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Health of the Nation: the Impact of Racial and Income Segregation on Food Insecurity in the United States

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THE IMPACT OF RACIAL AND INCOME SEGREGATION ON FOOD INSECURITY IN THE UNITED STATES

by

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ABSTRACT
HEALTH OF THE NATION: THE IMPACT OF RACIAL AND INCOME SEGREGATION ON FOOD INSECURITY IN THE UNITED STATES

by

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One in six Americans experience food insecurity as a result of not being able to consistently obtain the food they need. *Food insecurity* ranges from not being able to afford balanced meals to the skipping meals as a way to stretch food budgets. Food insecurity impacts many people in the United States, but it disproportionately impacts people of color and those living in poverty. Racial and income segregation may act to concentrate food insecurity in a few geographic areas with high concentrations of minority and/or poor residents. This is an issue of major concern because studies have shown that racial segregation is a strong predictor of differences in mortality and other health outcomes when looking at black-white and Hispanic-white segregation. While this research has shown a strong link between segregation and these health outcomes, no research has been done on racial and income segregation effects on food insecurity in the United States. This study used nationally representative datasets with information from multiple geographic levels to assess the connection between racial and income segregation and household and child food insecurity. For residential segregation by race, the results showed that (1) black-white segregation was not significantly associated with food insecurity rates and that (2) higher levels of Hispanic-white segregation were associated with increased rates of overall and child food insecurity, but only in counties with relatively large U.S.-born Hispanic populations. The results also showed that three dimensions of income segregation (the segregation of affluence, the segregation of poverty and overall income segregation) were generally associated with higher levels of overall and child food insecurity, especially in counties with relatively high proportions of poor children and relatively small affluent populations. However, poverty segregation was associated with lower rates of child food insecurity, especially in counties with relatively high child poverty rates. These results suggest that residential segregation by race and income are key factors that contribute to food insecurity rates nationally. This research contributes to the public health literature on how residential segregation impacts health outcomes and conditions by extending this line of research to include food insecurity.

To big feet, little giants, family far beyond my reach and those close at hand.

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Overview of Food Insecurity

Food is fundamental for human survival, and yet worldwide 800 million people currently do not have adequate access to food that would enable them to lead healthy and productive lives (Anderson 2012). In an effort to measure these issues of food access, researchers have developed a *food security survey* that assesses the extent of a households' ability to provide food for their family, and what decisions are made regarding quality and quantity (Carlson et al. 1999).

Food insecurity questions get at *three areas* of concern for respondents with regard to hunger: 1) not being able to afford to buy a balanced meal; 2) not being able to buy food from week to week; and, most severe, 3) skipping meals as a way to manage overall food costs (Carlson et al. 1999). As such, families can be arrayed on a spectrum of food insecurity, with some foregoing meals, while others may purchase lower quality foodstuffs in an effort to save money. Food insecurity in households with children raises issues of parents skipping meals to feed their children, and in extreme cases, children themselves not eating to stretch meals (Carlson et al. 1999). Throughout the world, large proportions of both urban and rural populations suffer from some form of food insecurity.

Measuring food insecurity in the United States differs in two critical areas from developing countries: food availability and how food insecurity is defined. Major reasons that populations in developing countries suffer from food insecurity are due to food shortages, civil unrest, crop failures, or lack of social infrastructure (Anderson 2012). In the United States, food is readily available because supply and demand lines are stable, allowing food to be accessed via a number of outlets, such as grocery stores, fast food restaurants, supermarkets and convenience stores. Carlson et al. (1999) draws this distinction as "hunger that is medically defined," vs. "hunger that is socially defined." In developing countries, hunger is medically assessed across the entire population as a result of prolonged food shortages or famine. Hunger is socially defined in the United States as food insecurity means not consistently having enough money to afford food, skipping meals in order to provide for others, and in extreme cases, children foregoing meals to save money as a result of the social conditions they live in.

Food insecurity in the United States is so critical to study today because of the sheer volume of residents who deal with these issues of hunger on a daily basis. As of 2012, 49 million U.S. residents were considered food insecure, with 16 million of them being children under the age of 18 (Gunderson et al. 2014). With almost one-fifth of the U.S. population being food insecure, these residents are found in communities, towns, cities and urban centers across the country, impacting the lives of residents around them.

Key Drivers of Food Insecurity in the United States

At the household level, the key drivers of food insecurity in the United States are poverty, unemployment, and homeownership. As rates of poverty and unemployment rise, and/or home ownership decrease, there is an increase in food insecurity (Gunderson et al. 2014). There are also racial disparities with regard to food insecurity at the county-level. Out of 101 counties surveyed that identified as majority black, a startling 93 percent of counties had high food insecurity. For the 86 counties that identified as majority Hispanic, just 9 percent had high food insecurity. For the majority white counties, just 6.2 percent of them were considered to have high food insecurity (Gunderson et al. 2014).

While the percentage of Hispanic counties is nominally larger than the percentage of white counties, the discrepancy between the percentage of black counties and percentage of white counties with high food insecurity is shocking. A plausible explanation for why there is not more of a disparity between Hispanic/ white counties is that some Hispanic counties may some have large, thriving immigrant populations that offer some of the protective benefits that may be associated with immigrant enclaves, while other are primarily home to U.S.-born Hispanic populations that have experienced downward assimilation (Logan and Turner 2013).

Differences in food insecurity for blacks and Hispanics can partially be accounted for by looking at racial disparities in household socioeconomic status (SES) such as poverty status and unemployment rates. As the *Map the Meal Gap* reports, those majority black counties that had high food insecurity rates had an *average* poverty rate of 29 percent, which is almost twice the national average for all U.S. counties at 16 percent. Additionally these counties on average had an unemployment rate of 13 percent, compared to an average of 9 percent for all U.S. counties (Gunderson et al. 2014). Given the high poverty rates in predominantly minority counties, it is plausible that the high rates of food insecurity in those counties reflect merely racial disparities in SES at the household level.

In part, aggregated inequalities in food insecurity (e.g., across counties) reflect racial disparities in socioeconomic resources between black and white households

(Gunderson et al. 2014). Consequently, taking racial disparities in household-level SES factors related to poverty status and unemployment into account partially explains why food insecurity rates are higher in predominantly black counties than in predominantly white ones (Coleman-Jensen et al. 2011). However, food insecurity tends to be higher for black households compared to white households regardless of their income or disposable income (Gunderson et al. 2011; Gunderson and Gruber 2001). These household-level predictors do not fully explain racial disparities in food insecurity at either the household or county levels, since race remains a significant predictor even when controlling for SES (again, at either the household or county level).

What is left unexplained, and what this dissertation attempts to address is why racial inequality persists with regard to food insecurity, *even after* controlling for household-level SES factors in the modeling of food insecurity (Gunderson et al. 2011; Gunderson 2008). Even after accounting for individual/ household SES, predominately black counties are substantially more likely than white counties to be food insecure. One promising explanation for this puzzling question may be found by focusing on place-based inequalities associated with residential segregation. This study attempted to use this potential explanation by analyzing the impact of residential segregation by *race* and *income* on food insecurity rates across the country.

Residential segregation refers to the relationship between the racial or socioeconomic composition of a larger area (e.g., a metropolitan statistical area or MSA) and the smaller units that constitute it (e.g., counties, municipalities or neighborhoods). Under conditions of high segregation, these smaller units (e.g., neighborhoods) are relatively racially or socioeconomically homogenous compared to the overall population of the larger area in which they are located (e.g., the entire metropolitan area). When groups are segregated from one another, they live in spaces where there is little or no opportunity for interaction as a result of sheer residential proximity with members of other racial, ethnic or socioeconomic groups.

The reason it is important to understand how residential segregation may help to explain persistent racial disparities in food insecurity comes from research done on other public health outcomes. This research shows that residential segregation by *race* directly contributes to *place-based* inequalities that exacerbate racial disparities in other health outcomes as a result of a lack of key resources (Osypuk and Acevedo-Garcia 2010; Landrine and Corral 2009; Williams and Collins 2001).

There are a number of reasons that residential segregation by *race* contributes to racial disparities in other health outcomes. First, blacks and Hispanics have relatively high rates of poverty compared to their white counterparts, so residential segregation by *race* tends to concentrate poverty and other forms of disadvantage in predominately minority neighborhoods (Massey and Denton 1993; Massey and Eggers 1990; Massey 1981). Second, concentrated poverty makes the effects of household poverty worse, as minority households are more likely to live in neighborhoods where households are overwhelmingly poor. Lastly, even middle class blacks and Hispanics tend to be exposed to high levels of poverty and neighborhood disadvantage, compared to white counterparts as a result of a long history of housing discrimination practices (Logan 2013; Rugh and Massey 2010; Iceland 2004; Jargowsky 1997; Wilson 1996; Massey and Denton 1993). This clustering of black and Hispanic residents into neighborhoods that have other residents who are overwhelming poor creates a lack of resources that translates into lower quality health outcomes as result of living in these segregated areas.

Racial Residential Segregation, Place-based Inequalities, and Health Outcomes

Public health literature shows that as a result of *placed-based* inequalities, populations that live in segregated neighborhoods have worse health outcomes related to number of chronic illnesses and mortality rates (Landrine and Corral 2009; Williams and Collins 2001). A number of these studies have found that residential segregation by *race* is a primary factor that contributes to health disparities between blacks and whites for rates of cancer, heart disease, deaths associated with the common flu virus, low-birth weights in children and obesity for adults (Borrell et al. 2013; Chang 2006; Acevedo-Garcia and Lochner 2003; Ellen 2000). This prior research suggests that residential segregation by *race* contributes to racial disparities in health by way of place-based inequalities.

Given that these public health outcomes, especially those related to malnutrition and obesity, have been discovered to be directly impacted by racial residential segregation, focusing on place-based inequalities associated with segregation may help to explain racial disparities in food insecurity rates. There are a number of key resources that are absent as a result of place-based inequalities that may contribute to increased food insecurity as a result of residential segregation. These include fewer organizational resources, a lack of retail investment, and inadequate transportation options, as well as increased exposure to violent crime and unsafe streets (Dinwiddie et al. 2014; Sharkey 2013; Hipp 2007; Small and McDermott 2006; Grannis 1998). Additionally, fewer local businesses can be sustained as a result of overall higher levels of neighborhood poverty and increased crime rates (Boyd 2010; Alwitt and Donely 1997).

Less business and retail investment has led to another form of place-based inequality, which is the lack of food accessibility in predominately black neighborhoods (Baker et al. 2006). Issues connected to food accessibility offer a direct connection that helps to explain why there might be higher rates of food insecurity in neighborhoods with higher rates of residential segregation by race. Kwate (2008) has shown that racial residential segregation is a primary mechanism that influences the location of food stores, such that supermarkets and grocery stores tend to be concentrated outside of predominately black neighborhoods, while convenience and fast food stores tend to be heavily concentrated in black neighborhoods. Additional research has discussed how fast food restaurants and convenience stores are able to take over predominately minority neighborhoods as a result of little competition and low startup costs (Beauclac et al. 2009; Powell et al. 2007; Block et al. 2007; Powell et al. 2004).

As a result of residential segregation by race, there are fewer nutritional food options. Larson, Story and Nelson (2009) have found that the absence of grocery stores and the prevalence of fast food and convenience stores in predominately black neighborhoods contribute to high food prices in these neighborhoods. Research has shown that due to a lack of nutritional food store availability and higher food prices, African-Americans tend to consume less overall fruits and vegetables than white residents in similar income neighborhoods (Zenk et al. 2005).

These place-based inequalities may directly contribute to racial disparities in food insecurity rates as a direct result of the residential segregation by *race*. The next two sections explain how residential segregation by *race* and *income* may also indirectly contribute to food insecurity by exacerbating racial disparities in household-level SES factors (e.g., income and educational attainment) as a result of two primary mechanisms: spatial mismatch and neighborhood effects on household SES. By contributing to racial disparities in household-level SES, these forms of segregation may influence food insecurity rates in ways that have yet to be studied in the public health literature.

Residential Segregation by Race, Household SES, and Food Insecurity

The previous literature clearly shows that residential segregation by race leads to concentration effects, which exacerbate the challenges faced by poor black and Hispanic households and undermines the some of the advantages that middle class black and Hispanic households might otherwise enjoy. These concentration effects can make the connection from residential segregation to poor health outcomes for blacks and Hispanics and thus more pronounced racial disparities in health outcomes, potentially including food insecurity.

In addition, residential segregation by race may be indirectly contributing to racial disparities in food insecurity by exacerbating racial inequality in relation to key SES factors, such as poverty and unemployment rates. The primary structural mechanisms that link residential segregation by *race* to racial disparities in household-level SES are: spatial mismatch and neighborhood effects. As result of these racial disparities in household-level SES, which has been shown to be a primary factor in heightened food insecurity rates, residential segregation by *race* may operate indirectly through these structural mechanisms to exacerbate racial disparities in food insecurity rates.

Spatial mismatch of job opportunities and negative neighborhood effects contribute to racial disparities in household-level SES as a result of increasing poverty and unemployment for minority residents. Spatial mismatch refers to the way that living wage jobs, i.e. those jobs that pay a good wage and offer benefits, are constantly being moved outside of the city, into edge cities and suburbs that are hard to access from predominately black and Hispanic neighborhoods, which tend to be concentrated closer to the central city (Rast 2015; Wilson 1996; Kain 1968). This has taken place in parallel to job loss in the central city as many industrial and factory jobs have been moved to developing countries to lower production costs. Through the mechanism of spatial mismatch, residential segregation by *race* has indirectly contributed to racial disparities in household-level SES, especially with regard to unemployment and poverty status. Both of these SES factors are driving forces that help to explain food insecurity, which may be influenced in a round-about way by residential segregation by *race*.

Neighborhood effects are a second important social mechanism to consider when thinking about the relationship between residential segregation by *race* and food insecurity rates. Neighborhood effects can be thought of as the negative or positive consequences that come from where you live. These effects have been connected to educational outcomes, home ownership values, and consumer choices (Rugh and Massey 2010; Cummins and Macintyre 2002; Orfield 2001). Partly as a consequence of neighborhood inequality by race and adverse neighborhood effects on blacks, overall whites tend to have higher graduation rates from primary and secondary education compared to black and Hispanic populations (Wodtke et al. 2011; Sampson et al. 2008). This is directly connected to the ability to gain employment or fall into poverty, as those with fewer resources and options to obtain educational skill sets, whether this is a bachelor's degree or a technical trade, will have fewer chances to find a job based on the places they live (Levine 2014; Jargowsky 1997; Wilson 1996).

The Role of Residential Segregation by Income, Household SES and Food Insecurity

There are a number of reasons to consider residential segregation *by income* as well as race in relation to food insecurity rates. Massey, Rothwell, and Domina (2009) have shown that the relative importance of race and income for residential segregation has changed over the past 30 years. In general, black-white segregation has declined, while segregation between other racial groups, particularly Hispanics, has remained stable (Glaser and Vigdor 2001). Conversely, income segregation has grown during this time, with a widening gap between those in poverty and those who are affluent (Reardon and Bischoff 2011).

Income segregation operates primarily as a result of the sorting process that occurs due to rising rates of income inequality (Reardon and Bischoff 2010). Income segregation is the geographic separation of populations by income (Reardon 2011; Moller et al. 2009; Reardon and O'Sullivan 2004). As a result in recent trends in these forms of segregation, a declining portion of income segregation (and thus exposure to neighborhood poverty and related forms of neighborhood disadvantage among poor blacks) is due to *racial* segregation. This is important to consider in relation to food insecurity as residential segregation by *income* may indirectly contribute to disparities in household-level SES.

Income segregation may influence racial disparities in food insecurity indirectly through the same two mechanisms as residential segregation by *race*, spatial mismatch and neighborhood effects. Reardon and Bischoff (2010) discuss how income segregation may mediate the effects of income inequality on social outcomes, by working to concentrate affluent and poor households into distinct, and often distant, geographic spaces. As a result of these distances, job growth takes place in areas where wealth is concentrated, as individuals have the capacity to invest in businesses, and be employed in larger organizations and corporations.

Recent studies have shown that job growth in suburbs on the outer edges of metropolitan areas has occurred *at the same time* that there has been continued decline in job availability in neighborhoods near the central city, where median income tends to be lower (Levine 2014). With job growth occurring in neighborhoods that are greater distances from lower income neighborhoods, spatial mismatch occurs between those who are unemployed and the places where jobs are being created. This spatial mismatch then works to concentrate poverty further as those individuals who want gainful employment cannot find it and end up unemployed and/or further in poverty.

Where jobs are located is also a factor of the educational requirements for those jobs. This is directly linked to the neighborhood effects that occur in relation to educational attainment. School tax base and the quality of school outcomes are linked to household income levels. With more money to spend on schools, there is the capacity to hire better quality teachers, provide more advanced curricula, and through these resources, graduate more students that may go onto colleges or universities (Orfield 2001). Students with secondary degrees have an easier time finding employment opportunities in higher paying jobs, many of which as noted before, are to be found in the outskirts of metropolitan areas. The inverse of this cycle is that students who go to school in poorer neighborhoods have a harder time graduating due to fewer available resources (Wodtke, Harding and Elwert 2011). This means that workers who have a higher level of education have the greater capacity to get better paying jobs, which translates into a higher wage than someone who has less educational attainment.

It is clear through this cycle of job growth, educational attainment, and higher wages, how the process of residential segregation by *income* contributes to disparities in household-level SES factors related to unemployment and poverty status. As a result of these disparities, residential segregation by *income* may indirectly contribute to disparities in food insecurity through the mechanisms of spatial mismatch of jobs and neighborhood effects on educational attainment.

Contribution to Public Health Literature in relation to Residential Segregation

Food insecurity is necessary to study today because it may be, at least in part, a *health-related consequence* of racial disparities in neighborhood living conditions. The purpose of this research was to assess how it was related to residential segregation by *race* and *income.* In a time with some of the highest rates of unemployment since the Great Depression, and 23 percent of all children living in poverty as of 2013, with almost 40% of all black children living in poverty, food insecurity will impact some populations more acutely than others (Population Reference Bureau 2013; Wilson 2010).

This is pertinent to other research conducted on segregation and health disparities. Recent research investigating how residential segregation may impact health outcomes at various scales has yet to separate out income segregation from racial segregation (Acevedo-Garcia et al. 2003). A body of public health literature studying health disparities has more generally focused on black-white health disparities related to mortality rates (Borrell et al. 2013; Williams and Mohammed 2009). Additionally, most of these studies conducted on health outcomes at the metropolitan statistical area (MSA)-level have primarily used racial composition as a way to measure racial segregation, and median income and poverty rate as ways to measure income segregation (White and Borrell 2011; Jargowsky 1996). While these are novel approaches, they do not provide a clear enough picture about the way that residential segregation contributes to *place-based* inequalities that may help to explain why there are racial disparities in particular health outcomes.

This study is innovative and needed for the broader body of public health literature in three distinct ways: it is the first study conducted on food insecurity rates to use measures of both residential segregation by *race* for blacks and Hispanics and residential segregation by *income*; second, it is the first study focused on a public health condition, food insecurity, to examine the role of residential segregation by income in terms of two distinct aspects, the segregation of poverty and segregation of affluence; third, it provides public health research with a better understanding of how these forms of segregation contribute to a given health condition nationally based on the most recent census data.

Building on a unique combination of datasets at the county- and metropolitan-levels, this study will provide new evidence about food insecurity and child food insecurity in relation to two forms of segregation. Food insecurity is a crucial, yet understudied dimension of inequality that is likely to make more sense when there is attention paid to how it relates to racial and income segregation. This contribution will be within the realm of public health and sociological theories as it asks the general question: how do levels of neighborhood segregation impact residents' overall levels of food insecurity? Studying this issue will enable a better understanding of how income inequality, and ultimately neighborhood living conditions impact food insecurity rates as a result of the mechanisms of place-based inequalities, spatial mismatch and neighborhood effects. This is relevant to public health research more broadly that focuses on race-based health disparities and the way in which forms of segregation contribute to these disparities.

Outline of Dissertation Chapters

The remainder of the dissertation is divided into six chapters. The second chapter reviews theory and prior research that shed light on how several forms of residential segregation impact neighborhood health conditions, potentially including food insecurity rates. Racial segregation will be discussed for non-Hispanic blacks, foreign-born Hispanics and U.S.-born Hispanics. Income segregation will be discussed in relation to two of its key aspects: the segregation of poverty and the segregation of affluence.

Chapter 3 goes into depth about the data, measures and methods for the dissertation. The research design will be discussed in relation to county- and MSA-level data measures. This design will detail the modeling of each segregation measure with the focal dependent variables. The primary dependent and independent variables will be discussed in relation to methodology and data sources. Both forms of segregation will be outlined based on differences in Black and Hispanic segregation measures, as well as differences in segregation measures related to poverty and affluence (Reardon 2011; Massey and Denton 1993).

Chapter 4 goes into the outcomes of the regression analysis for racial segregation and food insecurity for blacks. This chapter details the way in which black-white segregation may be increasing rates of household and child food insecurity rates in predominately black counties, but less so in counties that are not predominately black.

Chapter 5 reports out the regression analysis for Hispanics, both U.S.- and foreign-born, in relation to household and child food insecurity for both partial and full models. This chapter discusses the different ways that segregation for Hispanics may lead to higher rates of food insecurity in primarily U.S.-born Hispanic counties, but less so in counties that are predominately non-Hispanic and/or foreign-born Hispanic. This is done for both household and child food insecurity.

Chapter 6 examines the extent to which the segregation of affluence and the segregation of poverty are associated with rates of household and child food insecurity. This chapter also reports models that analyze *racial* and *income* segregation together to assess whether income segregation can account for any of the expected associations between residential segregation by race and food insecurity rates.

Chapter 7 concludes the dissertation by offering future directions for research based on the outcomes of the models. Chapter 7 also discusses more broadly, policies and practices that could be implemented at the state- and county-levels to address issues of food insecurity as they relate to racial and income segregation, and how policy makers within these levels of government could utilize this data to make informed decisions about how to fund programs that alleviate issues related to food insecurity.

CHAPTER 2: RESIDENTIAL SEGREGATION BY RACE AND INCOME, HEALTH DISPARITIES, AND FOOD INSECURITY

Overview

This chapter is going to provide a better understanding of how the dependent variable, food insecurity, is being influenced by the two major independent variables, racial and income segregation. Due to the complexity of both the dependent and independent variables, as well as their hypothesized relationships, three sections have been included that layout the argument.

The first section provides an overview of residential segregation. This section will conceptualize residential segregation based on race, income, and geography within the United States. The second section focuses on residential segregation by *race* and *income* in relation to recent historical trends. In the discussion of trends, it will show how residential segregation by *race* and *income* are important factors to consider when thinking about food insecurity. The final section will examine the relationship between each form of residential segregation (i.e., by race and by income) and food insecurity. In doing so, it will explain how each form of segregation contributes to place-based inequalities and neighborhood effects, which may directly or indirectly influence food insecurity rates.

Conceptualizing Residential Segregation

For the purposes of this dissertation, a segregated metropolitan area is one that is internally segregated by race, income or both. An internally segregated area (e.g., metropolitan area) consists of some smaller geographic units. These geographic units could be counties, municipalities, or neighborhoods that are relatively racially or socioeconomically homogenous in relation to the overall population of the metropolitan area as a whole. When groups are segregated from one another, they live in neighborhoods (and sometimes larger areas) where there is limited opportunity for interaction with members of other racial, ethnic or socioeconomic groups.

Some examples will help to illuminate this conceptualization of residential segregation. A good example of how residential segregation may operate by race and SES may be seen by looking at a portion of the Detroit-Warren-Dearborn metropolitan area that consists of the counties Oakland, Wayne, and Macomb in Michigan. Figure 1 illustrates residential segregation by race. What this figure shows it that northeast Wayne County, where Detroit is located, has high concentrations of Black residents compared to other census tracts within Wayne county and, even more so, to Oakland and Macomb counties within this region. As a result, Wayne County's predominately black neighborhoods are relatively homogenous in their racial make-up compared to the Detroit metropolitan area.

[Figure 1 here]

Figure 2 highlights the extent of residential segregation by socioeconomic status in the form of median income within the same three county region. A similar pattern emerges where the concentration of lower than average median earning census tracts are in the northeast of Wayne County, whereas Oakland County in the upper left has a concentration in the lower-center of the county with median earnings well above the national average. Neighborhoods in the northeast of Wayne County, where Detroit is located, are socioeconomically homogenous with regard to lower median incomes. Neighborhoods within cities such as Auburn Hills in the lower-center of Oakland County are socioeconomically homogenous in terms of median incomes that are four to five times that of the national average.

[Figure 2 here]

As racial residential segregation increases, predominately minority neighborhoods are more heavily concentrated in certain spaces within the metropolitan area (Massey and Denton 1989). Through this concentration of minority populations, and more general racial disparities in household-level factors related to poverty status and income, urban minority neighborhoods have higher concentrations of poverty compared to segregated predominately white neighborhoods (Massey and Fischer 2001; Massey and Eggers 1990).

Historical Trends in Residential Segregation by Race and Socioeconomic Status

In the United States, residential segregation of populations has been driven primarily by race and income, with the separation of Hispanics and especially blacks from non-Hispanic whites being most severe (Reardon 2011; Iceland 2009; Iceland 2004; Glaeser and Vigdor 2001; Massey and Denton 1989). In the past decade residential segregation *by race* has diminished between blacks and whites, while it has slightly increased between Hispanics and whites (Iceland 2009; Glaeser and Vigdor 2001; Cutler, Glaeser and Vigdor 1999). A brief section on residential segregation *by income* will show how the sorting of residents by income levels has more significance today than in previous decades (Bischoff and Reardon 2013; Reardon and Bischoff 2010; Watson

2009). The section will conclude by showing how residential segregation by *race and income* have influenced the way neighborhood resources in the forms of schools, jobs, living conditions, and food availability have been extracted from highly segregated minority and low-income neighborhoods in metropolitan areas (Wilson 2010; Watson 2009; Jargowsky 1996; Wilson 1996; Massey and Denton 1993).

Over the past one hundred years large-scale migration processes have funneled newly arriving black families into predominately minority neighborhoods, throughout the Midwest and Northern Atlantic cities. Especially prior to Civil Rights era legislation in the 1960s, this occurred partly as a result of *de jure segregation,* in which discriminatory federal and state laws in the housing market made it hard for black residents to find a place outside of particular urban neighborhoods to live. To summarize the totality of segregation in that era, "Negroes, regardless of their affluence or respectability, wear the badge of color. They are expected to stay in the Black Belt" (Cayton and Drake 1945: 206).

In the post-civil rights era, many of these laws were abolished, only to be replaced with forms of *de facto segregation,* in which individuals, organizations, or companies generated their own racially discriminatory practices that kept blacks from being able to find housing outside of certain urban neighborhoods. Over time this lead to an increase in racial residential segregation, this process was most pronounced in northern and Midwestern cities such as Philadelphia, Milwaukee, and Detroit, but not exclusive to those regions (Iceland 2004; Jargowsky 1997; Massey and Denton 1993).

