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Remedying Food Policy Invisibility with Spatial Intersectionality: A Case Study in the Detroit Metropolitan Area

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Prior research on food deserts not only lacks an integrated view of multiple social categories—called intersectionality—in explicating food store access, but it also fails to provide place-based policies to remedy food policy invisibility. This study examines the intersectionality of race/ethnicity and poverty in terms of geographic access to five types of 3,124 food stores (national chains, supermarkets, grocery stores, specialty food stores, and convenience stores) in the tri-county Detroit Metropolitan Area. The authors employ spatial statistical analyses to account for spatially varying access to neighborhood food stores. The results suggest that large food stores such as national chains and supermarkets tend to be located densely in certain areas. Poor neighborhoods with different races/ethnicities have full or limited access to different types of food stores in specific places. This research can assist policy makers in better understanding the intersectional characteristics of food store establishments and promote the implementation of place-based equitable food access.

Keywords: food store access, spatial dependence, spatial heterogeneity, geographically weighted regression

It has been observed that certain communities lack national chain supermarkets (e.g., Kroger) or grocery stores (e.g., ALDI) and instead rely on nearby convenience stores for their food shopping. This finding suggests that some neighborhoods have limited or no access to healthy foods. In the United States, more than 29 million Americans in low-income and minority communities lack access to healthy foods (USDA 2012a). According to a recent report by the Johns Hopkins Center for a Livable Future and the Baltimore Food Policy Initiative (Buczynski, Freishtat, and Buzogany 2015), one in four urban residents lives in a food desert, and neighborhoods with food deserts have higher rates of diseases linked to unhealthy diets, including cardiovascular disease and diabetes. Food store availability or food deserts may be one potential factor that affects these outcomes.

Numerous studies have found that particular communities may experience an insufficient quantity or quality of food or systematically higher food prices. For example, neighborhoods with more low-income residents have fewer chain supermarkets (Powell et al. 2007; Zenk et al. 2005) or more liquor stores (Zenk et al. 2006). Evidence suggests that neighborhoods with higher proportions of African Americans have fewer supermarkets and more grocery stores (Zenk et al. 2005). However, it is difficult to disentangle the impact of racial segregation versus poverty (Bower et al. 2014). Zenk et al. (2005) find that there is no relationship between supermarkets and racial composition in low poverty areas, but in high poverty areas, predominantly black neighborhoods are farther from supermarkets. Recently, Bower et al. (2014) examined the availability of different types of food stores in a nationwide sample and found that neighborhoods that are more impoverished have lower (higher) supermarket (grocery and convenience store) access. Furthermore, at equal levels of poverty, black (white) census tracts have the fewest (most) supermarkets. Many studies have used an additive approach (adding multiple demographic and socioeconomic status factors independently) to examine the determinants of food store access. However, a simultaneous

and intersectional perspective on race/ethnic composition and poverty level in food desert research has not been well studied.

The term intersectionality, coined by Crenshaw (1991), refers to the interactivity of multiple social categories, such as race, class, and gender, in shaping individuals' experiences. Individuals and collectives can be subject to various forms of discrimination that are often interconnected. The intersectional approach is particularly important in food desert research because racially segregated minority neighborhoods tend to be economically disadvantaged (Bower et al. 2014). The spatially unjust nature of food access, combined with the increasing availability of geodemographic data sets, prompted this paper, which aims to contribute to the development of strategies to remedy food deserts.

In this paper, we examine the intersectionality of two social categories, race/ethnicity and poverty, in terms of geographic access to different types of food stores (i.e., national chains, supermarkets, grocery stores, specialty food stores, and convenience stores) across 1,164 census tracts in the tri-county Detroit Metropolitan Area (hereafter called DMA). Building on multidisciplinary research in marketing and geography, we explore (1) the spatial clustering of food store establishments and (2) the spatially varying relationship between intersectional neighborhoods and the density of 3,124 food stores in the DMA. This paper expands on existing intersectionality studies in food deserts (Bower et al. 2014; Zenk et al. 2005) by providing empirical evidence on the importance of place-based food desert remedying that pinpoints prioritized areas for policy execution. Previous transformative consumer research has typically addressed "who gets what" in the context of the ways dominant ethnic groups ignore, avoid, and/or disparage the goods and services associated with societal minorities (Ouellet 2007). Our research extends the previous literature to consider "who gets what, where and to what extent," allowing the intersectional identification

of specific disadvantaged neighborhoods with limited or no access to food stores. Our research questions are as follows:

1. Are large food stores, particularly national chains and supermarkets, located densely in specific areas rather than locating evenly across areas (i.e., spatial dependence)? If such spatial dependences of store locations are present in certain areas, economies of agglomeration exist, whereas other areas are deemed food deserts. Therefore, policy makers can identify which areas of neighborhoods experience a lack of healthy food access.
2. Does the relationship between intersectional social categories (e.g., poor White Americans versus poor African Americans) and food store access vary across different locations (i.e., spatial heterogeneity)? If spatially varying relationships occur, this study will expand upon the prior method of generalizing those relationships without considering spatial variations and will offer a concrete place-based initiative to remedy food deserts.

Literature Review and Hypotheses

Types of Healthy Food Access

The term “food desert” was introduced to describe areas with an under-supply of stores offering healthy, affordable food in urban markets (Cummins and Macintyre 2002). The US Department of Agriculture (USDA) defines food deserts as parts of the country that lack fresh fruit, vegetables, and other healthful whole foods. Food deserts are usually found in impoverished areas, either urban or rural (American Nutrition Association 2017). Research suggests that food deserts can be characterized as areas without food stores (Cummins and Macintyre 2002; Morton et al. 2005), areas with stores that are far away (Coveney and

O'Dwyer 2009), or areas whose residents have low incomes and face difficulties reaching supermarkets in out-of-town locations due to a lack of car ownership (Coveney and O'Dwyer 2009; Short, Guthman, and Raskin 2007).

Given the existence of disadvantaged consumers and food deserts, there are three main types of barriers that affect access to healthy foods: informational, economic, and geographic (Guy and David 2004; McEntee and Agyeman 2010). Informational access may include a wide range of factors related to the educational, cultural, and social constraints that influence how and why people choose to eat certain foods. For example, food desert counties typically have a larger population of individuals without a high school diploma (Morton and Blanchard 2007), and reductions in food insecurity require economic growth strategies aimed at households with less-educated workers (Nord and Andrews 2002). Economic access involves not only poverty but also other financial elements that impact the ability to acquire food (e.g., food prices and transportation costs). Hendrickson et al. (2006) show that in areas with the highest poverty, food costs are typically higher and the quality of food is inferior. Finally, geographical access is the ability to reach stores that sell healthy food. Diets poor in fruits and vegetables may be a result of not only poor levels of geographical access but also economic problems (Ball, Timperio, and Crawford 2009; Guy and David 2004). Among these three types of barriers, our primary focus is the geographic access associated with economic access (e.g., poverty) of racial/ethnic segments (e.g., poor White or African Americans). By understanding the spatial patterns of food store establishments, policy makers can improve public health by effectively targeting disadvantaged segments with place-based food access policies (Sharma 2014).

