlighted. This study demonstrated the use of spatial microsimulation modeling as an alternative method to obtain reliable obesity prevalence rates at the local-level using existing health survey and census data. A similar methodology may be applied in other countries to obtain obesity prevalence rates at the local level to target appropriate interventions.

2.1. Background

Obesity is defined as abnormal and excessive fat accumulation which may result in the deterioration of health. Body mass index (BMI), a numeric value calculated from a person's weight in kilograms divided by the square of his height in meters (kg/m^2), is commonly used to classify obesity (BMI ≥ 30). Since the 1980s, the worldwide obesity prevalence of adults aged 20 years and older has more than doubled, from 6 per 100 population in 1980 to 12 in 2008 (World Health Organization (WHO), 2015). Obesity has many comorbidities, including but not limited to cardiovascular disease, Type-II diabetes, osteoarthritis, stroke and certain types of cancers, which are also contributing to the increase in chronic disease burden and reduction in population health and public health spending in developed and developing countries. Notably many low- and middle-income countries also have the paradoxical dual burden of obesity and malnutrition in their populations further complicating the need for interventions to address these different types of nutritional deficiencies (Kelly et al., 2008; WHO, 2013).

In the United States, the mean obesity prevalence rate was 15.0 in 1976-1980, increasing to 34.9 in 2011-2012. Furthermore, being overweight or obese were responsible for 300,000 premature deaths each year in the 1990s (Office of the Surgeon General, 2001). In 2001, the Surgeon General (Office of the Surgeon General, 2001) reported that rising overweight and obesity prevalence rates in the U.S. had reached nationwide epidemic proportions, calling for action-plans to intervene at the individual and community levels. In 2005, the costs associated with adult (aged 18 years or older) obesity and complications from related illnesses was about $190.2 billion, approximately 20.6% of annual health care spending (Cawley and Meyerhoefer, 2012) demonstrating the continued need to address obesity at the individual and population levels in the United States.

2.1.1. United States: Challenges in Monitoring Obesity at the Local Level

It is challenging, however, to monitor areas of high or increasing obesity prevalence at the local level in the United States because local data is not collected in national health surveys such as the Behavioral Risk Factor Surveillance System (BRFSS) due to sampling schemes that protect the confidentiality of local residents. The BRFSS is a state-based, self-reported health survey implemented each year in a sample of residents. The survey is performed through telephone interviews to collect information on health risk behaviors, preventive health practices, disease outcomes and health care access (Centers for Disease Control and Prevention (CDC), 2011). Residents are sampled and surveys are collected in state-specific sub-geographical units such as the county, public health district or other administrative unit. Survey respondents are assigned sampling weights to accurately reflect the demographic characteristics and spatial distributions of the populations in each respective state. Prior to 2010, landline telephone users were surveyed in the BRFSS. A new sampling methodology was introduced in 2011 to include both landline telephones and cell-phones to survey a more diverse selection of population groups, especially low-income and young adults. With this change in sampling methodology, there is a temporal divide (before 2010 and thereafter) when monitoring obesity prevalence using the BRFSS datasets.

Despite the detailed information collected on individuals to monitor public health in the BRFSS—the national survey has several limitations for health geographic and public health studies. First, the geographic identification information, e.g. Federal Information

Processing Standard (FIPS) codes, for rural or sparsely populated counties is not open to the public due to their small sample sizes and the need to protect the confidentiality of respondents, limiting researchers from directly estimating obesity prevalence rates at the county level. Second, the counties sampled and surveyed may vary from year to year with an increase in the number of counties surveyed since 2000 making it difficult to monitor spatial and spatio-temporal changes in obesity with older and newly surveyed counties. Consequently, the BRFSS cannot be used to *directly* calculate obesity prevalence at the county-local level in the United States (Rao, 2003).

2.1.2. Spatial Microsimulation: the Geographic Approach of Small Area Estimation

Accordingly there is growing attention to the use of *small area estimation* techniques to *indirectly* calculate reliable health statistics at the local level by borrowing strength from existing health surveys and census datasets (Rao, 2003; Rahman, 2009). There are two distinct approaches to small area estimation—the *statistical approach* and the *geographical approach*. Statistical small area estimation methods interpolate small area estimates from larger geographic units using complex statistical models, including multilevel models, Bayesian models and auxiliary datasets (Rahman, 2009; Zhang, 2010; Eberth, 2011). The use of the statistical approach is limited due to their design complexities and assumption that slope coefficients will be similar across different areas and geographic scales (National Cancer Institute, 2007).

Alternatively, the geographical approach—spatial microsimulation, generates hypothetical, simulated micro-level estimates by duplicating the characteristics of higher-level survey respondents to census-population data aggregated in each small area. Aggregated small area level data are then called *constraints* because survey respondents are duplicated according to their distributions in each area. Once a simulated micro-level dataset is generated, it is possible to perform spatial/aspatial analyses at the small area level. Since health survey data typically includes variables of interest for health studies across large geographic areas and census data have complete population information at the local level, the spatial microsimulation method is ideal to utilize these disparate datasets to estimate health outcomes in populations at-risk at the local level (Tanton et al., 2007; Rahman, 2009).

There are a growing number of studies in health geography and the related social sciences that have used the spatial microsimulation approach. Tomintz et al. (2009) used the General Household Survey, Health Survey for England and the United Kingdom (UK) census at the Output-Area (OA) level—the lowest level census geography in the UK—to estimate smoking rates at the OA level and proposed the locations of stop-smoking services in Leeds, UK. In addition, Morrissey et al. (2013) utilized the Living in Ireland Survey and the Irish Small Area Population Statistics datasets to investigate the spatial variation in acute hospital utilizations and related micro-level factors at the electoral division level in Ireland. Edwards, Clarke, Ransley, and Cade (2010) used the UK National Child Health Computer System and the UK census to calculate local obesity prevalence rates in the City of Leeds. This study found that local environmental characteristics, including neighborhood safety, fruits and vegetables consumption, Internet access, and access to supermarkets differentially impacted local obesity prevalence rates in high and low household-income census wards. Furthermore, Cataife (2014) used the Brazil Family Expenditure Survey and the Brazil census to simulate obesity prevalence rates at the census tract level in Rio de Janeiro, Brazil. This study found that inequalities in household income, physical activity, and food intake habits contributed to the dual burden of high malnutrition and high obesity prevalence in this highly populated Brazilian city. In summary, while there has been substantial research using spatial microsimulation in European and other countries, there are few studies using spatial microsimulation approaches to study populations and health outcomes in the United States. To our knowledge, Koh, Grady, and Vojnovic (2015) was the first study to investigate obesity prevalence rates at the census tract level in the United States using the BRFSS, census data and a spatial microsimulation approach. The findings from this study showed distinct patterns of elevated obesity rates clustered in the City of Detroit and neighboring northern suburbs.

The goals of this study were to utilize a spatial microsimulation approach to estimate county-level obesity prevalence rates in the United States and to assess their temporal, spatial and spatio-temporal changes from 2000 to 2010. This study builds on the techniques applied in the Koh et al. (2015) Detroit study to a broader U.S. geographical scale.

2.2. Methods

2.2.1. Study Area

The study area includes all counties and county equivalents (herein referred to as counties) in the 50 states in the United States and Washington D.C. from 2000 to 2010.

2.2.2. Data

Two types of data were used in this study. The data on individual-level obesity and related demographic characteristics were obtained from the CDC's BRFSS, from 2000 to

2010. County-level demographic data were collected from the U.S. Census data (2000 and 2010) and the American Community Surveys (ASC 5 years estimates, 2004-2008, 2005-2009, 2006-2010, 2007-2011, and 2008-2012). Since county-level population data from 2001 to 2003 were unavailable from the U.S. Census Bureau these populations were calculated based on a linear trend between the Census 2000 and the ACS 2004-2008 period at the county level.

2.2.3. Spatial Microsimulation

Following Lovelace and Ballas (2013) this study used an iterative proportional fitting (IPF)-based deterministic spatial microsimulation method. The first step in the spatial microsimulation was to identify common demographic variables known to be risk factors for obesity in the BRFSS and the census datasets (Flegal et al., 2010; Ogden and Carroll, 2010). These common variables included sex, age, race, educational attainment and marital status and were categorized in subgroups as outlined in Table 2.1.

Table 2.1. Spaital Microsimulation Modeling of BRFSS* and County Demographic Characteristics and their Subcategories.

Characteristics	Subcategories
Sex	Male
	Female
Age	18-24 years old
	24-34 years old
	34-44 years old
	44-64 years old
	65 years old and over
Race	White
	Black
	Asian
	American Indian and Native Alaskan
	Native Hawaiian and Pacific Islander
	Other
	Multiracial
Education Attainment	Below high school
	High school
	Some college
	College and above
Marital Status	Married
	Not married
	Separate
	Widowed
	Divorced

* BRFSS: Behavioral Risk Factor Surveillance System.

The second step was to recalculate the respondent's original sampling weights in the BRFSS. In this step the individual-level data structure in the BRFSS were transformed to the same structure as the census data. For this process all respondents in the BRFSS were grouped by county and the subtotals of each variable were calculated following the data structure in the census data. Then the original weight in the BRFSS for each respondent was iteratively multiplied by the ratios of the subtotals in the BRFSS and the census data by each variable and each subcategories. This process is explained in equations (1) and (2):

$$W_{ij}(k) = \frac{W_{ij}(k-1)C_{ij}(k)}{T_{ij}(k)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (1)$$

where, W_{ij} (k) is the new weight for person i in county j for the k^{th} demographic characteristic. W_{ij} (0) is the BRFSS respondent's original weight and C_{ij} (k) is element ij of the corresponding tabulation from the census data for the k^{th} characteristic. T_{ij} (k) is element ij of the corresponding summation of the BRFSS for the k^{th} characteristic. This reweight process was iteratively performed for all survey respondents and counties.

$$W_{ij}(k) = \frac{W_{ij}(k-1)\sum C_j(k)}{\sum W_j(k)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (2)$$

In equation (2) a new weight is calculated for each person i in county j. The sum of the new weights generated from equation (1) are equal to the weighted total population in each county. A new weight was calculated by multiplying (k-1)th weight and the ratio of the total number of respondents in the BRFSS and the population in the census datasets in the same subgroup category. Both equations were *iteratively* applied to one constraint after another until the final constraint was calculated.

The final step was to replicate each BRFSS respondent as its recalculated weight, which were integerized using conditional probabilities (Lovelace and Ballas, 2013). To minimize the differences in population characteristics between the simulated micro-level data and the census data the total absolute errors (TAEs) were calculated for each variable. As denoted in Equation (3) the TAE is defined as the difference between the simulated micro-level data tabulated by each variable in each county and the actual counts of the same variable in the census data:

$TAE = \Sigma_{ij} \mid O_{ij} - E_{ij} \mid$ …………………………..(3)

where O_{ij} is the actual count for the county *i* in a variable *j*, and E_{ij} is the simulated count for the county *i* in a variable *j* (Smith et al., 2009). The TAEs in this study remained less than 1 for all variables and counties meaning the simulated dataset had successfully approximated the same population characteristic-distributions in all counties. A set of sensitivity analyses informed the minimization of the TAEs when the five demographic characteristics (sex, age, race, education and marital status) were used in the spatial microsimulation modeling. Further details to explain the spatial microsimulation methodology can be found in Ballas et al. (2005), Edwards and Clarke (2009), O'Donoghue et al. (2013) and Lovelace and Ballas (2013).

Spatial microsimulation takes significant computing power because the iterative computing process is complex and the original datasets are often large. In this study, the final simulated micro-level dataset contained as many records as the total adult population for each year across all counties in the United States. The volume of the simulated micro-level data reached about 10^{11} bytes (100 gigabytes). It was very challenging to implement the spatial microsimulation with a personal computing device; therefore, the simulation was conducted using the supercomputer system located at

Michigan State University's High Performance Computing Center. The code for spatial microsimulation were written and performed in R 3.0.3 (R Core Team, 2013; Lovelace, 2014).

The simulated obesity prevalence rates at the county level across the United States were then joined to the county level geography and visualized in ArcGIS 10.2.2 (Environmental Systems Research Institute (ESRI), 2014). The spatio-temporal variations in obesity prevalence were illustrated using a manual classification scheme with 2.5% division between each threshold. This division was used because it cartographically best portrayed the temporal trends at a glance.

Following this mapping, high and low spatial clusters and outliers of obesity prevalence at the county level were detected using the Cluster and Outlier Analysis (Local Moran's I) tool in the ArcGIS Spatial Analysis Extension (ESRI, 2014). Spatial autocorrelation was detected using an inverse distance weighting scheme (Anselin, 1995). High-High clusters were defined as contiguous counties with high spatial autocorrelation–i.e., high-obesity prevalence rates; High-Low clusters were defined as high-prevalence counties located next to low-prevalence counties; Low-High clusters were defined as low-prevalence counties located next to high-prevalence counties; and Low-Low clusters were defined as contiguous counties with low spatial autocorrelation–i.e., low-obesity prevalence rates.

2.3. Results

2.3.1. Temporal and State-level Analyses

Figure 2.1. and Table 2.2 provide detailed information on the temporal changes in obesity prevalence between 2000 and 2010 by states in the United States and Washington D.C.

Importantly, all states showed an increase in obesity prevalence over the decade with overall obesity prevalence increasing from 21.7 per 100 population in 2000 to 29.2 in 2010 (34.5% increase over the decade).

Figure 2.1. Temporal Change in State-level Obesity Prevalence Rates in the United States, 2000-2010.

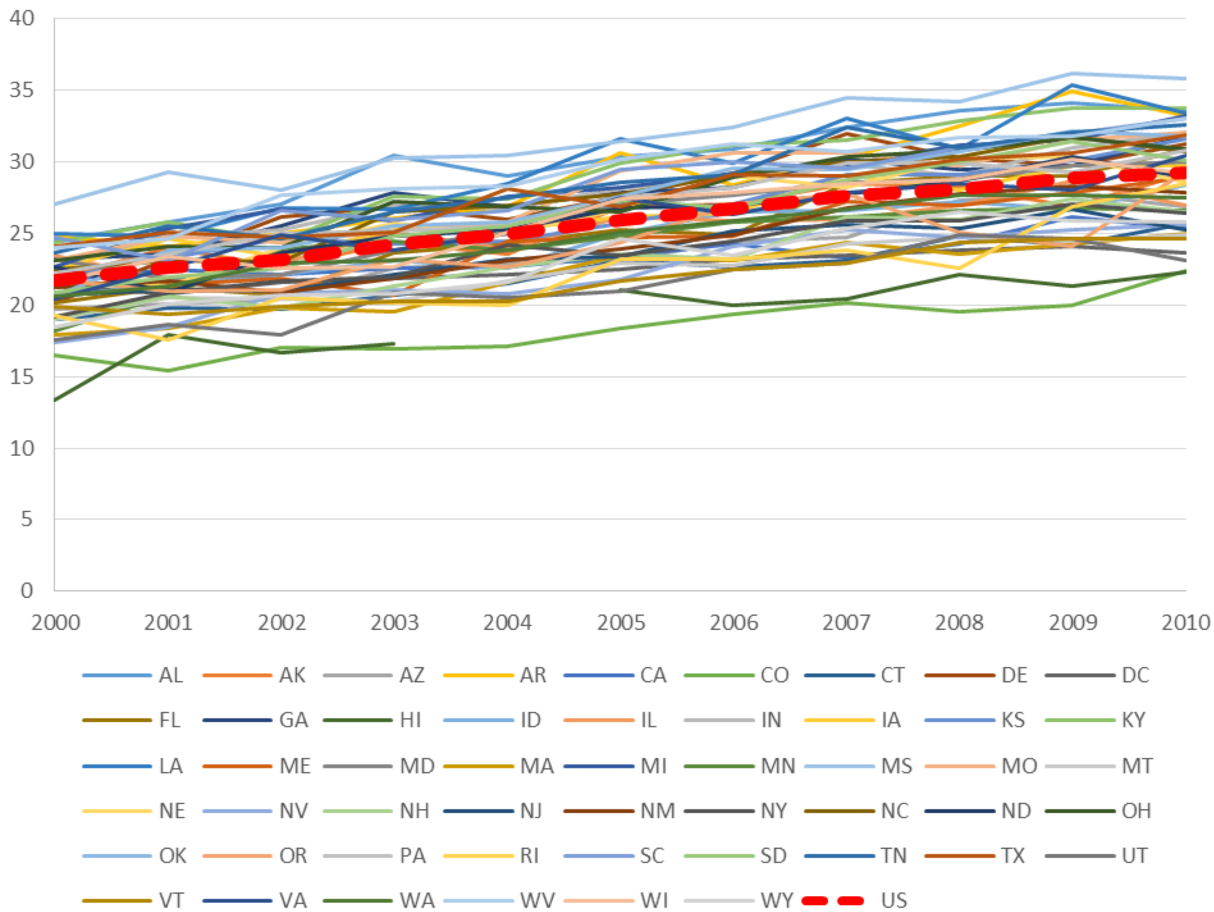


Table 2.2. Simulated State-level Obesity Prevalence Rates, United States 2000-2010.