Recent changes in residential segregation by *race* have occurred over the past twenty years as a result of primarily the integration of all-white neighborhoods (Frey

2010; Iceland 2004; Glaser and Vigdor 2001). While there is more integration of primarily white neighborhoods, the number of census tracts with black populations exceeding 80 percent nationwide has not changed in this time. Since 1990, the MSA's in the West and South have become more integrated than MSAs in the Northeast and Midwest, which remain highly segregated (Glaser and Vigdor 2001). A potential reason for these regional MSA differences in residential segregation by race is that cities that have large black populations are harder to integrate as a result of preexisting racial barriers that are more extreme than newer cities where there are multiple racial groups integrating simultaneously.

A newer trend has been the increase in differences in neighborhood income levels that have led to higher rates of residential segregation by *income*. (Reardon and Bischoff 2011). This trend is explained in large part by patterns of rising income inequality, in which there is a growing disparity between what high- and low-income families can afford to pay for housing (Watson 2009). This difference in housing affordability has led to increased residential sorting by income.

As a result of this sorting process, there are more neighborhoods today that are classified as either *affluent* (neighborhood median income is at least 150 percent greater relative to median income in the rest of the metropolitan area) or *poor* (neighborhood median income is at least 67 percent lower than the median income for the metropolitan area) compared to forty years ago (Reardon and Bischoff 2010). Additionally, affluent neighborhoods are more segregated from other middle- and low-income neighborhoods compared to poor neighborhoods. This means that these affluent neighborhoods tend to be more isolated from lower income populations, as exemplified by affluent neighborhoods in Auburn Hills, which is on average thirty-four miles from poorer neighborhoods in Detroit.

It is important to consider these historical trends in residential segregation by race and income in light of the main dependent variable, food insecurity, for a number of reasons. To begin, food insecurity has been shown to be driven in large part by a number of household SES factors related to poverty status, unemployment and homeownership (Gunderson et al. 2013; Gunderson 2008). There is a body of evidence which shows that there are real racial disparities in household SES as a result of differences in earned wages, accumulated wealth, occupational prestige and educational attainment (Chiteji 2010; Massey and Fischer 2001; Massey and Denton 1993; Massey et al. 1987). This partially explains why blacks and Hispanics are more likely to be food insecure, as a sheer result of differences in these household-level SES factors. Yet racial disparities for food insecurity rates persist even after accounting for this difference in household-level SES (Gunderson et al. 2011; Gunderson et al. 2008).

This unexplained variance is left unknown, and that is why residential segregation by *race* and *income* is so important to study in the context of food insecurity rates. Prior research has shown that there are racial disparities in health outcomes that are a result of *place-based inequalities* that are associated with residential segregation by *race.* Food insecurity impacts other health outcomes, such as diabetes and obesity, due to the way that it prevents individuals from accessing healthy and affordable foods (Morland and Filomena 2007; Zenk et al. 2005; Bhattacharya et al. 2004). Thus, it is important to understand how residential segregation by *race* predicts food insecurity rates, as this fills in a gap that currently exists in research that links residential segregation and particular health outcomes.

It is also important to study residential segregation by *income* due to recent historical trends that has shown a decrease nationally in black-white segregation (Iceland 2009) and rising income segregation (Bischoff and Reardon 2013). This is necessary because *racial* residential segregation has lost some of its explanatory power in predicting who gets exposed to concentrations of poverty, and thus other forms of disadvantage that may contribute to food insecurity rates. Residential segregation by *income* has taken on some of this explanatory power, and so a study of how residential segregation by *race* contributes to food insecurity rates must take this form of segregation into account. It also provides the additional advantage of filling another gap in the public health literature, as no studies to date have included residential segregation by *income* as a predictor variable on food insecurity outcomes, or other health outcomes more broadly.

The next section will be provide a better understanding of exactly how residential segregation by *race* and *income* may be contributing to racial disparities in food insecurity rates. This will be done by explaining three primary mechanisms through which this may be occurring as a result of residential segregation: place-based inequalities, spatial mismatch, and neighborhood effects on household SES.

Black-White Residential Segregation and Food Insecurity Rates

The separation of residents based on race changes the social environments they live in. This generates some social spaces where children and families have more opportunities, and other social spaces that offer fewer opportunities for accessing critical resources. Thus, it is important to understand how the place one lives may affect one's vulnerability to food insecurity. Specifically, black-white residential segregation concentrates poverty and related forms of neighborhood disadvantage in disproportionately black neighborhoods, exposing black households to a wide range of risk factors and limiting their access to key resources that would protect against food insecurity (Massey and Fischer 2001; Massey and Denton 1993; Massey and Eggers 1990). These risk factors include increased rates of petty and violent crime, fewer available food options that provide healthy and/or affordable foods, lack of transportation options from these places to areas that have food stores such as supermarkets or grocery stores, and public spaces where residents feel unsafe to venture through in order to find affordable food (Rast 2015; Krivo et al. 2009; Kwate 2008; Hipp 2007; Cummins and Macintyre 2002; Grannis 1998). Additionally, residential segregation by *race* has generated a spatial mismatch in job availability, and a number of "neighborhood effects" that have exacerbated racial disparities in household-level SES (Wilson 1996). Spatial mismatch and other neighborhood effects on household SES may then be indirectly contributing to differences in food insecurity rates as a result of these processes.

Racial Disparities in Food Insecurity as a Direct Result of Place-based Inequalities

Sociologists have long studied how the process of residential segregation by *race* influences residents' general well-being based on where they live. Over fifty years ago, Horace Cayton and St. Clair Drake (1945) found that the impact of racial segregation on the health of the black population caused higher infant mortality rates and higher death rates from tuberculosis compared to the white population in Chicago. Cayton and Drake (1945) described these neighborhoods as "black ghettos" that were void of economic and material incentives.

Racial residential segregation at the metropolitan level continues to generate *place-based* differences in relation to access to vital social and public resources. As a result of sheer differences in these socioeconomic factors, especially related to median income and poverty levels, which persist between black and white households, the net effect of concentrating populations *by race* is that predominately black neighborhoods will have *higher rates of overall neighborhood poverty and less economic capital to spend in their neighborhoods* (Massey and Denton 1993). Through this concentration, there is the direct impact of loss of *place-based* resources and the independent structural changes in neighborhood quality, also known as neighborhood effects.

Through this constant exchange of higher income residents exiting and lower income residents moving in, the built environment has been transformed in relation to a number of distinct features. Black neighborhoods in metropolitan areas with high levels of black-white segregation often have fewer organizational resources and lack retail investment (Sharkey 2013; Small and McDermott 2006). Additionally, fewer local businesses can be sustained as a result of overall higher levels of neighborhood poverty

(Boyd 2010; Alwitt and Donely 1997). For those businesses that do persist, it may become unsustainable as a result of increases in crime and drug use in the area that occur as joblessness rises, and residents in the area feel more hopeless with their living situations (Hipp 2010; Sampson and Raudenbush 1999; Grannis 1998; Wilson 1990). As well, neighborhoods that are predominately black or Hispanic tend have higher rates of violent and petty crime, especially homicides (Sharkey 2013; Krivo et al. 2009; Hipp 2007; Grannis 1998).

Through the degradation of the built environment and fewer public spaces that are safe to be in, more residents stay indoors and venture out for only the necessities such as work, food, and family interactions (Dwyer 2010). Additionally, neighborhoods where these place-based inequalities persist are typically areas that have limited transit options (Levine 2014). This occurs because bus routes to and from these spaces are continuously being consolidated or eliminated as a result of shrinking transportation budgets at the regional level (Rast 2015). Minority residents who typically live in these areas may be lower income, and therefore not be able to afford to buy, and maintain, a working automobile (Gautier and Zenou 2008; Raphael and Rice 2002).

Given residents are consigned to certain areas due to crime, as well as fewer transportation options, this limits the food options they have available. What makes matters worse is that another consequence of *placed-based* inequalities that occur as a result of residential segregation by *race* is its impact on the affordability and nutritional value of food options in these areas.

There have been very real historical processes that have created *food deserts* in predominately urban areas of cities across North America that directly relate to residential segregation by *race*. Researchers refers to *food deserts* as areas lacking supermarkets (Short et al. 2007; Cummins and Macintyre 2002), while others define them as zones absent of any retail stores that provide healthy foodstuffs (Caldwell et al. 2010; Wrigley et al. 2002). *Food deserts* are partially a result of large-scale supermarkets that have relocated into suburban areas, and small-scale grocery stores that have closed because of economic instability and rising crime rates, which has created urban areas void of healthy food options (Larsen and Gilliland 2008; Guy et al. 2004; Alwitt and Donley 1997).

Through this absence of healthy food options, spaces were created in predominately minority neighborhoods where convenience stores and fast food restaurants had little competition, low startup costs and a hungry population (Powell et. al. 2007; Block et al. 2004). There is typically double the amount of fast-food locations in predominantly minority neighborhoods as compared to predominantly white neighborhoods (Powell et al. 2007). Additionally, food prices tend to be higher in predominately black neighborhoods as a result of limited food stores options (Larson et al. 2009). With higher prices throughout these areas, this impacts the affordability of food and thus enabling residents few options when trying to purchase a "balanced meal" for themselves and their children.

This has led to deleterious effects on the health of residents within these neighborhoods. A study conducted by Drewnowski and Specter (2004) showed that convenience stores and fast food restaurants provide processed foods, filled with hydrogenated fats, salts and sugars void of any nutritional content. Through this notion of availability, Cummins and Macintyre (2002) research indicated that, as the number of food locations in neighborhoods (supermarkets and grocery stores) decreases, the rate of obesity increases. It is through these connections to other public health outcomes related to nutrition that makes the case for residential segregation by way of place-based inequalities as an influential mechanism that impacts racial disparities in food insecurity rates. While black households in general tend to be worse off compared to white households with regard to poverty rates and unemployment, the impact of residential segregation by *race* concentrates these household-level SES factors based on racial sorting into spaces that are worse off economically, and in turn socially, which leads to an overall loss of important health-based resources. Poor black households that are in metropolitan areas that have higher rates of segregation, and thus lower overall integration, are worse off because they are spatially concentrated with other poor minority households, and thus less overall resources to spend on, in this case, food for their families.

Racial Disparities in Food Insecurity as an Indirect Result of Spatial Mismatch and Neighborhood Effects

Racial residential segregation may also *indirectly* contribute to food insecurity by increasing racial disparities in household SES and overall levels of income inequality. This may occur due to a number of SES factors, which include differences in household income, poverty status, educational attainment, and home ownership rates that occur between black/Hispanic and white households. The spatial mismatch between jobs and black and Hispanic households and particular "neighborhood effects" on household SES are two other important social mechanisms that may be indirectly contributing to racial disparities in food insecurity due to the way they exacerbate these household SES factors.

Spatial mismatch refers to the geographic redistribution of jobs to the outer periphery of the city and suburbs that has occurred in large part over the last forty years (Hacker 2003; Massey and Denton 1993; Wilson 1990). These jobs are now located in places that are hard to access from predominately minority neighborhoods closer to the city center. As discussed before, access to transportation may be too costly, or mass transportation routes may not connect to these new job hubs in the outer periphery of metropolitan areas (Rast 2015; Wilson 1996).

This has taken place in parallel to job loss in the central city as many industrial and factory jobs have been moved to suburban areas, other regions of the United States and even developing countries to lower production costs. Job loss in these sectors has been most severe in Midwestern and Northeastern metropolitan areas, where large portions of black and Hispanic residents are concentrated in urban areas (Levine 2014). Through the mechanism of spatial mismatch, residential segregation by *race* has indirectly contributed to racial disparities in income inequality,

Limited employment opportunity as a result of spatial mismatch combined with preexisting racial disparities in other forms of household SES only makes matters worse. Statistics show that 1 in 4 black households reported incomes below the poverty line, whereas 1 in 11 Non-Hispanic white households reported incomes below the poverty line. Thus the median income for black households was $34,218, but for Non-Hispanic white households it was $55,530, meaning that for every $1 a white household earned, a black household earns just $.62 (U.S. Census Bureau 2013).

Major reasons for these racial disparities in household SES related to earnings are the neighborhood effects on educational attainment and homeownership rates.

Neighborhood effects are a second important social mechanism to consider when thinking about the relationship between residential segregation by *race* and food insecurity rates. Neighborhood effects can be thought of as the negative or positive consequences that come from where you live. These effects have been connected to educational outcomes, home ownership values, and consumer choices (Sharkey and Faber 2014; Galster 2008).

A consequential neighborhood effect relates to the quality of education that is available to students in a given school district. Historical evidence shows that residential segregation by *race* has caused a difference in the quality and availability of primary schools between black and white neighborhoods (Orfield 2001; Hacker 2003). Much like spatial mismatch, higher performing schools tend to be located in neighborhoods that are predominately white and more affluent in the outer periphery of metropolitan areas. The inverse of this is that underperforming schools tend to be in predominately minority and lower income neighborhoods in the urban centers of metropolitan areas (Massey et al. 1987; Wilson 1990).

Partly as a result of these trends, statistics show large gaps in educational attainment with regard to high school and college completion, when comparing white and black populations. For example, 18 percent of all blacks over 25 years old have a college degree, whereas for Non-Hispanic whites, 30 percent of all 25 year olds have a college degree (US Census Bureau 2013). For black children, living in a severely disadvantaged neighborhood context results in a loss in a learning equivalent to one full year of school (Sampson et al. 2008), and lowers graduation rates by as much as 20 percentage points (Wodtke et al. 2011). Educational attainment promotes higher wage jobs, which in turn raises income levels for households where these residents live (Hacker 2003; Wilson 1996). In 2013, just 19 percent of all black household made more than $75,000 a year, whereas 45 percent of non-Hispanic white households made over $75,000 (US Census Bureau 2013; Chiteji 2010).

Lastly, home ownership rates for black households were 45.6 percent, whereas non-Hispanic white families had homeownership rates at 71.6 percent (Kuebler and Rugh 2013). With more households in poverty being concentrated, the physical space around these residents become less functional and aesthetically desirable. Homeowners often lack enough money to invest in renovations to their properties, and landlords find little incentive to invest in rental properties that are in undesirable areas of the city (Flippen 2004; Flippen 2001). This impacts the quality of neighborhoods through a lack of investment by residents' and landlords as a result of less income to spend on upkeep and maintenance.

As discussed before, food insecurity is primarily driven by unemployment, poverty status, and homeownership (Gunderson et al. 2013; Gunderson et al. 2008). As the preceding paragraphs suggests, residential segregation by *race* indirectly contributes to racial disparities in income inequality through the structural influences of neighborhood effects. These neighborhood effects exacerbate racial disparities in educational opportunities, and thus earnings potentials, which indirectly contribute to higher rates of unemployment and poverty status. Additionally, racial disparities in home ownership rates occur as a result of these similar neighborhood effects. Since residential segregation by *race* influences the mechanism of neighborhood effects, it is indirectly contributing to racial disparities in household-level SES, the major driver that explains food insecurity rates.   These direct and indirect connections will be important to understand in order to draw implications to help justify hypotheses put forward in the next section.

Hypotheses

In this section, the information provided in the prior literature review sections on of this chapter will be used as basis to hypothesize about the relationship between segregation by race and income and food insecurity rates. This will be important in order to understand how the process of segregation operates through the direct path of *placed-based* inequalities, and the indirect paths of spatial mismatch and neighborhood effects to show how residential segregation may be able to account for racial disparities in food insecurity rates.

Black-White Segregation and Predicting Food Insecurity Rates

The first point is that residential segregation by *race* concentrates poverty and other forms of disadvantaged in predominately black neighborhoods. The second point is that under these impoverished conditions, black households have more difficulty in accessing adequate food supplies due to a lack of transportation options, the prevalence of "food deserts," higher overall crime rates, and feelings attributed to unsafe streets, makes going out to find resources in the form of work and food more daunting in these racially segregated neighborhoods (Sharkey 2013; Hipp 2007; Cummins and Macintyre 2002; Grannis 1998; Wilson 1996). The third point is that segregation may indirectly exacerbate food insecurity rates that occurs as result of job decline for black households due to the spatial mismatch of jobs being created in neighborhoods on the outer periphery of metropolitan areas, combined with the downturn of job growth in predominately minority urban areas (Levine et al. 2014; Wilson 1996). Additionally, the neighborhood effects of lower quality schools in predominately minority neighborhoods, makes it challenging for black residents in these areas to compete for job placement, and more generally find reliable incomes, and thus opportunities to accumulate wealth through housing options (Orfield 2001).

Place-based inequalities, particularly in relation to food deserts, may be a key mechanism that helps to explain the influence of residential segregation by *race* and racial disparities that persist with regard to food insecurity rates. Less access to affordable food and nutritional food means less chance that minority residents in segregated neighborhoods can adequately feed themselves and their families. Based on this discussion, the first hypothesis predicts a relationship between residential segregation by *race* and food insecurity rates that reads:

> *H1: Higher levels of black-white segregation at the metropolitan level will be associated with higher rates of food insecurity in predominately black counties, but less so in counties with fewer black residents.*

Hispanic-White Segregation, Immigrant Enclaves and Food Insecurity Rates

Residential segregation by *race* has produced similar place-based inequalities for predominately Hispanic neighborhoods across the United States. This is because many of the mechanisms that link Hispanic-white residential segregation to food insecurity are similar to those that link black-white residential segregation and food insecurity rates. These mechanisms may include fear of crime, limited transportation options, and the indirect effects of segregation in relation to racial disparities via household SES factors. An important mechanism that linked Hispanic-white segregation and food insecurity rates is through food deserts. Research on *food deserts* has shown similar outcomes in relation to fewer supermarkets, and more fast food in relation to increased racial composition of Hispanics (Powell et al. 2007; Baker et al. 2006; Block et al. 2004).

Racial residential segregation for U.S.-born Hispanics, foreign-born Hispanics, and blacks may be different. A number of studies have shown similarities between how racial residential segregation leads to place-based inequalities for black and for U.S.-born Hispanics. Typically, both groups live in areas that have higher rates of crime, less access to transportation routes, and fewer available education and job options. Additionally, blacks and U.S.-born Hispanics also have worse health outcomes compared to their white counterparts, at least partially as a result of racial residential segregation (Britton and Shin 2013; Osypuk, et al. 2010; Williams and Collins 2001;Williams 2001).

An important nuance to this relationship is the notion of "immigrant enclaves," where foreign-born Hispanic populations who are residentially segregated by *race* tend to have better health outcomes compared to their native counterparts (Osypuk et al. 2010; Crimmins et al. 2007; Logan et al. 2002). Additionally, evidence has shown a connection between high proportions of foreign-born residents and reduced violent crime (Sampson et al. 2008). This is also true in relation to food, as these communities tend to still have cultural connections to culinary traditions that may encourage them to cook with more whole grains and vegetables (Gabaccia 2009). In general, immigrant Hispanic populations may have a stronger reason *to segregate* due to the positive relationships that immigrant enclaves' help newly arrived immigrants adjust to the new host society in a variety of ways as described above (Massey 1984). Based on this research around health outcomes, food availability and the distinction of ethnic enclaves, a second and distinct hypothesis is needed for Hispanics that reads:

> *H2: Higher levels of Hispanic-white segregation at the metropolitan level will be associated with higher rates of food insecurity in predominately non-immigrant Hispanic counties, but less so in predominately non-Hispanic counties or predominately immigrant Hispanic counties.*

Income Segregation and Food Insecurity

Recent trends in segregation that show falling levels of black-white segregation, and rising levels of income segregation means residential segregation by *race* has lost some of its importance relative to more general processes of income segregation with regard to determining who gets exposed to concentrated poverty and disadvantage (Reardon and Bischoff 2010; Massey et al. 2009; Glaser and Vigdor 2001). Due to these trends, it is important that a study of how residential segregation by *race* contributes to racial disparities in food insecurity, also takes more general processes of income segregation into account.

The three measures of income segregation being used in this analysis are*,* the *segregation of poverty,* the *segregation of affluence* and *overall income segregation.* Each of these measures has their own hypothesis related to disparities in food insecurity rates. Both are related to the two of the major factors that drive food insecurity rates: unemployment and poverty status.

Extreme poverty concentration that has historically been associated with high levels of black-white residential segregation has begun to give way to more general processes of income segregation that has concentrated wealth and poverty into distinct neighborhoods (Dreier et al. 2004). More general processes of poverty concentration and income segregation are likely to be associated with food insecurity rates for a number of reasons. First, higher rates of poverty are linked to higher rates of crime and lack of transportation options that occur as a result of place-based inequalities, thus making it harder for residents in predominately lower-income neighborhoods to navigate the local environment to find available food options (Rast 2015; Hipp 2004; Wilson 1996). Second, poverty concentration limits household opportunities as a result of fewer job options that provide "living wages" (Massey and Fischer 2001), which may increase food insecurity rates at the metropolitan-level because it generates more neighborhoods that have residents who are overwhelmingly poor, unemployed or lack homeownership. Based on these mechanisms through which residential segregation by *income* operates a third hypothesis reads as follows:

> *H3: Higher levels of neighborhood poverty concentration in metropolitan areas will be associated with higher rates of food insecurity in relatively high poverty counties, but less so in counties with lower poverty rates.*

At the other extreme, a higher concentration of affluence in a metropolitan area means that income is not evenly dispersed across neighborhoods, but instead there are more neighborhoods that are predominately high-income residents (Reardon and O'Sullivan 2004). The *segregation of affluence* in metropolitan areas has the capacity to increase food insecurity rates because concentrating affluent households may draw vital resources, such as job opportunities and available food options away from impoverished and middle income neighborhoods (Rast 2015; Powell et al. 2007; Zenk et al. 2005). Residents in these neighborhoods, especially those in poverty, then will have fewer food options to access and thus may increase food insecurity overall at the MSA-level. For this reason, a fourth hypothesis has been put forward that reads:

> *H4: A higher concentration of affluence overall at the metropolitan level will be associated with higher rates of food insecurity.*

As noted above, concentrating affluence at the metropolitan-level may increase food insecurity rates because it generates more income inequality across neighborhoods, so there are fewer mixed-income neighborhoods and a handful of neighborhoods that are exceptionally affluent (Bischoff and Reardon 2013; Reardon 2011). While this works to increase food insecurity rates at the metropolitan-level, residential segregation by *income* as measured by the *segregation of affluence* may lower food insecurity rates for smaller geographic regions within this metropolitan area. To take the original example of Oakland-Wayne-Macomb counties from the conceptualizing residential segregation section, it is easy to comprehend how this might work. While overall metropolitan-level food insecurity rates may rise as a result of concentrating affluence, Oakland County may actually have much lower rates of food insecurity as a result of income concentration.

Concentrating *affluence* brings positive neighborhood effects and place-based advantages. Through higher-quality education programs, more residents are homeowners, and more may have more wealth to invest in retail and commercial businesses. More income brings more resources and the capacity to spend those resources on retail investment in the form of multiple food stores, as well as the ability to be able access these stores due to the advantage of owning a car (Nechyba 2003; Raphael and Rice 2002). Thus, a fifth hypothesis conditions what is being predicted in H (4):

> *H5: The effect predicted by H4 will be weaker in counties with high proportions of affluent residents.*

Lastly, *overall income segregation* may also be influencing food insecurity rates at the MSA-level. Since the two measures of income segregation that look at either end of the income spectrum, the *segregation of poverty* and the *segregation of affluence*, have been hypothesized to impact food insecurity rates, then it might be expected that *overall income segregation* will also negatively influence food insecurity rates. When families are more or less sorted by income throughout metro areas, with neighborhoods that are a mixture of residents with various incomes, or neighborhoods with a homogenous population of residents with similar incomes, this may also impact overall food insecurity rates. The final hypothesis predicts that as overall income segregation rises, such that residents in neighborhoods have income almost exactly the same as their neighbors, with more overall neighborhoods that are higher-, middle-, or low-income, then food insecurity rates will also rise at the metropolitan level. The hypothesis reads:

H6: Higher levels of overall income segregation in metropolitan areas will be associated with higher rates of food insecurity.

Residential Segregation by Race and Income: Implications for Food Insecurity Rates

Williams and Collins (2001) have shown that residential segregation plays a key role in racial health disparities. This occurs as a result of the way that residential segregation produces differences in household SES, which then contributes to the overall outcome of the neighborhood. In neighborhoods that are highly segregated based on a population that is both low-income and minority status, there is a lack of neighborhood wealth, which then contributes to a lack of neighborhood organizations and upkeep of the built environment. This then leads to a degradation of the social environment, which strains health-related social processes (Williams et al. 2003).

A number of studies have focused on racial and income disparities related to food insecurity (Gunderson et al. 2013; Coleman-Jensen et al. 2011; Gunderson 2008; Gulliford et al. 2006), yet none have addressed how residential segregation by *race and income* may impact food insecurity rates. In light of the diminished impact of residential segregation by *race* on racial disparities in household-level SES in recent decades, it is important to consider more general processes of income segregation when hypothesizing about food insecurity rates. Thus, it is important to consider how the segregation of affluence and poverty works to pull resources (jobs, education, or food stores) out of middle- and low-income neighborhoods to the benefit of affluent neighborhoods. As a result of this gap in the public health literature and changes in segregation patterns, a final discussion will be had that looks at how the various aspects of income segregation may account for part of the association between black-white and Hispanic-white segregation and food insecurity.

Racial residential segregation has historically been one of the key drivers of income segregation, given pronounced disparities in SES by race, especially when comparing blacks and non-Hispanic whites (Massey and Eggers 1990). Yet, the results for racial residential segregation could be spurious if one does not take income segregation into account. This is in part due to prior research showing that in the current era rising levels of income inequality have both increased income segregation and rendered income segregation a more general process that is now increasingly independent of racial residential segregation. In order to determine how robust the relationship between racial segregation and food insecurity is considering these more general processes of income segregation, a final set of models includes both *racial* and *income* segregation as predictors of food insecurity. There are no formal hypotheses for this modeling, as it merely a way to determine that any potential findings that occur between racial segregation and food insecurity remain significant even after including income segregation measures to the model.

CHAPTER 3: METHODS, DATA ANALYSIS, AND STATISTICAL MODELING

The purpose of this study was to determine to what extent specific forms of residential segregation (i.e., racial segregation between blacks and whites and between Hispanics and whites, as well as income segregation in the overall population) at the metropolitan-level effected county-level food insecurity rates, with county-level racial composition and socioeconomic factors as moderators of this relationship. The unit of analysis for this study was U.S. counties. The dependent variables (described in more detail below) were indicators of food insecurity rates measured at the county level, while the main independent variables were indices of residential segregation by race and income, measured for U.S. metropolitan areas, many of which included multiple counties. Additionally, racial (e.g., percent black) and socioeconomic composition (e.g., poverty rate) were measured at the county-level and included in the analysis both as control variables and in order to estimate cross-level (county-metropolitan area) interaction effects. MSA-level measures were calculated based on geographically contiguous census tracts that define given “neighborhoods” within a metropolitan area.

The remainder of this chapter discusses each data source in detail, and how these data sources fit into the regression modeling. A series of models focused on county-level food insecurity variables in order to test cross-level interaction effects that may have occurred between county-level measures of racial and/or socioeconomic compositions and metropolitan area-level measures of segregation. Through this modeling, it was determined to what extent county-level measures of race and SES moderated the effects of metropolitan-level measures of segregation.