Spatial Dependence in Food Store Establishments

Turning our attention to the supply side of food stores (i.e., store locations), the economic literature suggests that food stores consider the input costs of running a retail food store (Bitler and Haider 2011). Whereas fixed costs include store operating expenses (e.g., rent) that are independent of the quantity of goods sold, operating costs are associated with economies of scale, economies of scope, and economies of agglomeration (Bitler and Haider 2011). Economies of scale refer to the situation in which per-unit operating costs decline with the size of a store, and economies of scope refer to the situation in which per-unit operating costs decline with product variety. Large food stores such as supermarkets tend to pursue economies of scale and scope by carrying thousands of products and stocking healthy foods (Horowitz et al. 2004) at a lower cost (Cummins and Macintyre 2002)¹. In contrast, convenience stores are likely to stock more energy-dense, processed, and high-fat foods (Walker, Keane, Burke 2010). Finally, economies of agglomeration refer to the situation in which per-unit operating costs decline when more stores are co-located in a certain area (Krugman 1991). This phenomenon can be explained by the fact that a greater consumer base and greater buying power of the community strongly guides the site selection of larger food retailers (Hartford Food System 2006). Due to economies of scale, scope, and/or agglomeration in the retail food industry, large food stores may be clustered in certain areas, leaving other areas underserved and resulting in food deserts.

From the perspective of interactions among suppliers (food stores) and demanders (consumers), it is important to consider a market power perspective (Bitler and Haider 2011). A firm with market power in a certain area has an incentive to increase prices and restrict quantity to increase profits (Bitler and Haider 2011; Cotterill 1986). If food stores have high market power in an area, the food quantity may be low or food prices may be high; therefore,

¹ In 2015, the average supermarket carried 39,500 products. See <http://www.fmi.org/research-resources/supermarket-facts> (accessed April 28, 2017).

the area becomes a food desert. In contrast, if multiple food stores offer similar products in a certain area, they may become engaged in a price competition called the Bertrand Paradox² (Tirole 1997). To avoid such price competition, food stores attempt to locate in places where other stores are not located. If they locate near other stores, they should differentiate themselves from each other. Hence, it is assumed that large food stores are established densely in higher-income neighborhoods and that they differentiate themselves by price or non-price competition. In lower-income neighborhoods, fewer and smaller grocery stores tend to locate by setting higher prices and carrying more limited product assortments (McDonald and Nelson 1991). Therefore, depending on the type of food store, the density of large food stores varies across neighborhoods. As a result, food deserts occur in poor neighborhoods (Bader et al. 2010). Consequently, we hypothesize the following:

H₁: Large food stores such as national chains and supermarkets tend to co-locate in certain areas (where a greater consumer base exists), making other areas become food deserts.

Intersectionality and Spatial Heterogeneity in Food Store Establishments

Intersectionality is a theoretical and methodological approach that investigates how multiple social categories (e.g., ethnicity and poverty) come together to shape life. It has recently been used in research on consumer culture (Gopaldas 2013) and consumer vulnerability (Crockett et al. 2011). Intersectionality explicitly focuses on the diversity within social groups and differences across social groups. It offers various strategies to explore the similarities and differences across and within social groups that affect well-being (Crockett et al. 2011;

² The Bertrand Paradox is a situation in which two firms reach a state of Nash equilibrium where both firms charge a price equal to the marginal cost (Bertrand 1883).

Ozanne and Fischer 2012). From an intersectional perspective, each person should be understood based on an understanding of how social group characteristics are interrelated with one another, societal systems, and structures (Collins 2000).

Various theoretical and methodological classifications of intersectionality have been developed. We employ a widely accepted classification developed by McCall (2005), who identifies three distinct approaches: intra-categorical, anti-categorical, and inter-categorical (Corus et al. 2016). The intra-categorical approach focuses on the overlapping categories of disadvantage within the same social group, untangling similarities and distinctions within the same social context (McCall 2005). The disadvantage of this approach is that it displaces the focus from the larger social processes and structures that might cause inequalities (Walby, Armstrong, and Strid 2012). The anti-categorical approach highlights the ways, practices, and social processes through which analytical categories are considered. It prioritizes fluidity over stability of categories and thus makes practical analysis difficult (Sayer 1997). The inter-categorical approach adopts existing analytical categories to examine the dominant categories of similarity and difference and multiple inequalities (Winker and Degele 2011). McCall (2005) recommends the inter-categorical approach because it engages with the larger structures that generate inequalities. Furthermore, the inter-categorical approach enables researchers to compare and contrast multiple social groups within the same study (Corus et al. 2016) and allows for econometric analyses of macro-level data (e.g., demographics) and statistical methods to investigate interaction effects across social categories (Corus and Saatcioglu 2015).

The assumption of inter-categorical intersectionality is that all social categories are equally salient all of the time (Hancock 2007). However, the degrees of importance of their types of intersection vary within different societal arenas, such as different institutions or discourses, as well as within given social forces in different spaces (Anthias 2002). As noted

by Ferree (2012, p. 8), “It is an empirical matter in any given context to see what concepts are important to the configuration of inequalities in discourse and in practice.” For a more integrated framing of issues of social inequality, Anthias (2002, 2008) suggests a translocational lens, which is a tool for analyzing positions and outcomes produced through the intersections of different social structures and processes. The concept of translocations focuses on social locations rather than groups. Locations relate to stratification in local and national fields within a chronographic context (Anthias 2012). The translocation thus treats people as being located across multiple but interrelated social spaces of different types (Anthias 2012), resulting in multiple and uneven social patterns of domination and subordination (Anthias 2008).

In the context of food deserts, understanding the various challenges faced by disadvantaged consumers in relation to food access requires a better examination of context-bound spatial heterogeneity (McGuirt et al. 2015). The prevalence of a racial/ethnic group in a certain area compared to other areas may result in a specific food environment to meet cultural needs (Williams and Jackson 2005). This concern has led to a need for further research on the complex nature of food desert formations from a local perspective. Soja (2010) argues that unjust social conditions are accompanied by “consequential geographies” (p. 97) that facilitate and reproduce segregation or uneven access to opportunities (e.g., healthy food access). Recent research shows that poor African-American neighborhoods have the most limited access to quality food in urban areas but not in rural areas, suggesting that policy interventions should be developed locally, not universally (Bower et al. 2014). Even in a local area, the relationship between neighborhood racial composition and food store accessibility varies according to neighborhood poverty level (Zenk et al. 2005). Therefore, there may be different contextual influences that lead to spatial variation in the relationship between intersectional social categories and food store access. These contextual influences

may be underlying geographical, structural, or social conditions that are products of or are related to the intersectional categories of interest (McGuirt et al. 2015). Consequently, we hypothesize the following:

H₂: The relationship between intersectional social categories (i.e., race/ethnicity and poverty) and food store access varies across census tracts.