State/ Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
AL	24.5	25.8	27.1	30.5	29.0	30.4	30.9	32.4	33.6	**34.1**[c]	33.6
AK	21.8	24.0	22.7	24.4	23.6	26.9	27.1	28.5	28.3	26.9	**29.2**[c]
AZ	19.7	20.1	20.4	**22.6**[b]	22.9	23.1	24.5	24.7	27.3	27.8	26.9
AR	24.8	24.1	25.0	26.1	26.9	**30.6**[d]	28.4	30.3	**32.5**[d]	**34.9**[d]	33.2
CA	**21.7**[b]	22.5	**22.1**[d]	22.6	22.7	23.4	24.3	23.3	24.3	26.2	25.4
CO	**16.5**[b]	15.4	17.0	16.9	17.1	18.4	19.4	20.2	19.5	20.0	22.4
CT	**19.0**[b]	**19.8**[c]	**19.7**[b]	20.7	21.5	**23.1**[d]	22.7	23.1	**24.8**[d]	**24.2**[d]	**25.7**[c]
DE	**20.2**[d]	**23.2**[c]	**26.2**[d]	**26.9**[c]	**26.0**[e]	**27.6**[e]	**29.2**[d]	**32.0**[d]	**30.3**[b]	**29.7**[a]	**31.3**[b]
DC	21.3	20.8	21.6	21.9	22.1	22.5	23.2	23.5	23.8	**24.1**[e]	23.7
FL	**20.2**[b]	**21.2**[d]	**20.7**[a]	**23.7**[e]	24.3	**25.3**[d]	**24.9**[c]	**28.5**[e]	**29.0**[e]	**29.0**[c]	**30.9**[e]
GA	**23.2**[a]	23.6	**25.5**[b]	**27.9**[d]	26.9	27.9	28.2	30.2	29.5	**29.7**[a]	31.8
HI	13.4	17.9	16.7	17.3	N.A.*	21.1	20.0	20.4	22.1	21.3	22.3
ID	**20.6**[b]	21.4	**22.1**[c]	23.1	**22.6**[d]	25.0	**26.5**[d]	26.6	**27.2**[b]	26.7	28.4
IL	**23.5**[b]	21.8	22.9	25.1	23.9	26.2	25.9	26.0	27.0	28.7	27.0
IN	22.7	24.7	25.3	27.0	**26.8**[a]	28.1	29.1	**29.8**[c]	**29.0**[b]	31.0	**32.1**[b]
IA	22.5	**24.6**[b]	23.4	25.3	**25.3**[b]	26.2	26.4	29.1	28.0	29.7	29.7
KS	21.9	**23.3**[b]	**24.6**[b]	**24.3**[b]	**24.5**[b]	**25.7**[c]	27.1	**29.1**[b]	29.1	**30.1**[b]	**31.6**[a]
KY	24.4	25.8	24.5	**27.6**[b]	27.4	29.9	**31.2**[d]	**31.5**[c]	**32.9**[c]	33.8	**33.8**[b]
LA	**25.0**[b]	24.8	**26.8**[c]	26.7	28.5	**31.6**[c]	**29.9**[a]	**33.1**[d]	30.9	**35.4**[c]	**33.4**[b]
ME	21.6	**21.4**[a]	21.9	20.7	24.5	**24.7**[b]	**24.8**[a]	**27.2**[c]	27.0	**27.9**[b]	**28.9**[b]
MD	**23.2**[d]	21.9	**22.1**[d]	**23.8**[b]	25.3	**27.1**[d]	**27.7**	**28.6**[c]	**28.8**[c]	**29.7**[d]	**30.0**[c]
MA	**17.9**[a]	**18.4**[c]	**19.8**[b]	**19.5**[d]	**21.6**[e]	**23.5**[e]	**23.1**[d]	**24.4**[d]	**23.6**[c]	**24.3**[d]	**25.0**[b]
MI	22.7	25.4	26.7	25.9	**27.6**[d]	**28.2**[c]	29.2	**29.8**[b]	**31.2**[b]	31.5	**33.2**[a]
MN	18.2	20.7	**23.9**[a]	24.5	23.8	24.8	25.8	26.2	26.6	26.8	26.6
MS	27.1	**29.3**[b]	28.0	**30.3**[c]	30.5	31.4	32.4	**34.5**[b]	34.2	36.2	35.8
MO	23.1	24.8	24.4	25.2	25.8	**29.4**[c]	**30.6**[d]	**30.6**[c]	29.7	31.5	32.1
MT	**19.0**[d]	20.5	20.4	20.3	**21.7**[b]	**22.9**[a]	**22.8**[b]	**24.3**[b]	24.7	24.5	24.9
NE	22.5	21.3	24.0	25.7	**25.0**[c]	26.7	**29.0**[c]	**28.2**[a]	**30.3**[d]	**30.4**[c]	28.6
NV	17.4	18.5	20.8	21.1	20.8	21.8	24.1	25.3	24.7	25.3	**25.6**[b]
NH	19.1	20.6	**19.8**[c]	21.3	22.7	23.6	23.2	26.2	26.0	27.4	26.5
NJ	**20.7**[c]	**21.1**[a]	21.0	**22.1**[d]	**23.2**[b]	**23.4**[b]	**25.2**[e]	25.6	**25.4**[d]	**26.7**[d]	25.3
NM	**21.2**[b]	**21.7**[b]	20.9	**21.9**[c]	**23.1**[b]	**23.9**[c]	**24.9**[b]	**26.8**[a]	**27.8**[b]	**28.3**[d]	**27.9**[c]
NY	19.2	20.9	21.7	22.0	**24.2**[c]	**23.5**[a]	**24.5**[b]	25.9	25.9	**27.1**[d]	**26.4**[c]
NC	22.5	23.1	23.0	**26.5**[c]	**27.0**[d]	**27.8**[c]	**29.1d**	**30.0**[a]	30.4	**31.8**[b]	**30.7**[c]
ND	**22.7**[b]	20.9	23.7	24.8	25.3	26.8	27.0	27.8	28.7	**30.4**[b]	28.9
OH	23.1	24.1	24.0	**27.2**[c]	26.9	26.5	28.9	**30.4**[d]	**30.8**[b]	**31.7**[b]	30.9
OK	20.6	23.8	24.0	25.5	25.8	27.6	29.6	29.5	30.7	32.2	31.8
OR	21.8	21.0	21.1	**23.2**[b]	**22.7**[b]	24.4	**27.1**[c]	27.8	25.1	24.1	29.4
PA	22.2	23.6	**25.0**[a]	25.2	**25.5**[a]	**27.5**[c]	**28.2**[e]	**29.9**[c]	**29.9**[b]	29.3	**30.8**[b]
RI	19.3	17.6	20.5	20.2	20.0	23.2	23.2	23.8	22.6	26.9	28.5
SC	**24.7**[d]	23.1	26.6	**26.0**[b]	**26.6**[b]	29.5	30.0	29.6	31.0	**32.0**[b]	33.1
SD	20.9	22.0	22.6	**24.8**[c]	**25.5**[b]	**27.3**[b]	26.8	28.8	**30.0**[b]	31.4	**30.1**[d]
TN	23.7	**25.5**[b]	24.6	26.5	27.5	28.6	29.1	32.4	31.0	32.1	32.6
TX	24.1	25.1	24.7	25.1	**28.1**[d]	26.9	**29.1**[c]	29.0	30.2	30.6	31.9

Table 2.2. (cont'd).

State/ Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
UT	17.6	18.6	17.9	20.9	20.5	21.0	22.5	22.9	**24.9**[b]	24.6	23.1
VT	**19.9**[b]	**19.4**[c]	19.9	20.3	**20.3**[b]	**21.7**[b]	**22.5**[a]	22.9	24.4	24.6	24.6
VA	**20.4**[b]	22.6	24.9	23.8	**25.0**[b]	27.5	26.3	**27.9**[c]	**28.5**[c]	**28.0**[b]	**30.5**[d]
WA	**20.6**[b]	**21.3**[c]	**22.9**[a]	23.1	**23.8**[c]	**25.1**[d]	**25.9**[c]	26.7	**27.7**[c]	27.7	**27.5**[b]
WV	24.0	24.6	27.7	28.1	28.3	30.2	31.3	30.7	31.7	31.8	33.1
WI	21.6	23.4	22.6	**22.7**[b]	**25.1**[b]	**27.4**[d]	27.9	**28.5**[d]	**28.8**[c]	30.2	29.2
WY	18.5	20.1	20.7	20.8	21.6	24.6	23.5	25.4	**26.5**[a]	25.9	**25.8**[d]
US	21.7	22.6	23.1	24.2	24.9	25.9	26.7	27.6	28.1	28.9	29.2

Note: *BRFSS data were not provided by the CDC.
[a-e] categorize the differences between this simulated state-level obesity prevalence rates and the CDC's estimates accessible at the CDC BRFSS Prevalence & Trends Data website (2015): [a]: less than 0.1%; [b]: 0.2-0.5%; [c]: 0.6-1.0%; [d]: 1.1-2.0%; and [e]: more than 2.0%.

Table 2.3 lists the five states with the highest and lowest obesity prevalence rates during 2000-2010. In 2000, Hawaii (13.4), Colorado (16.5), Nevada (17.4), Utah (17.6), and Massachusetts (17.9) had the lowest obesity prevalence rates. Importantly, Mississippi (27.1), Louisiana (25.0), Arkansas (24.8), South Carolina (24.7) and Alabama (24.5) had the highest obesity prevalence. In contrast in 2010 the states with the lowest obesity prevalence were Hawaii (22.3), Colorado (22.4), Utah (23.1), Washington D.C. (23.7) and Vermont (24.6). The obesity prevalence rates in Nevada and Massachusetts were still below the U.S. mean rate in 2010 but their increasing rates (Nevada 47.1% and Massachusetts 38.8%) were higher than the rates of Washington D.C. (11.2%) and Vermont (23.6), which explains why they dropped off the list of the lowest-five states from the previous time period. In 2010, the states with the highest obesity prevalence were Mississippi (35.8), Kentucky (33.8), Alabama (33.6), Louisiana (33.4), and Arkansas (33.2). South Carolina dropped off the top-five state list because it had a smaller percent increase (34.0%) in obesity compared to Kentucky (50.8%) that was added to the top-five state list.

Table 2.3. Top 5 States with Highest or Lowest Obesity Prevalence Rates, United States 2000-2010.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Lowest	HI 13.4	CO 15.40	HI 16.70	CO 16.90	CO 17.10	CO 18.40	CO 19.40	CO 20.20	CO 19.50	CO 20.00	HI 22.30
	CO 16.5	RI 17.60	CO 17.00	HI 17.30	RI 20.00	UT 21.00	HI 20.00	HI 20.40	HI 22.10	HI 21.30	CO 22.40
	NV 17.4	HI 17.90	UT 17.90	MA 19.50	VT 20.30	HI 21.10	VT 22.50	VT 22.90	RI 22.60	OR 24.10	UT 23.10
	UT 17.6	MA 18.40	CT 19.70	RI 20.20	UT 20.50	VT 21.70	UT 22.50	UT 22.90	MA 23.60	DC 24.10	DC 23.70
	MA 17.9	NV 18.50	MA 19.80	MT 20.30	NV 20.80	NV 21.80	CT 22.70	CT 23.10	DC 23.80	CT 24.20	VT 24.60
Highest	MS 27.10	MS 29.30	MS 28.00	AL 30.50	MS 30.50	LA 31.60	MS 32.40	MS 34.50	MS 34.20	MS 36.20	MS 35.80
	LA 25.00	AL 25.80	WV 27.70	MS 30.30	AL 29.00	MS 31.40	WV 31.30	LA 33.10	AL 33.60	LA 35.40	KY 33.80
	AR 24.80	KY 25.80	AL 27.10	WV 28.10	LA 28.50	AR 30.60	KY 31.20	AL 32.40	KY 32.90	AR 34.90	AL 33.60
	SC 24.70	TN 25.50	LA 26.80	GA 27.90	WV 28.30	AL 30.40	AL 30.90	TN 32.40	AR 32.50	AL 34.10	LA 33.40
	AL 24.50	MI 25.40	MI 26.70	KY 27.60	TX 28.10	WV 30.20	MO 30.60	DE 32.00	WV 31.70	KY 33.80	AR 33.20

2.3.2. Validity Test

To validate the simulated-obesity prevalence results, the simulated statewide rates were compared with those provided by CDC (CDC, 2016) using survey statistics with sampling weights. Table 2.4 summarizes the margins between the simulated-obesity prevalence rates (shown in Table 2.3) and the CDC state-level obesity prevalence rates, available on the CDC's webpage (http://www.cdc.gov/brfss/brfssprevalence/). Overall the simulated-obesity prevalence rates were slightly higher than CDC's obesity prevalence estimates. There were 561 state/year cells (51 States/Washington DC x 11 years from 2000 to 2010) in both tables. Among these, 63% of the simulated obesity prevalence rates

(353 out of 561 cells) were within CDC's 95% confidence intervals. The remaining 37% of simulated obesity prevalence rates (208 out of 561 cells) were not within CDC's 95% confidence intervals; however, the differences between the two estimates were not greater than 1.0% in the majority (73%) of the 208 case-comparisons. The findings demonstrate the validity of the spatial microsimulation approach in the estimation of obesity prevalence.

Table 2.4. Differences in this Study's Simulation and the CDC's Statistical Estimation of Obesity Prevalence Rates.

Differences	≤0.1%[a]	0.2-0.5%[b]	0.6-1.0%[c]	1.1-2.0%[d]	2.0%≥[e]
N	23 (11%)	75 (36%)	53 (26%)	46 (22%)	11 (5%)

[a-e] categorize the differences between this simulated state-level obesity prevalence rates and the CDC's estimates accessible at the CDC BRFSS Prevalence & Trends Data website (2015): [a]: less than 0.1%; [b]: 0.2-0.5%; [c]: 0.6-1.0%; [d]: 1.1-2.0%; and [e]: more than 2.0%.
Source: The authors & CDC (2015)

2.3.3. County-level Analyses

Figure 2.2 illustrates the simulated obesity prevalence rates at the county level across the United States by decade. As obesity prevalence increased in all states, the numbers of higher obesity prevalence counties also increased. In 2000, county-states in the Southeast U.S. along the Mississippi River, particularly in Mississippi had the highest obesity prevalence rates. By 2003, higher obesity prevalence diffused eastward to Alabama and across the Southern states, through West Virginia. In particular, counties along the Appalachian Mountains and the southern Piedmont started to form a linear trend of higher obesity prevalence. In 2004-2005 more and more counties in the South and the Midwest had at least 25.0 or higher obesity prevalence. Counties located in the Appalachian Plateau in Kentucky and West Virginia and Alaska also experienced rapid increases in obesity prevalence. Counties in Alaska also showed a consistent increasing trend in obesity prevalence. By 2005, obesity prevalence was observably high across the East and Midwestern states. After 2006, obesity prevalence was exceedingly high across U.S. counties with the exception of western county-states, in particular Colorado with the lowest obesity prevalence. In 2007, the majority of Colorado counties however, reached 22.5% or higher obesity prevalence. By 2010, only 10 states in the far Northeast, West and Hawaii did not have counties with obesity prevalence rates > 30%. Counties in most Southern and many Midwestern states had obesity prevalence rates over 32.5% while Western states, especially, Colorado, Utah, Nevada and Hawaii had many counties with persistently lower obesity prevalence. Importantly many counties encompassing American Indian reservation sites, including Shannon (Oglala Lakota) County, South Dakota (SD), (36.54), Apache County, Arizona (AZ) (36.09) and neighboring Mckinley County, New Mexico (NM) (34.07), and Navajo County, AZ (29.09) in the four-corners (excluding Colorado) had disproportionately higher obesity prevalence rates (except 2007) across the decade.

Figure 2.2. Estimated Obesity Prevalence Rates at the County Level, United States 2000-2010.