Data

This research compiled a unique multilevel dataset in order to assess the association between segregation and food insecurity outcomes. The first dataset provided estimates of household and child food insecurity at the county-level and has been obtained through the Feeding America's *Map the Meal Gap* (hereafter "MMG") project, which assessed food insecurity nationally. Feeding America's MMG project started in 2011 to gain a better understanding of hunger at the local-level. MMG produced local-level estimates to identify strategies for populations that are most at risk of hunger. The MMG project derived its measures of food insecurity rates from a module within the Current Population Survey (CPS). The CPS is a nationally representative survey conducted by the Census Bureau for the Bureau of Labor Statistics, providing employment, income, and poverty statistics. In December of each year, 50,000 households respond to a series of questions on the Core Food Security Module (CFSM), in addition to questions about food spending and the use of government and community food assistance programs.

The second dataset provided measures of racial segregation based on the 2010 census at the MSA-level. This dataset has been generated by the Population Studies Center (PSC) at the University of Michigan using 2010 Census Decennial tract data. The PSC followed standard conventions when computing the segregation measures for racial groups (Frey 2010; Iceland 2004; Massey and Denton 1993), classifying the population into four distinct racial categories: non-Hispanic Whites, Hispanics, non-Hispanic blacks and non-Hispanic Asians.

The PSC used a threshold of 5,000 minority residents at the MSA-level to ensure that the minority populations being examined were large enough to ensure that segregation measures would be reliable (Walton 2009; Subramanian et al. 2005; Ellen 2000). For example, metropolitan areas had to have at least 5,000 black residents in order to be included in the analysis that focused on black-white segregation, even though there may have been less than 5,000 black residents within given counties in this MSA. This was also true for the analysis of Hispanic-white segregation where the threshold for being included required an MSA to have a minimum of 5,000 Hispanic residents.

This analysis began with 3140 counties connected to 387 MSAs. Overall, there were originally 3140 cases at the county-level and 387 cases at the MSA-level. There were 119 MSAs with one county, 76 MSAs with two counties, 42 MSAs with 3 counties, 38 MSAs with 4 counties, and the remaining MSA's had 5 or more counties associated with them. The average number of counties for an MSA was 3.09. Due to the required threshold of 5,000 minority residents, the total number of MSAs differed based on the specific racial segregation measure being used as noted in the description above. Using this minimum threshold requirement of 5,000 minority residents, 298 MSAs comprised of 966 counties were included in the analysis focused on black-white segregation. For the analysis focused on Hispanic-white segregation, there were 347 MSAs comprised of 1023 counties that had at least 5,000 Hispanic residents.

The third dataset consisted of income segregation measures at the MSA-level calculated through the US2010 project at Brown University[1]. Income segregation was calculated using the American Community Survey (ACS) 2005-2009 5-year estimates.

[1]http://www.s4.brown.edu/us2010/Data/Data.htm

The ACS is a nationally representative mandatory survey of three million addresses administered by the Census Bureau. Approximately one in thirty-eight households are invited to participate in the ACS survey. Median income was used as the primary variable from the ACS 2005-2009 data to calculate income segregation measures. A dataset calculated by Reardon and Bischoff (2010) includes data on income segregation in 381 MSAs, which included a total of 1098 counties.

The fourth group of datasets came from the Robert Wood Johnson (RWJ) County Health Rankings for 2014 and was used primarily for control variables at the county-level. RWJ compiled these variables from a number of sources that are described in detail below. The primary control variables included: percent African-American (black), percent Hispanic, high school graduation rate, percent some college attendance, percent unemployed, percent of children in poverty, median income, and total population. Control variable from this group of datasets were derived from a number of sources, which have been described at length in the "Control" section of this chapter.

These four datasets (MMG, PSC, US2010, and RWJ) have been merged using a County Crosswalk FIPS file that links unique identification numbers between counties and metropolitan statistical areas (MSAs). The crosswalk file connected the core-based statistical area (CBSA) codes for MSAs to FIPS codes at the county level. Merging these data enabled the analysis of cross-level interactions between racial and income segregation measures at the MSA-level, with racial composition and socioeconomic variables at the county-level (Roth 2012).

STATA 12 was used for data cleaning and missing value assessment. The analysis used mean imputation for 18 missing values on high school graduation rates, 7 missing values on percent of African-Americans, and 2 missing values on percent with some college education.

Measures

Dependent variables

The main dependent variables were county-level estimates of household and child food insecurity at the county-level obtained from Feeding America's *Map the Meal Gap* (MMG) data. These are synthetic estimates as they rely on MMG's modeling of food insecurity. The MMG project generated county-level estimates of food insecurity rates for two distinct populations: households and households with children. Both measures of *food insecurity* were based on the CFSM questions in the December CPS and information from the ACS 5-year estimates. The CFSM questions were developed by the USDA's Food and Nutrition Service as a way to document issues of hunger in the United States (Carlson et al. 1999). Appendix 1 provides the questions that were used in the CFSM section.

Household food insecurity was estimated for all households. Households were considered "food insecure" if they answered affirmatively to at least 3 of the 10 questions from the CFSM. Household food insecurity rates were calculated in a two-step process (Gunderson et al. 2013). Step 1 used aggregated household-level data from each of the 50 states drawn from the CPS and CFSM for 2001-2013. Variables from the CPS and CFSM were used to conduct a regression analysis that estimated the overall household food insecurity rate at the state-level. CPS provided state-level estimates of predictor variables, while the CFSM supplement provided information about state-level food insecurity rates. The analysis regressed state-level food insecurity rates on key predictors of food insecurity, including unemployment rates, poverty rates, median income, percent Hispanic, percent Black, homeownership rate, and fixed-effect terms for the year$_{(\mu)}$ and state $_{(v)}$.

The equation for household food insecurity was as follows:

$$FI_{st}= \alpha + \beta_{UN}UN_{st}+ \beta_{POV}POV_{st}+ \beta_{MI}Mi_{st} + \beta_{HISP}HISP_{st} + \beta_{BLACK}BLACK_{st}+ \beta_{own}OWN_{st}+ \mu_t + v_s + e_{st}$$

In order to obtain county-level estimates, Step 2 used the coefficient estimates from Step 1 plus information for counties on the same variables drawn from the ACS 2007-2011 and, for unemployment rates, data came from the Bureau of Labor Statistics 2007-2011 estimates (Gunderson et al. 2013).

In order to estimate child food insecurity rates at the county-level, a similar two-step process was employed. However, how households were defined as food insecure was different for households with children. Child food insecurity questions were administered to households that reported having one or more children under the age of eighteen (Gunderson et al. 2013). Child food insecurity was estimated based on households with children who answered affirmatively to at least 3 of the 18 questions on the CFSM (see Appendix 1). The predictor variables were also slightly different for the child food insecurity rate. County-level data included poverty among households with children, the unemployment rate, median income among households with children, percent Hispanic children, percent African-American children and homeownership rate among households with children. The estimates of child food insecurity rates were calculated by taking the estimated number of children in food insecure households in a given county divided by the total number of children in the same county.

Measuring Racial Segregation at the MSA-level

According to the interest of this analysis, racial segregation is one of the primary independent variables that may have an impact on food insecurity. The most commonly used measure of segregation is the index of dissimilarity (D). The index of dissimilarity has become a standard indicator for racial segregation between groups within a metropolitan area. The index of dissimilarity (D) measures the dimension of unevenness between minority/majority populations in a given metropolitan area (Massey and Denton 1989). The formula used to calculate the dissimilarity index for two racial groups within the metropolitan area was defined as:

$$D = \frac{1}{2}\sum_{i=1}^{n} \left| \frac{P1_i}{P1} - \frac{P2_i}{P2} \right|$$

where P_1 is the population of group 1 in the metropolitan areas, P_2 is the population of group 2 in the metropolitan area, P_{1i} neighborhood *i* population of Group one, P_{2i} neighborhood *i* population of Group two, and *n* is the number of neighborhoods in a given metropolitan area. "Neighborhoods" have been operationalized as census tracts. The index of dissimilarity (D) measures the dimension of unevenness between minority/majority populations within a given area. Based on a zero to one scale, this number represents a proportion of a given minority (or majority) group's members who would have to change census tracts within the metropolitan area to achieve an even distribution (Massey and Denton 1989). For example, a value of .2 on the black-white dissimilarity index would mean that 20 percent of the black (or white) population would have to move in order to achieve an even distribution of blacks and whites across census tracts in the metropolitan area. Numbers over .60 indicate a high degree of segregation between populations.

Indices were calculated for all metropolitan statistical areas (MSAs) with a 2010 population of at least 50,000 residents. An MSA is defined by the Office of Management and Budget as a Core Based Statistical Area (CBSA) associated with at least one urbanized area that has a population of at least 50,000 residents. The MSA is composed of a central county or counties containing the core of the population, plus adjacent outlying counties that have a high level of social and economic exchange based on commuting patterns (Office of Budget and Management 2010). These measures for the index of dissimilarity for Black-white and Hispanic-white groups are based on the 2010 census information provided from the University of Michigan's Population Studies Center (PSC) (Frey 2010). This census information provides population based information for every level of geography down to the tract level. The tract level was used as the geographic unit for calculating the index of dissimilarity, which also represents a "neighborhood" for the purposes of this analysis.

Measuring Income Segregation at the MSA-level

Income segregation was indicated by three measures: *overall income segregation, the segregation of poverty,* and *the segregation of affluence.* These three measures of segregation were derived from the *rank-order information theory index* (H^R) and one of its components, the so-called traditional information theory index (Reardon 2011; Reardon & Bischoff 2010). This index provides a measure of income segregation that uses overall income distribution of a given metropolitan area, and then produces percentile ranks from this distribution. For example, the median family income in the Milwaukee metropolitan is about $70,700, so this income would correspond to the 50th percentile rank in metro Milwaukee's family income distribution. The index uses the percentile rank (50), as opposed to the actual dollar amount of median income ($70,700) to measure income segregation.

Rank-ordering of incomes ensures that income segregation is being measured independent of differences across metropolitan areas in levels of income inequality. This has been a central flaw for other measures of income segregation such as the Gini coefficient or the Neighborhood Sorting Index (NSI), which conflate residential segregation by income with overall levels of income inequality (Jargowsky 1996). The rank-order information theory index measures the ratio of within-unit income rank variation to overall income rank variations. For the purposes of the analyses conducted for this dissertation, within-unit variation was defined as variation in family income percentile rank within census tracts, and overall variation was defined as a variation in family income percentile rank across entire metropolitan areas (Reardon et al. 2009).

Formally, the rank order information theory index is based on income percentile ranks, denoted as *p*, along with two more well-established measures, the entropy index of diversity, *E(p)*, and the traditional information theory index of segregation, *H(p)* (Reardon and Bischoff 2010).The rank-order information theory index is obtained by first computing the entropy index and the traditional information theory index for households above and below each point p in the income distribution and then taking a weighted average of the values of $H(p)$ across the entire income distribution, in which the weights are proportional to the values of $E(p)$ (see Reardon and Bischoff 2010: Appendix A for a more detailed description).[2] More precisely, the rank-order information theory is defined as follows:

$$H^R = 2\ln(2) \int_0^1 E(p)H(p)dp$$

Overall income segregation, H^R, ranges from a minimum of zero, where the income distribution in each tract is the same as the greater metropolitan area, and a maximum of one, where there is complete income segregation. In a hypothetical metropolitan area in which the income distribution among families within every census tract was identical (and therefore identical to the overall metro income distribution), the index would equal zero, indicating no segregation by income. In such a metropolitan area, household income would have no correlation with the average income of other households in the census tract. In contrast, in a hypothetical metropolitan area in which each tract contained households of only a single income level, the index would equal to one. In such a metropolitan area, segregation would be at its absolute maximum; no household would have a neighbor with a different income than its own. Income segregation index profiles can be computed for each metropolitan statistical area, and equally important, because they are calculated using income percentiles rather than

[2] Because $E(p)$ is maximized as when p = .5 (the median family income) and minimized when p = 0 or p = 1, this weighted averaging of the values of $H(p)$ has the effect of giving greater weight to typical values near the center of the income distribution and lesser weight to values at the extremes.

nominal income values, these profiles can be compared across metropolitan areas and racial groups.

As the preceding suggests, income segregation measures, *H(p)*, can be estimated for specific income thresholds to determine segregation between groups defined by those thresholds. The equation for H*(p)* is:

$$H(p) = 1 - \sum_j \frac{t_j E_j(p)}{TE(p)}$$

where T is the population of the metropolitan area and t_j is the population of neighborhood *j,* and *E is* the Entropy Index. .

If one wants to estimate the segregation of families in the top 10 percent of the income distribution and all others, *H(.9)* can be fitted for any number of metropolitan areas to measure the *segregation of affluence*. Poverty can be concentrated in the same manner as affluence, so fitting *H(.1)* to metropolitan areas would provide the *segregation of poverty*. The *segregation of poverty* captures the extent that low-earning households (specifically, the bottom 10 percent) in a metropolitan area live in separate neighborhoods from all other middle and higher earning families (those in the remaining 90 percent) (Reardon 2011; Reardon and Bischoff 2010)[3]. The three dimensions of income segregation will be measured separately in order to test the specific hypotheses proposed in Chapter 2 are overall income segregation (known as $H^{R)}$, the segregation of poverty, known as H (.1) and the segregation of affluence, known as H (.9).

[3] This *segregation of poverty* measured based on the *rank-order information theory* (Reardon 2010) differs from the dissimilarity index used to measure the segregation between poor and nonpoor households, as defined by the federal poverty thresholds. This measure focuses on relative poverty (i.e., on the segregation of households that are poor relative to others in the same metropolitan area) rather than on an absolute standard.

Control Variables

The household and child food insecurity variables have been computed by using an equation that includes racial percentages for blacks and Hispanics at the county-level (see “Dependent variables” above). As a result, food insecurity estimates may have had a significant relationship with the primary independent measure of racial composition. Previous studies have shown a high correlation between racial composition (e.g., percent black) and the dissimilarity index **(**D) (Massey and Denton 1989; Glaster 1984; Taeuber and Taeuber 1976)**.** There was also the potential that any association between income segregation and estimates of food insecurity may have been a statistical artifact due to the fact that food insecurity rates were calculated using median income, unemployment rate, and poverty rates. Using measures of income segregation that relied on income percentile ranks may have mitigated this concern, but it probably did not eliminate it entirely.

In order to address the possibility that any observed association between the measures of residential segregation by *race* and *income* and estimated food insecurity rates might be a statistical artifact, controls for racial composition and socioeconomic composition at the county-level were included in the analysis. In the present analysis, this was accomplished by including controls for the percent black, the percent U.S.-born and foreign-born Hispanic in each county, as well as socioeconomic variables related to high school graduation rate, percent with some college, percent unemployed, percent children in poverty, and median income. As described in more detail below (see “Statistical Model”), several of these variables were also used to test cross-level interaction effects between metropolitan-area-level measures of residential segregation and county-level racial and socioeconomic composition.

The variables that represented socioeconomic status were: *high school graduation rate*, *percent of residents who attended some college*, *percent of residents who are unemployed*, *percent of children in poverty*, and *median income*. As well for the *segregation of affluence* modeling, a control variable was created that calculates the *percent of high-income households* in a given county. The high school graduation rate variable was derived directly from http://data.gov. This indicator examined the percentage of public high school students who graduate on time with a regular diploma. The indicator used the *Averaged Freshman Graduation Rate* (AFGR), which is the number of high school diplomas expressed as a percentage of the estimated freshman class 4 years earlier.

The second education variable, *some college education*, was derived from the ACS 2008-2012 estimates. This variable was based off of the question, "At any time IN THE LAST 3 MONTHS, has this person attended regular school or college? *Include only nursery or preschool, kindergarten, elementary school, and schooling which leads to a high school diploma or a college degree.* If this question was answered affirmatively, then a follow-up question asked, "What grade or level was this person attending?" with "College Undergraduate years" as an option.

The *percent of unemployed residents, percent of children in poverty* and *median income* in a given county were used as additional measures of SES. The variable *percent of unemployed residents* came from the Bureau of Labor Statistics for the year 2012. This variable measured the "percent of population age 16+ unemployed but seeking work." In order to get this measure, the Bureau of Labor Statistics asked a number of questions related to employment. People were classified as unemployed if they do not have a job, have actively looked for work in the prior 4 weeks, and are currently available for work.

County-level child poverty rates have been calculated by the Small Area Income and Poverty Estimates (SAIPE) program for 2012. This measured the percent of children who are under the age of 18 in poverty. The estimation model for people under age 18 in poverty was based on five predictor variables:

- the log of the number of child exemptions indicated on tax returns whose adjusted gross income falls below the official poverty threshold for a family of the size implied by the number of exemptions on the form;
- the log of the number of SNAP benefits recipients in July of the previous year;
- the log of the estimated resident population under age 18 as of July 1;
- the log of the total number of child exemptions indicated on tax returns; and
- the log of the Census 2000 estimate of the number of people under age 18 in poverty.

Median income and total population size were based on the ACS 2007-2012 five year estimates.

The *percent of high-income households* in a given county was computed by using two variables from the income segregation dataset as a ratio. Specifically, the *total number of affluent households* was divided by the *total number of households* at the county-level to generate the variable, *percent of high-income households*. *Affluent* households refers to households that have median income ratio greater than 1.5, which means that based on an average national median income of approximately $75,000, affluent households would have incomes above $112,500.

A Census region control variable has been included because there may be regional differences that are correlated with segregation levels. Four census regions were used: Northeast, Midwest, South and West. For MSA's associated with black-white segregation, there were 83 counties in the Northeast region, 555 counties in the South, 79 counties in the West, and 249 counties in the Midwest region. For MSA's associated with Hispanic-white segregation, there were 90 counties in the Northeast region, 549 counties in the Northeast region, 127 counties in the West region, and 258 counties in the Midwest region.

Statistical models

Ordinary least squares (OLS) regression models with robust standard errors clustered by metropolitan area were used to test each hypothesis proposed in Chapter 2. This was an appropriate model for assessing the potential association between MSA-level segregation measures and estimates of county-level food insecurity rates, with potential cross-level interactions effects (i.e., interactions between segregation at the metropolitan level and racial or socioeconomic composition at the county level). Robust standard errors addressed possible non-independence of observations across counties within a given metropolitan area.

Racial Segregation Models

In order to test H (1) and H (2), *two models* were estimated for food insecurity, and *two models* were estimated for child food insecurity; thus, H (1) and H (2) were each assessed with *four models* total. The models testing H (1) used the black-white dissimilarity index as the primary predictor variable, whereas those testing H (2) used the Hispanic-white dissimilarity index as the main predictor variable.

For H (1), one model regressed the estimated food insecurity rate at the county-level on the MSA-level black-white dissimilarity index as the key predictor variable, with controls for county-level racial composition (i.e., percent black) and the additional control variables discussed above, and another added an interaction term that multiplied the black-white dissimilarity index (D_{BW}) at the MSA-level by the percent black at the county-level (i.e., D_{BW} X percent black). These interaction models provided direct tests of H (1); the additive models (i.e., without interaction terms) were estimated only to provide a basis of comparison (i.e., to assess whether adding the interaction terms significantly improved model fit).

Similarly, for H (2), one model regressed each outcome variable on the MSA-level Hispanic-white dissimilarity index, with controls for county-level racial and immigrant composition (i.e., percent U.S. born Hispanics and percent immigrant Hispanics) as well as the additional control variables discussed above. Another model added two-way interaction terms for the Hispanic-white dissimilarity index (D_{HW}) and the measures of county-level racial and immigrant composition (i.e., D_{HW} X percent U.S.-born Hispanics and D_{HW}X percent foreign-born Hispanics). These models tested cross-level interactions to assess how the prevalence of Hispanic immigrant and ethnic enclaves may have moderated the association between Hispanic-white segregation and food insecurity rates. An F test was conducted to assess whether adding the interactions significantly improved model fit.

Income Segregation Models

In order to test H(3) through H(6), an additional series of regression models were estimated for each of the two forms of food insecurity using income segregation as indicated by three measures, the *segregation of poverty, H (.1),* the *segregation of affluence, H (.9), and* the *overall income segregation*, H^R, as the main predictor variables. For H (3), *two models* examined the relationship between the *segregation of poverty* measure at the metropolitan-level and each form of food insecurity (household food insecurity and child food insecurity). Both of these models included county-level measures of socioeconomic composition that included: median income, high school graduation rate, percent of the population with some college, and percent of the population who are unemployed. For each measure of food insecurity rates, a second model added an interaction term (e.g., percent children in poverty at the county level X H (.1), the segregation of poverty measure).

For H (4), one model was used to examine the relationship between the MSA-level *segregation of affluence* measure and each form of food insecurity, while including these county-level measures of socioeconomic composition: median income, high school graduation rate, percent of the population with some college, and percent of the population who were unemployed. In order to test H (5) for household and child food insecurity rates, one model was used. For each form of food insecurity, an interaction term that combined the *segregation of affluence* measure at the MSA-level with the county-level measure of *affluence* (i.e., percent of high-income households in a given county) was included in addition to a MSA-level *segregation of affluence* measure*,* as well as the county-level socioeconomic composition measures previously mentioned. This interaction model was used to assess how the inclusion of this interaction term influenced model fit and to assess whether cross-level interactions were occurring between county-level socioeconomic composition and the MSA-level segregation of affluence.

Lastly, for H (6) one model was used to test the relationship between the MSA-level measure of overall income segregation and the two forms of food insecurity. This model included the MSA-level measure of overall segregation, along with these county-level measures of socioeconomic composition: median income, high school graduation rate, percent of the population with some college, and percent of the population who were unemployed.

Combined Racial and Income Segregation Models

A final set of models added the income segregation measures to the interaction models used to test H (1) and H (2). This was done separately for *segregation of poverty,* the *segregation of affluence,* and *overall income segregation*. This modeling was done to provide a better understanding of how any of these measures of income segregation may account for the expected interactions between county-level racial composition and MSA-level racial segregation for black-white and Hispanic-white segregation. *Six* models were generated for each form of food insecurity. This means that there were *twelve* models total in this final regression output.

The six models used these combinations of *racial* and *income* segregation measures: 1) the measure *segregation of affluence* and black-white dissimilarity index; 2) the measure *segregation of poverty* and black-white dissimilarity index; 3) the *overall measure of segregation* and black-white dissimilarity index; 4) the measure *segregation of affluence* and Hispanic-white dissimilarity index; 5) the measure *segregation of poverty* and Hispanic-white dissimilarity index; 6) the *overall measure of segregation* and Hispanic-white dissimilarity index. Each model had the appropriate racial composition measures, interaction terms and control variables.

CHAPTER 4: BLACK-WHITE RESIDENTIAL SEGREGATION AND FOOD INSECURITY RATES

Overview

The primary goal of this dissertation was to evaluate if residential segregation by *rac*e at the metropolitan-level may influence food insecurity rates at the county-level, based on three important considerations. First, racial disparities persist with regard to food insecurity even after accounting for a number of key socioeconomic factors. Second, these socioeconomic factors related to unemployment, poverty and median income have had large inequalities between white and black/Hispanic populations as a result of historical trends in racial residential segregation. Third, public health research has shown that racial residential segregation is an important factor that contributes to black-white health disparities related to a range of chronic health conditions (Landrine and Corral 2009; Williams and Collins 2001).

Based on these considerations, this chapter focused on residential segregation by *race* with regard to potential differences in food insecurity rates between primarily black and non-black counties. This may be occurring because of geographic influences occurring as a result of black-white segregation at the metropolitan-level. The main reason to look at MSA-level segregation is because it increases exposure to neighborhood poverty and disadvantage through the sorting of residents by race.   As noted below, H (1) is a hypothesis that was tested by estimating the regression models described in Chapter 3, while controlling for racial composition and socioeconomic correlates related to food insecurity rates. Additionally, an interaction term has been included in the second model for both food insecurity and child food insecurity. This interaction term multiplied the MSA-level index of dissimilarity for black-white segregation by the percentage of blacks at the county-level. An interaction term assesses potential variation in the strength of the association between black-white segregation and food insecurity as a function of the percent black in a given county.

It is also important to note that child food insecurity rates in relation to MSA-level racial residential segregation may vary slightly from overall food insecurity rates, but not to the extent that would have warranted another set of hypotheses. Thus, child food insecurity has been hypothesized to be positively associated with MSA-level black-white dissimilarity, such that as MSA-level black-white segregation rises in a given metro area, the predominately black counties will be expected to have higher rate of child food insecurity.

This discussion revolved around the main hypothesis for this chapter. That hypothesis predicted the relationship between black-white segregation and food insecurity states:

H1: Higher levels of black-white segregation at the metropolitan level will be associated with higher rates of food insecurity in predominately black counties, but less so in counties with fewer black residents.

The summary statistics (Tables 1-4) show a couple of important items worth mentioning. The average segregation level in the MSAs included in the analysis is fairly low (values of D in the .34 to .60 range are usually considered moderate). This reflects two things: the declining levels of black-white segregation in U.S. metropolitan areas generally, and potentially the inclusion of many small metropolitan areas with relatively small black populations in the analysis sample (Cutler, Glaeser, and Vigdor 1999). Percent black is highly correlated with food insecurity, which could be a result of this same measure being used in the synthetic estimate of food insecurity.

[Tables 1-4 here]

Interpretation of Regression Analyses

Food Insecurity Rates

Table 5 shows the output of the multivariate OLS regression analysis for food insecurity rates. These results were obtained by regressing food insecurity rates onto the main predictor variable, MSA-level black-white index of dissimilarity (D). An initial, additive model was estimated to provide a basis of comparison (i.e., to determine whether model fit would be improved significantly by including an interaction term that multiplied the MSA-level segregation measure by the county-level measure of racial composition).

[Table 5 here]

Looking at the regression analysis, there are number of significant variables ($p < .001$). The main predictor variable, the black-white dissimilarity index, was not significantly associated with food insecurity rates ($p = .287$). Percent African-American (black) at the county-level was positively associated with food insecurity rates at the county-level. In terms of standard deviation units, for every approximately 14 percent increase (standard deviation = 13.89) in the black population at the county-level, there will be a 1.4 percentage point increase in overall food insecurity at the county-level. This may be statistically significant for two reasons. First, because this same racial percentage is included in the model that estimates original food insecurity rates, it may be artificially inflating the relationship. The percent black is probably related to food insecurity in part because black people are more likely to be food insecure, as well as because the percent black was used to estimate the original county-level food insecurity rates.

A second point to consider is the historical trends that show residential segregation by *race* does not play as significant a role as it once did in explaining the racial disparities in household-level SES. This trend could help to explain why there is a non-significant relationship between residential segregation at the MSA-level, but still a significant positive relationship between the percentage of blacks in county-level and food insecurity rates. As a result of these findings, the predictor variable, MSA-level racial residential segregation between blacks and white, does not support H (1) in the additive model. The final discussion that includes models with *racial* and *income* segregation goes into more detail about racial segregation may also be less significant relative to income segregation in helping to explain overall food insecurity rates.

The second model for food insecurity rates tested H (1) more directly, as it included a variable that assessed a potential cross-level interaction taking place between counties and metropolitan areas. The interpretation of this interaction term was also to determine if the influence of MSA-level segregation on food insecurity rates was dependent in part on percentages of blacks at the county-level. Based on this non-significant interaction term, H (1) was not be supported by the data.