Application of Spatial Statistical Analysis in Food Desert

Research

Methodologically, most food desert studies have used non-spatial statistical approaches (e.g., ordinary least square (OLS) regression) to understand the relationship between neighborhood social categories and food store access. The OLS method assumes that observations are independent of one another and that there is a stationary relationship among variables (Fotheringham, Brunson, and Charlton 2002). However, because intersectionality processes may occur systematically and vary across local areas (McKenzie 2014), residuals from regression analyses may be spatially autocorrelated. Therefore, spatial dependence (e.g., spatial autocorrelation) may exist between neighborhood characteristics and food store accessibility across adjacent areas. Ignoring such spatial dependence renders conclusions regarding the relationship potentially invalid and results in mixed findings in the literature (Luan, Minaker, and Law 2016).

Food desert studies have employed a variety of spatial statistical analysis to address these problems. Lamichhane et al. (2013) utilize global measures of spatial autocorrelation and incorporate spatial effects into their models to examine the associations and clustering of both supermarket and fast food outlet availability with neighborhood composition. Their

results indicate that income, housing value and education level have a positive association with access to both supermarkets and fast food outlets. Apparicio et al. (2007) and Sharkey et al. (2009) also use spatial autocorrelation measures to explore spatial patterns of food store availability. Lee and Lim (2008) employ spatial statistics (G-statistic) to detect local hot spots of disparity between population need and grocery provision at various spatial scales in Buffalo, New York. Luan, Minaker, and Law (2016) use Bayesian spatial hierarchical models to explore the association between marginalization and food outlets and find that materially deprived neighborhoods (e.g., low-income neighborhoods) have lower access to healthy food. Finally, Lamichhane et al. (2015) apply a Bayesian spatio-temporal Poisson model to analyze the relationship between the sociodemographic characteristics and densities of supermarkets and convenience stores for four US cities. Their results indicate that neighborhoods with higher poverty have better access to both supermarkets and convenience stores.

As suggested by prior research, this study employs spatial statistical methods to comprehensively examine the existence of both spatial dependence and spatial heterogeneity in food store establishments. Moreover, this study constructs the intersectionality dimension of neighborhood characteristics, which differentiates this study from prior food desert research. For example, although prior studies employ spatial analytical methods (Lamichhane et al. 2013; Sharkey et al. 2009), they do not reveal whether and how associations between sociodemographic characteristics and food store availability may vary across places. Furthermore, although McGuirt et al. (2015) examine differences in the relationship between racial domination and corner store count across space, they fail to include the socioeconomic (e.g., poverty) differences between areas. Therefore, this research addresses the methodological limitations of past studies by considering two spatial effects: whether food stores cluster near each other (spatial dependence) and whether the influences of intersectional social categories on food store access vary across places (spatial heterogeneity).

Data and Variables

Data

To explore the existence of spatial dependence and spatial heterogeneity in food store establishments, we collected a dataset of food stores and the demographic and socioeconomic status of neighborhoods in the tri-county Detroit Metropolitan Area (DMA), including Macomb, Oakland and Wayne counties. We selected the DMA as the study area because the DMA is characterized by extreme economic inequalities across neighborhoods (Jargowsky 1997) with diverse racial/ethnic composition. Compared to the overall US composition, the DMA has more White Americans (70.1% versus 61.6%), more African Americans (22.8% versus 13.3%), and fewer Hispanic Americans (6.2% versus 17.6%). Therefore, the DMA has been the study area for previous research on food shopping and dietary behaviors (Budzynska et al. 2013; LeDoux and Vojnovic 2013) and food availability (Taylor and Ard 2015; Zenk et al. 2005).

Food stores were categorized as supermarkets, grocery stores, specialty food stores, and convenience stores based on the literature (Han et al. 2012; Powell et al. 2007) (Table 1). A supermarket has 4 or more cash registers, 2 or more independent butcher, deli, or bakery service departments, sells fresh meat, and carries 20 or more fresh fruits and vegetables (Block and Kouba 2006). Specialty food stores include bakeries, meat or fish stores, fruit or vegetable stores, candy or nut stores, and coffee or tea stores (Han et al. 2012). A convenience store refers to a non-specialty food store with no fresh meat, 10 or fewer fruits and vegetables, and 2 or fewer cash registers (Glanz et al. 2007). Grocery stores comprise food stores that do not meet the definition of a supermarket, specialty food store, or convenience store (Farley et al. 2010). Large supermarkets tend to stock more healthy foods,

whereas grocery and convenience stores are likely to stock more energy-boosting, processed, high-fat, sugary, and salty foods (Walker, Keane, and Burke 2010).

The data for food stores and their geographic locations were collected from the Simply Map database (<http://geographicresearch.com/simplymap>). Simply Map is web-based mapping and database software that facilitates the creation of thematic maps and business reports, including food stores. It allows access to Dun & Bradstreet (D&B) data that classifies food retail businesses into different types of food stores (Powell et al. 2007). The Simply Map database also provides a Standard Industrial Classification (SIC) code for each food store. The SIC code is used by the US Department of Labor to monitor business identification. The food stores in our study were identified as SIC 53 “General Merchandise Stores,” 54 “Food Stores,” and 55 “Automotive Dealers and Gasoline Service Stations.” Primary SIC codes were used as food store classification systems for the database lists. Table 1 reports the detailed list of the SIC codes by type of food store and examples of real store names. Compared to the food store distribution in the overall US population, the DMA has fewer supermarkets (23% versus 28%), a similar number of grocery stores (14%), more specialty food stores (44% versus 54%), and fewer convenience stores (9% versus 14%). In addition to the four types of food stores, we identified a group of national chain stores that have a supply chain advantage in terms of transportation to markets, warehouse, processing space, and storage facilities (Taylor and Ard 2015). National chains can be categorized as supermarkets (e.g., Save-A-Lot) or grocery stores (e.g., ALDI). As of 2016, there were 188 national chain stores, 291 supermarkets, 984 grocery stores, 489 specialty food stores, and 1,360 convenience stores in the DMA, for a total of 3,124 food stores.

[Insert Table 1 about here]

When analyzing spatial data, it is important to define the unit of analysis. This study utilized a census tract (CT), which is a subdivision of a county with a mean population of

approximately 4,000 people who have relatively similar socioeconomic characteristics (Moore et al. 2008). Geographic data such as CT and county boundaries were collected from the Michigan Open GIS Data Portal (<http://gis-michigan.opendata.arcgis.com>). Specifically, all 1,164 CTs were extracted from the Michigan Geographic Framework base map. Figure 1 illustrates the spatial distribution of food stores and the CT boundaries within the study area.