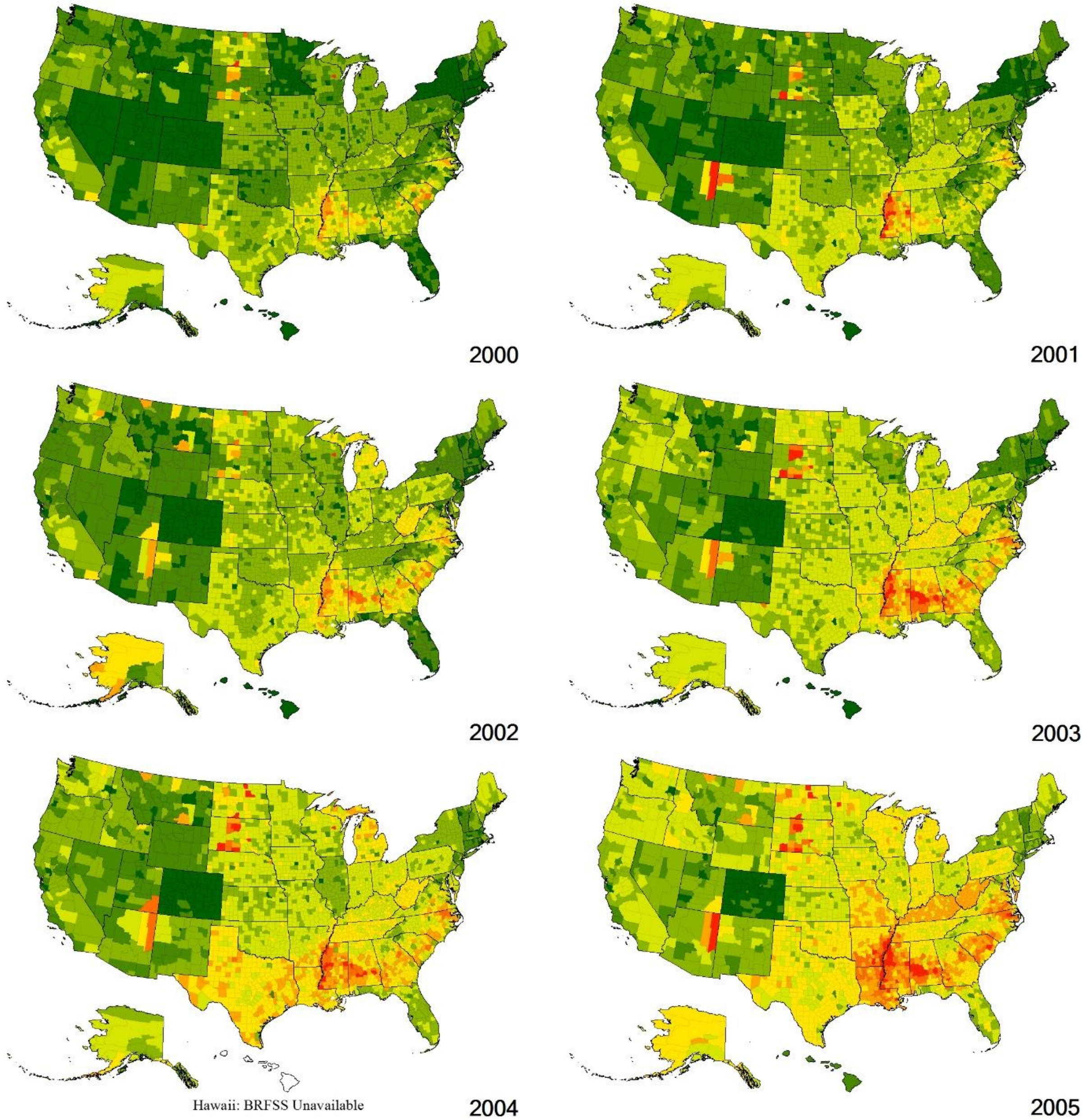
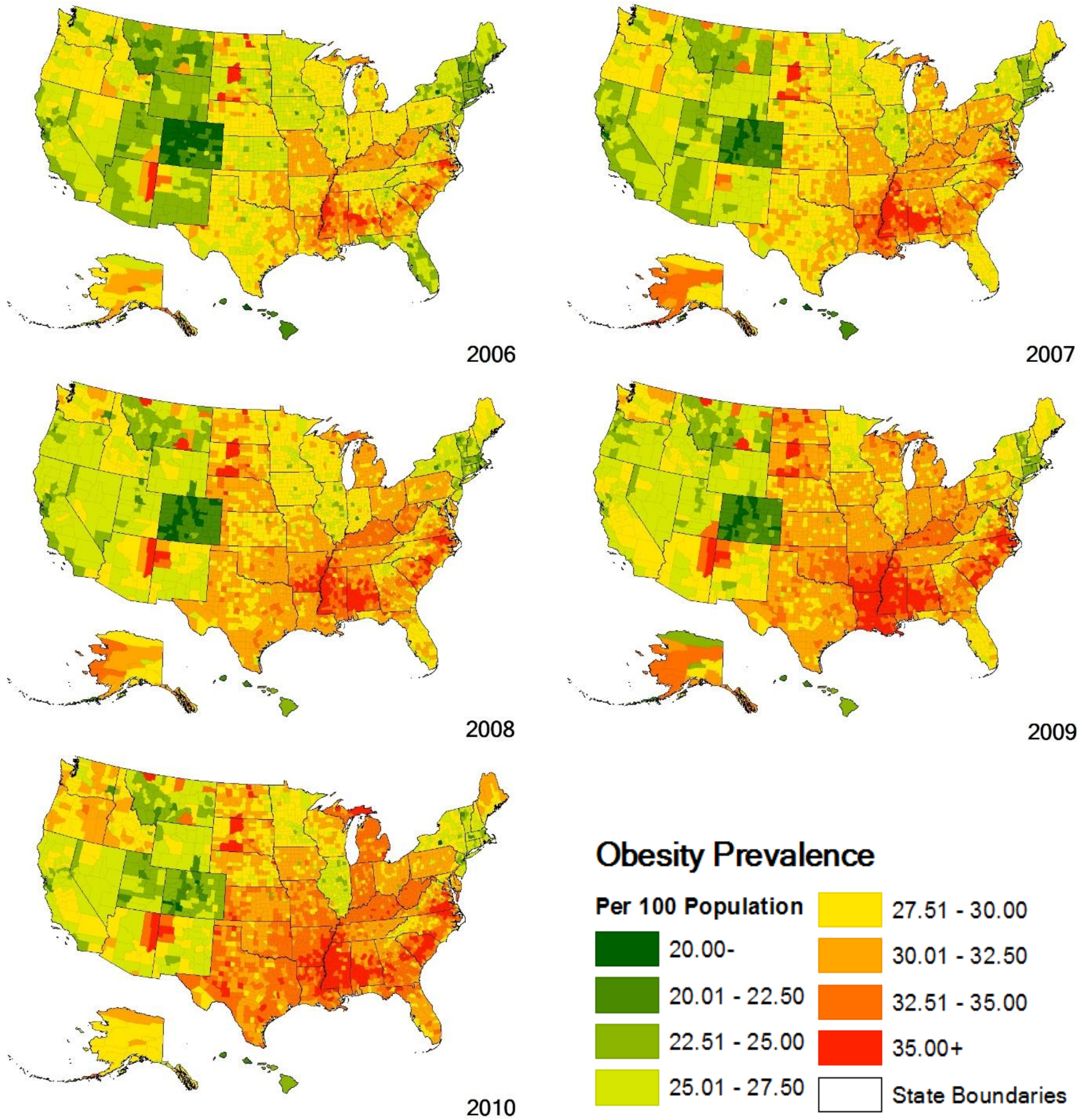


Figure 2.2. (cont'd).



Source: The Author

Tables 2.5a and 2.5b summarize the top 15 lowest and highest obesity prevalence counties, between 2000 and 2010. In 2000, the lowest five obesity prevalence counties were Kalawao, Hawaii (HI) (10.10), Honolulu, HI (13.11), Kauai, HI (13.70), Gunnison, Colorado (CO) (13.80), and Radford, Virginia (VA) (13.85). Many counties in Colorado, including Gunnison, Summit, Boulder, and San Miguel were among the top 15 lowest obesity prevalence counties during 2001 to 2010. On the contrary, in 2000 the top five counties with the highest obesity prevalence rates were Menominee, Wisconsin (WI) (36.18), Sioux, North Dakota (ND) (35.32), Jefferson, Mississippi (MS) (34.50), Rolette, ND (33.74), and Allendale, South Carolina (SC) (33.68). Over the 10 years, many counties remained in the top-highest or lowest obesity prevalence tables, e.g., counties in Colorado such as Gunnison, Boulder and San Miguel). In contrast, many counties in Mississippi, Alabama, and South Dakota, including Humphreys, MS, Greene, Alabama (AL) and Shannon, SD remained in the highest-obesity prevalence table over the study period.

Table 2.5a. Top 15 Lowest Obesity Prevalence Counties, United States 2000-2010.

2000	2001	2002	2003	2004	2005
Kalawao, HI (10.20)	Gunnison, CO (11.98)	Gunnison, CO (14.34)	Summit, CO (14.31)	Hinsdale, CO (13.46)	Boulder, CO (16.78)
Honolulu, HI (13.10)	Summit, CO (12.54)	Pitkin, CO (14.60)	Pitkin, CO (14.44)	Boulder, CO (14.78)	Gunnison, CO (17.05)
Kauai, HI (13.70)	Boulder, CO (12.71)	Boulder, CO (14.66)	Gunnison, CO (14.70)	Gunnison, CO (15.10)	Douglas, CO (17.07)
Gunnison, CO (13.80)	Pitkin, CO (13.04)	Summit, CO (14.78)	Boulder, CO (14.73)	Larimer, CO (15.47)	Larimer, CO (17.23)
Radford, VA (13.90)	Mineral, CO (13.31)	Douglas, CO (15.13)	San Miguel, CO (14.84)	Mineral, CO (15.58)	Pitkin, CO (17.25)
Madison, ID (13.90)	Larimer, CO (13.34)	Larimer, CO (15.26)	Douglas, CO (15.04)	Summit, CO (15.62)	Summit, CO (17.28)
Maui, HI (14.10)	San Miguel, CO (13.44)	Routt, CO (15.26)	San Juan, UT (15.07)	Pitkin, CO (15.68)	San Juan, CO (17.33)
Hawaii, HI (14.10)	Routt, CO (13.70)	San Miguel, CO(15.31)	Eagle, CO (15.41)	Douglas, CO (15.97)	San Miguel, CO (17.64)
Albany, WY (14.50)	Douglas, CO (13.82)	Mineral, CO (15.40)	Routt, CO (15.51)	San Miguel, CO (16.06)	Broomfield, CO (17.75)
Boulder, CO (14.50)	Eagle, CO (14.07)	San Juan, CO (15.66)	Larimer, CO (15.61)	Routt, CO (16.24)	Routt, CO (17.76)
Madison, ID (13.90)	Hinsdale, CO (14.19)	Eagle, CO (15.68)	La Plata, CO (16.29)	Madison, ID (16.25)	Cheyenne, CO (17.79)
Maui, HI (14.10)	La Plata, CO (14.29)	Cache, UT (15.74)	Jefferson, CO (16.46)	Eagle, CO (16.46)	Eagle, CO (17.91)
Hawaii, HI (14.10)	Jefferson, CO (14.68)	La Plata, CO (15.91)	Grand, CO (16.53)	Archuleta, CO (16.51)	La Plata, CO (17.98)
Albany, WY (14.50)	Grand, CO (14.84)	Utah, UT (16.04)	Arapahoe, CO (16.61)	La Plata, CO (16.51)	Cache, UT (18.01)
Boulder, CO (14.50)	Williamsburg City, VA (14.84)	Hinsdale, CO (16.09)	El Paso, CO (16.69)	Cheyenne, CO (16.54)	Arapahoe, CO (18.14)

2006	2007	2008	2009	2010
Mineral, CO (15.92)	Radford, VA (17.17)	Gunnison, CO (16.89)	Boulder, CO (17.36)	Mineral, CO (18.86)
Hinsdale, CO (16.93)	Boulder, CO (17.41)	Boulder, CO (17.06)	Gunnison, CO (17.69)	Boulder, CO (19.53)
Boulder, CO (17.13)	Lexington, VA (17.71)	San Miguel, CO (17.78)	Mineral, CO (18.06)	San Miguel, CO (19.62)
Gunnison, CO (17.55)	Gunnison, CO (17.82)	Larimer, CO (17.93)	San Juan, CO (18.17)	Tompkins, NY (19.86)
Douglas, CO (17.56)	Douglas, CO (18.31)	Douglas, CO (17.99)	Larimer, CO (18.43)	Hinsdale, CO (19.98)
Larimer, CO (17.70)	Larimer, CO (18.31)	Broomfield, CO (18.12)	San Miguel, CO (18.48)	Ouray, CO (20.09)
Summit, CO (17.72)	Mineral, CO (18.32)	Mineral, CO (18.34)	Douglas, CO (18.51)	Gunnison, CO (20.22)
Pitkin, CO (17.83)	Broomfield, CO (18.59)	Routt, CO (18.58)	Broomfield, CO (18.60)	San Juan, CO (20.25)
Broomfield, CO (18.06)	Harrisonburg, VA (18.72)	Summit, CO (18.63)	Summit, CO (18.90)	Broomfield, CO (20.29)
Routt, CO (18.12)	Routt, CO (18.73)	Pitkin, CO (18.97)	Kiowa, CO (18.94)	Albany, WY (20.45)
Archuleta, CO (18.21)	Pitkin, CO (18.74)	Eagle, CO (19.00)	Routt, CO (19.27)	Douglas, CO (20.48)
Eagle, CO (18.35)	San Francisco, CA (18.80)	Jefferson, CO (19.16)	Ouray, CO (19.29)	Larimer, CO (20.74)
San Miguel, CO (18.35)	Williamsburg City, VA (18.86)	Ouray, CO (19.21)	Eagle, CO (19.30)	San Francisco, CA (21.15)
Clear Creek, CO (18.54)	Summit, CO (18.88)	Hinsdale, CO (19.40)	Pitkin, CO (19.35)	Santa Clara, CA (21.24)
Cheyenne, CO (18.64)	Santa Clara, CA (18.97)	Archuleta, CO (19.46)	Jefferson, CO (19.60)	Lexington, VA (21.49)

Table 2.5b. Top 15 Highest Obesity Prevalence Counties, United States 2000-2010.

2000	2001	2002	2003	2004	2005
Menominee, WI (36.18)	Jefferson, MS (37.64)	Menominee, WI (46.48)	Shannon, SD (40.01)	Menominee, WI (43.67)	Rolette, ND (43.48)
Sioux, ND (35.32)	Holmes, MS (36.62)	Greene, AL(36.42)	Buffalo, SD (38.73)	Sioux, ND (43.18)	Sioux, ND (42.10)
Jefferson, MS (34.5)	Humphreys, MS (36.62)	Macon, AL (34.89)	Greene, AL (38.21)	Rolette, ND (41.63)	Macon, AL (41.03)
Rolette, ND (33.74)	Shannon, SD (36.54)	Hancock, GA (34.54)	Dewey, SD (38.18)	Jefferson, MS (37.33)	Greene, AL (40.14)
Allendale, SC (33.68)	Noxubee , MS (36.21)	Lowndes, AL (34.28)	Bullock, AL (38.15)	Greene, AL (37.06)	Sumter, AL (38.69)
Humphreys, MS (33.49)	Tunica, MS (36.11)	Wilcox, AL (34.21)	Ziebach, ND (38.09)	Buffalo, SD (36.74)	Bullock, AL (38.52)
Williamsburg, SC (33.21)	Apache, AZ (36.09)	Rolette, ND (33.87)	Todd, SD (37.94)	Humphreys, MS (36.68)	Wilcox, AL (38.33)
Noxubee , MS (32.77)	Coahoma, MS (35.66)	Perry, AL (33.84)	Lowndes, AL (37.71)	Noxubee , MS (36.36)	Buffalo, SD (38.27)
Tunica, MS (32.60)	Quitman, MS (35.44)	Jefferson, MS (33.83)	Wilcox, AL (37.37)	Dewey, SD (36.33)	Lowndes, AL (38.22)
Quitman, MS (32.60)	Claiborne, MS (35.37)	Sumter, AL (33.69)	Sumter, AL (36.88)	Shannon, SD (36.30)	Phillips, AR (38.22)
Holmes, MS (32.55)	Sharkey, MS (35.2)	Noxubee, MS (33.67)	Macon, AL (36.64)	Lowndes, AL (36.06)	Humphreys, MS (37.65)
Lee, SC (32.53)	Wilkinson, MS (35.01)	Williamsburg, SC (33.56)	Perry, AL (36.62)	Bullock, AL (35.91)	Perry, AL (37.61)
Shannon, SD (32.50)	Todd, SD (34.85)	Humphreys, MS (33.53)	Jefferson, MS (36.59)	Benson, ND (35.86)	Dallas, AL (37.60)
Buffalo, SD (32.43)	Washington, MS (34.83)	Allendale, SC (33.47)	Tunica, MS (36.46)	Holmes, MS (35.83)	Petersburg, VA (37.52)
Wilkinson, MS (32.33)	Tallahatchie, MS (34.36)	Bullock, AL (33.41)	Holmes, MS (36.37)	Coahoma, MS (35.67)	Chicot, AR (37.44)

2006	2007	2008	2009	2010
Sioux, ND (47.55)	Jefferson, MS (41.99)	Buffalo, SD (41.83)	Menominee, WI (48.39)	Petersburg, VI (44.07)
Rolette, ND (43.04)	Holmes, MS (41.85)	Wilcox, AL (41.78)	Rolette, ND (45.83)	Todd, SD (43.52)
Loving , TX (41.03)	Claiborne, MS (41.82)	Greene, AL (41.29)	Sioux, ND (45.80)	Shannon, SD (42.57)
Todd, SD (40.02)	Shannon, SD (41.13)	Shannon, SD (41.13)	Shannon, SD (43.12)	Macon, AL (42.22)
Shannon, SD (39.93)	Humphreys, MS (40.76)	Todd, SD (40.74)	Wilcox, AL (43.09)	Wilcox, AL (41.90)
Buffalo, SD (39.25)	Coahoma, MS (40.44)	Lowndes, AL (40.62)	Humphreys, MS (42.75)	Lowndes, AL (41.88)
Greene, AL (38.83)	Noxubee , MS (40.44)	Ziebach, ND (40.30)	Issaquena, MS (42.61)	Holmes, MS (41.88)
Benson, ND (38.75)	Tunica, MS (40.44)	Bullock, AL (40.08)	Phillips, AR (42.53)	Ziebach, SD (41.84)
Dewey, SD (38.40)	Sharkey, MS (40.44)	Dallas, AL (39.87)	Holmes, MS (42.30)	Humphreys, MS (41.76)
Humphreys, MS (38.06)	Issaquena, MS (40.17)	Macon, AL (39.49)	Greene, AL (42.26)	Greene, AL (41.75)
Hancock, GA (37.90)	Wilcox, AL (40.15)	Perry, AL (39.18)	Lee, AR (42.26)	Claiborne, MS (41.34)
Wilcox, AL (37.55)	Leflore, MS (40.15)	Humphreys, MS (38.93)	Lowndes, AL (42.01)	Buffalo, SD (41.32)
Ziebach, ND (37.34)	Quitman, MS (40.07)	Alleghany, NC (38.86)	Noxubee , MS (41.92)	Sussex, VA (41.30)
Holmes, MS (37.33)	Greene, AL (39.99)	Hale, AL (38.85)	Quitman, MS (41.91)	Rolette, ND (41.12)
Macon, AL (37.32)	Wilkinson, MS (39.94)	Sumter, AL (38.85)	Jefferson, MS (41.63)	Quitman, MS (41.11)

Figure 2.3 illustrates the estimated obesity clusters and outliers using Anselin Local Moran’s I, from 2000 to 2010. The global Moran’s I values ranged 0.48 to 0.54 indicating that there was clustering between counties across the U.S. The results support the findings in state and county-level analyses in the previous sections. Counties with High-High spatial autocorrelation were observed along the Mississippi River and the Appalachian Mountains, especially many counties in the Southern states of Alabama, Arkansas, Georgia, Louisiana, Kentucky and West Virginia. In North and South Dakota, Native American reservation sites and rural counties in Michigan and Texas had High-High clusters. On the contrary, many counties in Colorado, Utah, Nevada, Montana and the Northeast states, including New York, Massachusetts, Connecticut, Vermont, Rhode Island, and New Hampshire had Low-Low persistent clusters during the study time period, 2000-2010.