Overall, the R-squared values remained the same regardless of the inclusion of the interaction term for food insecurity. For the food insecurity, it was .754 with or without the interaction term. This means that 75.4 percent of the variance for food insecurity rates was explained using this model. To test whether the inclusion of the interaction term increased model fit, a partial F test was conducted. This test revealed that adding the interaction did not improve overall model fit for food insecurity rates (F = .89, p =.639).

A potential reason for the lack of explanatory power with regard to MSA segregation measures may have to do with the influence of SES factors that had a greater impact on the dependent variable, food insecurity. Median income was negatively associated with food insecurity rates, which means as median income rises, food insecurity rates are reduced. This is in line with previous research on food insecurity rates and household level earnings that shows a negative relationship between the two (Gunderson et al. 2011; Gunderson 2008). Additionally, the coefficient for the variable percent of children in poverty was positively associated with food insecurity rates, and was statistically significant. Poverty was a main predictor of food insecurity in the original *MMG* model for food insecurity. This coincides with the results that showed the coefficient for the variable *percent of children in poverty* as a statistically significant positive relationship with food insecurity rates. This means that as the percent of children in poverty at the county-level increases, so too does the food insecurity rate.

Looking at the percent unemployed variable, it shows a positive significant coefficient. This is to be expected for two reasons. First, the original *MMG* report on food insecurity, showed unemployment to be a major predictor of food insecurity rates, such that as unemployment increases, so to do food insecurity rates. The positive, statistically significant coefficient supports these findings. As the percent of unemployment goes up at the county-level, so too does the food insecurity rate. This outcome, coupled with the results from the prior SES variables on percent children in poverty and median income, seem to indicate that these factors had more explanatory power in determining food insecurity rates at the county-level.

With regard to another aspect of socioeconomic status, education, two variables were included in the model that measured this: high school graduation rates, and percent with some college education. The high school graduation rate was not statistically significant, but the percent some college was statistically significant, with a small positive relationship to food insecurity rates.

Some of the socioeconomic control variables may be statistically significant as a result of a potential artificial inflation due to the fact that they were included in the original model used to construct food insecurity rates by the *Map the Meal Gap* (MMG) project. These variables included unemployment and median income. The MMG model has a variable for percent poverty, but this analysis used percent of children in poverty, so this may also cause there to be a significant relationship between food insecurity rate and percent of children in poverty.

Child Food Insecurity Rates

Table 6 shows the outcomes for child food insecurity rates and the black-white dissimilarity index. For child food insecurity, the regression analysis has slightly different outcomes, but reflects similar patterns as overall household food insecurity rates. The black-white dissimilarity index remained statistically non-significant. Percent black was positively associated with food insecurity rates. Additionally the interaction term, while positive, remained statistically non-significant.

[Table 6 here]

Focusing on the SES factors related to economics and education, there are number of key differences. First, median household income becomes statistically non-significant in this model for child food insecurity rates. Second, high school graduation rate, which was statistically non-significant in the overall food insecurity model, became statistically significant with a small negative relationship with child food insecurity rates. Interpretation of this result indicates that as high school graduation rates rise, child food insecurity rates decreases. This means that as more people graduate high school at the county-level, child food insecurity rates decrease at the county-level. It is important to couple this with the other key finding, which is that the other education variable, percent some college, becomes statistically significant and has a negative relationship with child food insecurity rates. So as more people have some college education at the county-level, child food insecurity rates decrease.

In connection to this discussion around education, the unemployment rate and the percentage of children in poverty for the child food insecurity rate model were both statistically significant and the coefficients were positive. This means that as the unemployment rate and the percentage of children in poverty rises at the county-level, so, too, do child food insecurity rates increase at the county-level. This relate to the previous discussion around education because while residents with children may be able to find more jobs with a basic level of educational attainment, less job availability in a given county still has the capacity to increase food insecurity rates based on an interpretation of higher percent of unemployment rates at the county-level.

The inclusion of the interaction term for the child food insecurity model did not improve model fit over the original additive model. Overall, the R-squared values remained the same regardless of the inclusion of the interaction term for food insecurity. For the child food insecurity it was .658 with or without the interaction term, meaning that 65.8% of the variance for food insecurity rates was explained using this model. A partial F test indicated that model fit did not improve significantly when considering the cross-level interaction between MSA-level segregation measures and county-level racial composition measures ($F = .95$, $p = .388$).

To conclude this chapter, the focus of H (1), black-white dissimilarity index at the MSA-level, did not have a statistically significant relationship with the main dependent variables, food insecurity rates and child food insecurity rates. Since there were no significant interactions between D and percent black based on the interaction term, H(1) could not be supported. What was found is that many of the predictor variables associated with the original *MMG* modeling of food insecurity rates still remain statistically significant, especially those related to socioeconomic factors. The chapter on income segregation (Chapter 6) may shed some light on why black-white residential segregation was not statistically significantly related to overall food insecurity rates. But first, I turn in the next chapter to an examination of the relationship between Hispanic-white segregation and food insecurity.

CHAPTER 5: HISPANIC-WHITE RESIDENTIAL SEGREGATION AND FOOD INSECURITY RATES

Overview

The previous chapter focused on one of the main hypotheses related to residential segregation by race and food insecurity. This chapter focuses on a similar hypothesis, but instead of focusing on black-white segregation, the main aim was to determine to what extent MSA-level residential segregation between Hispanics and whites was associated with food insecurity rates at the county level. In doing so it addressed the second hypothesis, H (2), which reads:

> *H2: Higher levels of Hispanic-white segregation at the metropolitan level will be associated with higher rates of food insecurity in predominately non-immigrant Hispanic counties, but less so in predominately non-Hispanic counties or predominately immigrant Hispanic counties.*

This hypothesis posited outcomes for two distinct Hispanic populations based on their status within the United States: foreign-born or U.S.-born. The reason for this separation was twofold. First, to test to what extent the impact of immigrant enclaves has had on shielding foreign-born Hispanic populations from the indirect consequences of racial residential segregation with regard to food insecurity rates. Prior literature on public health outcomes with regard to birth weights and food preparation has provided clear evidence that these immigrant enclaves provide a buffering effect for predominately foreign-born Hispanic populations from racial disparities related to health and nutritional outcomes, due to the fact they can insulate themselves from potential disadvantages that may occur to native populations (Gabaccia 2009; Cagney et al. 2007; Crimmins et al. 2007). This occurs because ethnic enclaves may segregate populations to the advantage of those in communities where there are tighter familial bonds, better access to fresh foods, and more culinary traditions spread within inter-family networks. Additionally economic resources have the capacity to be more easily shared as a result of living in closer surroundings and sharing more social spaces.

There are a few items to point out with regard to the summary statistics (Tables 7-10). First, the overall mean for the Hispanic-white dissimilarity index is low, dramatically lower than the corresponding figure for black-white segregation in the previous chapter. Additionally the range for this index is smaller with only a maximum of .68. The correlation matrix shows that the two primary racial composition measures, as well as the overall segregation measure, are not highly correlated with either food insecurity or child food insecurity.

[Tables 7-10 here]

Interpreting Regression Analysis Outcomes

Food insecurity rates

A multivariate regression analysis was used to determine what association racial residential segregation between Hispanics and whites has on food insecurity rates. H (2) hypothesized that counties that were predominately U.S.-born Hispanics would have higher food insecurity rates in metropolitan areas with higher levels of residential segregation between Hispanics and whites. There was a qualification for foreign-born

Hispanics based on a previous literature review of immigrant enclaves. The modeling for overall food insecurity rates and child food insecurity rates proceeded by using an additive model and a model with an interaction term. The interaction term tested cross-level interactions between MSA-level racial residential segregation and county-level racial composition measures for U.S.-born Hispanics and foreign-born Hispanics.

The first model predicted overall food insecurity rates as an additive model with control variables, and a second model added the interaction term described above. In the first model, the coefficient for the primary predictor variable, the index of dissimilarity between Hispanics and whites, was statistically significant. This coefficient was positively associated with food insecurity rates. As the index of dissimilarity increases at the MSA-level between Hispanics and whites, so too did food insecurity rates rise overall across U.S. counties associated with these MSAs. When there is a greater dissimilarity between Hispanic and white populations, such that there is less and less of these populations living in similar areas, and more of them living in relatively racially homogenous neighborhoods, the model predicted increased food insecurity rates. With a coefficient of .024, a one standard deviation increase (.137) in the Hispanic-white dissimilarity index equates to a .3 percentage point increase in overall food insecurity rates. While this coefficient is significant, it is has a small effect on overall food insecurity.

[Table 11 here]

The percent U.S.-born Hispanic was also statistically significant ($p < .001$). Specifically, percent U.S.-born Hispanic at the county-level was positively associated with food insecurity rates at the county-level so, as the percent of U.S.-born Hispanics increases at the county-level, so, too, do county-level food insecurity rates. The coefficient for percent U.S.-born Hispanic was .0003 (rounded to .000 in Table 11), and the standard deviation was 12.47, so an approximately 12.5 percentage point increase in U.S-born Hispanics at the county-level equates to an approximately .4 percentage point increase in overall food insecurity rates. Percent overall Hispanic was included in the original *MMG* modeling of food insecurity rate estimates. Due to the inclusion of percent overall Hispanic in the modeling, this may have artificially inflated the relationship between percent U.S.-born Hispanic, percent foreign-born Hispanic and food insecurity rates at the county-level.

Turning to the socioeconomic factors related food insecurity rates in the first model, there were similar results as found in the previous chapter on black-white disparities with regard to a number of these variables. First, high school graduation rates had a negative relationship with food insecurity rates that were statistically significant. This meant that as high school graduation rates increased at the county-level, food insecurity rates decreased at the county-level.

The percent some college was positively associated with food insecurity rates, as was percent unemployed and percent children in poverty. This means that as the percentage of residents with some college in a given county rises, so to do food insecurity rates also rise. The other socioeconomic variables: percent unemployed and percent children in poverty were positively associated with food insecurity rates. Counties with higher percentages of either unemployed residents or children in poverty were statistically significant in relation to food insecurity rates. Similar outcomes were shown in the black-white dissimilarity modeling.

The interaction model included two interaction terms: one for the Hispanic-white dissimilarity index multiplied by the percent of *U.S.-born* Hispanics at the county-level, and one for the Hispanic-white dissimilarity index multiplied by the percent of *foreign-born* Hispanics at the county-level. To begin, this interaction model slightly improved model fit over the basic additive model that did not include these variables based on the differences in R-Squared value, and a partial F-test confirmed that adding these interaction terms resulted in a statistically significant increase in explained variation (F = 4.57, $p < .05$).

The use of percent overall Hispanic in the *MMG* model for food insecurity may have also caused there to be an issue with multicollinearity for the interaction terms in model. A post estimation assessment was conducted to determine if there were multicollinearity problems in the regression model. A variance inflation factor table indicated that the two interaction terms, Hispanic-white *D* x U.S.-born Hispanics and Hispanic-white *D* x Foreign-born Hispanics, had VIF scores above 10, and an overall mean VIF of 4.92. Chatterjee, Hadi, and Price CITE (2000) suggest that there is a presence of multicollinearity if the largest VIF is above 10 and/or the mean VIF is larger than one. Despite this loss of precision, the coefficients are still distinguishable from zero.. Additional testing that omitted the percent foreign-born Hispanic and related interaction term did not significantly change the results. As a result, this is plausible evidence to suggest that multicollinearity did not produce this result.

Additionally, this interaction model provided evidence of cross-level interactions between MSA-level Hispanic-white segregation and county-level racial composition measures of Hispanics. When these interaction variables were added, the overall Hispanic-white index of dissimilarity became statistically non-significant, whereas the interaction term that combined Hispanic-white index of dissimilarity and the county-level percent of U.S.-born Hispanics was statistically significant and positively associated with food insecurity rates. The foreign-born Hispanic interaction term was non-significant.

This means that the effect of Hispanic-white residential segregation (D) depends on racial and immigrant composition at the county level. There is no significant association in counties without any U.S.-born Hispanics, but there is a positive and significant one in counties to the extent that they have relatively large U.S.-born Hispanic populations. **Graph 1** shows the predicted outcomes for 4 different percentages of U.S.-born Hispanics in relation to the Hispanic-white dissimilarity index.

The results reinforce what has been stated, in that it shows that the positive association between Hispanic-white segregation and food insecurity became increasingly strong in counties with relatively larger U.S.-born Hispanic populations. As the percentage of U.S.-born Hispanics increases from 5 percent to 75 percent, the slope changes from slightly negative to positive, indicating that higher percentages of U.S-born Hispanics at the county-level, combined with higher overall rates of Hispanic-white segregation is positively associated with higher overall rates of food insecurity. The slopes of the regression lines for counties with relatively small U.S.-born Hispanic populations (5 to 25 percent) were essentially flat. Among counties with relatively large Hispanic populations (i.e., 75 percent), however, the predicted food insecurity rate increases from approximately .27 when Hispanic-white segregation is equal to zero to .31 when segregation reaches its maximum observed value (.687). A .31 - .27 = 4 percentage points is roughly equal to a one-standard deviation increase in the FI rate.

[Graph 1 here]

Child food insecurity rates outcomes

There a number of interesting outcomes with regard to the second primary dependent variable: child food insecurity rates. The additive model and the interaction model had two different outcomes. In the additive model, the coefficient for percent U.S.-born Hispanics was positive and statistically significant, but the Hispanic-white dissimilarity index remained non-significant. When there were more U.S.-born Hispanics overall in a given county, that county also tended to have higher rates of child food insecurity. The coefficient for U.S.-born Hispanic was .001, and the standard deviation was 12.47, so an approximately 12.5 percent increase in U.S-born Hispanics at the county-level equates to an approximately 1.2 percentage point increase in overall food insecurity rates. Median household income was negatively associated with food insecurity rates and was statistically significant. Counties with higher median incomes in general had lower rates of child food insecurity rates. Families who tend to have more overall income will have more disposable income to spend on necessary foodstuffs and thus their children will not suffer food insecurity rates as severely as those with less median income.

[Table 12 here]

Educational factors that were statistically significant and negatively associated with child food insecurity rates were: high school graduate rate and percent with some college education. More education is related to lower overall child food insecurity rates at the county-level. Overall higher rates of high school graduates and more residents who have some college education at the county-level were associated with, in general, lower rates of child food insecurity at the county-level. The coefficients for percent unemployed and percent of children in poverty in the regression analysis were statistically significant. These two variables showed that at the county-level, more parents who are unemployed and more children in who live in poverty is positively associated with overall rates of child food insecurity rates at the county-level. Last, the regions where counties are located were statistically significant for both forms of food insecurity. In general, living in the Northeast of the country was associated with slightly lower overall and child food insecurity rates, whereas living in the South and West was associated with higher rates of food insecurity and child food insecurity as compared to counties located in the Midwest.

While the additive model provided no evidence of a statistically significant partial association between child food insecurity and the Hispanic-white index of dissimilarity, the interaction model paints a very different picture. The Hispanic-white index of dissimilarity in the additive model was non-significant, whereas in the interaction model it was statistically significant and negative. However, the interaction term between the MSA-level Hispanic-white dissimilarity index and U.S.-born Hispanic at the county-level was statistically significant and positive. Thus, the effect of Hispanic-white dissimilarity index (D) depends on the county-level racial and immigrant composition, and particularly on the relative size of the U.S.-born Hispanic population. Specifically, the interaction term for percent U.S.-born Hispanic and Hispanic-white dissimilarity indicated that the higher percentages of U.S.-born Hispanics within these counties was associated with an increasingly positive association between Hispanic-white D and child food insecurity rates. Judging from the coefficients, it appears that Hispanic-white segregation is associated with lower food insecurity in counties that have no U.S.-born Hispanics, but may actually be associated with higher levels of FI in counties with relatively high proportions of U.S.-born Hispanics.

This interaction effect can be seen in **Graph 2,** which plots the predicted child food insecurity rate by the percentages of U.S.-born Hispanics in the county and the level of Hispanic-white segregation in the corresponding metropolitan area. The graph indicates that the Hispanic-white D was negatively associated with child FI in counties with no U.S.-born Hispanics, but increasingly less so in counties with larger shares of U.S.-born Hispanics and positively associated in those with high percentages of U.S.-born Hispanics.

[Graph 2 here]

To conclude this chapter, the main predictor variable, Hispanic-white dissimilarity index at the MSA-level, was positively and statistically significantly associated with food insecurity rates. Additionally, this same racial segregation measure of *D* was statistically significant and negative for child food insecurity rates with the inclusion of the interaction terms. For child food insecurity rates, this was interpreted that the Hispanic-white D is negatively associated with child FI in counties with no U.S.-born Hispanics, but increasingly less so in counties with larger shares of U.S.-born Hispanics. Thus for this chapter, H (2) could be supported based on the direction of the main effect for D and the interaction term, since it predicted D would be positively associated with measures of FI, but only in counties with relatively high proportions of U.S. born Hispanics. Additionally, many of the predictor variables associated with the original *MMG* modeling of food insecurity rates still remained statistically significant, especially those related to socioeconomic factors.

CHAPTER 6: RESIDENTIAL SEGREGATION BY *INCOME* AND FOOD INSECURITY RATES

Overview

This chapter investigates the potential impact of income segregation at the MSA-level on food insecurity rates by testing H (3), H (4), H (5), and H (6). Each of these hypotheses looked a different aspect of income segregation. Extreme poverty concentration has historically been associated with high levels of black-white residential segregation, but more general processes of income segregation have in recent decades assumed a larger role in concentrating wealth and poverty in distinct neighborhoods. Racial residential segregation likely still contributes to the exposure to concentrated poverty and related forms of neighborhood disadvantage that affect blacks (and perhaps even Hispanics). However, more general processes of income segregation have become *relatively* more important compared to racial residential segregation.

As discussed at length in Chapter 2, these more general processes of poverty and wealth concentration may be associated with food insecurity rates for a number of reasons. First, higher rates of poverty are linked to higher rates of crime and lack of transportation options that occur as a result of place-based inequalities, thus making it harder for residents in predominately lower-income neighborhoods to navigate the local environment to find available food options. Second, poverty concentration limits household opportunities as a result of fewer job options that provide "living wages"; this may increase food insecurity rates at the metropolitan-level because it generates more neighborhoods that have residents who are overwhelmingly poor, unemployed or lack homeownership.

H (3) made the following prediction:

H3: Higher levels of neighborhood poverty concentration in metropolitan areas will be associated with higher rates of food insecurity in relatively high poverty counties, but less so in counties with lower poverty rates.

At the other extreme, a higher concentration of affluence in a metropolitan area means that income is not evenly dispersed across neighborhoods, but instead there are a few neighborhoods that have predominately high-income residents (Reardon and O'Sullivan 2004). The *segregation of affluence* in metropolitan areas has the capacity to increase food insecurity rates because concentrating affluent households may draw vital resources, such as job opportunities and available food options away from impoverished and middle income neighborhoods (Rast 2015; Powell et al. 2007; Zenk et al. 2005). Residents in these neighborhoods, especially those in poverty, then will have fewer food options to access and thus may increase food insecurity overall at the MSA-level.

H (4) predicts the following about the relationship between the *segregation of affluence* and food insecurity rates:

> *H4: A higher concentration of affluence overall at the metropolitan level will be associated with higher rates of food insecurity.*

Concentrating *affluence* brings positive neighborhood effects and place-based advantages. Through higher-quality education programs, more residents are homeowners, and more may have more wealth to invest in retail and commercial businesses. More income brings more resources and the capacity to spend those resources on retail investment in the form of multiple food stores, as well as the ability to be able access these stores due to the advantage of owning a car (Nechyba 2003; Raphael and Rice 2002). H (5) qualified the conditions of H (4) with this additional hypothesis:

> *H5: The effect predicted by H4 will be weaker in counties with high proportions of affluent residents.*

Lastly, taken together, the previous hypotheses imply that *overall income segregation*, as denoted by the *rank-order information theory index,* H^R*,* may also be associated with higher food insecurity rates at the MSA-level. Since the two measures of income segregation that look at either end of the income spectrum, the *segregation of poverty* and the *segregation of affluence*, have been hypothesized to impact food insecurity rates, then it might be expected that *overall income segregation* will also negatively influence food insecurity rates. When families are more or less sorted by income throughout metro areas, with neighborhoods that are a mixture of residents with various incomes, or neighborhoods with a homogenous population of residents with similar incomes, this may also impact overall food insecurity rates. The final hypothesis predicts that as overall income segregation rises, such that residents in neighborhoods have income almost exactly the same as their neighbors, with more overall neighborhoods that are higher-, middle-, or low-income, then food insecurity rates will also rise at the metropolitan level. The hypothesis read:

H6: Higher levels of overall income segregation in metropolitan areas will be associated with higher rates of food insecurity.

A summary of the descriptive statistics (Tables 13-15) reveals some important outcomes in relation to income segregation. First, each of the measures of income segregation had relatively small ranges compared to the measures of racial segregation. The largest range was for overall income segregation and this did not exceed the .45 limit in the analysis sample. This means that while each of these measures ranges in principle from zero to one, the MSAs included in this analysis are all scored below .43, which is indicative of less segregation. Second, the correlation matrix shows that the percent of children in poverty was highly negatively correlated with both forms of food insecurity. This may have been a result of including the percent of overall residents in poverty in the original estimates of food insecurity. Third, the percent of affluent households was moderately negatively correlated with both forms of food insecurity, which would indicate that there may be a relationship between these two variables.

[Tables 13-15 here]

Interpretation of Regression Analysis Outcomes

H (3) assessed the impact of *segregation of poverty (.1)* on food insecurity rates and child food insecurity rates. **Table 16** shows the outcomes of an additive multivariate regression model and an interaction model for food insecurity rates. Similarly, **Table 17** shows the outcomes of an additive multivariate regression model and an interaction model for child food insecurity rates.

Focusing first on the food insecurity model, the *segregation of poverty* measure was statistically significant and positively associated with food insecurity rates. The coefficient for the segregation of poverty measure was .089. This means that based on a standard deviation of .035, for every one standard deviation increase in the segregation of poverty, there will be an increase in food insecurity of .3 percentage points. Since the segregation of poverty measures the extent to which poverty is concentrated or spread across an MSA, higher concentrations of poor neighborhoods in MSA's result in a statistically significant, but nominal increase in overall food insecurity at the county-level.

[Table 16 here]

In model 2, the interaction term was also statistically significant and positive. With the addition of the interaction term, the *segregation of poverty* H (.1) became non-significant. A partial f-test indicated that adding this interaction term significantly improved the fit between the data and model ($F = 7.86$, $p < .01$).

Hypothesis 3 predicted an interaction effect, such that counties in metropolitan areas with high levels of the segregation of poverty are expected to have higher FI rates, but only to extent that these same counties have high poverty rates themselves. As model 1 shows, there is a positive association overall and that, as model 2 shows, this overall positive association between the segregation of poverty and FI is driven by a stronger relationships in counties with relatively high child poverty rates. Accordingly, results from these models do support H3.

Graph 3 shows the predicted values for the segregation of poverty measure in relation to food insecurity rates. By changing the value of the percent of children in poverty at the county-level, it is shown that the overall food insecurity rates are also changing. For example, with 5 percent children in poverty there is an overall increase of approximately .1 or 1 percentage point. At the extreme of 35 percent children in poverty, predicted values increase from .2 to .26, in the order .04 or 4 percentage points in the observed range of food insecurity rate.

[Graph 3 here]

The socioeconomic control variables were all statistically significant. Median household income and high school graduate rates were both negatively associated with food insecurity, such that as median income and high school graduation rates increase at the county-level, there will be a decrease in food insecurity rates. This is reversed for the percent of some college, percent unemployed, and percent of children in poverty, which were all positively associated with food insecurity rates. Each of these aligns with the *MMG* program's report on food insecurity rates except percent with some college. It would be expected that this variable is negatively associated with food insecurity, yet this variable in previous modeling in this analysis has also been positive and statistically significant. A possible explanation is that while some college may be helpful for those students who graduate, for those who go to college and accrue student loan debt without earning a degree, they may be more prone to be in poverty as a result of this debt load.

As shown in **Table 17**, an interesting finding was that, for child food insecurity rates, the *segregation of poverty* was statistically significant and *negatively* associated with the variable based on the additive model. The interpretation of this coefficient, -.122, means that a change in the segregation of poverty from zero (i.e., no segregation between poor and non-poor households) to one (i.e., complete segregation of poor households from non-poor households) is associated with a 12.2 percentage point decrease in the predicted overall child food insecurity rates at the county-level. A better way to interpret this outcome is based on standard deviation changes. This means that based on a standard deviation of .035, for every one standard deviation increase in the segregation of poverty, there will be a decrease in child food insecurity of .4 percentage points.

[Table 17 here]

In the interaction model, the *segregation of poverty* measure became non-significant once the interaction term was added. Additionally, the interaction term was statistically significant and negatively associated with child food insecurity rates. A partial f-test revealed that adding this interaction term to the model significant increased explained variation (F =11.86, p < .01). So while the main prediction variable was non-significant, the interaction term was negative and statistically significant in the model, indicating that the negative association between the segregation of poverty and child food insecurity was even stronger in counties with higher child poverty rates. Since H (3) requires that the interaction term be significant and positively associated with child food insecurity, H (3) could not be supported based on the model with the additional interaction term for the *segregation of poverty.*

Results from the control variables also seem to show that outcomes related to socioeconomic factors are related to child food insecurity. The percent of residents with some college was statistically significant and negatively associated with child food insecurity, which is opposite from the food insecurity rate model. More people who have some college education may be able to earn more for their children in such a way to provide basic foodstuffs. The percent of resident unemployed and percent of children in poverty were both statistically significant and positively associated with child food insecurity. With a higher proportion of parents who do not have work, and more children living in poverty, it will be harder to provide funding that enables families to buy food. The next section details the outcomes for the *segregation of affluence* measure and food insecurity rates.

Segregation of Affluence Outcomes

Turning to the *segregation of affluence* H (.9) measure, there were four models total as H (4) and H (5) predicted slightly different outcomes. H (4) predicted that higher overall rates of food insecurity with more segregation of affluence, whereas H (5) conditioned this statement, by predicting a diminished effect for counties with a relatively large share of affluent households. **Table 18** showed that for food insecurity rates in the additive model there was a statistically significant, positive relationship between the *segregation of affluence* and food insecurity rates. The coefficient for the segregation of affluence measure was .109. There are two ways to interpret this. A one unit change in the segregation of affluence would amount to a 10.9 percent increase in overall food insecurity. This one unit change would amount to going from affluent households being evenly distributed across neighborhoods to affluent households being concentrated into a few neighborhoods. Focusing on a one unit change might overestimate the size of the effect since the actual range only goes to .423. Thus a second way to measure the outcome is based on the standard deviation. This means that based on a one unit standard deviation change of .047, for every increase in the standard deviation of the segregation of affluence, there will be an increase in food insecurity of .5 percentage points.

[Table 18]

This supports H (4) for food insecurity rates because it shows that as the *segregation of affluence* increases at the MSA-level, counties will have higher rates of child food insecurity. The control variables for the additive model showed similar, and statistically significant, outcomes as those discussed for the *segregation of poverty* modeling for food insecurity rates. Median income and high school graduation were negatively associated with food insecurity rates, whereas percent with some college education, percent unemployed, and percent of children in poverty were all positively associated.