[Insert Figure 1 about here]

Dependent Variables

To investigate the spatially varying effects of intersectional social categories on access to different types of food stores, we developed measures of the dependent and independent variables (summarized in Table 2). We created six dependent variables to measure the different degrees of geographic access to different types of food stores: (1) national chain; (2) supermarket; (3) grocery store; (4) specialty food store; (5) convenience store; and (6) all stores. Specifically, we employed kernel density estimation (KDE) to measure the degree of food store access for each CT. As a non-parametric density estimation, KDE can calculate the density of features in a neighborhood based on the concept of spatial dependence (O’Sullivan and Unwin 2003). KDE has been used to estimate the geographic distribution of customers in a market (Donthu and Rust 1988), the density of recreational facilities and parks (Moore et al. 2008), and access to supermarkets (Thornton et al. 2012). When we employed the KDE, we used a 1-kilometer radius as the bandwidth and created a 50-meter resolution raster surface (Maroko et al. 2009). The use of a 1-kilometer radius is justified because 1 kilometer is approximately a 10- to 15-minute walk for an adult to shop for food in an urban setting (Apparicio et al. 2007; Bader et al. 2010). As the final measure for the dependent variable, we calculated the per capita food store density for each CT (Lee and Lim 2009).

[Insert Table 2 about here]

Independent Variables

As independent variables, we used demographic and socioeconomic status data from the US Census Bureau to develop measures of intersectional and other neighborhood deprivation. An intersectional variable was created to identify the proportion (%) of a specific racial/ethnic American population below the federal poverty line for each CT. Using the four racial/ethnic compositions (i.e., White, African, Asian, Hispanic) and poverty levels, four combined intersectional variables were created: White Poverty, African Poverty, Asian Poverty, and Hispanic Poverty. Of these four intersectional variables, the US Census Bureau shows Hispanic Poverty data across only 283 CTs out of 1,164 CTs (24.3%) in the DMA; therefore, we excluded the Hispanic Poverty variable in our final model. We used White Poverty, African Poverty, and Asian Poverty as the final intersectionality variables.

We controlled for seven social deprivation variables that might affect food store access. From the perspective of economic efficiency, we identified two determinants of supply and demand (Bitler and Haider 2011): (1) land cost to run a retail food store, which was measured as the median house price (\$) per CT (House Value) and (2) food shopping demand, measured by the median household income (\$) per CT (Income). From an equity perspective, we identified five variables related to the proportion of vulnerable segments in a given CT (e.g., Coveney and O'Dwyer 2009; Guy and David 2004; Motley and Perry 2013): (1) the percentage of the population below the federal poverty level (Poverty); (2) the junior population, measured by the percentage of the population under age 15 (Age15); (3) the senior population, measured by the percentage of the population over 64 (Age64); (4) the percentage of the population that does not speak English at home (Language); and (5) the percentage of households without a vehicle (Vehicle). As such, we define vulnerable segments as including those with low income, a high poverty level, more young and elderly

residents, non-English speaking households, and no vehicle. All racial/ethnic and socioeconomic data were acquired from the US Census Bureau based on the 2011-2015 American Community Survey 5-Year Estimates (<https://factfinder.census.gov>).

Data Analysis

First, to examine the existence of spatial dependence between the two food stores (H_1), we used the global Moran's I statistic as a numeric measure of spatial autocorrelation (Li, Calder, and Cressie 2007). The global Moran's I measures the level of spatial association among adjacent food stores and is calculated as follows:

$$(1) \quad I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (x_i - \mu)(x_j - \mu)}{\sum_i (x_i - \mu)^2},$$

where w_{ij} is the matrix of weights such that $w_{ij} = 1$ if store i and store j are adjacent; otherwise, $w_{ij} = 0$, x_i is the attribute value of a specific variable at store i , x_j is the attribute value of a specific variable at store j , μ is the average attribute value of a specific variable, and N is the total number of stores. Furthermore, to identify the local patterns of spatial clusters, we applied the local indicator of spatial association (LISA) (Anselin 1995). The LISA is calculated as follows:

$$(2) \quad I_i = \frac{(x_i - \mu)}{m_2} \sum_j w_{ij} (x_j - \mu),$$

where m_2 is calculated by $\sum_i (x_i - \mu)^2 / N$. The results of LISA analysis can be presented in the form of a LISA cluster map with information regarding the types of spatial clusters (Anselin 1995). The results of a LISA cluster map can be classified into five types: (1) HH: spatial clusters with high values, indicating positive spatial autocorrelation (also called hot spots); (2) HL: spatial clusters with high values adjacent to low values, indicating negative spatial autocorrelation (also called spatial outliers); (3) LH: spatial clusters with low values adjacent

to high values, indicating negative spatial autocorrelation (also called spatial outliers); (4) LL: spatial clusters with low values, indicating positive spatial autocorrelation (also called cold spots); and (5) not significant: no spatial clusters between locations.

Second, to investigate the spatially varying relationship between intersectional social categories and food store access (H₂), we employed geographically weighted regression (GWR) (Fotheringham, Brunson, and Charlton 2002) in addition to the OLS regression. The GWR produces a set of local regression coefficients to explore spatially varying relationships between variables (e.g., intersectionality and food store access). We ran the OLS regression (R 3.1) to investigate the global relationship between intersectional and controlled variables and food store access (Equation 4) and used GWR 4.0 to explore the existence of spatial heterogeneity using the same variables (Equation 5). We estimated the following two models:

$$(4) \text{ Access}_j = \beta_0 + \beta_1 \text{White Poverty} + \beta_2 \text{Black Poverty} + \beta_3 \text{Asian Poverty} \\ + \beta_4 \text{House Value} + \beta_5 \text{Income} + \beta_6 \text{Poverty} + \beta_7 \text{Age15} + \beta_8 \text{Age64} \\ + \beta_9 \text{Language} + \beta_{10} \text{Vehicle} + \varepsilon, \text{ and}$$

$$(5) \text{ Access}_{ij} = \beta_{i0}(u_i, v_i) + \beta_{i1}(u_i, v_i) \text{White Poverty}_i + \beta_{i2}(u_i, v_i) \text{Black Poverty}_i \\ + \beta_{i3}(u_i, v_i) \text{Asian Poverty}_i + \beta_{i4}(u_i, v_i) \text{House Value}_i + \beta_{i5}(u_i, v_i) \text{Income}_i \\ + \beta_{i6}(u_i, v_i) \text{Poverty}_i + \beta_{i7}(u_i, v_i) \text{Age15}_i + \beta_{i8}(u_i, v_i) \text{Age64}_i \\ + \beta_{i9}(u_i, v_i) \text{Language}_i + \beta_{i10}(u_i, v_i) \text{Vehicle}_i + \varepsilon_i ,$$

where i and j , respectively, refer to the food store and the specific model: national chain ($j=1$), supermarket ($j=2$), grocery store ($j=3$), specialty food store ($j=4$), convenience store ($j=5$), and all stores ($j=6$); (u_i, v_i) is the coordinate of the food store's location point i ; $\beta_{i0}(u_i, v_i)$ is the intercept parameter at point i ; $\beta_{ik}(u_i, v_i)$ is the local regression coefficient

for the independent variable k at point i ; and β_{ik} is the value of the independent variable k at point i . To minimize AIC_c , we determined the optimal kernel size through an iterative statistical optimization process. Finally, we used ArcGIS 10.4.1 to create visualized maps to explain where spatial heterogeneity occurs across specific places (ESRI 2016).