Figure 2.3. Estimated Obesity Prevalence Rates County-Clusters and Outliers Using Anselin Local Moran's I, United States 2000-2010.

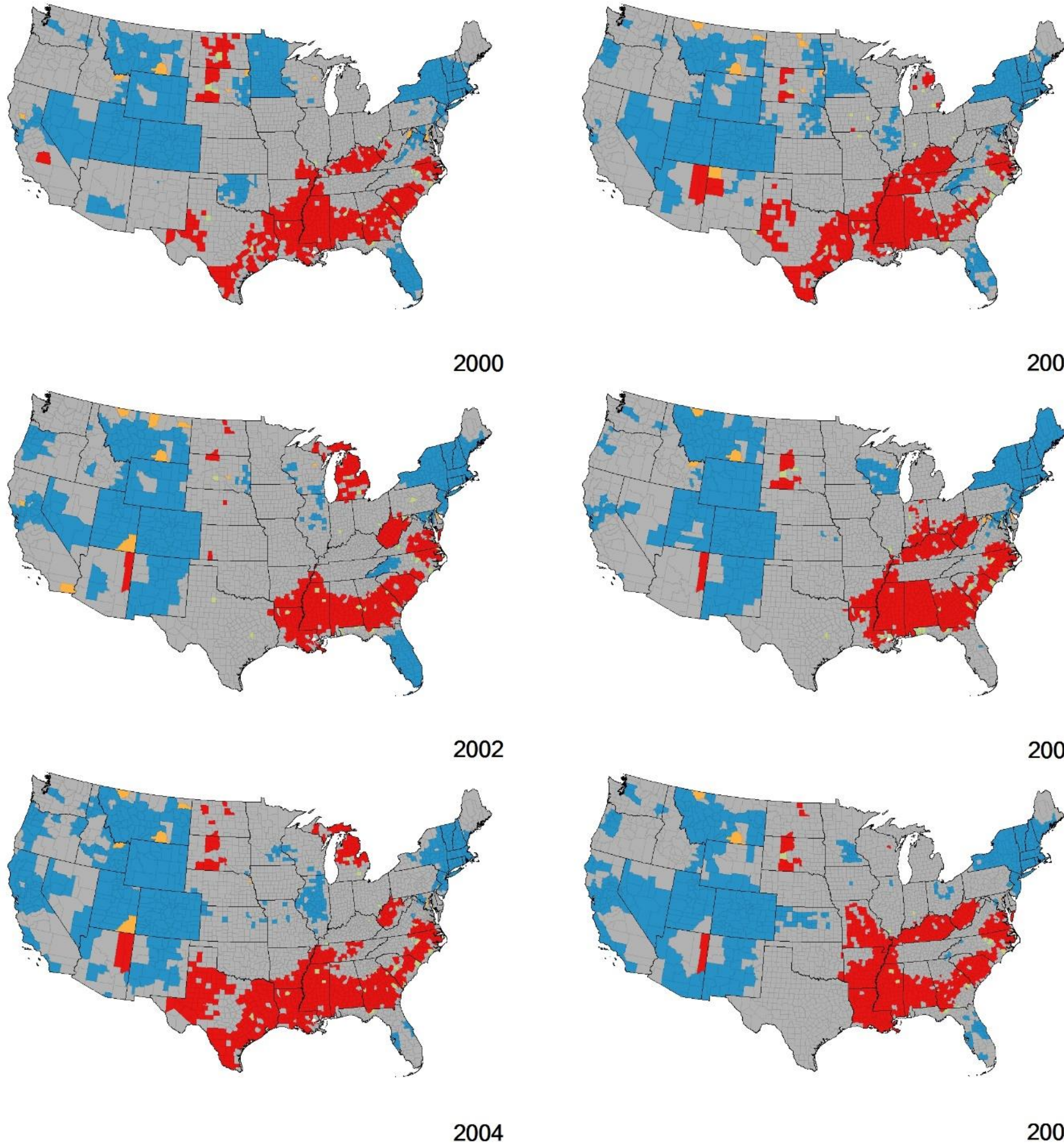
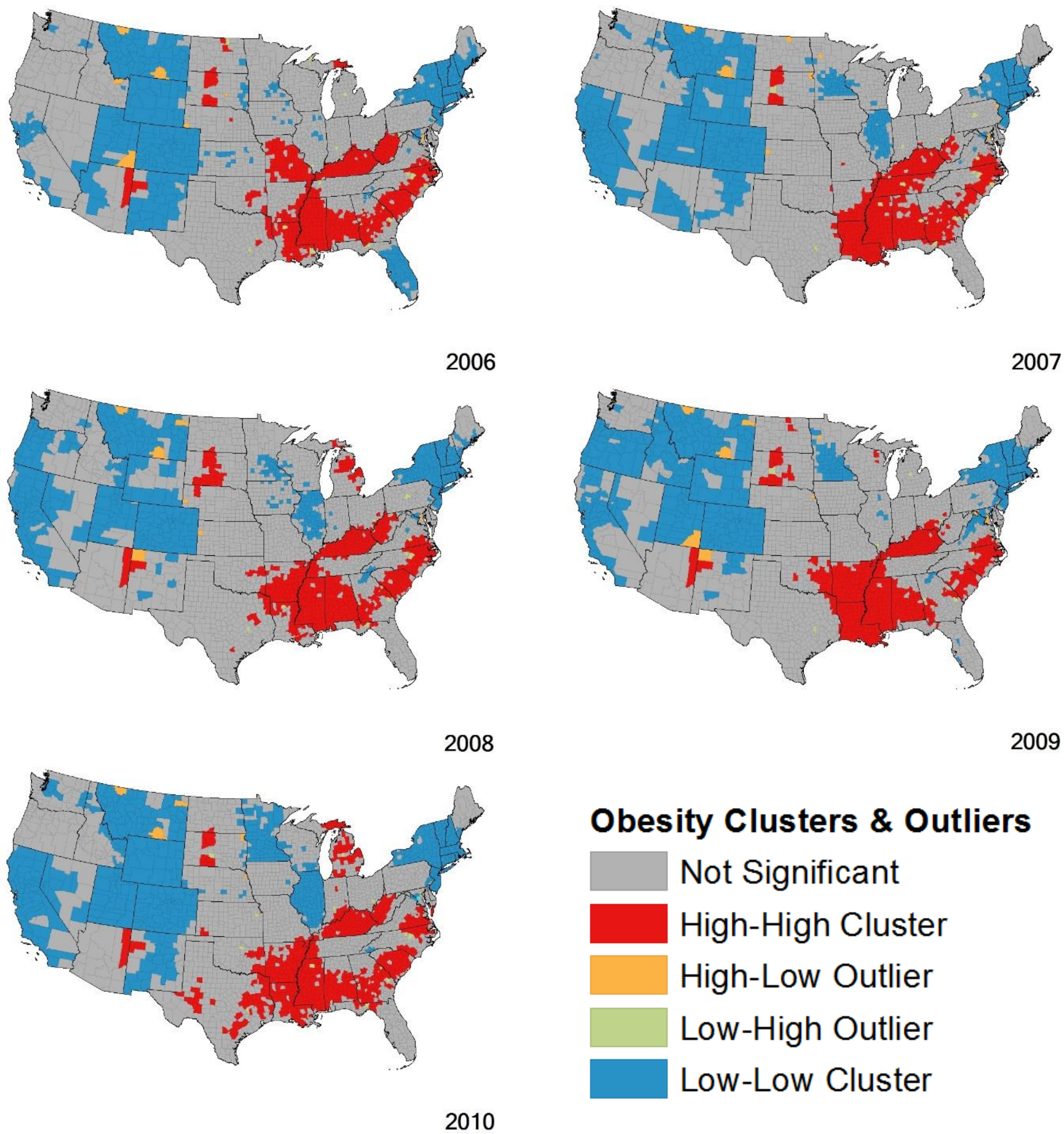


Figure 2.3. (cont'd).



Source: the author.

2.4. Discussion & Limitation

Adult obesity prevalence is rising worldwide and is becoming a major public health problem in many countries. It is difficult however, to monitor changes in obesity at the local level due to data unavailability. This study exemplified and validated the use of spatial microsimulation to report persistent and rising trends in obesity prevalence at the county level in the United States. Other countries may adopt this method using national health surveys and census data to monitor obesity and target areas for culturally appropriate interventions.

The important findings in this U.S. study are summarized below: first, counties in southern states, especially along the Mississippi River and the Appalachian Mountains had higher obesity prevalence rates during the 10-year study time period compared to other county-state regions. This highest obesity prevalence may be explained by known risk factors for obesity including but not limited to low socioeconomic status, lower education and families with parents who are not married (Wang & Beydoun, 2007; Akil & Ahmad, 2011) compared to other regions. Future interventions could target these social factors (increase education and employment opportunities and help with family stability in Southern county-states to improve access to healthy food choices and reduce the burden of rising and persistent obesity prevalence.

Second obesity prevalence in many counties in Midwestern states also increased from 2000 to 2010. Contributing factors may include the increase in middle-aged population, urban segregation and concentrated poverty and poor rural populations as a result of deindustrialization. Future obesity interventions could focus on identifying the association between local obesity prevalence and multifaceted obesity risk factors in urban centers and rural areas, including fruit/vegetable consumption, walkability, public transportation use, and the accessibility to healthy food options and health care to reduce obesity prevalence in county-states in the Midwest region.

Third, counties near or within American Indian reservation sites were also identified as having higher obesity prevalence. American Indian reservation sites are, in general, geographically isolated from urbanized areas, which may be a major hindrance to good access to health care, fresh groceries, higher education and employment opportunities. In addition, the American Indian population in the U.S. has higher chronic disease prevalence compared with other racial/ethnic groups (Indian Health Service, 2015) which may be associated with increased obesity. For example, American Indian or Alaska Native adults have 60% higher obesity prevalence and 250% higher diabetes prevalence compared with non-Hispanic Whites (U.S. Department of Health and Human Services Office of Minority Health, 2015).

Fourth, there were distinct differences in obesity prevalence across state boundaries during the study years. For example, Colorado had counties with lower obesity prevalence rates, whereas there were many counties with higher obesity prevalence rates across the Colorado’s border lines in Kansas, also during the study period. These differences can be found even in the same geographical regions. Another example, Minnesota and Illinois appears to have more counties with lower obesity prevalence rates compared with the other Midwestern states. Although federal and state governments share the same public health goals and objectives to address obesity and other chronic diseases, there might be differences in policy and programmatic priorities, organizational culture and performance, and/or the amount of resources allocated to state health departments. In addition, there may exist differences in environments and cultures that contribute to obesity that are unobservable by conventional research methods. National-level obesity studies may be necessary to further understand these distinct differences in obesity prevalence across state boundaries. Finally, this study found that county level obesity prevalence rates fluctuated from year to year even though there was an overall, increasing trend. This finding implies that obesity prevalence would be better understood with a multiple year's trend instead of focusing on single year prevalence rates.

There are limitations of this study. First there exists remaining differences in this study's simulated obesity prevalence and CDC's statistical-estimated obesity prevalence rates at the state level. These differences may be attributed to difference in the underlying population datasets and survey weights. Second, the findings from this study were based on the constraint variables used between the BRFSS and census data. Spatial microsimulation results in the future may be different with a different set of constraint variables. Finally, this study was conducted at the county level and a change in scale or zone design may result in different obesity prevalence results due to the modifiable areal unit problem (Swift, Liu, & Uber, 2014).

Despite of these limitations the current study contributes to the study of obesity in several ways. First this study provided a comprehensive illustration of spatial and spatio-temporal variations in estimated obesity prevalence at the county level in the United States from 2000 to 2010. These findings demonstrate the benefit of using a spatial microsimulation approach to estimate and monitor obesity prevalence at the local level for programmatic and policy makers implement area-specific interventions at the local level in the United States. Second this study revealed the usability of the spatial microsimulation technique in public health research. Recently more and more countries have adopted public health surveys like the BRFSS to monitor the health of the public and implement adequate policy interventions (CDC, 2011). Since most public health surveys innately represent a broader level of geography (e.g. BRFSS officially represents each state-level health conditions), spatial microsimulation would make it possible to estimate local level health conditions in a reliable, cost-efficient way by combining existing survey and census datasets. For example a small city or municipal government may estimate obesity or other health condition prevalence rates without conducting a costly survey by combining their national health survey and census datasets using the spatial microsimulation approach. Finally this study has shown the possibilities of combining population health and environmental datasets at the local level. With progress in geospatial technology and quantitative methods it has become much easier to have downscaled environmental datasets by which to integrate. In contrast obtaining a local level population health dataset is still challenging for researchers and policy makers due to the cost and confidentiality constraints.

2.5. Conclusions

This study reported the temporal, spatial and spatio-temporal changes in obesity prevalence at the county level from 2000 to 2010 by utilizing a spatial microsimulation approach. The findings from this study showed rising obesity prevalence at the local level across the United States with substantial regional and local variations. These findings are important for public health departments and policy makers to address the rising obesity rates and related comorbidities in their states. This study also demonstrated that spatial microsimulation is an alternative analysis tool for health geographers and public health practitioners to examine changes in disease prevalence at the local level.

3. STUDY II: IMPACTS OF FEDERALLY FUNDED STATE OBESITY PROGRAMS ON ADULT OBESITY PREVALENCE IN THE UNITED STATES, 1998-2010.

ABSTRACT

Since 2000 the Division of Nutrition, Physical Activity, and Obesity (DNPAO) Centers for Disease Control and Prevention (CDC) has funded 37 state health departments to address the obesity problems in their states. The purpose of this research is to investigate the impacts of CDC-DNPAO statewide intervention programs on adult obesity prevalence in the United States. This study utilized a set of a logistic modeling and a quasi-experimental analysis to evaluate overall effect of CDC-DNPAO before and after its implementation using the CDC's Behavioral Risk Factor Surveillance System, 1998-2010. Living in a state with CDC-DNPAO program was associated with 2.4-3.8% reduction in the odds of being obese during 2000-2010. The effect of CDC-DNPAO is variant with the total duration of implementation. A Quasi-experimental analysis found that longer duration of CDC-DNPAO implementation does not necessarily occurs with the reduction in the odds of being obese. Statewide obesity interventions can contribute to reduce in the odds of being obese in the United States. Future research should evaluate CDC-DNPAO programs in detail with other important environmental obesity risk factors.

3.1. Introduction

Obesity is a major health problem in the United States, resulting in additional premature deaths and public health spending. The adult obesity prevalence rate in the United States has more than doubled from the early 1970s (14 per 100 population) to 2010 (36 per 100 population). (Centers for Disease Control and Prevention (CDC), 2012a). In 1999 the U.S. Congress authorized the CDC to establish the Division of Nutrition, Physical Activity, and Obesity (DNPAO) to address the growing obesity epidemic and other chronic diseases in response to "complex obesogenic environmental challenges (Hamre et al., 2007; CDC, 2012b). The theoretical framework within which CDC-DNPAO programs were designed is a five-level Social-Ecological Model (SEM), first proposed by McLeroy et al. (1988), which implies that human behavior can be influenced by distinct yet intertwined levels of society (Hamre et al., 2007). From the SEM perspective a society has five levels of interactions that include intrapersonal, interpersonal, organizational, community, and society (CDC, 2013). Through the DNPAO the CDC granted state health departments with federal funding to implement obesity-related health promotion and intervention programs (CDC, 2007; Hamre et al., 2007). CDC-DNPAO programs are cooperative agreements between the CDC and funded state health departments (CDC, 2007). Specifically, the purpose of the funded programs is to "reduce the prevalence of obesity and other chronic diseases by changing Americans' behaviors and environments" (Hamre et al., 2007). Moreover, these programs aim to decrease current obesity prevalence, increase physical activity, and improve dietary habits (CDC, 2012b).