H (5) was tested by including a cross-level interaction term in the model that combined the MSA-level *segregation of affluence* with a county-level measure of the proportion of *affluent* households. **Table 18** showed a number of results worth discussing. First, H (5) was supported based on the statistically significant outcomes associated with the primary independent variable, *segregation of affluence,* and the interaction term. In the interaction model, the main effect of .209 quantifies the partial association between the segregation of affluence and the food insecurity in counties with no affluent households. A one unit change in the segregation of affluence would amount to a 20.9 percent increase in overall food insecurity in such counties. However, a one unit change (i.e, from zero to one) is outside the observed range of the segregation of affluence in the sample of metropolitan areas analyzed here. Accordingly, it is more informative to consider the size of the effect in terms of standard deviation units.

Given the standard deviation of .047, for every increase in the standard deviation of the segregation of affluence, the model predicted that there will be an increase in food insecurity of 1percentage point. This main effect was accompanied by a statistically significant, negative interaction term. This interaction term had a coefficient of -.329. A post estimation F-test of the interaction term provides an F-value of 5.42 and a p-value statistically significant at the .05 value, which means it significant in the model, and thus slightly improved model fit over the additive model.

These statistically significant coefficients that go in opposite directions supported the hypothesis H (5), because what they showed was that overall segregation of affluence at the MSA-level still increases the overall amount of food insecurity in a given MSA, yet the negative coefficient for the interaction term indicates that, in those counties with high proportions of affluent residents, this association actually diminishes, producing a weaker association with food insecurity rates.

This is visualized in **Graph 4,** which makes it clear how the data support the hypotheses (H4 and H5) for overall food insecurity. This is so because, as predicted, more segregation of affluence is associated with higher food insecurity, but decreasingly so in more affluent counties, such that those that are majority affluent (70 percent) tend to have lower food insecurity rates in more segregated metros. Based on the graph, the effect of the segregation of affluence on food insecurity varies as a function of the variable percent of affluent or high income (H.I.) As shown, counties with 10 percent affluent or high income (H.I.) households increase their food insecurity rates approximately by .04 or 4 percentage points. Looking at counties with 70 percent of affluent households, the overall food insecurity decreases marginally by .01 or 1 percentage point.

[Graph 4 here]

Slightly different outcomes occurred when models were used for child food insecurity. **Table 19** provided results for the additive and interaction models which were used to test H (4) and H (5) for child food insecurity rates. The additive model results showed a significant, positive coefficient for the *segregation of affluence* measure, which means that H (4) was supported in relation to child food insecurity rates. Similar to food insecurity rates, in general, as more affluent households are concentrated in neighborhoods where there are predominately other affluent households, overall MSA-level child food insecurity will increase. Looking at a standard deviation change is an effective way to understand this relationship. This means that based on a one unit standard deviation change of .047, for every increase in the standard deviation of the segregation of affluence, there will be an increase in child food insecurity of .3 percentage points.

When the model included a cross-level interaction term, the results for the *segregation of affluence* became statistically non-significant. While the overall main predictor variable, *segregation of affluence,* was not statistically significant, the added interaction term was statistically significant and negatively associated with child food insecurity rates. This non-significance appears to be primarily due to the increase in the standard error in the model, going from .021 in Model 1 to .06 in the interaction model. A partial f-test showed that the p-value for this interaction term was significant with a p-value of .05, and a small F-value of 6.87. This pattern of results supports H4 and H5. Consistent with H4, the segregation of affluence is associated with higher (in this case, child) FI rates, as shown in Model 1. Consistent with H5, model 2 shows that this association is significantly weaker in affluent counties. The final section of this chapter discusses overall income segregation and food insecurity rates.

[Table 19 here]

This is visualized in **Graph 5,** which makes it clear how the data support the hypotheses (H4 and H5) for child food insecurity. This is so because, as predicted, more segregation of affluence is associated with higher FI, but decreasingly so in more affluent counties, such that those that are majority affluent (70 percent) tend to have lower child food insecurity rates in more segregated metros. Based on the graph, the effect of the segregation of affluence on food insecurity varies as a function of the variable percent of affluent or high income (H.I.) As shown, counties with 10 percent affluent or high income (H.I.) households increase their child food insecurity rates approximately by .03 or 4 percentage points. Looking at counties with 70 percent of affluent households, the overall food insecurity decreases marginally by .02 or 2 percentage points.

[Graph 5 here]

Overall Income Segregation and Conclusion

Table 20 shows the results of modeling the relationship between overall income segregation measure, H^R, and both overall food insecurity and child food insecurity rates. For food insecurity, overall income segregation was statistically significant and positively associated with the overall food insecurity rate, with a coefficient of .157. The overall income segregation index ranges from a minimum of zero, where the income distribution in each tract is the same as the greater metropolitan area, and a maximum of one, where there is complete income segregation. Thus a one-unit change, or going from zero to one in this range is associated with a .157 change in food insecurity rates. This means that going from no income segregation to total income segregation would result in a 15.7 percentage-point increase in the predicted county-level food insecurity rate. Since this is outside of the observed range (see Table 14), it is also important to look at a one unit change in the standard deviation of overall income segregation. Based on a one unit standard deviation change of .037, for every increase in the standard deviation of the segregation of affluence, there will be an increase in food insecurity of .5 percentage points. Thus H (6) was supported, since it predicted higher levels of overall income segregation would be associated with higher food insecurity rates. For child food insecurity, there was not a statistically significant relationship with the overall income segregation measure, thus H (6) could not be supported for child food insecurity rates.

[Table 20 here]

In conclusion, the first part of this chapter has tested H (3)- H(6) to determine to what extent measures of income segregation are associated with overall food insecurity rates and child food insecurity rates. H (3) was supported for both forms of food insecurity. H (4) was supported for both food insecurity, and child food insecurity. H (5) was supported for food insecurity, and for child food insecurity. H (6) was supported for food insecurity rates, but not child food insecurity.

The next section included *racial* and *income* segregation measures in a series of models. This was done in order to determine how robust the relationship between racial segregation and food insecurity was considering these more general processes of income segregation, a final set of models includes both *racial* and *income* segregation as predictors of food insecurity. These models were not aimed at testing any formal hypotheses, but rather merely provided a way to determine whether any potential findings that occurred between racial segregation and food insecurity remained significant even after including income segregation measures in the model.

Racial and Income Segregation Measures on Food Insecurity Rates

The second part of this chapter focused on the way that residential segregation by *income* may have accounted for part of the relationship between residential segregation by *race* and food insecurity rates. The way this was completed was with a series of models that were developed which combined one of the racial residential segregation measures and one of the measures of income segregation. So there were *12 models* total. This was because there were two forms of food insecurity – child food insecurity rate and food insecurity rate that had six *models* estimated for each one, which comes from the combination of three different measures of income segregation (overall income segregation, segregation of affluence, and segregation of poverty) and two measures of racial segregation (black-white dissimilarity index and Hispanic-white dissimilarity). Due to this modeling procedure, whenever a model was run that had interaction terms in previous models, they were included in these new combination models.

Black-white dissimilarity index and income segregation measures

The first series of *six models* examined the relationship between the black-white dissimilarity index and the three measures of income segregation: overall income segregation, segregation of affluence, and segregation of poverty. **Table 21** shows the results of overall income segregation combined with the black-white dissimilarity index. These results had a number of statistically significant outcomes. First, the MSA-level black-white dissimilarity index was not statistically significant.

Percent black at the county-level had different results for food insecurity rates and child food insecurity rates. For child food insecurity rates, percent black had a slight negative association, indicating that in terms of racial composition, counties with a smaller percentage of black residents as part of the total population was associated with a reduction in child food insecurity rates. In the original model with just the racial residential segregation measures (see Table 6 in Chapter 4), the coefficient for percent black had a positive, yet weak, relationship with child food insecurity.

Overall income segregation was statistically significant and positively associated with both forms of food insecurity. The black-white dissimilarity index was not statistically significant either with or without this income segregation measure in the model (see Table 5). The control variables for this model had similar outcomes compared to the original model with the racial residential segregation measures only. In general, high school graduation rate was negatively associated with child food insecurity rates, whereas the percent of unemployed and percent of children in poverty is positively associated with food insecurity rates and child food insecurity rates. The proposition of H (6) was supported based on this modeling with the *overall segregation* measure.

[Table 21 here]

Table 22 presents the results of models that assess how adjusting for the *segregation of affluence* affects the relationship between black-white racial segregation and food insecurity rates. Regression outcomes for this model showed that the black-white dissimilarity index remained non-significant, even when the *segregation of affluence* measure is included. This measure, also known as H (.9), is positive and statistically significant. Additionally, the interaction term that combines the MSA-level H (.9) measure with a county-level measure of high-income percentage, was negative and statistically significant. These coefficients show that overall segregation of high-income households from middle- and low-income households at the MSA-level is positively associated with both forms of food insecurity rates, yet counties within MSAs that have a greater of proportion of high-income households is negatively associated with both forms of food insecurity rates. Socioeconomic controls included in this model continue to have similar outcomes compared to the original model with the racial residential segregation measures only. In general, these outcomes were the same as those in the overall income segregation model in relation to food insecurity rates.

[Table 22 here]

Table 23 shows the regression coefficients for the final model that investigated how adjusting the models presented in Chapter 4 for a measure of income segregation, in this model *the segregation of poverty,* impacted the overall relationship between black-white racial segregation and food insecurity rates. While the overall income segregation measure and the segregation of affluence were statistically significant and positive, the segregation of poverty measure had different outcomes. With regard to the food insecurity rate, the segregation of poverty measure was not statistically significant. In relation to the child food insecurity rate on the other hand, the segregation of poverty was statistically significant and negative. Additionally, the percent black at the county-level was positively associated with food insecurity rates, and negatively associated with child food insecurity rates.

[Table 23 here]

Hispanic-white dissimilarity index and income segregation measures

The next *six models* tested to what degree controlling for income segregation diminishes the impact of Hispanic-white racial segregation on food insecurity and child food insecurity. The income segregation measures were *overall income segregation, segregation of affluence, and segregation of poverty.* **Tables 24-29** have two columns. The first column in each table repeats the interaction model results from Chapter 5 (i.e., Model 2 in Tables 11 and 12). The second column adds the income segregation measure. **Table 24** showed the results of adding the *overall income segregation* to the Hispanic-white racial residential segregation model. The Hispanic-white dissimilarity index was statistically significant and positively associated without the interaction term, and then lost its significance when the interaction term was added (see Table 11 in Chapter 5).

[Table 24 here]

The main effect for Hispanic-white dissimilarity was positive and statistically significant, it remained very small (i.e., it predicted an increase of only 2.2 percentage points in the food insecurity rate for an increase from 0 to 1 on the dissimilarity index). Of more importance is that the interaction term (D X % U.S.-born Hispanic) remained statistically significant and positive. As such, the results still supported H3, which predicted that Hispanic-white segregation would be more strongly associated with food insecurity in predominantly U.S.-born Hispanic counties, but less so in counties with fewer U.S.-born Hispanics.

Table 25 shows the modeling of child food insecurity rates had slightly different outcomes that did not support the influence of overall income segregation because even though the overall income segregation measure was included in the model, the Hispanic-white dissimilarity index remained statistically significant, and negatively associated with child food insecurity rates. This negative coefficient was similar to the original model that excluded the overall income segregation measure. Additionally, the two-way interaction terms were positively associated with child food insecurity rates. The interaction term remains unchanged, suggesting that racial residential segregation between Hispanics and whites still matters, despite rising income segregation. These coefficient outcomes are also consistent with the original H (2) hypothesis even after controlling for overall income segregation.

[Table 25 here]

Tables 26 and 27 provide the regression outcomes for the modeling that looked at the *segregation of affluence*, as a measure of income segregation, to determine if this measure of income segregation accounted for any of the relatively strong association between Hispanic-white segregation and food insecurity in counties with relatively large U.S.-born Hispanic populations. The results for food insecurity rates and child food insecurity rates were slightly different. For the overall food insecurity rates, the Hispanic-white dissimilarity index was non-significant in either model, but the *segregation of affluence* measure, was statistically significant and positive in the model. Additionally, the percent U.S.-born Hispanic and the interaction term with U.S.-born Hispanic were statistically significant and positively associated with food insecurity rates. Since the interaction terms did not change substantially, controlling for income segregation did not change the results presented in Chapter 5.

[Table 26 here]

Child food insecurity rates in this model showed different outcomes. The Hispanic-white dissimilarity index was negatively associated with child food insecurity rates, but only in counties with no U.S.-born Hispanics. The segregation of affluence was also negatively associated with child food insecurity rates, but only in counties with relatively large proportions of affluent households.

The two-way interaction term that included U.S.-born Hispanics was positive and statistically significant, whereas the interaction term that included foreign-born Hispanics was not significant. The percent of affluent households, and the interaction term that combined this percentage with the MSA-level *segregation of affluence* were both statistically significant and negatively associated with child food insecurity rates. Results show that for Hispanic-white segregation, there is an association with higher food insecurity rates, but only in counties that tend to have relatively large U.S.-born Hispanic populations. Based on Graph 2, this association is close to a flat line in counties that were less than about 50 percent U.S.-born Hispanic. This is purely a conjecture as the *segregation of affluence* measure was not statistically significant. Most importantly, adding the income segregation measures did not change the main result already presented in Chapter 5.

[Table 27 here]

Tables 28 and 29 completed the discussion by looking at how the *segregation of poverty*, as a measure of income segregation, may diminish the impact of Hispanic-white segregation on food insecurity and child food insecurity rates. For food insecurity rates, none of the main racial or income segregation measures were statistically significant. The two-way interaction term for Hispanic-white segregation multiplied by the percent U.S.-born Hispanic county, along with the main effect of percent U.S.-born Hispanic were positively and statistically significantly associated with food insecurity rates. With regard to child food insecurity, the Hispanic-white dissimilarity index and the segregation of poverty were both were non-significant. The interaction terms for the segregation of poverty, and U.S.-born Hispanics x D were statistically significant. Controlling for the segregation of poverty and its interaction term with child poverty rates doesn't change the main result found in Chapter 5. This result was a statistically significant positive association between the interaction term that multiplied the Hispanic-white dissimilarity index with U.S.-born Hispanics and child food insecurity rates. This means that Hispanic-white segregation was positively associated with child food insecurity, but only in counties with relatively large U.S.-born Hispanic populations.

The final chapter concludes with a summary of the research analysis, and a final discussion around the limits of this data, and how despite these limitations, the research outcomes can be utilized by public health researchers and public policy experts when investigating new mechanisms that may influence food insecurity, and more generally health conditions.

CHAPTER 7: FINAL DISCUSSION AND POLICY REVIEW

To conclude this research project, the final chapter will be broken into four broad sections: importance of the study, summary of the findings, limitations of the research, and future policy and research recommendations.

Importance of Study

This analysis posed a number of research questions that sought to understand the many ways in which residential segregation plays a role in influencing food insecurity rates throughout the country. These general research questions were:

1) What is the relationship between racial segregation and food insecurity in the United States?
2) Does this relationship differ when examining household food insecurity and child food insecurity?
3) If there is a relationship between racial segregation and food insecurity, how does this differ for blacks and Hispanics?
4) What effects do different aspects of income segregation (e.g. the segregation of poverty or the segregation of affluence) have on food insecurity in the United States?
5) Can income segregation account for associations between racial segregation and food insecurity?

These questions were the basis of a research plan that included conducting a multivariate analysis regressing racial and income segregation indices on food insecurity and child food insecurity rates. This was by done using MSA-level segregation measures and county-level food insecurity rates. There was good reason to consider variation at these levels, as opposed to focusing on individual level measures of food insecurity. Understanding overall rates of food insecurity at these levels is potentially useful to public health departments, non-profit organizations and charitable groups focused on alleviating hunger because they focus on larger populations. Counties are large enough to encompass multiple government and non-profit sectors that can combine resources, staff and leadership in order to improve population health (Zahner et al. 2014).

The reason residential segregation by *race* was used as the primary independent variable was that there are a number of place-based inequalities associated with it that may directly or indirectly impact food insecurity rates. Sociologists who study residential segregation have shown these place-based inequalities to be important components in explaining racial disparities in household SES factors related to poverty, unemployment, and educational attainment (Massey and Fischer 2000; Wilson 1996; Massey and Denton 1993). Since SES factors related to poverty and unemployment are important factors that tend to increase food insecurity rates, residential segregation by *race* was seen as an important mechanism that by way of exacerbating racial disparities of poverty and unemployment may influence food insecurity rates.

A number of studies have shown that blacks tend to have poorer public health outcomes in relation to cancer, heart disease, deaths from the common flu, obesity and low-birth weights compared to whites, partly as a result of place-based inequalities and associated racial disparities in household SES (Borrell et al. 2013; Chang 2006; Boardman et al. 2005; Acevedo-Garcia and Lochner 2003; Ellen 2000). Additionally, a smaller body of public health research has linked racial residential segregation directly to more pronounced racial disparities in public health outcomes between blacks and whites (Greer et al. 2013; Gee and Food 2011; Williams and Collins 2001; Acevedo-Garcia 2000). While these studies have shown a range of public health outcomes to be directly impacted by racial disparities in household SES factors as well as residential segregation, few have focused on health conditions related to food insecurity.

Within the body of literature on food insecurity, there has been a good deal of research that focuses on how food insecurity impacts other health outcomes such as obesity and children's nutritional intake (Casey et al. 2006; Kaiser and Townsend 2005). With regard to the scale of prior research, one study focused primarily on Native American populations at the national level (Gunderson 2008). At the state-level, McCurdy's and Metallinos-Katasara's (2011) research focused on outcomes experience by low-income blacks and Hispanics in Massachusetts in relation to food insecurity. This study adds to the body of literature, by showing outcomes at the national-level for black and Hispanic populations for food insecurity in relation to racial and income segregation measures. This was the first study to do so for these racial populations.

The *Map the Meal Gap* project provided a basis for this research by identifying poverty and unemployment as driving factors that influence food insecurity rates, as well as showing racial disparities in food insecurity nationally

(Gunderson et al. 2014). But it did not go far enough in combining these two trends with a larger body of research literature on residential segregation that acts as a key link influencing racial disparities related to poverty and unemployment (Jargowsky 1996; Wilson 1996; Massey and Denton 1993).

What no prior studies had done, and what made this research project important in filling a gap in both the public health literature more generally, and the literature on food insecurity more specifically, was to look at the way that residential segregation influences food insecurity rates. While residential segregation has been studied in relation to other public health outcomes, no studies have been conducted examining the effects of residential segregation on food insecurity. This research was also timely in nature; since food insecurity impacts one in six Americans, it is a public health issue that impacts a large swath of the population, and as discussed, has the capacity to influence other public health outcomes related to nutritional uptake and obesity, and more broadly, with regard to educational attainment (Gunderson et al. 2014; Dinour et al. 2007; Casey et al. 2006; Jyoti 2005). Thus it was important to shed light on how segregating groups of people into geographic spaces based on their race, may influence their ability to find balanced meals and feed themselves and their families.

A second major contribution to the public health literature in relation to food, is that there has been ample research given to the study of "food deserts" or geographic spaces that are void of grocery stores and supermarkets, while at the same time being saturated with fast food and convenience stores (Beauclac et al. 2009; Cummins and Macintyre 2002). While these studies are important in determining food store access and availability, they do not actually measure a *social health condition*, just the locations of stores in space that may influence these conditions. This research utilized an actual survey of the population that measured food insecurity at the national-level. Future research should attempt to link measures of food insecurity, racial and income segregation with research done on food deserts in order to ground more general claims about food accessibility and availability with a real measure of human need in relation to finding food.

Summary of Findings

Multiple datasets were compiled, merged, cleaned and subjected to regression analysis in order to test a set of six hypotheses. Each hypothesis predicted either a main effect or an interaction effect with regard to either residential segregation by race or income and food insecurity rates. **Table 30** shows all of the hypotheses and if they were supported or not based on the models.

[Table 30 here]

H (1) was a prediction that was tested by estimating an interaction model, which allowed the effect of black-white segregation to vary as a function of the percent of black residents at the county-level. The prediction of H (1) could not be supported because there was no any evidence of a statistically significant association between black-white segregation and food insecurity rates overall or in counties with relatively large black populations.

This was an unexpected finding because a body of prior literature has shown racial residential segregation between blacks and whites tends to influence public health outcomes more generally. First, there are racial disparities in health outcomes with regard to mortality rates, cardiovascular diseases and diabetes between blacks and whites (Williams and Mohammed 2009; Acevedo-Garcia et al. 2008). Second, racial discrimination against blacks tends to have a negative effect on more general processes of health and mental well-being (Brown et al. 2000; Collins and Williams 1999; Broman 1996.) Third, research has shown that racial residential segregation is a contributing factor in racial disparities with regard to public health outcomes between blacks and whites (Hearst et al. 2008; Williams and Collins 2001; Acevedo-Garcia 2000).

There a couple of potential, and speculative reasons, why the results with respect to food insecurity were not significant. First, this dissertation relied on synthetic estimates of county-level food insecurity that were obtained by MMG by regressing state-level food insecurity rates on predictive factors such as racial composition (i.e. percent black or percent Hispanic),poverty and median income. The lack of direct county-level measures of food insecurity rates may have contributed to my finding of no significant association between black-white segregation measure and food insecurity rates, particularly since percent black is a strong predictor of both food insecurity rates and metropolitan segregation levels. The findings of this dissertation should be confirmed by future research that employs direct measures of outcomes related to food insecurity, such as the data collected by the Food Research and Action Center on food hardship in U.S. congressional districts. .

Lastly, research has shown that black-white segregation levels are on the decline, primarily in areas where the black population is changing, i.e. growing or shrinking (Glaeser and Vigdor 2001). As a result of this trend, black-white segregation may not have the same explanatory power it once did in being able to impact a given outcome, in this case food insecurity. A final point is that the measure of black-white segregation, the dissimilarity index, is one of five measures of segregation. The dissimilarity index is not spatially sensitive to geographic distributions of populations because it measures the percentage of a group's population that would have to change in each neighborhood in order to have the same percentage at the MSA-level (Massey and Denton 1990). This is because the dissimilarity index only takes differences in the percentage of the groups being compared (e.g. blacks and whites) in each census tract into account, not the spatial relationships between those census tracts. Future research studying black-white segregation and food insecurity could try using a different measure of black-white segregation, such as the exposure or clustering, to see if those results vary from the ones reported in this research.

H (2) was a prediction that was tested by estimating an interaction model, which allowed the effect of Hispanic-white segregation to vary as a function of the percent of Hispanics by immigrant status (i.e, by both percent foreign-born Hispanics and percent U.S.-born Hispanics) at the county-level. The prediction of H (2) was supported for child food insecurity, as well as for overall food insecurity. This means that for both forms of food insecurity, Hispanic-white segregation predicted higher rates, but only in counties with relatively large U.S.-born populations.

These outcomes are consistent with a broad range of research around differences in Hispanic populations that are U.S.-born vs. foreign-born and public health outcomes. The research has shown that foreign-born populations more generally tend to be able to buffer the effects of negative health outcomes by enacting strong social support networks as a result of concentrating in given neighborhoods within metropolitan areas (Osypuk et al. 2010; Becares et al. 2009; Gabaccia 2009; Cagney et al. 2007). Outcomes from this research did not explicitly show that foreign-born populations have reduced food insecurity rates in relation to residential segregation, but it did show that U.S.-born Hispanics do tend to have nominally higher rates of food insecurity. This is in line with prior research on Hispanic-white residential segregation and physical health (Lee and Ferraro 2007).

A potential, and purely exploratory, explanation for this difference in food insecurity rates between U.S.-born and foreign-born populations is that as generations of Hispanics settle two things may occur. First, these two populations may separate from one another, with U.S.-born Hispanic populations moving and concentrating into other areas of the city, where they lose the buffering capacity that was provided in the foreign-born communities. This loss may amount to fewer ethnic grocery stores that provide fresh foodstuffs; as opposed to new locations that tend have a higher concentrations fast food and convenience stores, and potentially a lack of grocery stores and supermarkets. It may also amount to a loss of culinary knowledge, where second and third generation U.S.-born Hispanics do not have the capacity to cook meals that a more nutritional, instead turning to processed foods. Due to these losses, it may be harder to find affordable food that would enable families and households to produce balanced meals, and may actually cost more because processed foods tend to be more expensive than basic foodstuffs such as grains, beans and vegetables.

Turning to income segregation, H (3) through H (6), these hypotheses used three measures of income segregation: overall income segregation, segregation of poverty, and segregation of affluence as the main independent variables related to food insecurity and child food insecurity. H (3) was a prediction that was tested using an interaction model that used the segregation of poverty measures, H (.1) as the main independent variable predicting food insecurity and child food insecurity.

The prediction of H (3) was supported for food insecurity, but not for child food insecurity. The evidence supporting H (3) for overall food insecurity gives credence to the notion that living in a place with higher overall poverty concentration is related to poorer access to resources that would enable a healthy diet (Macintyre 200; Morland et al. 2002). If residents who live in poorer neighborhoods are surrounded by other poor neighborhoods this may make large geographic areas with fewer available food stores that provide nutritionally rich food.

The significant negative coefficient was a particularly interesting, and unexpected finding for child food insecurity. It would seem to indicate that concentrating poverty into fewer neighborhoods at the MSA-level actually reduces child food insecurity rates overall at the county-level. Since research has never been conducted using these types of measures, there is an explanation that remain purely speculative in nature.

From a public health policy perspective, perhaps metropolitan areas where there increased segregation of households with low-incomes may also have government agencies that are more effective at reducing child food insecurity through public health programs that focus on alleviating hunger and food accessibility. Some research does support these claims more broadly that deals with food insecurity, nutrition and poverty. Bhattacharya et al. (2004) found that poverty and food insecurity were not associated with nutritional outcomes for children. They caution making this connection without further analysis. Rose (1999) also found that in food insecure households, preschoolers did not suffer from low consumption of nutrients. This may make the case that while overall food insecurity may be associated with poverty, and more specifically, the segregation of poverty, households that are food insecure may not necessarily also have child food insecurity. Future research should utilize the segregation of poverty measure with an actual estimate of child food insecurity, as opposed to the synthetic estimate.

H (4) was a prediction that was tested by using a main effects model for a different measure of income segregation, the segregation of affluence. This hypothesis predicted that an increase in the overall MSA-level segregation of affluence would coincide with an increase in food insecurity rates. Based on the models for food insecurity and child food insecurity, the prediction of H (4) was supported for both of them. The prediction of H (5) was tested using an interaction model that helped to qualify H (4) as a function of the county-level measure of the percent of affluent households. H (5) was supported based on the modeling for food insecurity, as well as for child food insecurity rates.

The results for H (4) and H (5) also support literature more broadly that has shown the segregation of affluence to be an important force in relation to overall income segregation (Reardon 2011; Reardon and Bischoff 2010). By concentrating affluent households at the metropolitan level, there is also a concentration of resources that are drawn towards counties with higher incomes in relation to transportation and jobs opportunities (Rast 2015; Levine 2014). Also, other important resources related to diet and nutrition may be reduced as grocery stores and supermarkets may tend to concentrate in counties where there are more affluent residents.