Results

Descriptive Results

Table 3 summarizes the descriptive statistics of all the variables. The average value of per capita food store density varies across national chains (0.17), supermarkets (0.29), grocery stores (1.15), specialty food stores (0.51), and convenience stores (1.51). The density of convenience stores is 9 times larger than that of national chains and 5 times larger than that of supermarkets. The DMA has a relatively higher proportion of African Americans below the federal poverty line than other races/ethnicities (23%), followed by poor White Americans (15%) and poor Asian Americans (15%). The average house value is 147.39 (thousand dollars) with a range of 16.19–674.90, and the average medium household income is 60.55 (thousand dollars) with a range of 13.01–538.87. The average percentages of junior and senior populations are 18.81% and 14%, respectively. The average poverty level is 15.06, the average percentage of non-English speaking households is 14.72%, and the percentage of no vehicle ownership is 8.31%. We tested for multicollinearity among the independent variables and found that the largest variance inflation factor is 2.81, suggesting that multicollinearity is not a concern in our analysis.

[Insert Table 3 about here]

Results of Spatial Dependence in Food Store Access

Table 4 summarizes the descriptive statistics for the average percentage values of each type of food store according to spatial segments such as hot spots (HH) and cold spots (LL) in the DMA. If we consider all the food store establishments in the DMA, food stores seem to be located randomly across 903 CTs (77.7%) rather than densely (9.7%) or sparsely (8.3%). However, if we examine the spatial clustering by store type, food stores with a similar type are more either densely or sparsely located. In particular, large food stores and convenience stores tend to cluster across certain CTs: national chains (238 CTs, 20.4%), supermarkets (259 CTs, 22.2%), and convenience stores (259 CTs, 22.2%). The spatial clustering also occurs in other stores, such as grocery stores (218 CTs, 18.7%) and specialty food stores (230 CTs, 19.7%). Table 5 shows that the global Moran's I values for the six dependent variables are all positive at 0.51, 0.54, 0.87, 0.45, 0.77, and 0.70, respectively. The results show that food stores, by type or altogether, are significantly and spatially correlated (Luan, Minaker and Law 2016). Finally, Figure 2 displays the visualized information about spatial clustering in each food store type. The red-colored areas represent hot spots (high-high cluster) with a high density of food stores, and the blue-colored areas represent cold spots (low-low cluster) with low density. Thus, both the statistical and visual results confirm the existence of spatial dependence in large food store establishments, supporting H₁.

[Insert Tables 4 and 5 about here]

[Insert Figure 2 about here]

Results of Spatial Heterogeneity in Food Store Access

Table 5 reports the estimation results of OLS and GWR models depending on the type of food store. According to the OLS model results, White neighborhoods below the poverty level have no relationship with food store access. African-American neighborhoods below the poverty level have lower access to national chains ($\beta = -.0442$) and supermarkets ($\beta = -.0530$),

and Asian neighborhoods below the poverty level have higher access to supermarkets ($\beta=.0810$), grocery stores ($\beta=.3834$), specialty stores ($\beta=.1145$), convenience stores ($\beta=.4436$), and all stores ($\beta=.4892$). In contrast, the estimation results of GWR models show that the relationship between the intersectionality variables and food store access varies across CTs. For example, although poor African-American neighborhoods, on average, are negatively associated with national chain access ($\beta_{OLS} = -.0442$), the GWR results indicate that, depending on CT, the negative relationship may be even larger ($\beta_{GWR} = -.0682$) or smaller ($\beta_{GWR} = -.0241$). A similar phenomenon occurs for the poor White neighborhoods, with a range from $-.0877$ to $-.0426$, and poor Asian neighborhoods, with a range from $.0006$ to $.0233$. In addition, the adjusted R^2 , which represents the explanatory power of the current food access model, varies across CTs. For example, whereas the adjusted R^2 of the OLS regression is $.0944$ in Model 1, the GWR shows that the average adjusted R^2 ranges from $.0945$ to $.1401$, meaning that the predictive power of the current model varies across cities and townships. As such, the results of other OLS and GWR coefficients (e.g., House Value, Income, Poverty) from Model 2 to Model 6 can be interpreted accordingly.

Figures 3 to 8 map the spatial distribution of local coefficients of the intersectionality variables in the GWR models. Specifically, the focal variable in dark-colored areas is more positively or more negatively associated with food store access than it is in light-colored areas. In the case of national chain accessibility (Figure 3), the White Poverty variable is more negatively associated in the dark-colored Oakland County but less negatively associated in the light-colored Wayne County (3a). On the contrary, the African Poverty variable is more negatively associated in Macomb County but less negatively associated in Oakland County (3b). The Asian Poverty variable is more positively associated in Oakland County but less with Macomb and Wayne counties (3c). Racial/ethnic neighborhoods with high poverty levels can have different levels of food store access across different neighborhoods. Poor

White neighborhoods have less access to supermarkets in north Oakland County (Figure 4a) but more access to convenience stores in south Wayne County (Figure 7a). Poor African neighborhoods have less access to both supermarkets (Figure 4b) and convenience stores (Figure 7b) in south Wayne County, and poor Asian neighborhoods have less access to both supermarkets (Figure 4c) and convenience stores (Figure 7c) in east Wayne County. In summary, the level of food store access varies depending on the type of food store (i.e., national chain, supermarket, grocery store, specialty food store, convenience store) and the specific place (i.e., county, census tract).

[Insert Figures 3, 4, 5, 6, 7, and 8 about here]

We found that the GWR model improved the overall model fit (high adjusted R^2) and performance (low corrected Akaike's information criterion: AIC_c) compared to the OLS model (Gilbert and Chakraborty 2011). If the adjusted R^2 value of the GWR model is higher and the AIC_c is lower than in the OLS model, we conclude that the GWR model significantly improves upon its corresponding OLS model. Table 5 shows that the adjusted R^2 (AIC_c) value in the GWR increased (decreased) from the value of the OLS regression. For example, Model 1 shows an increase in adjusted R^2 from .0944 to .1067 (Figure 9 also shows the spatial distribution of local R^2 across different CTs) and a decrease in AIC_c from 1,125.81 to 1,119.29. These findings indicate that the GWR model provides significantly better goodness of fit than the OLS model when assessing the spatially varying distribution of food store access in the DMA.

[Insert Figure 9 about here]

Discussion

This study contributes to the understanding of the spatial intersectionality in food desert research in terms of (1) how food stores are located densely or sparsely (spatial dependence) and (2) how the relationship between intersectional social categories and food store access varies across locations and types of food stores (spatial heterogeneity) in the tri-county DMA. As demonstrated empirically, both large and small food stores are clustered in certain areas, and vulnerable neighborhoods with multiple social categories have different access to food stores. Although prior research presents evidence of food deserts, it lacks multidisciplinary research (i.e., whether and how neighborhoods with overlapping social categories (who) are associated with geographic access to a certain type of food store (what) in different places (where)). The empirical results show that the GWR model not only outperforms the traditional OLS model but also supports the development of place-based food access implementation when combined with maps.