Five states received the initial pool of funding but between 2000 and 2010 an additional 37 states have developed and implemented science-based nutrition and physical activity interventions with CDC-DNPAO programmatic funding (Hamre et al., 2007; Hersey et al., 2011). The program funding has been granted at either Capacity Building (CB) or Basic Implementation (BI) levels. The CB funding is intended to help states build essential infrastructure and partnership including staffing, training, and developing a state plan. The BI funding is for expanding existing state plans through states' policy implementation and the collaboration with government and private sectors (Hamre et al., 2007; Hersey et al., 2011). The amount of funding varies by level. In 2007, CB funding ranging from $270,000 to $526,000 per year (the median, $450,000) and BI funded programs ranging from $800,000 to $1,100,000 (the median, $1,000,000) (Hamre et al., 2007; The National Alliance for Nutrition and Activity, 2012).

Each funded state program develops its own nutrition, physical activity, and obesity plans through public and/or private partnerships. Programmatic interventions are therefore, state-specific to meet the needs of their populations. CDC requests all funded states to submit annual-fiscal performance reports on the effectiveness of the CDC-DNPAO program in their state. Based on these reports and new requests from other states, CDC-DNPAO will make funding decisions to continue the support for existing participants, remove the support or provide new funding for non-participating states (Yee et al., 2006; Hamre et al., 2007). Table 3.1 summarizing the CDC-DNPAO funded and non-funded states by cumulative duration and duration by year of the program participation.

The purpose of this research is to investigate the impacts of CDC-DNPAO statewide intervention programs on the adult obesity in the United States. This study utilizes longitudinal survey data from 1998 to 2010 and a quasi-experimental study design comparing before-after obesity interventions to produce valid results in naturally occurring circumstances (Petticrew et al., 2005; Craig et al., 2010).To-date there are no studies to my knowledge that have evaluated the impacts of CDC-DNPAO funded programs on adult obesity in the United States. While each state's annual performance report is submitted to CDC-DNPAO and provides important information on the effectiveness of their obesity program, it is still unknown what the impacts are of state-county interventions on adult obesity in the U.S. Understanding the impact of CDC-DNPAO obesity programs on the geography of obesity prevalence is extremely important for targeting where programs are successful and where future intervention efforts should be focused.

Table 3.1. CDC-DNPAO and Non-DNPAO States, United States from 2000 to 2010.

Current DNPAO states	No Interruption‡	11 years	MA, NC, TX (2000-2010)*
		10 years	CO, WA (2001-2010)
		8 years	GA, NY, SC, WI, WV (2003-2010)
		7 years	AR, IA (2004-2010)
		3 years	IN, MN, NE, NH, NJ, TN, UT (2008-2010)
		2 years	HI (2009-2010)
	With Interruption	10 years	RI (2000-2002, 2004-2010)
		9 years	MI, MT (2001-2002, 2004-2010)
		7 years	NM (2003-2007, 2009-2010)
		6 years	CA (2000-2002, 2008-2010)
Non-current DNPAO states	Stopped	7 years	FL, PA (2001-2007)
		5 years	AZ, IL, KY, ME, MD, MO, OR (2003-2007)
		4 years	SD, OK, VT (2004-2007)
	Never participated	0 year	AL, AK, CT, DE, ID, KS, LA, MS, NV, ND, OH, VA, WY

Source: The authors.
Note: ‡ Interruption means that there is one or multiple year(s) of discontinuation of funding.
* indicates specific years of the CDC-DNPAO program implementation in each state.

Table 3.2. States with DNPAO Programs and their Duration, United States 1999 to 2010.

States	Before 1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
MA	No DNPAO	O	O	O	O	O	O	O	O	O	O	O
NC		O	O	O	O	O	O	O	O	O	O	O
TX		O	O	O	O	O	O	O	O	O	O	O
RI		O	O	O	-	O	O	O	O	O	O	O
CO		-	O	O	O	O	O	O	O	O	O	O
WA		-	O	O	O	O	O	O	O	O	O	O
MI		-	O	O	-	O	O	O	O	O	O	O
MN		-	O	O	-	O	O	O	O	O	O	O
FL		-	O	O	O	O	O	O	O	-	-	-
PA		-	O	O	O	O	O	O	O	-	-	-
IL		-	-	-	O	O	O	O	O	-	-	-
KY		-	-	-	O	O	O	O	O	-	-	-
ME		-	-	-	O	O	O	O	O	-	-	-
MD		-	-	-	O	O	O	O	O	-	-	-
MO		-	-	-	O	O	O	O	O	-	-	-
AZ		-	-	-	O	O	O	O	O	-	-	-
OR		-	-	-	O	O	O	O	O	-	-	-
SD		-	-	-	-	O	O	O	O	-	-	-
VT		-	-	-	-	O	O	O	O	-	-	-
OK		-	-	-	-	O	O	O	O	-	-	-
NM		-	-	-	O	O	O	O	O	-	O	O
GA		-	-	-	O	O	O	O	O	O	O	O
NY		-	-	-	O	O	O	O	O	O	O	O
SC		-	-	-	O	O	O	O	O	O	O	O
WI		-	-	-	O	O	O	O	O	O	O	O
WV		-	-	-	O	O	O	O	O	O	O	O
AK		-	-	-	-	O	O	O	O	O	O	O
IA		-	-	-	-	O	O	O	O	O	O	O
CA		O	O	O	-	-	-	-	-	O	O	O
IN		-	-	-	-	-	-	-	-	O	O	O
MT		-	-	-	-	-	-	-	-	O	O	O
NE		-	-	-	-	-	-	-	-	O	O	O
NH		-	-	-	-	-	-	-	-	O	O	O
NJ		-	-	-	-	-	-	-	-	O	O	O
TN		-	-	-	-	-	-	-	-	O	O	O
UT		-	-	-	-	-	-	-	-	O	O	O
HI		-	-	-	-	-	-	-	-	-	O	O
Total	0	5	11	11	20	28	28	28	28	23	25	25

Source: The authors.
* Note.
O: DNPAO Program.
-: No DNPAO Program has been implemented.

3.2. Methods

3.2.1. Study Area

The study area in this research includes the 50 states and the District of Columbia with a total sample (n=2,774,697) representing nearly 2 billion (n=1,965,992,351) of U.S. adults aged 18 years and older from 1998 to 2010.

3.2.2. Data

The data used for this study were obtained from the CDC's Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS is one of the CDC's public health surveys which collects information on health risk behaviors, preventive health practices, disease outcomes and health care access (CDC, 2014). Since 2010, the CDC and each state collaborated to perform telephone interviews to collect self-reported behavioral health risk information and to manage the survey data. Since 2011, CDC adopted a new survey methodology to collect data by both landline telephones and cell-phones to include more diverse demographic groups, especially low-income and young adults. The CDC therefore, recommends not to compare the BRFSS datasets collected before 2010 and the ones collected thereafter due to this change in sampling methodology. For this study, the BRFSS data regarding the implementation of CDC-DNPAO in each state from 1998 to 2010 were collected by the authors. This study assumes that all residents living in CDC-DNPAO participating states were exposed to protective effects of CDC-DNPAO based on social-ecological model as aforementioned.

Individual-level obesity risk factors used in the current study included sex, age group, race, marital status, educational attainment, household income level and smoking behaviors. Sex was classified male (reference) and female. Age group was categorized into 18-24 years old (reference), 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, and 65 years old and older. Race was divided into Whites (reference), Blacks, Asians/Pacific Islanders, American Indian/ Alaska Native, and Others. Marital status was grouped into Married (reference), Divorced, Widowed, Separated, Never married and Unmarried couple. Educational attainment was categorized into Under high school, High school, Some college (reference), and College and higher. Household income level was classified into Under $25,000, $25,000-35,000, $35,000-50,000, $50,000-75,000 (reference) and $75,000+. Smoking behavior was categorized into Current daily smoker (reference), Current occasional smoker, Former smoker, and Never smoked.

3.2.3. Analysis

Following work by Monheit et al. (2011) and Pande et al. (2011), this study utilized a set of a logistic modeling and a quasi-experimental analysis to evaluate overall effect of CDC-DNPAO before and after its implementation. The first analysis uses logistic regression to estimate the overall effects of the CDC-DNPAO on obesity prevalence using the total sample of this study from 1998 to 2010. The default year of implementing CDC-DNPAO is 2000, which means the effects of CDC-DNPAO on the odds of obesity is examined before and after 2000.

$$Obesity_{ist} = a_1 + a_2\ STATE_s + a_3\ YEAR_t + a_4\ TREND_t + a_5\ (STATE_s \times TREND_t) + a_6\ DNPAO_{ist} + a_7\ DURATION_{ist} + a8X_{ist} + e_{ist}$$

In this model, the dependent variable ($Obesity_{ist}$) is a binary outcome of the i^{th} individual in state s at time t ($Obesity_{ist}$ = 1 when one is obese; otherwise 0). Obesity is defined by body mass index (BMI) of 30 (kg/m^2) or greater. The coefficients for STATE is state-specific fixed effects to account for time-invariant differences across states that may result in differences in obesity. YEAR controls for year-specific fixed effects possibly contribute to obesity. TREND is a linear time trend to account for secular changes in obesity apart from CDC-DNPAO implementation and state effects. The interaction term (STATE x TREND) accounts for any time-varying state-specific changes in obesity. DNPAO is set to 1 for all years that a state was funded from CDC-DNPAO in a year and is 0 otherwise. DURATION is the total number of years a state participated in CDC-DNPAO program (coded 1 in 2000 and 11 in 2010). The vector X contains a set of important obesity risk factors to control for in the logistic models, including sex, age group, educational attainment, racial group, marital status, household income level, and smoking habit. Finally, e_{ist} is a stochastic error term.

The current study also examined the effects of natural occurrence in obesity policy by using a quasi-experimental analysis design, which compared overall obesity prevalence before-after the implementation of CDC-DNPAO. In this analysis three states (Massachusetts, North Carolina, and Texas) with CDC-DNPAO program in all study period (from 2000-2010) as a treatment group were compared with a pool of the thirteen states never funded from CDC-DNPAO as a control group. Considering their geographic proximity before-after obesity prevalence rates of three treatment states were compared with their corresponding control states within the same census regions, i.e. Massachusetts vs. Connecticut, North Carolina vs. Delaware and Virginia, and Texas vs. Alabama, Louisiana, and Mississippi.

All the analyses included BRFSS sampling weights and post-stratification adjustments to account for differences in probabilities of sampling selection and nonresponse, and to adjust for noncoverage of households without landline telephone (CDC, 2014). Stata version 14 was used for the all analyses performed in this current study (StataCorp, 2015).

3.3. Results

3.3.1. Logistic Regression Analysis

Table 3.2 shows the results from the logistic analysis. Living in a state with CDC-DNPAO program was associated with 2.4% (95% Confidence Interval (CI): 1.0%-4.0%) reduction in the odds of being obese during the study year. The total duration of a state's CDC-DNPAO participation was associated with 0.1% (95% CI: 0.1%-0.7%) reduction in the odds of being obese.

Females has a slightly lower odds of obesity (OR = 0.93 95% CI 0.92-0.94) compared to males. Compared with the youngest age group (18-24 years old) all age groups had a higher odds of being obese with the 55-64 year age group at high odds (OR = 2.73, 95% CI 2.64-2.83) followed by 45-54 years (OR = 2.71, 95% CI 2.62-2.81) and 35-44 years (OR = 2.38, 95% CI 2.31-2.47) demonstrating with increasing age, obesity increased. Compared with Whites, Asian/Pacific Islanders were at substantially lower odds of being obese (OR = 0.35, 95% CI 0.33-0.37); Blacks were at highest odds of being obese (OR = 0.1.67, 95% CI 1.64-1.70) followed by American Indian/Alaska Native (OR = 1.38, 95% CI 1.31-1.45). Compared with people having some college education, people with less than a high school education (OR = 1.15, 95% CI 1.12-1.18) and people with a high school education (OR = 1.04, 95% CI 1.2-1.05) were also at increased odds of being obese. People with college and more education were less likely to be obese compared to people with some college (OR = 0.67, 95% CI 0.66-0.68) demonstrating a linear relationship between higher education and lower obesity. Interestingly, all non-married groups had a lower odds of obesity compared to married people (e.g., divorced OR = 0.91, 95% CI 0.89-0.93). Compared with people with household income \$50,000-\$75,000, people with household income under \$25,000 had the highest odds of being obesity (OR = 1.25, 95% CI 1.22-1.27). Finally, former smokers compared to current smokers were at increased odds of obesity (OR = 1.54, 95% CI 1.51-1.57) followed by never smoked (OR = 1.39, 95% CI 1.37-1.42) and occasional smoker (OR = 1.08, 1.04-1.11) supporting the literature that smoking may inhibit appetite (Eid et al., 2008).

In Table 3.3 the total duration of a state's CDC-DNPAO participation was used as a categorical variable. Interestingly, the effect of total duration was mixed; two years of CDC-DNPAO was associated with a 3.9% (95% CI: 0.5%-7.3%) increase in the odds of being obese but three and seven years of CDC-DNPAO were associated with 3.1% (95% CI: 0.1%-6.0%) and 4.4% (95% CI: 1.7%-7.0%) reduction in the odds of being obese, respectively. Eleven years of CDC-DNPAO was associated with a 6.0% (95% CI: 0.2%-12.7%) higher probability of being obese. The other years in duration were not statistically significant. The effect of CDC-DNPAO was associated with 3.8% (95% CI: 1.6%-6.1%) lower probability of being obese. These results were controlling for the same risk factors as those outlined in Table 3.3.

Table 3.3. The Effects of DNPAO and its Duration on the Odds of Being Obese.

Variables	**Odds Ratio**	**95% Confidence Interval**	**Std. Err.**	**P>|t|**
DNPAO (Ref.=No)	0.98	(0.96, 0.99)	(0.01)	***
Duration (continuous, 1-11 yrs.)	1.00	(0.99, 1.00)	(0.00)	***
Sex (Ref.=Male)	0.93	(0.92, 0.94)	(0.01)	***
Age Group (Ref.=18-24 yrs.)				
25-34	1.94	(1.87, 2.00)	(0.03)	***
35-44	2.38	(2.31, 2.47)	(0.04)	***
45-54	2.71	(2.62, 2.81)	(0.05)	***
55-64	2.73	(2.64, 2.83)	(0.05)	***
65+	1.56	(1.51, 1.62)	(0.03)	***
Race (Ref.= Whites)				
Blacks	1.67	(1.64, 1.70)	(0.02)	***
Asian/Pacific Islanders	0.35	(0.33, 0.37)	(0.01)	***
American Indian/ Alaska Native	1.38	(1.31, 1.45)	(0.04)	***
Others	1.08	(1.06, 1.11)	(0.01)	***
Educational Attainment (Ref.=Some College)				
Under High School	1.15	(1.12, 1.18)	(0.01)	***
High School	1.04	(1.02, 1.05)	(0.01)	***
College+	0.67	(0.66, 0.68)	(0.01)	***
Marital Status (Ref.=Married)				
Divorced	0.91	(0.89, 0.93)	(0.01)	***
Widowed	0.91	(0.89, 0.93)	(0.01)	***
Separated	0.96	(0.93, 1.00)	(0.02)	**
Never Married	0.96	(0.94, 0.98)	(0.01)	***
Unmarried couple	0.94	(0.90, 0.97)	(0.02)	***
Household Income (Ref.= $50,000-75,000)				
Under $25,000	1.25	(1.22, 1.27)	(0.01)	***
$25,000-35,000	1.08	(1.06, 1.10)	(0.01)	***
$35,000-50,000	1.06	(1.04, 1.08)	(0.01)	***
$75,000+	0.80	(0.79, 0.82)	(0.01)	***

Table 3.3. (cont'd).

Variables	Odds Ratio	95% Confidence Interval	Std. Err.	P>|t|
Smoking (Ref.=Current Daily Smoker)				
Current Occasional Smoker	1.08	(1.04, 1.11)	(0.02)	***
Former Smoker	1.54	(1.51, 1.57)	(0.02)	***
Never Smoked	1.39	(1.37, 1.42)	(0.01)	***

Notes. *p <.010; **p< 0.05; ***p<0.01 for two-tailed test.
Data Sourced: BRFSS 2000-2010.

Table 3.4. The Effects of DNPAO and its Duration (categorized) on the Odds of Being Obese

Variables	Odds Ratio	95% Confidence Interval	Std. Err.	P>|t|
DNPAO (Ref.=No)	0.96	(0.94,0.98)	(0.01)	***
Duration				
1 yr	1.01	(0.97,1.05)	(0.02)	
2 yr	1.04	(1.01,1.07)	(0.02)	***
3 yr	0.97	(0.94,1.00)	(0.02)	***
4 yr	0.99	(0.96,1.02)	(0.02)	
5 yr	1.00	(0.98,1.03)	(0.01)	
6 yr	0.99	(0.96,1.02)	(0.02)	
7 yr	0.96	(0.93,0.98)	(0.01)	***
8 yr	0.97	(0.94,1.01)	(0.02)	
9 yr	1.01	(0.96,1.05)	(0.02)	
10 yr	0.98	(0.93,1.04)	(0.03)	
11 yr	1.06	(1.00,1.13)	(0.03)	*

Notes. *p <.010; **p< 0.05; ***p<0.01 for two-tailed test.
Controlling for risk factors outline in Table 3.