The prediction of H (6) was tested using an additive model that predicated that as overall MSA-level income segregation rises, so too would food insecurity rates. This was supported for food insecurity, but not for child food insecurity. These outcomes seem to support a couple of more general trends in the public health and residential segregation literature. With regard to the public health literature, there is evidence that shows how poverty and resource allocation more generally diminish the capacity of individuals to get access to food (Baker et al. 2006; Malat et al. 2005; Pebley and Sastry 2004). Looking at residential segregation by income, the significant results for H (4) through H (6) in relation to overall food insecurity rates supports the more general research showing that rising levels of income segregation are helping to determine who get exposed to concentrated poverty and disadvantage (Dwyer 2010; Crowder and South 2005; Glaser and Vigdor 2001; Coulton et al. 1996).

In conclusion, a major question to resolve is whether racial segregation or income segregation plays a more significant role in influencing food insecurity rates. Based on the research findings, it would seem to indicate that income segregation has more explanatory power in relation to food insecurity rates. This seems to be true for a number of reasons. First, the black-white segregation measure was non-significant, and while the Hispanic-white dissimilarity index was significant for counties with large proportions of U.S-born Hispanic populations, the effect size was small (refer to Tables 11-12 and Graphs 1-2).

Second, all three measures of income segregation were statistically significant and positively associated with overall food insecurity rates. The segregation of affluence measure was also positively associated with child food insecurity rates, with the condition of lower overall child food insecurity rates for counties with higher percentages of affluent households. The distribution of income more generally, and more specifically the distribution of the income bands at the bottom and top of the income spectrum, is a significant factor that impacts food insecurity rates. This finding aligns with other research that has shown increased residential isolation of poor and affluent families into distinct geographic areas over the past four decades (Reardon and Bischoff 2011), most pronounced for black and Hispanics since the year 2000. Their findings also suggest that with the concentration of income and wealth there tends to also be a concentration of important resources related to public services. An important public resource, food stores, may also be concentrated in the same way, and provides a story that accompanies the support of income segregation as a major factor that contributes to higher rates of food insecurity overall.

Lastly, in the modeling of black-white segregation and overall income segregation in relation to child food insecurity (see Table 21) something interesting occurred with the results. In the original model with just the racial residential segregation measures (see Table 6 in Chapter 4), the coefficient for percent black had a positive, yet weak, relationship with child food insecurity Yet, when the overall income segregation measure was added, percent black had a slight negative association, indicating that counties with larger percentages of black residents as a share of their total populations had lower child food insecurity rates. This finding is significant because it suggests that some of the strong positive association between percent black and both measures of child food insecurity shown in Chapter 4 (Tables 5 and 6) is actually explained by income segregation. It is also important to consider that the effect size for the Hispanic-white segregation measure was similar to the size of the effects for income segregation as noted in Chapters 5 and 6. This would also seem to suggest that while racial segregation is still important to consider, income segregation has become just an important factor that contributes to food insecurity rates by way of racial disparities in household SES.

Limitations of the Study

There are a few important limitations to this study that need to be addressed in order to guide future studies using these types of methods and modeling. As discussed above, the first major limitation is that the main dependent variables, food insecurity and child food insecurity, are synthetic estimates that have been developed by the MMG project. They are synthetic in the sense that these are estimates of food insecurity rates based on a number of socioeconomic and racial variables such as poverty, unemployment, percent black and percent Hispanic that predict food insecurity rates at the state level rather than direct measures of food insecurity at the county level.

This has the potential to be problematic for a few reasons. First, racial composition has been shown to be highly correlated with racial residential segregation measures. To deal with this limitation, a racial composition measure was included as a control variable, and interaction terms were used to test cross-level effects of racial segregation on counties as it related to the percentage of minority residents. In the same regard, the inclusion of the poverty and median income variable in the synthetic estimate of food insecurity had the potential to artificially inflate the relationship with income segregation measures. To deal with issue, socioeconomic variables were included in the modeling as well as interaction terms that tested cross-level effects of income segregation as it related to the percent of children in poverty and affluent households at the county-level.

A second minor limitation was that this was a cross-sectional study. Since this is a cross-sectional study, there is no way to show causality from increases in particular forms of segregation to increases in food insecurity rates over time. While this study has shown evidence that there are statistically significant relationships between the independent variables Hispanic-white racial segregation, and some measures of income segregation, with forms of food insecurity, these relationships represent a moment in time. Residential segregation by race and income may vary over time based on broader social factors and historical trends. Future studies that look at how residential segregation may influence food insecurity rates, could add to the research literature by measuring these rates over a given time period.

Despite these limitations, this research and the datasets it used were groundbreaking and novel for a few reasons. This was the first study to be conducted nationally on the relationship between racial and income segregation and food insecurity. To ensure that this study was as robust as possible in capturing all of the ways that residential segregation as well as racial and socioeconomic factors may influence food insecurity rates, a number of variables were included in the analysis. Lastly, this research combined a number of datasets that have been recently released and thus have not been utilized as thoroughly in the public health or food insecurity literature.

Future Research and Policy Recommendations

Based on these findings, there are a number of research recommendations that could help to support a growing body of research that focuses on residential segregation and food insecurity. To begin with future research that could be done, this was a cross-sectional study that has been conducted at the national level. This does not offer a "fine-tuned" analysis of certain neighborhoods or unique MSAs that may differ from these general findings. There may be smaller regional variations than provided by the four categories in the modeling that were not picked up as a result of the coarse measure of region for counties. Additionally, more localized studies that focus on a smaller sample sizes, but use more fine-tuned measures may find different results for some of the hypotheses that were predicted. The specific difference it could make is that a local study would be better positioned to examine the relationship between *neighborhood racial composition* and food insecurity outcomes at the household level. Important variables to consider at this local level may include the distribution of public assistance funding, small-scale health and wellness surveys conducted by local non-profit agencies, the distribution of food stores and food pantries, and place-based factors such as types of crimes reported across neighborhoods, transportation options, and localized food prices within available food stores.

These studies would be able to connect the dots to determine if what is being seen at the national-level also fits patterns at more localized levels. Localized studies would be helpful in fine tuning this research, but they may not be able to address issues of residential segregation more generally. This is because neighborhood racial composition is obviously related to, but analytical distinct from metropolitan residential segregation. In order to provide a more complete picture, future national studies could hone in a single segregation measure and focus on how this measure is associated with food insecurity. In doing so, it would be able to provide a better estimate of for example, black-white segregation and food insecurity based on a concentration or clustering index. This could also be done for one of the three measures of income segregation, as no studies to date, excluding this one, have used these measures in relation to food insecurity or child food insecurity.

Future studies could also include a different set of variables for racial segregation measures and/or socioeconomic and racial control variables. To be specific, programs such as WIC or SNAP could be used as data sources within given counties or MSAs to better understand the relationship between food insecurity and low-income residents resource availability. McCurdy and Metallinos-Katsaras (2011) study utilized information from the Massachusetts WIC program to assess changes to food insecurity rates. Future studies could be done in other states, or within given MSA's. More studies like this could flush out possible contributing factors that either alleviate or exacerbate food insecurity rates as a result of available programs.

This study also contributes to a broad public health research literature, and more specifically to the literature on health conditions related to food. Prior research on food insecurity had to yet to utilize racial residential segregation measure for Hispanics, and no other research to date has utilized income segregation measures to analyze food insecurity rates (Gunderson et al. 2011; Gunderson 2008). Future research was important because it provided a better understanding of the specific issues related to food insecurity with regard to residential segregation. It also contributed to the broader literature that focuses on the relationship between segregation and food-related and other health outcomes. In doing so, it supports this literature that shows residential segregation tends to exacerbate racial disparities in health outcomes (Landrine and Corral 2009; Williams and Collins 2001). This research could also be used to show how residential segregation by race and income impacts the health of minority groups by way of food insecurity. With higher rates of food insecurity, other health conditions such as obesity and diabetes may also increase as a result of poorer diets due to the availability and accessibility of food for residents (Link and McKinlay 2009; Dinour et al. 2007; Boardman et al. 2005).

Results from this analysis have also provided an updated snapshot of what is occurring between racial and income segregation in relation to this particular health condition. While there is a robust literature focused on racial and income segregations relationship to the home foreclosure crisis, this relationship has yet to be extensively researched in relation to public health outcomes, including food insecurity (Landrine and Corral 2009). Lastly, public health literature that focuses on forms of racial segregation in relation to health outcomes has yet to be updated to include the newest census estimates. With new information on the relationship between racial and income segregation in relation to health outcomes, theoretical explanations in the public health field will have additional pragmatic outcomes to draw from for future postulation (Acevedo-Garcia et al.2008; Acevedo-Garcia and Lochner 2003; Acevedo-Garcia et al. 2003).

This study could also be compared with other public health research at the county- level in order to provide a more complete picture of population health outcomes nationally. Public health research has shown that higher levels of income inequality and minority racial concentration are significantly related to higher mortality outcomes (Sudano et al. 2013; Williams and Jackson 2003; McLaughlin and Stokes 2002; Shi and Starfield 2001; Williams 2001). Food insecurity rates are impacted by factors related to food accessibility and availability that cut across local municipalities. Additionally, the extent of food options may vary from county to county, within a metropolitan region.

Results from this regression analysis could also provide a number of beneficial outcomes for state planners. Findings from this research could enable state and local agencies to focus on counties that are most food insecure as a result of segregation. By identifying key metropolitan regions where these counties are located, agencies related to food distribution and access found with the departments of human services and health would be better able to target funding to programs that focus on the counties that are most impacted by food insecurity rates. This is important as state and federal public health agencies can focus large-scale projects on counties and districts that are both highly food insecure and lack the access to nutritional foodstuffs. Funding from these agencies, as well as non-profit organizations, would be able to target the most neglected populations within these areas. Steisel and Morse (2012) have written about the ways that state governance needs to serve a vital role in reducing hunger through the implementation of more coordinate efforts around food accessibility. Findings from this research could be combined with these congressional mandates to show where prime places for program implementation could take place.

This research could also be utilized by the number of non-profit entities such as Hunger Task Force, Feeding America, Oxfam, and the Hunger Project. These organizations could take these results and focus in on particular counties, such as those with higher rates of U.S.-born Hispanics or households in poverty, when thinking about to deliver food. A new and novel approach to providing people with balanced meals has been the rise of mobile food pantries. Entities like the Feeding America, Seeds that Feed, and the Eastern Michigan Food Pantry have created trucks that go into targeted communities and provide much needed food to people who do not have access to food stores and/or cannot afford to buy food as a result of poverty or unemployment[4,5]. Utilizing this research as a basis for looking at the relationship

[4] http://www.feedingamerica.org/about-us/we-feed-families/mobile-food-pantry-program/?referrer=https://www.google.com/
[5] https://www.fbem.org/programs/mobile-food-pantry/mobile-food-pantry-delivery-schedule/

between MSAs and counties, these entities could more precisely use these food trucks in counties with higher U.S.-born Hispanic populations and households in poverty that are couched within MSAs where there are higher than normal levels of racial and income segregation.

Thinking more broadly, it is also important to think about the "upstream" causal factors that generate residential segregation in the first place. This means getting at ways to improve transportation routes, and thus access to jobs, which may go a long way in helping households to not only get access to food, but also earn more money that would enable them to afford food on a week to week basis. This requires investment in transportation routes beyond highways systems, as cars are costly to maintain. It also means reinvesting in urban city centers by way of large-scale job creation programs. Since the 1970's, the massive amount of industrial and manufacturing jobs that were outsourced in urban areas across the country have not been adequately filled by job creation in any other sectors. While service sector jobs do provide income, they often do not pay enough to support a family, and usually do not provide employee benefits that would offset the cost of private insurance. With greater access to job stability, some of the conditions of food insecurity may be alleviated through more opportunities to find gainful employment.

In conclusion, this analysis has set out to see to what extent residential segregation by race and income plays in influencing food insecurity rates. In doing so, it has provided new clarity about the direct and indirect mechanisms that link some forms of residential segregation by *race* and *income* to food insecurity rates via routes related racial composition and the concentration of households based on income.

Food insecurity in the United States is not as open and all-consuming as it is in developing countries. Yet, there is something more pernicious about the fact that in a country of excessive food store options and cheap caloric intake, there are pockets of the overall population that go without food on often throughout the year, a proportion of which are children. That is why this study sought to look at how the concentration of people by race or income into separate and distinct geographic areas could impact their ability to feed themselves. In doing so, it attempted to shed much needed light on an intricate and complex puzzle that circuitously links forms of residential segregation to food insecurity. As a result, this research provided some general outcomes that could enable a better understanding of this complex puzzle for future researchers to develop into new research designs and government agencies to use as the basis for growing programs focused on reducing food insecurity for residents across the country.

TABLES AND FIGURES

Figure 1: Residential Segregation by *race* based on U.S. 2010 Census by tract within the county area defined as Macomb-Wayne-Oakland counties

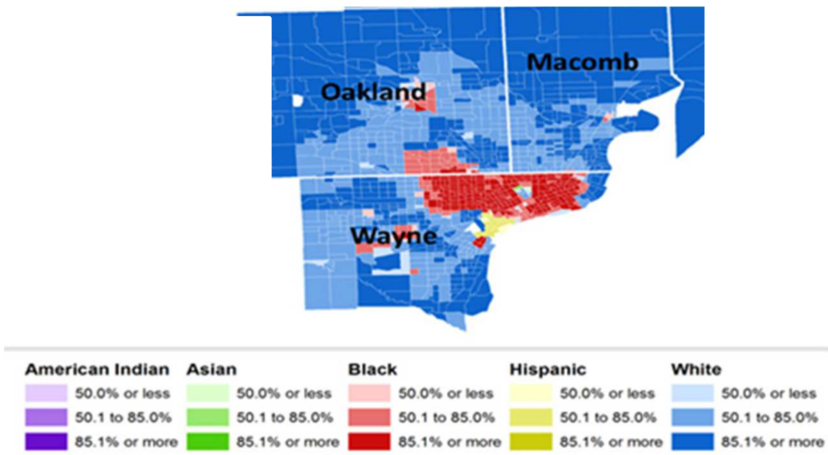


Figure 2: Residential Segregation by *income* based on U.S. 2011 Census by tract

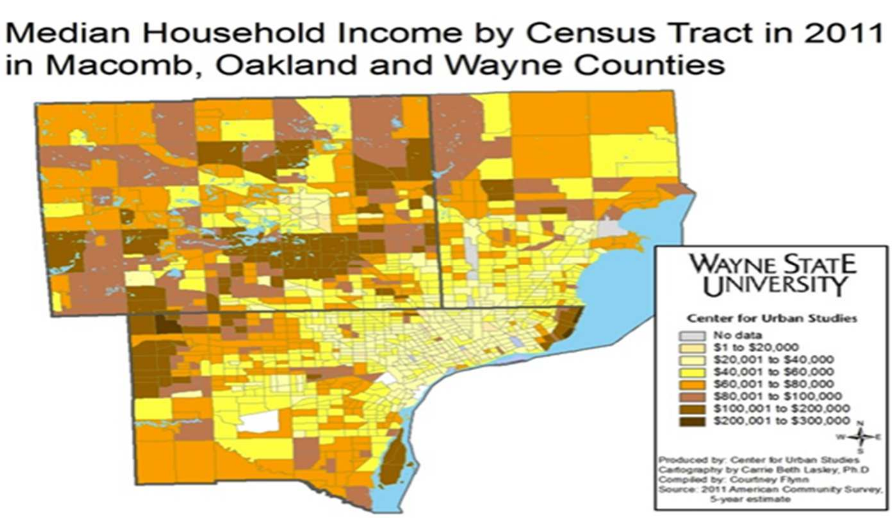


Table 1: Black-White *D:* Summary Statistics for All Major Dependent Variables at the County Level

Variable	N	Mean	Min	Max	Std. Dev.	Skewness	Kurtosis
Food Insecurity Rate	966	.14	.056	.48	.039	.902	4.83
Child Food Insecruity Rate	966	.21	.076	.44	.5	.17	3.23

Table 2: Black-White *D:* Summary Statistics for Control Variables at County-Level

Variable	N	Mean/Prop.	Min	Max	Std. Dev.
Percent Black	966	12.37	0	79.1	13.89
Median Household Income	966	44859.72	19829	111582	1.4e+08
High School. Graduation Rate	966	81.54	26.67	100	87.43
Percent some college	966	54.78	23.03	87.86	131.04
Percent Unemployed	966	9.41	2.7	28.2	.026
Percent Children in Poverty	966	21.21	2.8	55.4	73.16
Total Population	966	246658.7	1901	9818605	527397.1
Region: Northeast	83	.085	0	1	
Region: Midwest	249	.258	0	1	
Region: South	555	.574	0	1	
Region: West	79	.081	0	1	

Table 3: Black-White *D:* Summary Statistic for Black-White Dissimilarity Index at the MSA-level

Variable	N	Mean	Min	Max	Std. Dev
Black-White Dissimilarity Index (D)	298	.39	0	.87	.16

Table 4: Black-White *D*: Correlation Matrix for Primary Independent and Dependent Variable

	Percent black	Index of black-white dissimilarity(D)
Food Insecurity Rate	.626	.146
Child Food Insecurity Rate	.145	.058

Table 5: OLS Regression Coefficients of Black-White Index of Dissimilarity on Food Insecurity Rates

(966 Counties in 298 MSA's)

VARIABLES	(1) Food Insecurity Rate	(2) Food Insecurity Rate
MSA Black-White Dissimilarity (D)	-.007	-.01
	(.005)	(.006)
Percent Black (County-level)	**.001*** **	**.001*** **
	(.000)	(.000)
Black-White (D) x Percent Black County		.000
		(.000)
Median Household Income (x10,000)	**-.001*** **	**-.001*** **
	(.000)	(.000)
High School Graduation Rate	.000	.000
	(.000)	(.000)
Percent Some College	**.001*** **	**.001*** **
	(.000)	(.000)
Percent Unemployed	**.004*** **	**.004*** **
	(.000)	(.000)
Percent Children in Poverty	**.002*** **	**.002*** **
	(.000)	(.000)
Total County Population	**.000** **	**.000** **
	(.000)	(.000)
Region: (Midwest Reference)		
Northeast	**-.009*** **	**-.009*** **
	(.002)	(.002)
South	**.003** **	**.003** **
	(.002)	(.002)
West	**.027*** **	**.027*** **
Constant	.047***	.05***
	(.014)	(.014)
Observations	966	966
R-squared	.754	.754

Robust Standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.0**

Table 6: OLS Regression Coefficients of black-white index of Dissimilarity on Child Food Insecurity Rates

(966 Counties in 298 MSA's)

VARIABLES	(1) Child Food Insecurity Rate	(2) Child Food Insecurity Rate
MSA Black-White Dissimilarity (D)	-.004	-.006
	(.004)	(.005)
Percent Black (County-level)	**.001*** **	**.001*** **
	(.000)	(.000)
Black-White (D) x Percent Black County		.000
		(.000)
Median Household Income (x10,000)	.000	.000
	(.000)	(.000)
H.S. Graduation Rate	**-.000*** **	**-.000*** **
	(.000)	(.000)
Percent Some College	**-.001*** **	**-.001*** **
	(.000)	(.000)
Percent Unemployed	**.005*** **	**.005*** **
	(.000)	(.000)
Percent Children in Poverty	**.004*** **	**.004*** **
	(.000)	(.000)
Total County Population	**.000*** **	**.000*** **
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.009*** **	**-.009*** **
	(.003)	(.002)
South	**.019*** **	**.019*** **
	(.002)	(.003)
West	**.023*** **	**.023*** **
	(.003)	(.003)
Constant	**.172*** **	**.173*** **
	(.012)	(.012)
Observations	966	966
R-squared	.658	.658

Robust Standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Table 7: Hispanic-White *D:* Summary Statistics for Control Variables at the County Level

Variable	N	Mean	Min	Max	Std. Dev.
Food Insecurity Rate	1023	.16	.062	.39	.041
Child Food Insecurity Rate	1023	.24	.081	.44	.5

Table 8: Hispanic-White *D:* Summary Statistics for Control Variables at the County Level

Variable	N	Mean	Min	Max	Std. Dev.
Percent U.S.-born Hispanic	1023	9.1	.4	94.5	12.47
Percent Foreign-born Hispanic	1023	6.7	1.5	77.8	9.87
Median H.H. Income	1023	52239.95	26001	111502	13129.8
H. S. Grad. Rate	1023	80.85	26.67	98.67	9.17
Percent Some College	1023	59.82	24.66	87.86	11.01
Percent Unemployed	1023	8.97	4	28.2	2.53
Percent Children in Poverty	1023	17.42	3.1	45.1	7.29
Total Population	1023	241560.2	1599	9818605	513464.5
Region: Northeast	90	.088	0	1	
Region: Midwest	258	.252	0	1	
Region: South	549	.537	0	1	
Region: West	127	.124	0	1	

Table 9: Hispanic-White *D:* Summary Statistics for Hispanic-White Dissimilarity Index

Variable	N	Mean	Min	Max	Std. Dev
Hispanic-White Dissimilarity Index (D)	347	.28	0	.687	.137

Table 10: Hispanic-White *D:* Correlation Matrix for Primary Independent and Dependent Variables

	Percent U.S.-born Hispanic	Percent foreign-born Hispanic	Percent Overall Hispanic	Hispanic-white (D)
Food Insecurity Rate	.251	.146	.214	.172
Child Food Insecurity Rate	.424	.113	.283	.077

Table 11: OLS Regression Coefficients of Hispanic-white index of Dissimilarity on Food Insecurity Rates

(1023 Counties on 287 MSA's)

VARIABLES	(1) Food Insecurity Rate	(2) Food Insecurity Rate
MSA Hispanic-White Dissimilarity (D)	**.024*****	-.001
	(.006)	(.013)
Percent Foreign-born Hispanic	.000	-.000
	(.000)	(.000)
Percent U.S.-born Hispanic	.000	**.000****
	(.000)	(.000)
Hispanic-White (D) x Percent Foreign-born Hispanic		-.000
		(.000)
Hispanic-White (D) x Percent U.S.-born Hispanic		**.001****
		(.000)
Median Household Income (x10,000)	**-.001*****	**-.001*****
	(.000)	(.000)
High School Graduation Rate	**-.001*****	**-.000*****
	(.000)	(.000)
Percent Some College	**.001*****	**.001*****
	(.000)	(.000)
Percent Unemployed	**.004*****	**.004*****
	(.000)	(.000)
Percent Children in Poverty	**.003*****	**.003*****
	(.000)	(.000)
Total County Population	**.000****	**.000****
	(.000)	(.000)
Region:		
Northeast	**-.009*****	**-.008****
	(.003)	(.003)
South	**.012*****	**.012*****
	(.002)	(.002)
West	**.015*****	**.015*****
	(.002)	(.002)
Constant	.055***	.054***
	(.009)	(.009)
Observations	1,023	1,023
R-squared	0.719	0.721

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Graph 1: Predicted Food Insecurity by Hispanic-White Segregation in the Metro Area and Percent U.S.-born Hispanic in the County

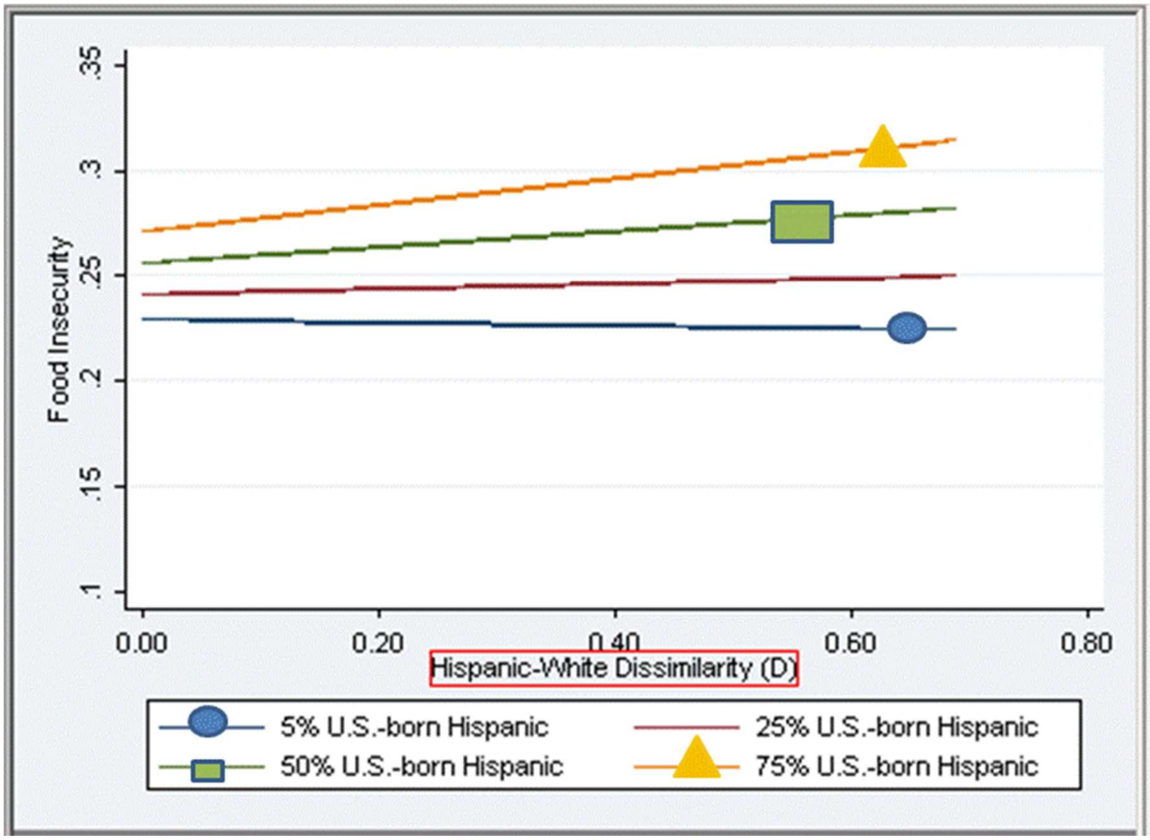


Table 12: OLS Regression Coefficients of Hispanic-white index of Dissimilarity on Child Food Insecurity Rates

(1023 Counties on 287 MSA's)

	(1)	(2)
VARIABLES	Child Food Insecurity Rate	Child Food Insecurity Rate
MSA Hispanic-White Dissimilarity (D)	-.003	**-.027*** **
	(.005)	(.016)
Percent Foreign-born Hispanic	-.000	-.000
	(.000)	(.000)
Percent U.S.-born Hispanic	**.001*** **	**.001*** **
	(.000)	(.000)
Hispanic-White (D) x Percent Foreign Hispanic		-.001
		(.001)
Hispanic-White (D) x Percent U.S.-born Hispanic		**.001*** **
		(.000)
Median Household Income (x10,000)	**-.007*** **	**-.008*** **
	(.001)	(.001)
High School Graduation Rate	**-.000** **	.000
	(.000)	(.000)
PercentSome College	**-.000*** **	**-.000*** **
	(.000)	(.000)
Percent Unemployed	**.005*** **	**.005*** **
	(.000)	(.000)
% Children in Poverty	**.002*** **	**.002*** **
	(.000)	(.000)
Total County Population	**-.000** **	**-.000** **
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.01*** **	**-.008*** **
	(.002)	(.002)
South	**.012*** **	**.01*** **
	(.002)	(.002)
West	**.014*** **	**.014*** **
Constant	.185***	.184***
	(.011)	(.011)
Observations	1,023	1,023
R-squared	0.734	0.736