Consistent with prior research on the spatial clustering of food stores (Lamichhane et al. 2013), our findings demonstrate the existence of spatial dependence among large or small food stores. This can be explained because greater demand from advantaged consumers attracts large food stores in a certain area (i.e., food oasis), and small food stores meet disadvantaged consumers' demand (i.e., food desert) (Hartford Food System 2006). Some researchers argue that supermarkets are established in wealthier neighborhoods with a large population base and that fast food outlets may co-occur around supermarket locations (Lamichhane et al. 2013). However, our conjecture is that food stores cluster in different areas depending on a certain type. For example, national chain stores are densely located in the suburbs of the City of Detroit where wealthier and predominantly White neighborhoods are located and land costs are relatively low. On the contrary, grocery and convenience stores are clustered in the City of Detroit where less wealthy and predominantly African-American neighborhoods are located. Specialty food stores are densely located in both the downtown

and suburbs of the City of Detroit. The current study suggests that the spatial clustering of food stores of a certain type may provide a clear understanding about how food stores have been established densely and sparsely in specific areas.

This research further examines the existence of spatially varying relationships between intersectional social categories and food store access. Depending on the store type, food store accessibility varies with respect to different racial/ethnic and poverty compositions as well as other demographic and socioeconomic statuses. For instance, poor White neighborhoods in west Oakland County face a double jeopardy with the most limited access to healthy food because they have lower access to national chains (Figure 3a), supermarkets (Figure 4a), and specialty food stores (Figure 6a). On the contrary, poor White neighborhoods in south Wayne County have relatively higher access to all types of food stores, such as national chains, supermarkets, grocery stores, specialty food stores, and convenience stores. Interestingly, poor African-American neighborhoods in south Wayne County suffer from food deserts due to limited access to supermarkets (Figure 4b), grocery stores (Figure 5b), and convenience stores (Figure 7b). These mixed results cannot be explained by a generalized theory that more supermarkets are located in or near Whites compared to Africans or affluent compared to low-income/deprived neighborhoods (Powell et al. 2007; Zenk et al. 2005). The spatial differences in food store availability suggest that healthy and unhealthy food access varies by a specific place (McGuirt et al. 2015). Food retailers normally decide the locations of food stores while considering tradeoffs between locating close to favorable demand (e.g., income) and supply (e.g., land and labor costs) conditions and differentiating themselves geographically from rivals (Bitler and Haider 2011; Orhun 2013).

Finally, this study suggests that a critical approach to food deserts allows for the examination of the spatial intersectionality of overlapping social categories (i.e., race/ethnicity and poverty) to understand the complex nature of marketplace vulnerabilities

(Gopaladas 2013). Analysis of the role of race without regard to poverty and of poverty without regard to race provides an incomplete picture of the potential importance of these categories in shaping the spatial accessibility of food stores (Bower et al. 2014; Zenk et al. 2005). This study implicitly suggests that food store availability should be regarded as a dynamic, complex social system, leaving the open question of why and how multiple social categories co-construct one another and are associated with food store access. Furthermore, this study extends the intersectionality literature by using a translocational lens to analyze the intersections of overlapping social categories across locations and types of food stores (Anthias 2012). It confirms that uneven social patterns of food access are accompanied by consequential geographies that reproduce segregation or uneven access to healthy food (Soja 2010).

Implications for Public Policy

Food deserts have been a long-standing subject for policy makers. The findings of our study are important and informative for food environment planning and interventions for remedying food deserts. Since the Obama Administration proposed a \$400 million Healthy Food Financing Initiative (HFFI) in 2010, local governments have helped finance healthy food retailers' moves to underserved urban and rural communities (USDA 2010b). The numerous federal and state-sponsored programs designed to support healthy food projects (e.g., HFFI) would benefit from place-based implementations to ensure the local relevance of health intervention strategies. It seems important for policy makers to distinguish between supply and demand factors that may lead to food deserts in certain areas.

First, if the existence of food deserts were driven by supply factors, then government interventions on the supply side might be effective. Our findings reveal that poor White

neighborhoods in northwest Oakland and poor African-American neighborhoods in south Wayne have extremely limited access to supermarkets, and poor African-American neighborhoods in northeast Macomb lack nearby national chains. Figure 10 displays the hot spot neighborhoods in terms of intersectionality (race/ethnicity and poverty categories) and large food stores (national chain and supermarket). Although some poor neighborhoods in south Macomb County and middle Wayne County have full access to national chains, poor Whites densely residing in the City of Detroit and poor Africans in south Wayne (shaded areas in Figure 10a) are still in need of new national chain construction. Furthermore, poor Asians in the City of Detroit have full access to supermarkets, but poor Africans in south Wayne have limited or no access to supermarkets (shaded areas in Figure 10b). These results can help local government agencies not only understand the intersectional characteristics of food store establishments but also provide tax incentives to national chains and/or supermarkets to develop new food stores in the neediest places. This development can also enhance local economic vitality by creating new jobs, increasing the local tax base, and offering foods at reasonable prices (Pothuskuchi 2005).

[Insert Figure 10 about here]

Second, although local government can attract large food stores to open in poor areas and sell a variety of fresh fruits and vegetables, this may not affect the food purchases of the working poor due to budget constraints. In the short term, increasing the benefit levels of the Supplemental Nutrition Assistance Program (SNAP) or cash assistance to the poor would likely be more effective because SNAP recipients who live closer to supermarkets consume more fruit and vegetables (Rose and Richards 2004). Furthermore, with regard to the “full price” of food availability, the full price needs to include the list price of a product and the individual-level transportation costs to purchase it (Capozza and Van Order 1978). Therefore, local governments can improve public transportation routes from areas with limited access to

supermarkets and/or subsidize supermarket shuttle services. These public transportation improvements can also help disadvantaged consumers access other services, such as banks or hospitals, on their trips to supermarkets. However, the number of Michigan SNAP recipients dropped 23 percent from December 2010 to March 2016 (Mack 2016), and the budget will decrease further in the Trump Administration (Worstell 2017). Therefore, in the long term, general economic development of poor neighborhoods could be more effective than food assistance programs because job creation pays a fair wage, improves education quality, and attracts large food stores and other new businesses (Zenk et al. 2005). Policy makers expect that developing small healthy food retailers and farmers' markets would alleviate the lack of healthy food access. Although many independent stores provide affordable, nutritious food staples, encouraging smaller food stores to open in underserved areas might result in high prices because economies of scale could not be exploited (Bitler and Haider 2011).