3.3.2. Quasi-experimental Analysis

Table 3.5 a-c shows the result from a quasi-experimental study design by comparing the longest CDC-DNPAO states (MA, NC, and TX) as the treatment group and a pool of no participation states as the control group considering their geographic proximity.

Table 3.5a compares the before-after obesity prevalence rates between Massachusetts (Treatment State) and Connecticut (Control State). In 1998-1999 the difference in obesity prevalence between Massachusetts (Treatment State) and Connecticut (Control State) was 0.2% (=17.4%-17.2%). In 2010 the Massachusetts' obesity prevalence was 26.3% whereas the Connecticut's obesity prevalence rate was 24.6%. The difference in 2010 was 1.7% (=26.3%-24.6%). The differences in difference was 1.5% meaning the differences in obesity prevalence between the treatment and control groups increased with the 11 years (from 2000 to 2010) of CDC-DNPAO implementation but it was not statistically meaningful.

In Table 3.5b, North Carolina as a treatment group and Delaware and Virginia as a control group were compared. During the study period the differences in obesity prevalence between two group remained same.

Table 3.5c summarizes the before-after obesity prevalence differences between Texas (Treatment State) and Alabama, Louisiana, and Mississippi (Control States). Before the implementation of CDC-DNPAO Texas has a slightly higher obesity prevalence rate compared with the control group but it increased 2.4% less with the CDC-DNPAO.

Table 3.5a. Results from a Quasi-experimental Analysis 1: between Massachusetts (Treatment State) and Connecticut (Control State)

States	Before (1998-1999)	Sample size	After (2010)	Sample size
Treatment states	17.4%	6246	26.3%	12669
Control states	17.2%	3007	24.6%	5381
Difference (T-C) [a]	0.2%		1.7%**	
Difference-in-Differences [b]		1.5%		

Notes. *p <.010; **p< 0.05; ***p<0.01 for two-tailed test.
a. Difference is the gap in obesity prevalence between the treatment and control states.
b. Difference in differences compares the before-after difference among states with CDC-DNPAO funding with the before-after difference among states without CDC-DNPAO funding.

Table 3.5b. Results from a Quasi-experimental Analysis 2: between North Carolina (Treatment State) and Delaware and Virginia (Control States)

States	Before (1998-1999)	Sample size	After (2010)	Sample size
Treatment states	20.5%	2651	29.6%	13273
Control states	21.7%	4922	30.8%	16813
Difference (T-C) [a]	-1.2%*		-1.2%*	
Difference-in-Differences [b]		-0.0%*		

Notes. *p <.010; **p< 0.05; ***p<0.01 for two-tailed test.
a. Difference is the gap in obesity prevalence between the treatment and control states.
b. Difference in differences compares the before-after difference among states with CDC-DNPAO funding with the before-after difference among states without CDC-DNPAO funding.

Table 3.5c. Results from a Quasi-experimental Analysis 3: between Texas (Treatment State) and Alabama, Louisiana, and Mississippi (Control States)

States	Before (1998-1999)	Sample size	After (2010)	Sample size
Treatment states	29.0%	2651	37.1%	13273
Control states	28.8%	4922	39.5%	16813
Difference (T-C) [a]	0.2%		-2.4%***	
Difference-in-Differences [b]		-2.6%**		

Notes. *p <.010; **p< 0.05; ***p<0.01 for two-tailed test.
a. Difference is the gap in obesity prevalence between the treatment and control states.
b. Difference in differences compares the before-after difference among states with CDC-DNPAO funding with the before-after difference among states without CDC-DNPAO funding.

3.4. Discussion & Limitation

This study revealed several important findings. First the effect of CDC-DNPAO statewide interventions was protective to reduce the likelihood of being obese during the study period. With the CDC-DNPAO funding each state can develop its own obesity interventions. Major target policies across all CDC-DNPAO programs includes (1) to increase breastfeeding initiation, duration and exclusivity; (2) to increase physical activity; (3) to increase the consumption of fruits and vegetables; (4) to decrease the consumption of sugar sweetened beverages; (5) to reduce the consumption of high energy dense foods; and (6) to decrease television viewing (Mattessich, 2013). While each states decides on its target policies and programs the interventions are generally implemented at a local level; thus, residents within a CDC-DNPAO funded state may have different targeted interventions depending on their geographic location and population composition. However the positive effects of CDC-DNPAO in reducing the odds of obesity document that obesity interventions can impact not only on the target population but also all other population through the intertwined social structure as the social ecological model assumes. For example the Minnesota Department of Health supported building bicycle rental kiosk throughout Minneapolis and Saint Paul, MN to increase physical activity in its state residents with partnership with several non-governmental organizations. This program was evaluated as a successful environmental change to increase additional physical activity in a CDC-DNPAO participating state (CDC, 2015).

The findings on the associations of individual demographic risk factors and obesity were similar and added another evidence on the obesity research. The current study confirms that there are variations in being obese controlling individual-level obesity risk factors. Most importantly, being blacks, lower household income, and lower education significantly increases the odds of being obese. Future obesity interventions should continue to focus on those disadvantaged populations at higher odds of obesity.

Second, this study found that the effect of CDC-DNPAO is variant with the total duration of implementation. The CDC has consulted CDC-DNPAO funded states with important milestones for funding period. The program objectives in Year 1 and Year 2 suggested by the CDC focused on developing policy plans, building partnership and educating local health department staffs and collaborative partners. On the contrary, Year 3 to 5 Year's objectives included implementing statewide obesity interventions and evaluating them. As such 3.9% of the higher odds in obesity in the two years of duration imply that there is a delay to having a positive impact of CDC-DNPAO in participating states. Contrarily, the likeliness of reduction in the odds of obesity in three and seven years of CDC-DNPAO duration implies that CDC-DNPAO participating states have successfully set and implemented their statewide obesity interventions.

In addition, it is notable that the longest duration of CDC-DNPAO was associated with 6.0% (95% CI: 0.2%-12.7%) higher probability (calculated from the odds ratio) of being obese, suggestive that with this longest duration of program implementation that obesity protection slightly decreased. This finding is also compatible with the finding of quasi-experimental analysis—with the 11 years of CDC-DNPAO participation from 2000 to 2010 the protective effect of the CDC-DNPAO were mixed in Massachusetts, North Carolina and Texas. With the statewide obesity program Massachusetts (11 years) experienced a higher obesity increase than Connecticut (never participated). The CDC-DNPAO made North Carolina (11 years) having the same obesity prevalence differentials between control states (Delaware and Virginia). The protective effect of CDC-DNPAO was most prominent in Southern states where Texas (11 years) had a smaller increase in obesity prevalence from 1998 to 2010 compared with control states (Alabama, Louisiana and Mississippi). Future research should be followed to further investigate why the effects of CDC-DNPAO vary by year, duration and states.

There are limitations in this study. First this study only evaluated the overall effects of CDC-DNPAO from two years before its implementation (1998) to 2010 due to inaccessibility of detailed information in the BRFSS. Therefore this study's results do not evaluate the effect of individual CDC-DNPAO programs implemented in many states in many different years prior to 2000. Second the use of BRFSS data may also limit the validity of this study's findings. Since individuals' information in the BRFSS data were collected via self-report there may be self-reporting biases. Although this study's analysis results were adjusted with BRFSS' sampling weights there may be possible biases due to non-landline telephone users before 2011, remote areas and small population groups. Third due to inconsistency in the BRFSS data the information of individual physical activity, one of the important obesity risk factors, was not included in the estimation model. Finally the analysis models in this study could not control for other environmental risk factors that could possibly influence an individual's obesity prevalence during the study period. Contrary to individual-level data like BRFSS, it is challenging to obtain datasets regarding environmental risk factors reported annually.

3.5. Conclusion

The statewide obesity intervention programs from CDC-DNPAO have been widely implemented across the United States since 2000. With the funding each state public health department was able to design and implement obesity interventions. This study revealed that the implementation of CDC-DNPAO can reduce the odds of obesity in the funded states during the study period. However, there is a delay in those benefits and they may vary across by specific years and states. Importantly, the states with the longest duration of CDC-DNPAO did not have the strongest protective effects of CDC-DNPAO. Future research should continue to evaluate CDC-DNPAO programs into the future including the impacts on obesity associated with environmental risk factors.

4. STUDY III: EXPLAINED AND UNEXPLAINED RACIAL AND REGIONAL INEQUALITY IN OBESITY PREVALENCE IN THE UNITED STATES.

ABSTRACT

There are substantial racial and regional inequalities in obesity prevalence in the United States. This study partitioned the mean Body Mass Index (BMI) and obesity prevalence rate gaps between non-Hispanic blacks and non-Hispanic whites into the portion attributable to observable obesity risk factors and the remaining portion attributable to unobservable factors at the national and the state levels in the United States. This study used a simulated micro-population dataset combining common information from the BRFSS and the U.S. Census data to obtain a reliable, large sample representing the adult populations at the national and state levels. It then applied a Blinder-Oaxaca reweighting decomposition method to decompose the black-white mean BMI and obesity prevalence inequalities at the national and state levels into the portion attributable to the differences in distribution of observable obesity risk factors and the remaining portion attributable to black-white differences in effects of risk factors. The mean racial difference in BMI was 18.5%. The racial difference in obesity prevalence was 20.6%. These differences represent the disparities in obesity between non-Hispanic blacks and non-Hispanic whites due to known obesity risk factors. There were substantial variations in how much the differences in distribution of known obesity risk factors explained the black-white gaps in mean BMI (-67.7% to 833.6%) and obesity prevalence (-278.5% to 340.3%) across states. The results from this study demonstrate that known obesity risk factors explain a small proportion of the racial, ethnic and regional inequalities in obesity prevalence in the United

States. Future etiologic studies are needed to further understand the causal factors underlying obesity and racial, ethnic and geographic inequalities.

4.1. Introduction

The World Health Organization (WHO) defines obesity as a medical condition of abnormal or excessive adipose tissue accumulation that increases the risk of other health problems (World Health Organization, 2011). The body mass index or BMI is the individual's weight in kilograms divided by their height in square meters (kg/m^2). The BMI is the most frequently used measure to diagnose and describe obesity in medical and population studies. The BMI thresholds defined by the WHO are 18.5 to 24.9 for normal weight, 25.0 to 29.9 for overweight and 30.0 or greater for obesity (WHO, 2011). Obesity is now referred to as a chronic disease that can result in reduced quality of life and premature death due to its strong association with many comorbidities, including but not limited to cardiovascular disease, Type-II diabetes, osteoarthritis, stroke and certain types of cancers.

Obesity is a major public health problem in the United States. The obesity prevalence rate for American adults was approximately 14 per 100 population in the early 1970s but it reached 36 in 2010 (CDC, 2010). There are also large racial and regional inequalities in obesity prevalence in the United States (CDC, 2010) with a significantly higher obesity prevalence among non-Hispanic blacks (herein after referred as blacks: 35.7, 95% CI: 35.6-36.3) compared to non-Hispanic whites (herein after referred as whites: 23.7, 95% CI: 23.5-23.9) in 2006-2008 (Rate Ratio: 1.5). This black-white obesity prevalence gap was consistent across U.S. states but it varied substantially, ranging from Oklahoma (5.4) to the District of Columbia (23.9) in 2006-2008 (CDC, 2009). Today obesity is responsible for 216,000 preventable deaths each year (Danaei et al., 2009) and the national health care spending directly and indirectly incurred from obesity is about

$190 billion. To reverse the increasing trends in obesity prevalence in the United States the Centers for Disease Control and Prevention (CDC) Division of Nutrition, Physical Activity, and Obesity (DNPAO) has funded participating state health departments to implement programs to reduce obesity prevalence since 2000 (CDC, 2012b; 2016). With this program funding, state health departments strengthened their ability to provide better health promotion, to implement effective nutrition and physical activity interventions, and to accumulate scientific evidence on obesity and its risk factors (Hamre et al., 2008).

The obesity literature has shown little evidence of biological differences between blacks and whites to explain the racial disparities in obesity prevalence. More than 300 human genes or gene markers are potentially involved in causal obesity pathways but as of yet, genetics do not explain racial disparities in obesity (Bouchard et al., 2003; Health Central, 2015). Importantly, obesity researchers consider race as a social construct and therefore, focus on social factors that may contribute to the high rates of obesity among blacks in the United States. These researchers measure racial inequalities in obesity using the following approaches. First, mean obesity prevalence rates or mean BMI between blacks and whites is simply compared after stratifying known obesity risk factors. For example, Seo and Torabi (2006) found that the mean BMI of black women with a high school diploma was 31.0 compared to college graduates 27.7, while their white counterpart groups were 28.1 and 25.3, respectively. Second, an index or a measure is designed and used to calculate the racial inequalities in obesity. For example, Zhang and Wang (2004) use the *Concentration Index* to assess the degree of inequality in the distribution of obesity across socioeconomic status (SES) levels using the 1988-1994 National Health and Nutrition Examination Survey (NHANES) dataset. In their study, lower SES was significantly associated with higher obesity prevalence rates for black men compared to white men but not for black women compared to white women, controlling for differences in age, low education and low income. This finding demonstrated that the role of SES may vary across gender within race. Third, racial disparities in obesity prevalence may be estimated using regression modeling. For example, Wen and Kowaleski-Jones (2012) using the 2003-2008 NHANES found that blacks were 1.2 times (odds ratio = 1.2) more likely to be obese than whites, controlling for differences in education and poverty levels. Fourth, obesity researchers have focused on the differences in neighborhood context characteristics. For example, the "food desert theory" hypothesizes that economically, socially disadvantaged populations have been exposed to higher food prices, and limited access to food stores in their neighborhood (Raja et al., 2010). For instance, Zenk et al. (2005) found that distance to the nearest supermarket was 1.1 miles further from impoverished black-predominant census tracts than from white-predominant census tracts in Detroit metropolitan area (Wayne, Oakland, Macomb counties) and this inaccessibility may have been a factor that explained the higher obesity prevalence in Detroit's inner-city areas. Moreover, Jetter and Cassady (2006) reported that higher prices of groceries were a hindrance to consume healthier food in low-income neighborhoods using market-basket surveys conducted in 25 stores in Los Angeles and Sacramento, California. Lastly, the differences in cultural norms or attitudes may also explain racial inequalities in obesity (Robert and Reither, 2004). In terms of culture, Millstein et al (2008) using the National Physical Activity and Weight Loss Survey (2002) found that black women were more accepting of larger body sizes as perceived ideal body; while Jackson and McGill (1996) found that black male college students preferred females with larger body types compared to white male college students. Caprio et al. (2008) argued that these attitudes and perceptions on body image are shared and transmitted from black parents to their children. In sum, these previous approaches to measure racial disparities in obesity improve our understanding of the problem by reporting racial rate gaps and explaining blacks' higher likelihood of obesity in relation to contextual risks. There is a need to partition the racial gaps in obesity in itself the portions explainable and unexplainable with known risk factors in order to target future obesity policy and programmatic interventions.

This study therefore, used an advanced Blinder-Oaxaca decomposition technique to decompose the black-white obesity gap into the *explained portion*—i.e. due to the differences in the values of covariates; and the *remaining portion that was unexplainable*—i.e., due to differences in the effects of covariates. There are a handful of studies using Blinder-Oaxaca decomposition techniques to examine racial gaps in obesity among population groups. For example, Dutton and McLaren (2011) used a standard decomposition technique to study the regional disparities in mean BMI at the province level in Canada. Using data from the 2004 Canadian Community Health Survey, these researchers found that men's average BMI differences between Quebec and the Atlantic (the highest mean BMI in Canada) provinces were explained by the differences in known obesity risk factors. In contrast, females' mean BMI differences between those two regions were mostly explained by the unexplainable differences in effects of obesity risk factors on BMI. Johnston and Lee (2011) used the 2003-2006 NHANES and found that differences in energy intake explained approximately 48% of the difference in the black-white mean BMI, 44% of the average waist-to-height ratio differences between blacks and whites and 38% of the obesity prevalence differences between black and white females aged 20-74 years. They also found that differences in energy expenditure contributed to 13% of the black-white mean BMI difference, 16% of the average waist-to-height ratio difference between blacks and whites and 11% of the obesity prevalence difference, between black and white females 20-74 years. Finally, Sen (2014) using a sample drawn from the BRFSS found that the mean BMI gap between black and white females in Alabama and Mississippi was 4.07 BMI units, only 8% of which was explained by demographic and health behavioral variables. Interestingly Sen also found that there was no statistically significant difference in the mean BMI between black and white males in these same states suggestive of some differences in obesity underlying causal factors

While the previous studies using Blinder-Oaxaca decomposition techniques have begun to shed light on the racial or regional gaps in obesity, they are limited by their population diversity and geography distribution: *i.e.* Johnston and Lee (2011) used only women in their analysis; Sen (2014) analyzed a sample only from Alabama and Mississippi; and the study of Dutton and McLaren (2011) was for Canadian populations and provinces. This study thus aims to partition the black-white gap in BMI and obesity prevalence into the explained and unexplained portions of contributing factors at the national and state levels in the United States by adopting a Blinder-Oaxaca reweighting decomposition method.