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Graph 2: Predicted Child Food Insecurity by Hispanic-White Segregation in the Metro Area and Percent U.S.-born Hispanic in the County

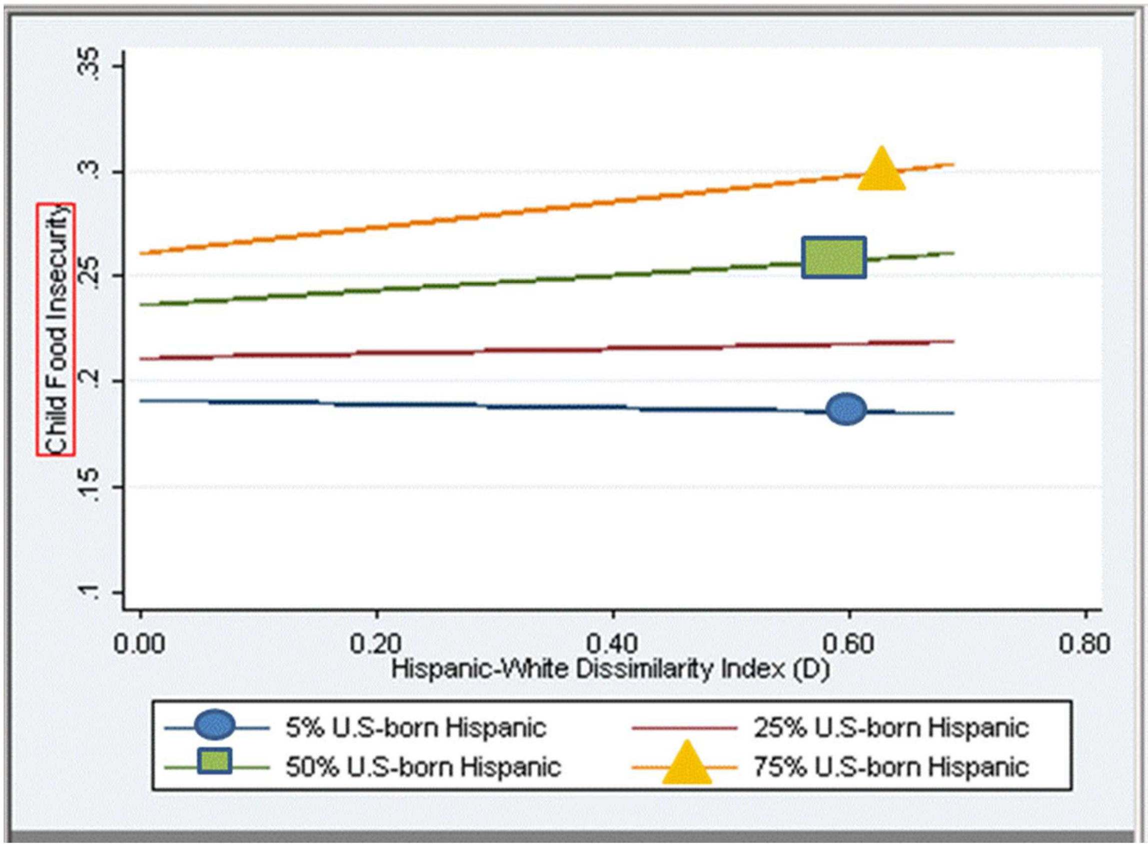


Table 13: Income Segregation: Summary Statistics for Control Variables at County-Level

Var Name	Obs	Mean/Prop	Min	Max	Std. Dev.
Median H.H. Income	1098	51653.25	26001	112582	13002.98
H. S. Grad. Rate	1098	80.85	26.67	98.67	9.17
Percent Some College	1098	59.82	24.66	87.86	11.01
Percent Unemployed	1098	8.97	4	28.2	2.53
Percent Children in Poverty	1098	17.42	3.1	45.1	7.29
Percent Affluent Households	1098	.311	.12	.71	.1
Total Population	1098	241560.2	1599	9818605	513464.5
Region: Northeast	90	.082	0	1	
Region: Midwest	258	.235	0	1	
Region: South	548	.499	0	1	
Region: West	127	.116	0	1	

Table 14: Income Segregation: Summary Statistics for Independent Variables at County-Level

VarName	Obs	Mean	Min	Max	Std. Dev
Overall Income Segregation (H^R)	381	.13	.045	.423	.0373
Segregation of Poverty H(.1)	381	.15	.06	.24	.035
Segregation of Affluence H(.9)	381	.18	.067	.3	.047

Table 15: Income Segregation: Correlation Matrix for Independent, Dependent and Control Variables

	Percent Child Poverty	Percent Affluent Households	H^R	H (.1)	H(.9)
Food Insecurity Rate	.76	-.56	-.001 6	-.014 5	.012
Child Food Insecurity Rate	.73	-.6	-.13	-.28	-.07

Table 16: OLS Regression of *Segregation of Poverty* on Food Insecurity Rates

(1098 Counties on 381 MSA's)

VARIABLES	(1) Food Insecurity Rate	(2) Food Insecurity Rate
Segregation of Poverty H(.1)	**.089***	-.074
	(.021)	(.054)
H(.1) x Percent Children in Poverty		**.009**
		(.003)
Median Household Income (x10,000)	**-.001***	**-.001***
	(.000)	(.000)
High School Graduation Rate	**-.000***	**-.000***
	(.000)	(.000)
Percent Some College	**.001***	**.001***
	(.000)	(.000)
Percent Unemployed	**.004***	**.004***
	(.000)	(.000)
Percent Children in Poverty	**.003***	**.002***
	(.000)	(.000)
Total County Population	**.000**	**.000**
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.008**	**-.007**
	(.003)	(.003)
South	**.014***	**.014***
	(.002)	(.003)
West	**.02***	**.02***
	(.002)	(.002)
Constant	.029**	.044**
	(.015)	(.015)
Observations	1098	1098
R-squared	0.704	0.708

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Table 17: OLS Regression of *Segregation of Poverty* on Child Food Insecurity Rates

(1098 Counties on 381 MSA's)

VARIABLES	(1) Child Food Insecurity Rate	(2) Child Food Insecurity Rate
Segregation of Poverty H(.1)	**-.122*** **	.126
	(.03)	(.07)
H(.1) x Percent Children in Poverty		**-.014*** **
		(.004)
Median Household Income (x10,000)	**-.000** **	**-.000** **
	(.000)	(.000)
High School Graduation Rate	.000	.000
	(.000)	(.000)
Percent Some College	**-.000** **	**-.000** **
	(.000)	(.000)
Percent Unemployed	**.006*** **	**.006*** **
	(.000)	(.000)
Percent Children in Poverty	**.003*** **	**.005*** **
	(.000)	(.000)
Total Population County	**.000** **	**.000** **
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.008*** **	**-.008*** **
	(.002)	(.002)
South	**.011*** **	**.01*** **
	(.002)	(.002)
West	**.028*** **	**.028*** **
	(.003)	(0.003)
Constant	**.135*** **	**.114*** **
	(.023)	(.023)
Observations	1098	1098
R-squared	0.663	0.668

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Graph 3: Predicted Food Insecurity by *Segregation of Poverty* in the Metro Area and Percent Children in Poverty in the County

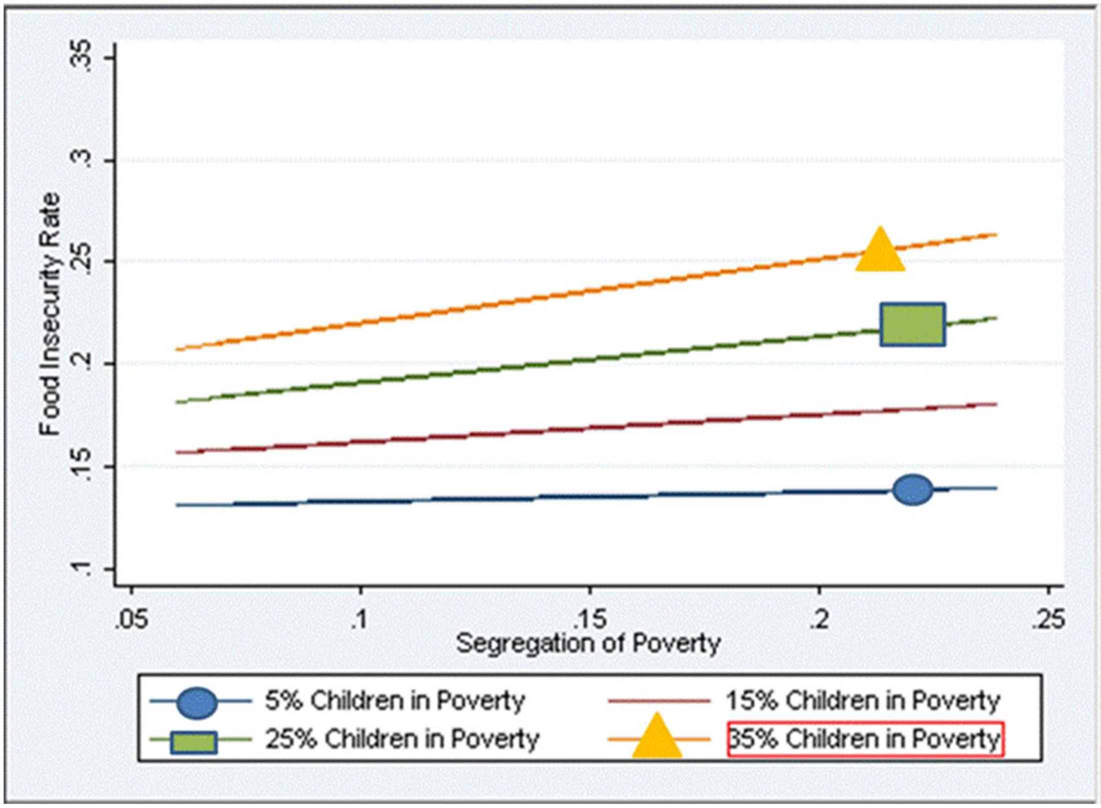


Table 18: OLS Regression of *Segregation of Affluence* on Food Insecurity Rates

(1098 Counties on 381 MSA's)

VARIABLES	(1) Food Insecurity Rate	(2) Food Insecurity Rate
Segregation of Affluence H (.9)	**.109*** **	**.209*** **
	(.016)	(.039)
H (.9) x Percent H.I Homes		**-.329** **
		(.109)
Percent High Income	-.046	.017
	(.024)	(.037)
Median Household Income (x10,000)	-.000	-.000
	(.000)	(.000)
High School Graduation Rate	**-.001*** **	**-.001*** **
	(.000)	(.000)
Percent Some College	**.001*** **	**.001*** **
	(.000)	(.000)
Percent Unemployed	**.004*** **	**.004*** **
	(.000)	(.000)
Percent Children in Poverty	**.004*** **	**.004*** **
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.006** **	**-.006** **
	(.003)	(.003)
South	**.011*** **	**.012*** **
	(.002)	(.002)
West	**.02*** **	**.019*** **
	(.002)	(.002)
Constant	.049**	.018
	(.016)	(.016)
Observation	1098	1098
R-squared	0.712	0.713

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

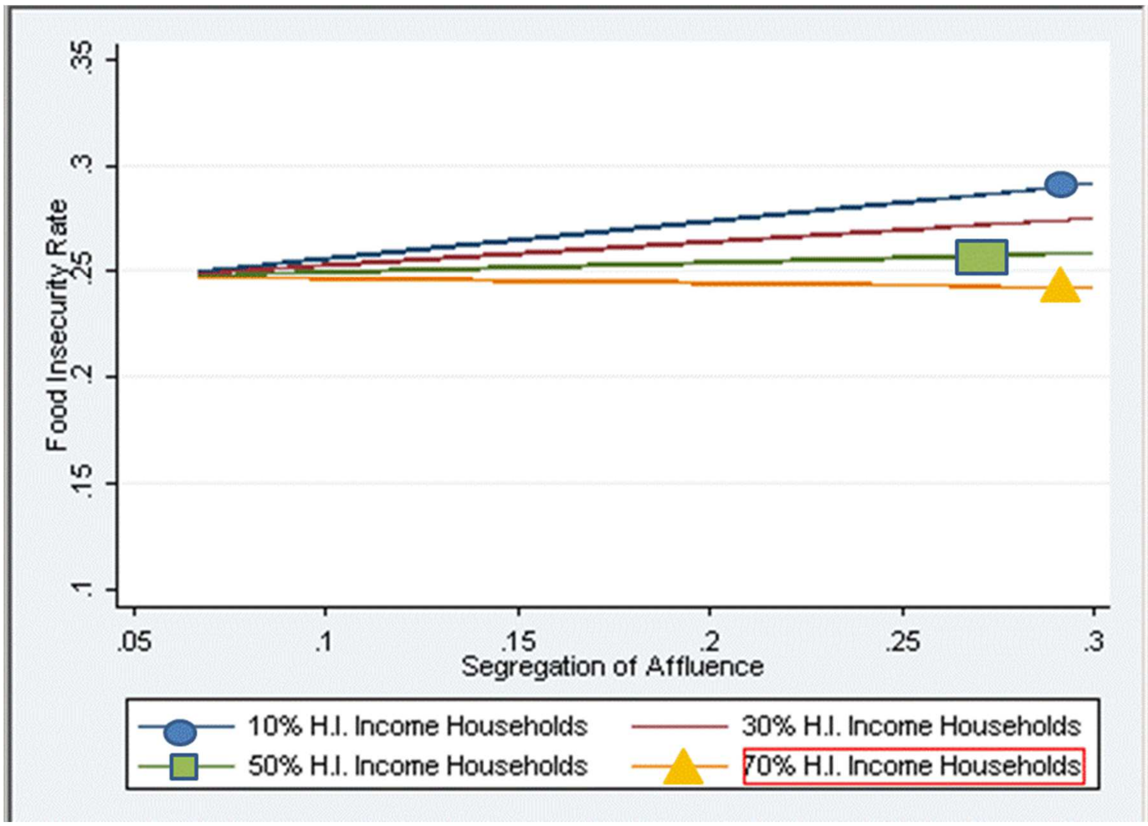
Table 19: OLS Regression of *Segregation of Affluence* on Child Food Insecurity Rates

(1098 Counties on 381 MSA's)

VARIABLES	(1) Child Food Insecurity Rate	(2) Child Food Insecurity Rate
Segregation of Affluence H (.9)	**.074***** (.021)	.062 (.06)
H (.9) x Percent H.I Homes		**-.523***** (.147)
Percent H.I. Income	**-.132***** (.033)	**-.014**** (.044)
Median Household Income (x10,000)	-.000 (.000)	-.000 (.000)
High School Graduation Rate	.0000 (.000)	.0000 (.000)
Percent Some College	**-.000**** (.000)	**-.000**** (.000)
Percent Unemployed	**.006***** (.001)	**.001***** (.000)
Percent Children in Poverty	**.003***** (.000)	**.004***** (.000)
<u>Region:</u>		
Northeast	-.005 (.002)	-.005 (.002)
South	**.011***** (.002)	**.011***** (.002)
West	**.04***** (.003)	**.035***** (.003)
Constant	**.138***** (.03)	**.09**** (.03)
Observations	1098	1098
R-squared	0.611	0.617

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Graph 4: Predicted Food Insecurity by the Segregation of Affluence in the Metropolitan Area and the Percent Affluent Households in the County



Graph 5: Predicted Food Insecurity by the Segregation of Affluence in the Metropolitan Area and the Percent Affluent Households in the County

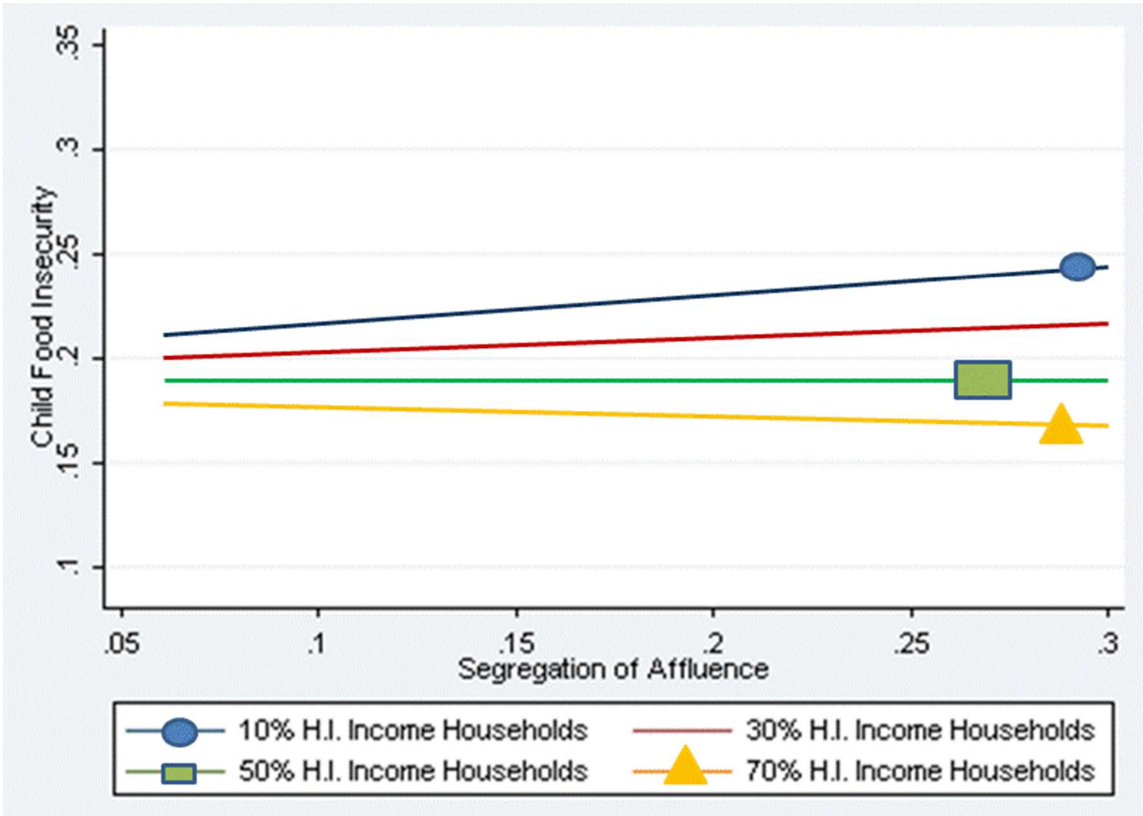


Table 20: OLS Regression of Overall Income Segregation, H^R, on Food Insecurity Rates

(1098 Counties on 381 MSA's)

VARIABLES	(1) Food Insecurity Rate	(2) Child Food Insecurity Rate
Overall Income Segregation (H^R)	**.157*** **	.005
	(.026)	(.029)
Median Household income (x10,000)	**-.001*** **	**-.000** **
	(.000)	(.000)
High School Graduation Rate	**-.001*** **	.000
	(.000)	(.000)
Percent Some College	**.001*** **	**-.001*** **
	(.000)	(.000)
Percent Unemployed	**.004*** **	**.005*** **
	(.000)	(.000)
Percent Children in Poverty	**.003*** **	**.003*** **
	(.000)	(.000)
Total County Population	**.000** **	**.000*** **
	(.000)	(.000)
Region:		
Northeast	**-.006** **	**-.008*** **
	(.003)	(.003)
South	**.013*** **	**.013*** **
	(.002)	(.002)
West	**.02*** **	**.033*** **
	(.002)	(.003)
Constant	**.059** **	**.176*** **
	(.019)	(.027)
Observations	1098	1098
R-squared	0.681	0.657

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Table 21: OLS Regression of black-white index of Dissimilarity/Overall Income Segregation (H^R) on Food Insecurity Rates

(966 Counties in 298 MSA's)

VARIABLES	(1) Food Insecurity Rate	(2) Child Food Insecurity Rate
MSA Black-White Dissimilarity (D)	-.001	-.014
	(.006)	(.008)
Black-White (D) x Percent Black County	.000	.000
	(.000)	(.000)
Overall Income Segregation (H^R)	**.068*** **	**.062** **
	(.016)	(.023)
Percent Black (County-level)	**.000*** **	**-.001*** **
	(.000)	(.000)
Median Household Income (x10,000)	**-.001*** **	.000
	(.000)	(.000)
High School Graduation Rate	.000	**-.000** **
	(.000)	(.000)
Percent Some College	**.000*** **	-.000
	(.000)	(.000)
Percent Unemployed	**.003*** **	**.005*** **
	(.000)	(.000)
Percent Children in Poverty	**.002*** **	**.004*** **
	(.000)	(.000)
Total County Population	**.000** **	**.000** **
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.009*** **	**-.009*** **
	(.002)	(.002)
South	**.003** **	**.003** **
	(.002)	(.002)
West		
Constant	**0.04** **	**0.05** **
	(0.03)	(.013)
Observations	966	966
R-squared	0.759	0.649

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Table 22: OLS Regression of black-white index of Dissimilarity/Segregation of Affluence H (.9) on Food Insecurity Rates

(966 Counties in 298 MSA's)

VARIABLES	(1) Food Insecurity Rate	(2) Child Food Insecurity Rate
MSA Black-White Dissimilarity (D)	-.001	-.013
	(.006)	(.008)
Black-White (D) x Percent Black	.000	.0002
	(.000)	(.000)
Segregation of Affluence H (.9)	**.112*** **	**.081** **
	(.022)	(.031)
H (.9) x Percent H.I Homes	**-.053** **	**-.135*** **
	(.021)	(0.035)
Percent H.I. Homes	**-.021*** **	**-.013*** **
	(.025)	(.031)
Percent Black	**.001*** **	**-.001*** **
	(.000)	(.000)
Median Household income	**-.000** **	**.001** **
	(.000)	(.000)
High School Graduation Rate	.000	-.001
	(.000)	(.000)
Percent Some College	**.001*** **	-.000
	(.000)	(.000)
Percent Unemployed	**.004*** **	**.005*** **
	(.000)	(.000)
Percent Children in Poverty	**.002*** **	**.004*** **
	(.000)	(.000)
Total County Population	**.000** **	**.000** **
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.0009*** **	**-.008002*** **
	(.00(3)03)	(.00(2)03)
South	**.0043** **	**.003.003** **
	(.00(2)01)	(.00(1)02)
West	**.003*** **	**.002004*** **
	((.013))	(.01(3)01)
Constant	.0367**	.146***
	(.014)	(.022)
Observations	966	966
R-squared	0.762	0.656

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Table 23: OLS Regression of black-white index of Dissimilarity/Segregation of Poverty H (.1) on Food Insecurity Rates

(966 Counties in 298 MSA's)

VARIABLES	(1) Food Insecurity Rate	(2) Child Food Insecurity Rate
MSA Black-White Dissimilarity (D)	-.009	-.012
	(.006)	(.008)
Black-White (D) x Percent Black	.000	.000
	(.000)	(.000)
Segregation of Poverty H (.1)	-.04	**-.178*** **
	(.022)	(.032)
H(.1) x Percent Children in Poverty	-.000	**-.012*** **
	(.000)	(.014)
Percent Black (County-level)	**.001*** **	**-.001*** **
	(.000)	(.000)
Median Household Income (x10,000)	**-.001*** **	.000
	(.000)	(.000)
High School Graduation Rate	.000	**-.000** **
	(.000)	(.000)
Percent Some College	**.001*** **	**-.000** **
	(.000)	(.000)
Percent Unemployed	**.004*** **	**.005*** **
	(.000)	(.000)
Percent Children in Poverty	**.002*** **	**.004*** **
	(.000)	(.000)
Total County Population	**.000** **	**.000** **
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.002*** **	**-.002*** **
	(.003)	(.003)
South	**.003** **	**.003** **
	(.002)	(.002)
West	**.004*** **	**.004*** **
	(.001)	(.001)
Constant	.034	.036
	(.025)	(.023)
Observation	966	966
R-Squared	.689	.689

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.0**

Table 24: OLS Regression of Hispanic-white index of Dissimilarity/Overall Income Segregation (H^R) on Food Insecurity Rates

(1,023 Counties on 347 MSA's)

VARIABLES	(1) Food Insecurity Rate	(2) Food Insecurity Rate
Hispanic-White Dissimilarity (D)	-.008	**.022****
	(.013)	(.01)
Percent Foreign-born Hispanic	-.000	-.000
	(.000)	(.003)
Percent U.S.-born Hispanic	**.000****	**.000****
	(.000)	(.000)
D x Percent Foreign-Born	-.000	-.000
	(.000)	(.000)
D x Percent US-Born	**.000****	**.000****
	(.000)	(.000)
Overall Income Segregation (H^R)		**.097*****
		(.017)
Median Household Income (x10,000)	**-.001*****	**-.001*****
	(.000)	(.000)
High School Graduation Rate	**-.000*****	**-.000*****
	(.000)	(.000)
Percent Some College	**.001*****	**.001*****
	(.000)	(.000)
Percent Unemployed	**.004*****	**.004*****
	(.000)	(.000)
Percent Children in Poverty	**.003*****	**.003*****
	(.000)	(.000)
Total County Population	**.000****	.000
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.009****	**-.007****
	(.003)	(.003)
South	**.012*****	**.011*****
	(.002)	(.002)
West	**.015*****	**.02*****
	(.002)	(.002)
Constant	**.055*****	**.04****
	(.009)	(.014)
Observations	1023	1023
R-squared	.719	.73

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Table 25: OLS Regression of Hispanic-white index of Dissimilarity/Overall Income Segregation (*H^R*) on Child Food Insecurity Rates
(1,023 Counties on 347 MSA's)

VARIABLES	(1) Child Food Insecurity Rate	(2) Child Food Insecurity Rate
Hispanic-White Dissimilarity (D)	**-.027****	**-.029****
	(.016)	(.012)
Percent Foreign-born Hispanic	-.000	-.000
	(.000)	(.000)
Percent U.S.-born Hispanic	**.001*****	**.002*****
	(.0001)	(.000)
D x Percent Foreign-Born	-.001	-.001
	(.001)	(.001)
D x Percent U.S.-Born	**.001*****	**.001*****
	(.000)	(.000)
Overall Income Segregation (*H^R*)		-.023
		(.02)
Median Household Income (x10,000)	**-.008*****	**-.001*****
	(.001)	(.000)
High School Graduation Rate	.000	.000
	(.000)	(.000)
Percent Some College	**-.000*****	-.000
	(.000)	(.000)
Percent Unemployed	**.005*****	**.006*****
	(.000)	(.000)
Percent Children in Poverty	**.002*****	**.002*****
	(.000)	(.000)
Total County Population	**-.000****	**-.000****
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.008*****	**-.009*****
	(.002)	(.002)
South	**.01*****	**.01*****
	(.002)	(.002)
West	**.014*****	**.013*****
	(.003)	(.003)
Constant	**.184*****	**.17*****
	(.011)	(.019)
Observations	1023	1023
R-squared	.736	.736

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Table 26: OLS Regression of Hispanic-white index of Dissimilarity/Segregation of Affluence H (.9) on Food Insecurity Rates

(1023 Counties on 287 MSA's)