Finally, another public policy implication centers on a more participatory decision-making process through map-based outcomes of food store accessibility and increasing access to and interaction with information. Access to healthy food information is a prerequisite to create positive attention and attitudes that directly trigger enhanced action (Yang et al. 2012). To understand not only the impact of marketing on society but also the interests of disadvantaged groups, food retailers and policy makers should introduce deliberative democracy methods specifically designed to engage multiple stakeholders in the decision-making process through social interaction (Ozanne, Corus, and Saatcioglu 2009). To identify optimal locations for new healthy food stores, deliberative democracy should evolve by examining various types of public engagement about food, including consultation by submission, consensus and citizen conferences, citizens' juries, and local food planning (Ankeny 2016), eventually maximizing stakeholder value and long-term brand well-being.

Limitations and Further Research

Despite significant implications for theory and practice, several limitations of this study should be acknowledged. First, when examining the food environment in the DMA, this study focused on five types of food stores: national chains, supermarkets, grocery stores, specialty food stores, and convenience stores. However, healthy food can be accessed from farms, community and school gardens, farmers' markets, allotments that produce food, and food assistance programs (Taylor and Ard 2015). This study also assumes that all stores of the same type are similar. However, the square footage of vegetable and fruit departments and the assortment, including the quality, variability and price of food, vary across food stores of the same type (e.g., supermarkets). Future research should consider alternative food outlets and food assortment variables that may affect residents' assessments of overall accessibility and destination choice (Križan et al. 2015; Taylor and Ard 2015).

Second, this study does not include variables related to the health or nutrition status of the geographic unit in the model. Future data collection efforts should explicitly measure the response variables (e.g., health or nutrition levels) that may occur from the lack of food store access. Research shows mixed results in examining the impacts of food store accessibility on public health. Increased supermarket availability may be unrelated to dietary intake levels (Cummins et al. 2008). Although supermarkets are sources of affordable nutritious foods, they are also sources of affordable unhealthful foods (Stern et al. 2016). Therefore, future research should reflect the spatial intersectionality of multiple social categories in the food access-health relationship to examine spatially varying relationships among variables for place-based health policy implementation.

Third, this study faces a methodological obstacle in terms of the validity of the food store data from the secondary data sources. Research finds that the agreement between retail

food outlet classifications and field measurements varies by tract characteristics (Bader et al. 2010; Powell et al. 2011). However, commercial datasets for supermarkets and grocery stores tend to be reliable, although classifications for convenience and specialty food stores are subject to some systematic bias by neighborhood racial/ethnic composition (Han et al. 2012). Since D&B has a higher classification match rate than InfoUSA for supermarkets and grocery stores (Han et al. 2012), we used food store datasets from the D&B source. Nevertheless, future research using ground-verified data including all local food outlets could minimize the misclassification and confirm the robustness and validity of our findings.

Finally, this study, like other studies, used defined geographic units such as census tracts as the unit of analysis. This container-based approach to calculate accessibility faces a major issue called the Modifiable Aerial Unit Program (MAUP) (Zhang, Lu, and Holt 2011); that is, the spatial relationship between neighborhood characteristics and food store access may change depending on different units of analysis (e.g., census tracts and census blocks). Hence, future studies should conduct multiple sensitivity analyses with census tracts and census blocks to compare their results and further examine whether MAUP may be a major issue in the study.

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Table 1. Detailed NAICS and SIC Codes for Food Store Classification

Type of store	NAICS code	NAICS description	SIC code	SIC code description	Example (Detroit)	US population		Tri-country DMA	
						Number	Percentage	Number	Percentage
Supermarket	452210	Department Stores	53119901	Department stores, discount	Meijer	12,065	5.1%	35	1.1%
	445110	Supermarkets and Other Grocery Stores	54110100	Supermarkets	Save-A-Lot	8,312	3.5%	100	3.2%
			54110101	Supermarkets, chain	Whole Foods	11,680	4.9%	112	3.6%
			54110103	Supermarkets, independent	Wonder Food Supermarket	1,652	0.7%	44	1.4%
<i>Supermarket total</i>						<i>65,536</i>	<i>28%</i>	<i>703</i>	<i>23%</i>
Grocery store	445110	Supermarkets and Other Grocery Stores	54110000	Grocery stores	Alcapone Market	60,504	25.6%	639	20.5%
			54119901	Cooperative food stores	Glory Foods	404	0.2%	2	0.1%
			54119902	Delicatessen stores	Family Fair Deli	4,505	1.9%	59	1.9%
			54119903	Frozen food and freezer plans	East Lansing Burgers	123	0.1%	3	0.1%
			54119904	Grocery stores, chain	ALDI	2,084	0.9%	29	0.9%
			54119905	Grocery stores, independent	Bangla Town Market	10,441	4.4%	252	8.1%
<i>Grocery store total</i>						<i>31,927</i>	<i>14%</i>	<i>439</i>	<i>14%</i>
Specialty food store	445210	Fresh, frozen, or cured meats and poultry	54210000	Meat and fish markets	Seafood Supreme	10,552	4.5%	36	1.2%
	445230	Fruit and Vegetable Markets	54310000	Fruit and vegetable markets	Peaches & Greens	5,653	2.4%	77	2.5%
	445292	Confectionery and Nut Stores	54410000	Candy, nut, and confectionery stores	D-Jays Place	2,316	1.0%	32	1.0%
	445299	Miscellaneous specialty foods	54510000	Dairy products stores	R&M Dairy Mart	881	0.4%	13	0.4%
	311811	Retail Bakeries	54610000	Retail bakeries	Sweetheart Bakery	19,743	8.4%	306	9.8%
	445299	Miscellaneous specialty foods	54990000	Miscellaneous food stores	Linnbonn Flea Mart	1,831	0.8%	25	0.8%
	<i>Specialty food store total</i>						<i>105,056</i>	<i>44%</i>	<i>1,691</i>
Convenience store	445120	Convenience Stores	54110200	Convenience stores	Laith & R Mini Mart	27,443	11.6%	249	8.0%
	447190	Gasoline Stations	55410000	Gasoline service stations	BP Gas Station	22,714	9.6%	519	16.6%
			55419901	Filling stations, gasoline	Waterman Gas & Go	32,337	13.7%	585	18.7%
			55419903	Truck stops	Detroiter Truck Stop	988	0.4%	7	0.2%
<i>Convenience store total</i>						<i>33,709</i>	<i>14%</i>	<i>291</i>	<i>9%</i>
Food store total						236,228	100%	3,124	100%

Table 2. Measures and Sources of Variables

Variable	Measure	Source
Dependent variable		
National chain	Kernel density of national chain stores per capita for each census tract	Geographic Research Inc. (via SimplyMap database)
Supermarket	Kernel density of supermarkets per capita for each census tract	
Grocery store	Kernel density of grocery stores per capita for each census tract	
Specialty food store	Kernel density of specialty food stores per capita for each census tract	
Convenience store	Kernel density of convenience stores per capita for each census tract	
All stores	Kernel density of all food stores per capita for each census tract	
Independent variable		
White poverty	Proportion (%) of White American population below the poverty line for each census tract	U.S. Census Bureau, 2011- 2015 American Community Survey 5-Year Estimates (https://factfinder.census.gov)
Black poverty	Proportion (%) of African American population below the poverty line for each census tract	
Asian poverty	Proportion (%) of Asian American population below the poverty line for each census tract	
Control variable		
House value	Median household price in thousand dollars for each census tract	
Income	Median household income in thousand dollars for each census tract	
Poverty	Proportion (%) of population below the poverty line for each census tract	
Age15	Proportion (%) of population under age 15 for each census tract	
Age64	Proportion (%) of population over age 64 for each census tract	
Language	Proportion (%) of population speaking non-English language at home for each census tract	
Vehicle	Proportion (%) of households without a vehicle for each census tract	