4.2. Methods

4.2.1. Study Area

The study area includes all 50 states and Washington D.C. in the United States using the 2010 county-census boundaries.

4.2.2. Data

This study utilized the CDC's 2010 BRFSS and the 2010 SF1 U.S. Census data to create a simulated dataset by which to calculate obesity prevalence. The BRFSS is a state-based, self-reported health survey system collected by the CDC to gather information on disease outcomes, health risk behaviors, preventative health practices, and health care access (CDC, 2013). However, the sample sizes of some population groups in the BRFSS are too small to estimate stable race-stratified obesity prevalence rates across all states. In addition the county identifiers for some rural or sparsely-populated counties are not released in the BRFSS to protect the confidentiality of respondents. To address these problems, a simulated population dataset was generated by using a spatial microsimulation technique (Ballas et al., 2005; Rahman, 2009; Lovelace and Ballas, 2013; Koh et al., 2015).

This study's simulated population sample were all adults 18 years or older at the county level across states in the United States. There were a total of over 211 million records of adults (blacks, n= 29,903,955 (14%); whites, n=181,225,439 (86%)). The variables of interest to study the racial gap in obesity included the black and white mean BMI and their respective obesity prevalence rates. The individual variables were categorized into: sex (male and female); age (18-24, 25-34, 35-44, 45-54, 55-64, 65 years old and older); marital status (never married, married, separated, widowed, and divided);

educational attainment (under high school, high school, some college, and college and higher); household income levels (under $35,000, $35,000-50,000, $50,000-75,000, and $75,000 and higher); and smoking behaviors (current daily smoker, current occasional smoker, former smoker, and never smoked).

The contextual-level variables to evaluate the environmental differences between blacks and whites included county level poverty rates, county Gini coefficients of income inequality (the 2010 U.S. Census), and the number of healthy grocery stores (USDA, 2011). In addition, the implementation (yes or no) and total duration (0-10 years) of the CDC's DNPAO state obesity program, collected by the authors from the CDC's website and the literature, were also used in this study's analysis. The classification of census region (ref. Northeast, Midwest, South and West) for each state was also included for general geographic reference (the 2010 U.S. Census). The predicted power of these individual and contextual-level variables was validated with a linear regression model of estimating individual level BMI or obesity as the outcome variable (Table 4.1).

Table 4.1. Estimated Mean BMI and Obesity Using Ordinary Least Squares and Logit Regression and Explanatory Risk Factors, United States, 2010.

	Dependent Variables					
	BMI (OLS)			Obese (Logit)		
	Coeff.	Std.Err.	P>|t|[2]	Coeff.	Std.Err.	P>|t|
Black (ref. White)	1.6113	0.0013	***	0.4425	0.0004	***
Sex (ref.=Male)	-0.4068	0.0009	***	0.0091	0.0003	***
Age (ref. 18-24 yrs old)						
25-34	2.6166	0.0017	***	0.6800	0.0007	***
35-44	3.5394	0.0017	***	0.9388	0.0007	***
45-54	3.5983	0.0017	***	0.9433	0.0007	***
55-64	3.6914	0.0018	***	0.9686	0.0007	***
65+	2.0473	0.0019	***	0.4524	0.0007	***
Marriage (ref.= Not Married)						
Married	-0.1403	0.0012	***	-0.0008	0.0004	**
Separated	0.1037	0.0021	***	0.0591	0.0007	***
Widowed	-0.8055	0.0021	***	-0.1852	0.0008	***
Divided	-0.3934	0.0016	***	-0.0671	0.0006	***
Education (ref.=Under High School)						
High School	-0.1839	0.0014	***	-0.0387	0.0005	***
Some College	-0.2232	0.0014	***	-0.0709	0.0005	***
College+	-1.2923	0.0016	***	-0.4257	0.0006	***
Household Income (ref.=Under $35,000)						
$35,000-$50,000	-0.6059	0.0013	***	-0.1654	0.0005	***
$50,000-$75,000	-0.7689	0.0013	***	-0.2229	0.0005	***
$75,000+	-1.4760	0.0013	***	-0.4491	0.0005	***
Smoking (ref.=Current Daily Smoker)						
Current- Some Days	0.5334	0.0021	***	0.0953	0.0008	***
Former Smoker	1.8569	0.0014	***	0.5015	0.0005	***
Never Smoked	1.4614	0.0013	***	0.3858	0.0005	***
County Poverty Rates	0.0111	0.0001	***	0.0039	0.0000	***
County Gini Coeff.	-0.9274	0.0142	***	-0.3658	0.0052	***
No. Grocery Stores	-0.5385	0.0043	***	-0.1528	0.0016	***
DNPAO[3]	-0.1374	0.0011	***	-0.0319	0.0004	***
DNPAO Duration	0.0029	0.0002	***	0.0010	0.0001	***
Census Region (ref.=Northeast)						
Midwest	0.2589	0.0015	***	0.0827	0.0005	***
South	0.3007	0.0014	***	0.0944	0.0005	***
West	-0.2972	0.0015	***	-0.0989	0.0006	***
Constant	25.8399	0.0063	***	-1.5539	0.0023	***
R^2/ Pseudo R^2	0.0649			0.034		

Table 4.1. (cont'd).

Notes:

1. Two regression models were used to validate the effects of covariates on BMI (OLS) and obesity prevalence rates (logit). The categorical variables and their reference groups (hereafter ref.) were race (ref.: whites); sex (ref. male); age (ref .: 18-24, 25-34, 35-44, 45-54, 55-64, 65 years old and older); marital status (ref.: never married, married, separated, widowed, and divided); educational attainment (ref.: under high school, high school, some college, and college and higher); household income levels (ref. under \$35,000, \$35,000-50,000, \$50,000-75,000, and \$75,000 and higher); smoking behaviors (ref.: current daily smoker, current occasional smoker, former smoker, and never smoked); and census region (ref. Northeast, Midwest, South and West). County level poverty rates, county Gini coefficients and the number of healthy grocery stores. the implementation (yes or no) and total duration (0-10 years) of the CDC's DNPAO state obesity program were continuous variables.
2. *** p<0.005
3. DNPAO: Division of Nutrition, Physical Activity, and Obesity

Data Source: The Authors; U.S. Census Bureau (2010); USDA (2011).

4.2.3. Analysis

A spatial microsimulation technique was used to generate the simulated population data. As aforementioned the original BRFSS may have blurred county identifiers for some respondents. Spatial microsimulation is a data generating process to create 'hypothetical' population data for small geographic areas where existing survey and/or census data are unavailable (Rahman, 2009; Koh et al., 2015). This study's simulated dataset was generated through an iterative proportional fitting (IPF)-based deterministic spatial microsimulation method (Lovelace and Ballas, 2013). With this technique, each respondent in the 2010 BRFSS was replicated and allocated to counties based on the proportion to common demographic characteristics in the 2010 BRFSS and 2010 SF1 U.S. Census data.

Racial and regional gaps in obesity were decomposed using an inverse probability weighting (IPW) decomposition method proposed by Elder et al. (2011). Unlike the original Blinder-Oaxaca decomposition technique to focus the mean differences of covariates between groups, this method assumes that the differences in distributions of covariates (e.g. age and education) between population groups are attributable for the gap in the outcome variable (e.g. BMI or obesity prevalence). A population group (e.g. the whites) is reweighted so that it has similar distributions of covariates with the other population group (e.g. the blacks) in this method. This study reweighted the individual and contextual level characteristics (obesity risk factors) of whites to have a similar distribution as those of blacks.

Suppose f (o | g) is the probability density of obesity for group g and F(o | g) is the cumulative distribution of obesity risk factors x for group g. B and W denote black and white population groups, respectively. Then f (o | g) for the whites and the blacks are defined as the equation (1) and (2):

(1) $f\,(o \mid g = W) = \int_x f\,(o \mid g = W, x)\ dF\,(x \mid g = W) \equiv f\,(o;\ g_{o|x} = W,\ g_x = W)$; and

(2) $f\,(o \mid g = B) = \int_x f\,(o \mid g = B, x)\ dF\,(x \mid g = B) \equiv f\,(o;\ g_{o|x} = B,\ g_x = B)$.

The equation (3) represents the counterfactual condition when the whites have the blacks' distributions of population characteristics with its own associations with characteristics and obesity:

(3) $f\,(o;\ g_{o|x} = W,\ g_x = B) \equiv .\ \int_x f\,(o \mid g = W,\ x)\ dF\,(x \mid g = B)$.

The equation (4) and (5) explain how the counterfactual density in (3) can be calculated from a weighted function of the actual whites with the weights of $\Psi_{W\rightarrow B}\,(x)$:

(4) $f\,(o;\ g_{o|x} = W,\ g_x = B) \equiv \int_x f\,(o \mid g = W, x)\ \Psi_{W\rightarrow B}(x)\ dF\,(x \mid g = W)$,

where the weights of $\Psi_{W\rightarrow B}\,(x)$ are calculated from

(5) $\Psi_{W\rightarrow B}\,(x) \equiv \frac{dF\,(x \mid g = B)}{dF\,(x \mid g = W)} = \frac{Pr(g=B \mid x)}{Pr(g=W \mid x)} \times \frac{Pr\ (g = W)}{Pr\ (g = B)}$

Bayes' Rule is applied in the equation (5). In the right hand the first fraction can be calculated with a binary model of group membership using a function of obesity risk factors x. The second fraction refers to the proportions of each group's individuals. After applying these processes the whites' distribution in the covariates used in this study (sex, age, marital status, educational attainment, household income, smoking behaviors, county level poverty rates, county income Gini coefficients, the number of healthy grocery stores, the implementation and total duration (0-10 years) of the CDC's DNPAO state obesity program, and census region) becomes similar as the blacks' distribution. Finally the obesity prevalence gaps between blacks and whites are estimated as the equation (6):

$$(6)\ f(o \mid g = B) - f(o \mid g = W)$$

$$= [f(o;\ g_{o|x} = W,\ g_x = B) - f(o \mid g = W)] + [f(o \mid g = B) - f(o;\ g_{o|x} = W,\ g_x = B)].$$

In the right hand of the equation (6), the first part defines the explainable portion of the obesity prevalence gaps between the blacks and whites and the latter part defines the unexplainable portion of the gaps with obesity risk factors used in this study. The Blinder-Oaxaca decomposition technique analyses were performed with STATA 13 (StataCorp, 2013).

Table 4.2. Proportions of Black and White Racial Groups and Other Descriptive Statistics, United States, 2010.

Variables	Mean		
	Black	White	White Weighted*
Sex			
Male	0.4058	0.4940	0.4175
Female	0.5942	0.5060	0.5826
Age			
18-24	0.1693	0.1231	0.1685
25-34	0.2183	0.1576	0.2170
35-44	0.1706	0.1599	0.1703
45-54	0.1835	0.1908	0.1849
55-64	0.1399	0.1716	0.1404
65+	0.1183	0.1971	0.1189
Education			
High School-	0.1895	0.1279	0.1956
High School	0.3114	0.2824	0.3026
Some College	0.3176	0.3230	0.3138
College+	0.1815	0.2666	0.1880
Household Income			
$35,000-	0.6543	0.4198	0.6519
$35,000-$50,000	0.1271	0.1466	0.1267
$50,000-$75,000	0.1053	0.1576	0.1053
$75,000+	0.1133	0.2761	0.1161
Smoking Behaviors			
Current-everyday	0.1455	0.1518	0.1464
Current-someday	0.0796	0.0522	0.0802
Former Smoker	0.1631	0.2760	0.1655
Never Smoked	0.6117	0.5200	0.6080
County Poverty Rates	17.4576	14.9819	17.3555
County Income Gini Coeff.	0.4617	0.4447	0.4622
Grocery Stores	0.2350	0.1978	0.2364

Table 4.2. (cont'd).

Variables	Mean		
	Black	White	White Weighted*
DNPAO	0.5346	0.5783	0.5475
DNPAO Duration	5.7492	6.0206	5.8750
Census Region			
Northeast	0.1693	0.1815	0.1693
Midwest	0.1734	0.2360	0.1734
South	0.5683	0.3611	0.5683
West	0.0890	0.2213	0.0890

* White Weighted denotes the estimates obtained under the hypothetical condition that the whites have the blacks' distributions of population characteristics with its own associations with characteristics and obesity.
Source: The Authors; U.S. Census Bureau (2010); USDA (2011).

4.3. Results

Table 4.2 reports the descriptive characteristics of the variables used in this study by racial group. As noted "White Weighted" in the Table 4.2, the population characteristics of the whites became similar to blacks after the reweighting process. For example the proportions of males and females are 41% and 59% for blacks and 49% and 51% for whites, respectively but weighted whites have similar distribution in sex (male 41% and female 59%). Compared to whites, blacks had disadvantaged status in terms of age structure, education, and household income. Blacks have also higher mean county poverty rates and income Gini coefficients than whites.

As summarized in Table 4.3, the mean BMI for whites and blacks at the national level was 27.6 and 29.6, respectively. The total BMI gap between whites and blacks was therefore, 1.9. The hypothetical (reweighted) BMI for whites was 28.02 under the counterfactual that the whites had the same population characteristic distributions as the blacks. This implies that 18.6% (0.4) of the mean BMI gap between whites and blacks were explained by the differences in distributions of age, marital status, education, household income, smoking habit (individual-level variables), county poverty rates, county Gini coefficient, the number of grocery stores, DNPAO, the duration of DNPAO, and census region (contextual-level variables). At the national level obesity prevalence rates for whites and blacks were 28.3 and 40.4, respectively; only 20.1% of the difference in the black-white gap was explained by the differences in population characteristic distributions and known obesity risk factors.

Table 4.3. Differences in Mean BMI and Obesity Prevalence for Blacks and Whites, United States, 2010.

	White (A)	White Weighted (B)	Black (C)
Mean BMI	27.66	28.02	29.60
Total Gap (C-A)		1.94	
Gap (%)	Explained (B-A): 0.36 (18.56%)		Unexplained (C-B): 1.58 (81.44%)
Obesity Prevalence Per 100 Population	28.29	30.77	40.35
Total Gap (C-A)		12.06	
Gap (%)	Explained (B-A): 2.48 (20.56%)		Unexplained (C-B): 9.58 (79.43%)

Source: The Authors; U.S. Census Bureau (2010); USDA (2011).

Table 4.4 list the gaps in the mean BMI and mean obesity prevalence rates between whites and blacks by state. Compared with whites, the mean BMI gaps for blacks were 3.0 or larger in the states of Oregon (B-W: 5.3), Washington D.C. (3.7), Hawaii (3.3), and Virginia (3.0), while whites had higher mean BMIs than blacks in Idaho (B-W: -1.98), New Hampshire (-0.6), Wyoming (-0.6), Utah (-0.5), Montana (-0.5), and Maine (-0.4). Over 40% of mean BMI gaps were explained by the differences in distributions of age, marital status, education, household income, smoking habit, county poverty rates, county Gini coefficient, the number of grocery stores, DNPAO, the duration of DNPAO, and census region in four states, including Washington, Minnesota, Kansas, and Oklahoma. On the contrary, the known obesity risk factors used in this study could only explain 10% or less of the mean BMI gap in Florida, Delaware, South Carolina, Louisiana, Maryland, Oregon, New York, and New Jersey.

Table 4.4. Mean BMI Gaps between Blacks and Whites, United States, 2010

States	Overall Mean BMI	White BMI (A)	White Weighted BMI (B)	Black BMI (C)	Explained Gap (B-A)	Explained Gap %
North Dakota	27.68	27.62	27.88	27.65	0.26	833.6%
Nevada	27.36	27.46	28.44	27.72	0.98	375.1%
Washington	27.57	27.74	28.19	28.51	0.45	58.6%
Minnesota	27.34	27.37	27.64	27.98	0.27	44.6%
Kansas	28.13	28.03	28.70	29.57	0.67	43.4%
Oklahoma	28.17	27.96	28.55	29.36	0.58	41.7%
West Virginia	28.34	28.38	28.68	29.19	0.30	37.0%
Utah	26.67	26.62	26.43	26.09	-0.19	36.4%
Georgia	28.02	27.68	28.16	29.06	0.48	34.5%
South Dakota	27.96	27.76	27.97	28.43	0.21	31.6%
Indiana	28.27	28.14	28.66	29.82	0.52	31.0%
California	27.13	27.42	27.88	28.92	0.46	30.8%
Iowa	27.93	27.96	28.27	29.00	0.31	29.8%
Massachusetts	27.15	27.21	27.45	28.02	0.23	28.9%
Alaska	28.04	28.11	28.45	29.41	0.34	26.0%
New Mexico	27.61	27.31	27.75	29.17	0.43	23.2%
Texas	28.17	28.04	28.44	29.82	0.40	22.4%
Nebraska	27.86	27.85	28.10	29.01	0.25	21.8%
Mississippi	28.97	28.29	28.70	30.38	0.41	19.5%
Arizona	27.40	27.28	27.37	27.73	0.09	19.0%
Colorado	26.71	26.60	26.84	27.96	0.24	17.3%
Tennessee	28.27	28.07	28.38	29.93	0.31	16.8%
Arkansas	28.41	28.18	28.46	29.96	0.28	15.9%
Michigan	28.37	28.17	28.46	29.99	0.28	15.5%
Connecticut	27.37	27.10	27.51	29.77	0.40	15.0%
Missouri	28.26	28.11	28.33	29.72	0.22	13.7%
Rhode Island	27.77	27.68	28.00	30.01	0.31	13.5%
Alabama	28.62	27.98	28.32	30.55	0.34	13.4%
North Carolina	28.14	27.65	27.96	30.09	0.31	12.8%
Pennsylvania	28.11	27.93	28.19	30.00	0.26	12.6%
Virginia	28.00	27.57	27.93	30.59	0.37	12.1%
Illinois	27.46	27.17	27.46	29.62	0.28	11.6%
Vermont	27.07	27.06	27.34	29.52	0.27	11.1%
Kentucky	28.44	28.25	28.55	31.01	0.30	10.8%
Ohio	28.14	27.95	28.16	29.93	0.21	10.6%
Florida	28.09	27.76	28.02	30.35	0.26	10.0%

Table 4.4. (cont'd).