VARIABLES	(1) Food Insecurity Rate	(2) Food Insecurity Rate
Hispanic-White Dissimilarity (D)	-.001	.016
	(.013)	(.009)
Percent Foreign-born Hispanic	-.000	-.000
	(.000)	(.000)
Percent U.S.-born Hispanic	**.000****	**.000****
	(.000)	(.000)
D x Percent Foreign-Born	-.001	-.001
	(.000)	(.000)
D x Percent U.S.-Born	**.001****	**.001****
	(.000)	(.000)
Segregation of Affluence H (.9)		**.173*****
		(.022)
H (.9) x Percent H.I Homes		**-.005****
		(.002)
Percent H.I. Income		**-.067****
		(.022)
Median Household Income (x10,000)	**-.001*****	**-.000****
	(.000)	(.000)
High School Graduation Rate	**-.000*****	**-.000*****
	(.000)	(.000)
Percent Some College	**.001*****	**.001*****
	(.000)	(.000)
Percent Unemployed	**.004*****	**.004*****
	(.000)	(.000)
Percent Children in Poverty	**.003*****	**.003*****
	(.000)	(.000)
Total County Population	.000**	.000
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.008****	-.005
	(.003)	(.003)
South	**.012*****	**.011*****
	(.002)	(.002)
West	**.015*****	**.019*****
	(.002)	(.002)
Constant	.054***	.04**
	(.009)	(.013)
Observations	1023	1023
R-squared	.721	.740

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.1**

Table 27: OLS Regression of Hispanic-white index of Dissimilarity/Segregation of Affluence H (.9) on Child Food Insecurity Rates

(1023 Counties on 287 MSA's)

VARIABLES	(1) Child Food Insecurity Rate	(2) Child Food Insecurity Rate
Hispanic-White Dissimilarity (D)	**-.027****	**-.03****
	(.016)	(.012)
Percent Foreign-born Hispanic	-.000	-.000
	(.0002)	(.000)
Percent U.S.-born Hispanic	**.001*****	**.002*****
	(.000)	(.000)
D x Percent Foreign-Born	-.001	-.001
	(.001)	(.001)
D x Percent U.S.-Born	**.001*****	**.001*****
	(.000)	(.000)
Segregation of Affluence H (.9)		-.024
		(.025)
H (.9) x H.I Homes-County		**-.087****
		(.023)
Percent H.I. Income		**-.144*****
		(.032)
Median Household Income (x10,000)	**-.008*****	-.000
	(.001)	(.000)
High School Graduation Rate	.000	.000
	(.000)	(.000)
Percent Some College	**-.000*****	-.000
	(.000)	(.000)
Percent Unemployed	**.005*****	**.006*****
	(.000)	(.000)
Percent Children in Poverty	**.002*****	**.002*****
	(.000)	(.000)
Total County Population	**-.000****	**-.000****
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.008*****	**-.006****
	(.002)	(.003)
South	**.01*****	**.009*****
	(.002)	(.002)
West	**.014*****	**.013*****
	(.002)	(.003)
Constant	.184***	.165***
	(.011)	(.018)
Observations	1023	1023
R-squared	.736	.748

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.1**

Table 28: OLS Regression of Hispanic-white index of Dissimilarity/Segregation of Poverty H (.1) on Food Insecurity Rates

(1023 Counties on 287 MSA's)

VARIABLES	(1) Food Insecurity Rate	(2) Food Insecurity Rate
Hispanic-White Dissimilarity (D)	-.008	.008
	(.013)	(.009)
Percent Foreign-born Hispanic	-.000	-.000
	(.000)	(.000)
Percent U.S.-born Hispanic	**.000****	**.000****
	(.000)	(.000)
D x Percent Foreign-Born	-.001	-.001
	(.000)	(.000)
D x Percent U.S-Born	**.000****	**.001****
	(.000)	(.000)
Segregation of Poverty H (.1)		-.034
		(.06)
H(.1) x Percent Children in Poverty		**.007****
		(.003)
Median Household Income (x10,000)	**-.001*****	**-.001*****
	(.000)	(.000)
High School Graduation Rate	**-.000*****	**-.000*****
	(.000)	(.000)
Percent Some College	**.000*****	**.001*****
	(.000)	(.000)
Percent Unemployed	**.004*****	**.004*****
	(.000)	(.000)
Percent Children in Poverty	**.003*****	**.002*****
	(.000)	(.000)
Total County Population	**.000****	.000
	(1.95e-09)	(1.44e-09)
<u>Region:</u>		
Northeast	**-.008****	**-.008****
	(.003)	(.003)
South	**.012*****	**.012*****
	(.002)	(.0018)
West	**.015*****	**.018*****
	(.002)	(.002)
Constant	**.054*****	**.06*****
	(.009)	(.014)
Observations	1023	1023
R-squared	.721	.727

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.01**

Table 29: OLS Regression of Hispanic-white index of Dissimilarity/Segregation of Poverty H (.1) on Child Food Insecurity Rates

(1023 Counties on 287 MSA's)

VARIABLES	(1) Child Food Insecurity Rate	(2) Child Food Insecurity Rate
Hispanic-White Dissimilarity (D)	**-.027****	-.018
	(.016)	(.012)
Percent Foreign-born Hispanic	-.000	-.000
	(.000)	(.000)
Percent U.S.-born Hispanic	**.001*****	**.001*****
	(.000)	(.000)
D x Percent Foreign-Born	-.001	-.001
	(.001)	(.001)
D x Percent U.S.-Born	**.001*****	**.001****
	(.000)	(.000)
Segregation of Poverty H (.1)		.16
		(.06)
H(.1) x Percent Children in Poverty		**-.014*****
		(.003)
Median Household Income (x10,000)	**-.008*****	**-.001*****
	(.001)	(.000)
High School Graduation Rate	.000	-.000
	(.000)	(.000)
Percent Some College	**-.000*****	-.000
	(.000)	(.000)
Percent Unemployed	**.005*****	**.006*****
	(.000)	(.000)
Percent Children in Poverty	**.002*****	**.004*****
	(.000)	(.001)
Total County Population	**-.000****	-.000
	(.000)	(.000)
<u>Region:</u>		
Northeast	**-.008*****	**-.009*****
	(.002)	(.002)
South	**.01*****	**.008*****
	(.002)	(.002)
West	**.014*****	**.010*****
	(.003)	(.003)
Constant	.184***	.161***
	(.011)	(.018)
Observations	1,023	1,023
R-squared	.736	.747

Robust standard errors in parentheses
***** p<0.001, ** p<0.05, * p<0.1**

Table 30: Key Findings and Supported Hypotheses

Hypothesis	Food Insecurity Supported	Child Food Insecurity Support
H(1) Black-White *D*	**No**	**No**
H (2) Hispanic-White D	**Yes**	**Yes**
H (3) Seg. of Poverty	**Yes**	**No**
H (4) Seg. of Affluence	**Yes**	**Yes**
H (5) H.I. Counties	**Yes**	**Yes**
H (6) Overall Income Seg.	**Yes**	**No**

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APPENDIX:

U.S. HOUSEHOLD FOOD SECURITY SURVEY MODULE:

THREE-STAGE DESIGN, WITH SCREENERS

Economic Research Service, USDA

September 2012

Revision Notes: The food security questions are essentially unchanged from those in the original module first implemented in 1995 and described previously in this document.

Household Stage 1: Questions HH2-HH4 (asked of all households; begin scale items).

[IF SINGLE ADULT IN HOUSEHOLD, USE "I," "MY," AND "YOU" IN

PARENTHETICALS; OTHERWISE, USE "WE," "OUR," AND "YOUR HOUSEHOLD."]

HH2. Now I'm going to read you several statements that people have made about their food situation. For these statements, please tell me whether the statement was often true, sometimes true, or never true for (you/your household) in the last 12 months—that is, since last (name of current month).

The first statement is "(I/We) worried whether (my/our) food would run out before (I/we) got money to buy more." Was that often true, sometimes true, or never true for (you/your household) in the last 12 months?

[ ] Often true

[ ] Sometimes true

[ ] Never true

[ ] DK or Refused

HH3. "The food that (I/we) bought just didn't last, and (I/we) didn't have money to get more." Was that often, sometimes, or never true for (you/your household) in the last 12 months?

[ ] Often true

[ ] Sometimes true

[ ] Never true

[ ] DK or Refused

HH4. "(I/we) couldn't afford to eat balanced meals." Was that <u>often</u>, <u>sometimes</u>, or <u>never</u> true for (you/your household) in the last 12 months?

[ ] Often true

[ ] Sometimes true

[ ] Never true

[ ] DK or Refused

<u>Screener for Stage 2 Adult-Referenced Questions:</u> If affirmative response (i.e., "often true" or "sometimes true") to one or more of Questions HH2-HH4, OR, response [3] or [4] to question HH1 (if administered), then continue to ***Adult Stage 2;*** otherwise, if children under age 18 are present in the household, skip to ***Child Stage 1,*** otherwise skip to ***End of Food Security Module.***

<u>NOTE:</u> In a sample similar to that of the general U.S. population, about 20 percent of households (45 percent of households with incomes less than 185 percent of poverty line) will pass this screen and continue to Adult Stage 2.

<u>Adult Stage 2: Questions AD1-AD4</u> (asked of households passing the screener for Stage 2 adult-referenced questions).

AD1. In the last 12 months, since last (name of current month), did (you/you or other adults in your household) ever cut the size of your meals or skip meals because there wasn't enough money for food?

[ ] Yes

[ ] No (Skip AD1a)

[ ] DK (Skip AD1a)

AD1a. [IF YES ABOVE, ASK] How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

[ ] Almost every month

[ ] Some months but not every month

[ ] Only 1 or 2 months

[ ] DK

AD2. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food?

[ ] Yes

[ ] No

[ ] DK

AD3. In the last 12 months, were you every hungry but didn't eat because there wasn't enough money for food?

[ ] Yes

[ ] No

[ ] DK

AD4. In the last 12 months, did you lose weight because there wasn't enough money for food?

[ ] Yes

[ ] No

[ ] DK

<u>Screener for Stage 3 Adult-Referenced Questions:</u> If affirmative response to one or more of questions AD1 through AD4, then continue to ***Adult Stage 3;*** otherwise, if children under age 18 are present in the household, skip to ***Child Stage 1,*** otherwise skip to ***End of Food Security Module.***

<u>NOTE:</u> In a sample similar to that of the general U.S. population, about 8 percent of households (20 percent of households with incomes less than 185 percent of poverty line) will pass this screen and continue to Adult Stage 3.

<u>Adult Stage 3: Questions AD5-AD5a</u> (asked of households passing screener for Stage 3 adult-referenced questions).

AD5. In the last 12 months, did (you/you or other adults in your household) ever not eat for a whole day because there wasn't enough money for food?

[ ] Yes

[ ] No (Skip AD5a)

[ ] DK (Skip AD5a)

AD5a. [IF YES ABOVE, ASK] How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

[ ] Almost every month

[ ] Some months but not every month

[ ] Only 1 or 2 months

[ ] DK

<u>Child Stage 1: Questions CH1-CH3 (Transitions and questions CH1 and CH2 are administered to all households with children under age 18)</u> Households with no child under age 18, skip to ***End of Food Security Module.***

SELECT APPROPRIATE FILLS DEPENDING ON NUMBER OF ADULTS AND NUMBER OF CHILDREN IN THE HOUSEHOLD.

<u>Transition into Child-Referenced Questions:</u>

Now I'm going to read you several statements that people have made about the food situation of their children. For these statements, please tell me whether the statement was OFTEN true, SOMETIMES true, or NEVER true in the last 12 months for (your child/children living in the household who are under 18 years old).

CH1. "(I/we) relied on only a few kinds of low-cost food to feed (my/our) child/the children) because (I was/we were) running out of money to buy food." Was that <u>often</u>, <u>sometimes</u>, or <u>never</u> true for (you/your household) in the last 12 months?

[ ] Often true

[ ] Sometimes true

[ ] Never true

[ ] DK or Refused

CH2. "(I/We) couldn't feed (my/our) child/the children) a balanced meal, because (I/we) couldn't afford that." Was that <u>often</u>, <u>sometimes</u>, or <u>never</u> true for (you/your household) in the last 12 months?

[ ] Often true

[ ] Sometimes true

[ ] Never true

[ ] DK or Refused

CH3. "(My/Our child was/The children were) not eating enough because (I/we) just couldn't afford enough food." Was that <u>often</u>, <u>sometimes</u>, or <u>never</u> true for (you/your household) in the last 12 months?

[ ] Often true

[ ] Sometimes true

[ ] Never true

[ ] DK or Refused

<u>Screener for Stage 2 Child Referenced Questions:</u> If affirmative response (i.e., "often true" or "sometimes true") to one or more of questions CH1-CH3, then continue to ***Child Stage 2;*** otherwise skip to ***End of Food Security Module.***

<u>NOTE:</u> In a sample similar to that of the general U.S. population, about 16 percent of households with children (35 percent of households with children with incomes less than 185 percent of poverty line) will pass this screen and continue to Child Stage 2.

<u>Child Stage 2: Questions CH4-CH7</u> (asked of households passing the screener for stage 2 child-referenced questions).

<u>NOTE:</u> In Current Population Survey Food Security Supplements, question CH6 precedes question CH5.

CH4. In the last 12 months, since (current month) of last year, did you ever cut the size of (your child's/any of the children's) meals because there wasn't enough money for food?

[ ] Yes

[ ] No

[ ] DK

CH5. In the last 12 months, did (CHILD’S NAME/any of the children) ever skip meals because there wasn't enough money for food?

[ ] Yes

[ ] No (Skip CH5a)

[ ] DK (Skip CH5a)

CH5a. [IF YES ABOVE ASK] How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

[ ] Almost every month

[ ] Some months but not every month

[ ] Only 1 or 2 months

[ ] DK

CH6. In the last 12 months, (was your child/were the children) ever hungry but you just couldn't afford more food?

[ ] Yes

[ ] No

[ ] DK

CH7. In the last 12 months, did (your child/any of the children) ever not eat for a whole day because there wasn't enough money for food?

[ ] Yes

[ ] No

[ ] DK

END OF FOOD SECURITY MODULE

User Notes

(1) Coding Responses and Assessing Household Food Security Status:

Following is a brief overview of how to code responses and assess household food security status based on various standard scales. For detailed information on these procedures, refer to the *Guide to Measuring Household Food Security, Revised 2000,* and *Measuring Children's Food Security in U.S. Households, 1995-1999.* Both publications are available through the ERS Food Security in the United States Briefing Room.

Responses of "yes," "often," "sometimes," "almost every month," and "some months but not every month" are coded as affirmative. The sum of affirmative responses to a specified set of items is referred to as the household's raw score on the scale comprising those items.

- Questions HH2 through CH7 comprise the U.S. Household Food Security Scale (questions HH2 through AD5a for households with no child present). Specification of food security status depends on raw score and whether there are children in the household (i.e., whether responses to child-referenced questions are included in the raw score).
  - For households with one or more children:
    - Raw score zero—High food security
    - Raw score 1-2—Marginal food security
    - Raw score 3-7—Low food security
    - Raw score 8-18—Very low food security
  - For households with no child present:
    - Raw score zero—High food security
    - Raw score 1-2—Marginal food security
    - Raw score 3-5—Low food security
    - Raw score 6-10—Very low food security

  Households with high or marginal food security are classified as food secure. Those with low or very low food security are classified as food insecure.

- Questions HH2 through AD5a comprise the U.S. Adult Food Security Scale.
    - Raw score zero—High food security among adults
    - Raw score 1-2—Marginal food security among adults

- Raw score 3-5—Low food security among adults
- Raw score 6-10—Very low food security among adults

- Questions HH3 through AD3 comprise the six-item Short Module from which the Six-Item Food Security Scale can be calculated.
  - Raw score 0-1—High or marginal food security (raw score 1 may be considered marginal food security, but a large proportion of households that would be measured as having marginal food security using the household or adult scale will have raw score zero on the six-item scale)
  - Raw score 2-4—Low food security
  - Raw score 5-6—Very low food security

- Questions CH1 through CH7 comprise the U.S. Children's Food Security Scale.
  - Raw score 0-1—High or marginal food security among children (raw score 1 may be considered marginal food security, but it is not certain that all households with raw score zero have high food security among children because the scale does not include an assessment of the anxiety component of food insecurity)
  - Raw score 2-4—Low food security among children
  - Raw score 5-8—Very low food security among children

(2) Response Options: For interviewer-administered surveys, DK ("don't know") and "Refused" are blind responses—that is, they are not presented as response options, but marked if volunteered. For self-administered surveys, "don't know" is presented as a response option.

(3) Screening: The two levels of screening for adult-referenced questions and one level for child-referenced questions are provided for surveys in which it is considered important to reduce respondent burden. In pilot surveys intended to validate the module in a new cultural, linguistic, or survey context, screening should be avoided if possible and all questions should be administered to all respondents.

To further reduce burden for higher income respondents, a preliminary screener may be constructed using question HH1 along with a household income measure. Households with income above twice the poverty threshold, AND who respond <1> to question HH1 may be skipped to the end of the module and classified as food secure. Use of this preliminary screener reduces total burden in a survey with many higher-income households, and the cost, in terms of accuracy in identifying food-insecure households, is not great. However, research has shown that a small proportion of the higher income households screened out by this procedure will register food insecurity if administered the full module. If question HH1 is not needed for research purposes, a preferred strategy is to omit HH1 and administer Adult Stage 1 of the module to all households and Child Stage 1 of the module to all households with children.

(4) 30-Day Reference Period: The questionnaire items may be modified to a 30-day reference period by changing the "last 12-month" references to "last 30 days." In this case, items AD1a, AD5a, and CH5a must be changed to read as follows:

AD1a/AD5a/CH5a [IF YES ABOVE, ASK] In the last 30 days, how many days did this happen?

______ days

[ ] DK

Responses of 3 days or more are coded as "affirmative" responses.

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EDUCATION:

(PhD) **University of Wisconsin**, **Milwaukee,** Sociology (Expected: Spring 2015)

Exam fields: Sociology of Cultural Theory and Global Political Economy
Dissertation Topic: The Impact of Racial and Income Segregation on Food Insecurity

MA **University of Wisconsin**, **Milwaukee**, Sociology (2011)
Thesis: "Finding Hidden Wells on Food Desert Islands: Concentrated Poverty, Racial Composition and Providing New Dietary Options."

MS Certificate **University of Wisconsin**, **Milwaukee**, Geographic Information Systems (2011)
Thesis: "Community supported agriculture (CSA) drop sites correlated with race, income and education in the Milwaukee Metro Area."

BA **University of Wisconsin, Milwaukee,** Sociology and Africology (2007)
Honors in Major; Certificate in Cultures and Communities.

Dissertation Title: Health of the Nation: The Impact of Racial and Income Segregation on Food Insecurity in the United States

RESEARCH AND TEACHING INTERESTS:

Social Theory	Sociology of Culture	Social Inequality
Research Methods	Food Insecurity	Public Health Outcomes

PUBLICATIONS:

Linnea Laestadius and Mark Caldwell. (Forthcoming). "Is the future of meat palatable?: Perceptions of in-vitro meat as evidence by online news comments." *Public Health Nutrition*. Revise and resubmit.

Mark Caldwell. “Defining and Operationalizing food insecurity and child food insecurity.” (Forthcoming) in *Food and Poverty: Food Insecurity and Food Sovereignty among America’s Poor*, edited by Leslie Hossfeld, Brooke Kelly, and Julia Waity. Chapel Hill, SC: University of South Carolina Press.

Mark Caldwell. “Defining food deserts based on place and space, a case study of Milwaukee, WI.” (Forthcoming) in *Food and Poverty: Food Insecurity and Food Sovereignty among America’s Poo,* edited by edited by Leslie Hossfeld, Brooke Kelly, and Julia Waity. Chapel Hill, SC: University of South Carolina Press.

Mark Caldwell. 2014. “The rise of the gourmet hamburger.” *Contexts Trends* Summer 2014 Issue.

Mark Caldwell. 2014. “Little Free Libraries.” *Contexts In-Briefs* Spring 2014 Issue.

Mark Caldwell. 2014. “Lone Wolf Terrorism.” *Contexts In-Briefs* Winter 2014 Issue.

Mark Caldwell, Woonsup Choi, Chulsue Hwang. 2010. “The Spatial and Socioeconomic Features of Drop-off Site for CSA Farms within the Milwaukee Metro Area. ”*The Geographical Journal of Korea,* 44 (3): 281-288.

GRANTS AND AWARDS:

2013 ASA Sydney Spivak Community Action Research Initiative (CARI) grant in partnership with Sweet Water foundation to develop a survey for their online certification program in Aquaponics.

2012 Chancellor’s Graduate Student Award (UW-Milwaukee)

2011 Chancellor’s Graduate Student Award (UW-Milwaukee)

2011 Graduate Travel Award (UW-Milwaukee)

2010 Graduate GIS Competition Winner (UW-Milwaukee)

2010 Graduate Scholar Award(Health, Wellness and Society Conference)

2009 Chancellor’s Graduate Scholarship for Academic Excellence (UW-Milwaukee)

2007 Wisconsin Be SMART Coalition Conservation Scholarship (Wisconsin Department of Land Management)

RESEARCH EXPERIENCE:

Data Collection and Analysis

7/14-12/14 **University of Wisconsin-Milwaukee Sociology Department**

Position: Provided research support to Prof. Nancy Mathiowetz, PhD on a quantitative study using Robert Woods Johnson County Health Estimates for 2014 and American Community Survey (ACS) 2013 3-year estimates to assess impact of race on health outcomes.

Responsibilities: Completed literature review and data collection of public health publications; generated research design for linear regression modeling of racial and socioeconomic characteristics on particular health outcomes. Conducted data preliminary analysis and nested regression modeling using STATA software. Composed research findings into a technical report under review for publication.

11/13-6/14 **University of Wisconsin-Milwaukee School of Public Health**

Position: Provided research support to Linnea Laestadius, PhD on an inductive qualitative study of online public opinion on in-vitro/lab-grown meat.

Responsibilities: Collected data through content analysis of online comments on news articles using HypeResearch software; conducted literature reviews, co-authored and proofread manuscripts, and formatted references. The outcome of this process resulted in an article that is currently under review for publication. Communicated complex research techniques and findings to a general audience.

06/12-Present **Department of Neighborhood Services, City of Milwaukee, Milwaukee, WI**

Responsibilities: Utilized ArcGIS, Microsoft Excel, and City-specific software programs to develop maps for inspection interns, the Safe Neighborhoods Initiative Program, and other projects dealing with foreclosed properties and neighborhood maintenance. Collaborated with administrative management, executive officers and other personnel from several government agencies to complete this task.

Survey Design and Implementation

08/12-08/13 **Sweet Water Foundation, Milwaukee, WI**

Project: Worked in an academic/non-profit partnership to design an online survey instrument that measured outcomes for the AQUAPONs online certification program. The target population included high school students who were enrolled in STEM-based curricula. The survey design included cluster sampling procedure to evaluate new online learning models, and to create a research study that used outcomes from these models to ensure good model fit based on organizational expectations.

06/11-11/11 **Office of Institutional Research, Marquette University, Milwaukee, WI**

Responsibilities: Revised 24,000 freshmen using SAS and SPSS software to reduce production costs and create measurable outcomes related to educational satisfaction and job placement.

Redesigned the Alumni survey using InVivo software and sent this survey out to 800 alumni members via postal mail. Collected, stored, and maintained 300 faculty curriculum vitae in Digital Measures, an online faculty database.

5/10-1/11 **Fondy Food Center, Milwaukee, WI**

Project: Designed a qualitative survey questionnaire to be implemented at an Open Air Food Market, with an emphasis on time use, spending habits, and market programs. Generated ArcGIS spatial maps for future grants related to Food Stamp and and Women, Infant, and Children (WIC) voucher distribution for healthier lifestyle choices.

CONFERENCE PRESENTATIONS:

Mark Caldwell, "A State of Crisis: How do city governments' create programs and policies to deal with the rise of home foreclosures?" *Applied Research Conference,* Portland, OR 2013.

Mark Caldwell, "Mapping the Foodweb: GIS, Public Sociology and the Culture of Food." *Applied Research Conference,* Portland, OR 2013.

Mark Caldwell, "Basemapping the Globe: Creating a New Visual Communication Medium." *Midwest Popular Culture Association Conference*. Milwaukee, WI 2011 and the *International Conference on the Constructed Environment.* Chicago, IL 2011 and the *Midwest Interdisciplinary Graduate Conference.* Milwaukee, WI 2011

Mark Caldwell, "Finding Hidden Wells on Food Desert Islands: Concentrated Poverty, Racial Composition and Providing New Dietary Options." *University of Wisconsin-Milwaukee*

Urban Studies Forum, Milwaukee, WI2011

Mark Caldwell, "Doubling the Green Investment: How PPGIS can strengthen the food web." *Wisconsin Land Information Association Conference.* Madison, WI 2011

Mark Caldwell, "Data Collection Methods and Establishing Digital Drop off Sites for CSA Farms Within the Milwaukee Metro Area." International *Conference on Health, Wellness and Society*. Berkeley, CA 2011

LEADERSHIP AND MANAGERIAL EXPERIENCE:

Lecturer

07/14-Present *World Society,* UW-Milwaukee

06/14-Present *Introduction to Sociology-Online*, Marian University

09/12-06/14 *Social Change in the Global Economy,* UW-Milwaukee

As the instructor for these courses, designed and generated lesson plans and presentations in coordination with assigned textbook. Learner-centered teaching approaches involving group work and class discussions were implemented in classes. Responsible for communicating course expectations to students, dealing with grading issues, and maintaining positive relationships with diverse students in large-enrollment courses.

Adjunct Faculty

06/14-06/15 *Poverty in America Today,* Milwaukee Institute of Art and Design

06/12-12/14 *Plant Yourself: Connecting Agriculture, Food and Society*, Milwaukee Institute of Art and Design

As the instructor for this course, I created a course design based on the relationship between social issues and food consumption. This included the creation of weekly assignments, small group discussions, final research projects, and teaching modules. Utilized a Sociological perspective to infuse critical thinking into classroom discussions. Created a grading rubric for all assignments, assessments and evaluations.

Graduate Student Instructor

09/11- 06/12 *Introduction to Sociology (U-PACE course),* UW-Milwaukee

09/10-06/11 *Social Problems in American Society,* UW-Milwaukee

09/09-06/10 *Introduction to Sociology (Online Course),* UW-Milwaukee

As a Graduate Student Instructor (GSI),responsible for assessing student postings in online course format. Responded effectively in writing to student feedback, recommending improvements on assignments. Maintained accurate and updated records for clear reporting of progress.

DATA AND SOFTWARE SKILL SETS:

General: Microsoft Office, Blackboard, Adobe Illustrator, Adobe Acrobat, and Microsoft Front Page Professional.

Social Statistics: SPSS, Stata, StatTransfer , SAS, Payek, IRB and FERPA certified

GIS: ArcGIS, ArcGIS Server, ArcIMS, Microsoft Expression, Microsoft Silverlight, Adobe FLEX, ArcGIS Explorer, ArcGIS Services, HTML, KML, Bing and Google Map Mashups, HTTP, Javascript and ArcGIS Active X Controls

PROFESSIONAL DEVELOPMENT:

Applied and Clinical Sociology Association, 2012-Present

American Sociological Association, 2012-Present

Alpha Kappa Delta, International Sociology Honor Society

Hip Hop Area Chair, *Midwest Popular Culture Association/ American Culture Association.* 2012-Present

Midwest Sociological Society, 2011-2013