States	Overall Mean BMI	White BMI (A)	White Weighted BMI (B)	Black BMI (C)	Explained Gap (B-A)	Explained Gap %
Delaware	28.15	27.79	27.99	29.83	0.20	9.7%
South Carolina	28.37	27.71	27.94	30.20	0.23	9.4%
Louisiana	28.54	27.91	28.06	29.85	0.16	8.1%
Maryland	28.06	27.75	27.82	29.21	0.07	4.5%
Oregon	27.65	27.73	27.90	33.02	0.17	3.3%
New York	27.44	27.24	27.28	28.56	0.04	2.7%
New Jersey	27.09	27.11	27.14	28.48	0.03	2.1%
Wisconsin	27.81	27.73	27.71	29.85	-0.02	-1.0%
Washington D.C.	26.72	24.71	24.55	28.43	-0.17	-4.6%
Hawaii	26.61	26.30	26.04	29.60	-0.26	-7.9%
Idaho	27.43	27.37	27.56	25.38	0.19	-9.6%
Montana	27.21	27.09	27.27	26.64	0.17	-38.2%
Wyoming	27.44	27.44	27.66	26.88	0.22	-39.8%
New Hampshire	27.50	27.56	27.83	26.97	0.26	-44.7%
Maine	27.77	27.78	28.01	27.41	0.23	-62.7%

In Table 4.4, Oregon, Washington D.C., Alaska, Virginia, and Connecticut were among the top 4 states with the highest black-white obesity prevalence gaps while whites had higher obesity prevalence rates in South Dakota, Montana, North Dakota, Arizona, and Idaho.

Over the 40% of black-white obesity prevalence gaps in Washington, Minnesota, Kansas and Oklahoma were explained with obesity risk factors whereas less than 10% of the gaps were explainable in Delaware, South Carolina, Louisiana, Maryland, Oregon, New York and New Jersey.

Table 4.5. Gaps in Mean Obesity Prevalence Rates per 100 Population (%) between the Blacks and the Whites, 2010.

States	Overall Obesity Rates	White (A)	White Weighted (B)	Black (C)	Explained Gap (B-A)	Explained Gap %
Maine	28.86	28.84	30.95	29.46	2.11	340.3%
Washington	27.52	28.42	32.02	31.51	3.60	116.6%
New Hampshire	26.51	26.81	29.58	30.44	2.77	76.4%
Iowa	29.68	29.99	31.54	32.96	1.55	52.3%
California	25.44	26.58	29.76	34.09	3.18	42.4%
West Virginia	33.11	33.33	35.20	37.92	1.87	40.7%
Arkansas	33.20	32.60	35.66	40.33	3.06	39.6%
Nevada	25.61	25.35	28.40	33.44	3.05	37.7%
Minnesota	26.59	26.61	29.35	34.07	2.74	36.7%
Oklahoma	31.81	30.12	33.70	40.05	3.58	36.1%
Kansas	31.65	30.64	34.86	42.66	4.22	35.1%
Indiana	32.15	31.82	34.67	40.18	2.85	34.0%
Louisiana	33.40	30.00	32.90	40.93	2.90	26.5%
Vermont	24.62	24.60	26.63	32.49	2.03	25.8%
Missouri	32.13	31.43	33.13	38.39	1.70	24.5%
Massachusetts	24.98	24.91	26.34	31.08	1.43	23.2%
Kentucky	33.79	33.07	35.70	44.95	2.63	22.2%
Connecticut	25.73	24.11	27.94	41.41	3.83	22.1%
Colorado	22.40	21.90	24.13	32.54	2.23	21.0%
Delaware	31.26	28.83	31.27	40.83	2.44	20.3%
Texas	31.93	31.13	32.81	39.42	1.68	20.3%
Michigan	33.21	31.85	34.25	44.00	2.40	19.8%
Rhode Island	28.51	28.12	30.25	38.93	2.13	19.7%
Georgia	31.85	28.38	30.43	40.04	2.05	17.6%
Virginia	30.55	27.83	30.95	45.70	3.12	17.4%
North Carolina	30.69	27.59	30.25	43.25	2.66	17.0%
New Mexico	27.90	25.46	27.69	38.70	2.23	16.9%
Wyoming	25.85	25.91	26.70	30.77	0.79	16.2%
Alabama	33.62	29.58	32.18	45.96	2.60	15.8%
Tennessee	32.55	30.91	33.16	45.57	2.25	15.3%
Pennsylvania	30.75	29.74	31.67	42.69	1.93	14.9%
South Carolina	33.08	29.08	31.35	44.70	2.27	14.6%
Florida	30.90	28.87	30.91	44.57	2.04	13.0%
Nebraska	28.64	28.45	29.81	39.19	1.36	12.6%
New Jersey	25.28	25.42	26.41	33.96	0.99	11.5%

Table 4.5. (cont'd).

States	Overall Obesity Rates	White (A)	White Weighted (B)	Black (C)	Explained Gap (B-A)	Explained Gap %
Mississippi	35.77	31.88	33.19	44.16	1.31	10.6%
Alaska	29.15	29.82	31.93	52.72	2.11	9.2%
Maryland	30.01	28.17	29.00	37.45	0.83	9.0%
Illinois	26.96	24.99	26.37	41.73	1.38	8.2%
Wisconsin	29.24	28.54	29.56	44.38	1.02	6.5%
Utah	23.06	22.59	23.21	33.42	0.62	5.7%
Oregon	29.36	29.58	31.59	67.44	2.01	5.3%
Ohio	30.88	29.47	30.14	43.67	0.67	4.7%
Washington D.C.	21.43	9.07	9.50	32.13	0.43	1.8%
New York	26.36	25.80	25.86	34.42	0.06	0.7%
Hawaii	22.30	20.93	20.42	34.36	-0.51	-3.8%
South Dakota	30.14	28.82	30.88	13.31	2.06	-13.3%
Montana	24.87	23.90	25.83	14.21	1.93	-19.9%
Arizona	26.88	26.54	28.13	21.76	1.59	-33.2%
North Dakota	28.85	28.22	30.61	21.45	2.39	-35.3%
Idaho	28.43	27.56	30.18	26.62	2.62	-278.5%

4.4. Discussion & Limitation

This study documented that there were large gaps in mean BMI and mean obesity prevalence rates between whites and blacks at the national and state levels. This is the first research, to my knowledge, to report the gaps in mean BMI and obesity prevalence for all states in the United States without any omitted state. This study found that there were substantial differences in the distribution of obesity risk factors at the individual and contextual levels between blacks and whites. The whites appeared to have more protection from obesity (i.e., being married, college educated, and having high-household income) and less obesogenic environments (i.e., lower poverty, higher income equality), and positive CDC's DNPAO experiences. Future obesity interventions should consider this difference in obesity risk factor distributions between two racial groups.

This study implies that the combined effect of all obesity risk factors on racial disparities in obesity varied by states. For example 59% of the state of Washington's mean BMI gap between blacks and whites were explained by known obesity risk factors. This implies that the black-white mean BMI gap could be narrowed if future obesity interventions could contribute to the differences in obesity risk factors in Washington. On the contrary only 3% of the New York's black-white mean BMI inequality was explained by these known risk factors, indicating there might exist other unknown obesity risk factors potentially influencing racial obesity inequality in New York. Therefore future obesity interventions need to examine the individual roles of each obesity risk factor on racial obesity inequalities to select target population or areas. In addition researchers need to focus finding other possible obesity risk factors from other perspectives including comorbidities, attitudinal and cultural norms, and/or other obesogenic environmental variables, including walkability and physical activities.

This study had some limitations. First this study used a cross-sectional study design for the year 2010 BRFSS data. Examining other years' of BRFSS data might be necessary to further understand the temporal variations in racial obesity gap in the United States. Second, while this study reported the overall gaps in mean BMI and mean obesity prevalence rates between blacks and whites the effect of each obesity risk factor on the gap(s) were not analyzed due to computational difficulty. Fourth, studies may need to investigate the role of each risk factor on racial disparities in obesity. Third the information of individual physical activity, one of the important obesity risk factors, was not included in the analysis model because the BRFSS over-simplied the information. Finally while this study focused on black-white obesity gap/inequality there might be obesity inequality between other racial and ethnic groups that could be studied in the future. Despite these limitations this study's finding appear to be a good starting point to further investigate the black-white obesity prevalence gaps from a qualitative approach.

4.5. Conclusion

In 2010 there were large racial and regional inequalities in mean BMI and obesity prevalence in the United States and across states. This study found that that 19% of the mean BMI difference and 21% of the obesity prevalence inequality between blacks and whites were explained by known obesity risk factors. There are substantial variations in the mean BMI, obesity prevalence, and their decomposition results at the state level. The results from this study suggest that a small portion of known obesity risk factors are attributable to racial and regional inequalities in obesity prevalence in the United States. Future studies are needed to further explain the unknown portion of these the inequality in obesity prevalence between other races/ethnicities and geographies.

5. CONCLUSIONS

5.1. Overall contribution

The principal contributions of this dissertation to the field of obesity research includes (1) investigating the spatial and spatio-temporal obesity prevalence at the county level in the United States from 2000 to 2010; (2) evaluating the CDC-DNPAO statewide obesity interventions to obesity prevalence and (3) decomposing racial obesity inequality between blacks and whites into explainable and unexplainable portions at the national and state levels in the United States. Thus, this dissertation research has demonstrated methodological advancement to measure obesity prevalence for surveillance, to identify risk factors for obesity research and to evaluate interventions to reduce obesity prevalence. The findings from this research can help to target populations and new areas for future programmatic interventions.

The study utilized a spatial microsimulation approach to investigate spatial and spatio-temporal changes in obesity prevalence at the county level from 2000 to 2010. Previous use of the BRFSS to monitor obesity prevalence has occurred at the state and national level. This study found that obesity prevalence substantially varied across counties in the U.S. Especially, many counties in Southern states, especially along the Mississippi River and the Appalachian Mountains were identified as the clusters of obesity. The first area is referred to as the Southern black belt. According to 2010 U.S. Census, 55 percent of the black population lived in the South. Blacks also had a higher likelihood of obesity than other racial groups in the U.S. (U.S. Census, 2011; Frank et al., 2004; Robert and Reither, 2004). In addition, the poverty rate of blacks is also highest among those of all other racial groups in the U.S., which is an important risk factor of obesity by limiting the accessibility of healthful foods (Lopez and Hynes, 2006). Poverty also may prohibits poor populations from education opportunities, which lead to a limited income and knowledge toward one's health. Midwestern states also retained many counties with higher obesity prevalence rates compared to Western and Northeastern states. Economic decline in the Midwestern states may negatively influence on high obesity prevalence in this region. Another vulnerable areas of obesity are counties containing or in proximity to American Indian reservation sites where the geographical isolation hinders American Indian population from health care accessibility, fresh food groceries, employment and education opportunities (Indian Health Service, 2015). These findings are important for public health departments and policy makers to address the rising obesity rates and related comorbidities in their states by the county level during the study years. The findings of this study will inform the federal government's public health experts of overall spatial and spatio-temporal patterns of obesity interventions. The clusters of obesity and their patterns of spatial expansion—i.e. particularly the wide expansion in Southern and Midwestern states since 2006—should be considered for future interventions. This study also demonstrates that spatial microsimulation is an alternative analysis tool for health geographers and public health specialists to identify and examine changes in disease prevalence at the local-county level. When state public health departments prepare for future interventions, spatial microsimulation will help them to identify areas where those interventions should be considered a priority. By so doing the efficiency and effectiveness of obesity interventions will be increased.

Study II examined the effect of the statewide obesity intervention programs funded by the Division of Nutrition, Physical Activity and Obesity (CDC-DNPAO) in the Centers for Disease Control and Prevention (CDC) which has been implemented since 1999. Each state public health department participating in the CDC-DNPAO designed and implemented a variety of obesity interventions following the CDC's guidelines. The CDC-DNPAO program assumes that obesity interventions at any level of society, e.g. intrapersonal, interpersonal, organizational, community, and society would positively impact on the other levels in society based on the Social-Ecological Model (SEM). While 37 states participated in the CDC-DNPAO program by 2010, thirteen states had never participated in the program. This study found that the implementation of CDC-DNPAO reduced the odds of obesity in the funded states during the study period. However, the effects of CDC-DNPAO and the total years of implementation varied by specific years and states. There may be some delay from the initiation of programmatic interventions. Importantly, states with the longest duration of CDC-DNPAO did not necessarily mean the strongest protective effects of CDC-DNPAO. This finding implies that the overall protective effect of the CDC-DNPAO program was limited yet positive from 1999 to 2010. Based on the fact that the CDC-DNPAO program was most positive in controlling obesity in the Southern states (Texas as intervention states versus Alabama, Louisiana, and Mississippi as control states) states with higher obesity prevalence may have the highest potential to have the best effect of this statewide obesity interventions.

Study III focused on the large racial and regional inequalities in mean BMI and obesity prevalence in the United States and across states using a Blinder-Oaxaca decomposition technique. Blinder-Oaxaca decomposition method is often used to quantify differences between groups attributable to explained and unexplained reasons—for example, the racial differences in income level between blacks and whites. Instead of using a traditional B-O decomposition method based on regression models, this study utilized an advanced B-O decomposition technique based on reweighting method (Elder et al., 2013). This study found that mean BMIs for blacks and whites in 2010 were 29.60 and 27.66, respectively at the national level. About 19% (0.36) of the total difference in mean BMI between the two racial groups (1.94) was found explainable with the known risk factors utilized in the study. The mean obesity rates for blacks and whites in 2010 were 28.29 and 40.35, respectively nationwide. About 21% (2.48) of the total gap in mean obesity rates between two racial groups (12.06) was explained by the known risk factors. This study also found that there existed substantial variation in the mean BMI and the obesity prevalence rates across the states. The portions of obesity gap between racial groups explained by the known risk factors also varied by states. The results from this study implies that only a small portion of racial and regional obesity gaps are attributable to known obesity risk factors in the United States. Since this study was conducted at the state level, future studies are needed to further quantify the obesity gap between racial groups into explainable and unexplainable portions by different levels of geographies, especially at the local levels, to understand how differently obesity risk factors act at the different levels of areas.

5.2. Future Studies

Obesity research has focused in the areas of individual and contextual risk factors, with most studies using public health surveys performed at the broader level of geography, e.g. national or state levels. In this regard it is very difficult to identify vulnerable populations at risk of obesity and to disentangle individual and environmental risk factors at the local level, i.e. county or lower level. This study used a spatial microsimulation modelling approach has been shown to be an alternative option to study population health at the local level since it provides a simulated population dataset for any local geographic unit where public health surveys and census data are available. It is expected that other chronic diseases and their spatial patterns across time may be investigated with spatial microsimulation. In particular overlaying the spatial patterns of demographic and environmental measures and estimated disease prevalence at the local level would be helpful to investigate the associations between population, environment and disease prevalence. For example overlaying downscaled air pollution data and asthma prevalence at the local level will be useful to identify vulnerable populations at risk of chronic diseases.

Evaluating the effect of public health policy is important when reviewing the effectiveness of public health interventions and designing future policies. A quasi-experimental study design is useful to investigate the effect of policy, which naturally divides intervention and control groups. Natural occurrence usually happens when policy interventions are implemented within and across population group(s) or geography. Future studies can utilize a quasi-experimental study design to parsimoniously examine the effect of policy interventions.

Using a Blinder-Oaxaca technique is beneficial for researchers to investigate inequality in health among different population groups. Unlike other analysis methods a Blinder-Oaxaca technique decomposes the current health outcome differences into the portion explainable by known risk factors and the portion caused by unexplainable causes. By so doing it is possible for researchers to quantify each variable's role to health outcome inequalities and the existing inequalities, where the future studies need to focus on to reduce obesity, related chronic diseases and improve population health.

This dissertation research demonstrated the utilization of new techniques in the study of obesity prevalence and the evaluation of populations, policies and programmatic interventions in the United States. It implemented these techniques to answer important theoretical and applied questions regarding obesity. Future research should continue to advance theory and new methods to address the important obesity and chronic disease epidemics in the United States and worldwide.

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