Table 3. Descriptive Statistics and Correlation Coefficients (n=784)

Variable	Mean	Min	Max	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. National Chain	0.17	0.00	0.82	0.12	1.00															
2. Supermarket	0.29	0.00	1.50	0.22	0.58	1.00														
3. Grocery Store	1.15	0.00	12.02	1.25	0.16	0.74	1.00													
4. Specialty Food Store	0.51	0.00	4.21	0.43	0.55	0.77	0.68	1.00												
5. Convenience Store	1.51	0.00	11.49	1.35	0.32	0.79	0.85	0.72	1.00											
6. All Stores	1.98	0.00	10.95	1.67	0.30	0.49	0.52	0.50	0.57	1.00										
7. White Poverty	0.15	0.00	1.00	0.16	-0.09	0.28	0.44	0.22	0.44	0.21	1.00									
8. Black Poverty	0.23	0.00	1.00	0.25	-0.09	0.13	0.23	0.09	0.25	0.15	0.39	1.00								
9. Asian Poverty	0.15	0.00	1.00	0.28	0.01	0.27	0.33	0.21	0.35	0.21	0.44	0.27	1.00							
10. House Value	147.39	16.19	674.90	86.75	-0.10	-0.28	-0.33	-0.27	-0.46	-0.25	-0.47	-0.32	-0.31	1.00						
11. Income	60.55	13.01	538.87	36.58	0.01	-0.19	-0.32	-0.21	-0.39	-0.19	-0.44	-0.28	-0.21	0.63	1.00					
12. Poverty	15.06	0.28	67.92	13.95	-0.07	0.39	0.54	0.30	0.56	0.26	0.76	0.42	0.43	-0.58	-0.56	1.00				
13. Age15	18.81	3.14	34.85	4.24	-0.23	-0.05	-0.02	-0.12	-0.07	-0.13	0.25	0.13	0.06	-0.11	-0.01	0.30	1.00			
14. Age64	14.00	1.05	34.98	5.52	0.18	0.00	-0.10	0.02	-0.08	0.00	-0.24	-0.14	-0.07	0.21	0.06	-0.31	-0.60	1.00		
15. Language	14.72	0.00	86.45	11.54	-0.14	-0.03	0.05	0.03	-0.15	-0.18	0.08	-0.02	-0.03	0.17	0.11	0.06	0.26	-0.07	1.00	
16. Vehicle	8.31	0.00	58.43	9.23	-0.04	0.36	0.54	0.28	0.54	0.34	0.63	0.34	0.38	-0.45	-0.51	0.75	-0.01	-0.05	-0.08	1.00

Table 4. Distribution of Spatial Dependence by Type of Food Store (n=1,164)

Type of food store	HH (%)	HL (%)	LH (%)	LL (%)	Others (%)	Total
National Chain	238 (20.4)	8 (0.6)	2 (0.1)	259 (22.2)	657 (56.7)	1,164
Supermarket	259 (22.2)	2 (0.1)	18 (1.5)	267 (22.9)	618 (53.3)	1,164
Grocery Store	218 (18.7)	0 (0.0)	9 (0.7)	149 (12.8)	788 (67.8)	1,164
Specialty Food Store	230 (19.7)	1 (0.0)	17 (1.4)	207 (17.8)	709 (61.1)	1,164
Convenience Store	259 (22.2)	1 (0.0)	14 (1.2)	281 (24.1)	602 (52.5)	1,164
All Stores	113 (9.7)	11 (0.9)	40 (3.4)	97 (8.3)	903 (77.7)	1,164

Notes: The figures are calculated based on the 5% pseudo-significance. HH: hot spots with high-high density values; HL: outlier spots with high-low density values; LH: outlier spots with low-high density values; LL: cold spots with low-low density values; Others: spots with no statistical significance.

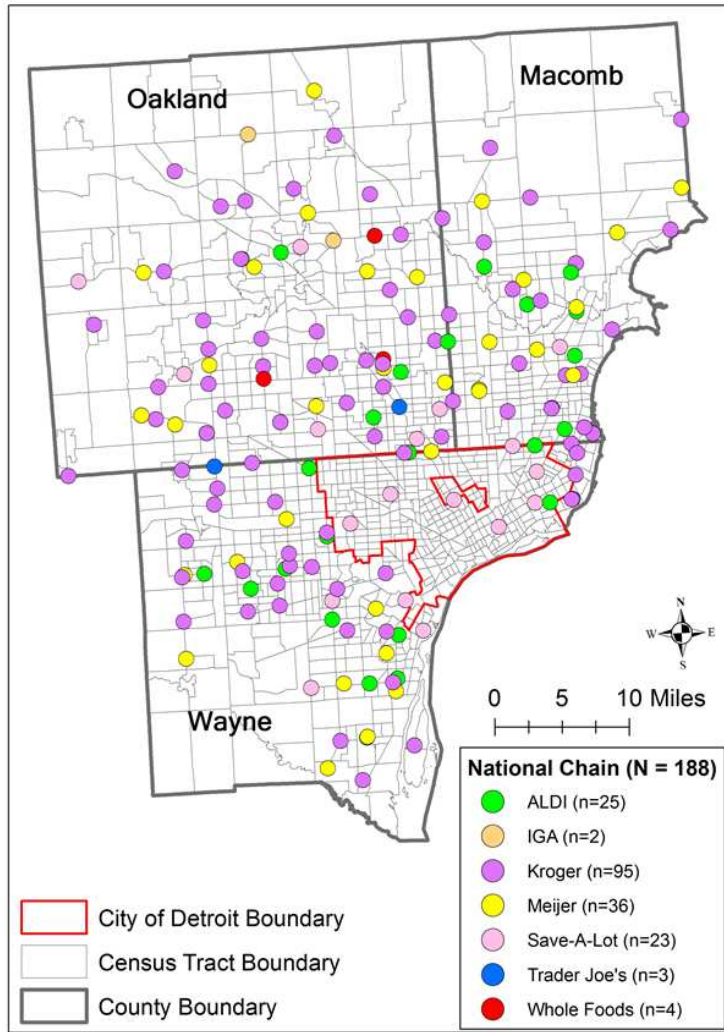
Table 5. Results of OLS and GWR Models Depending on Type of Food Store

	Model 1 (National Chain)			Model 2 (Supermarket)			Model 3 (Grocery Store)			Model 4 (Specialty Food store)			Model 5 (Convenience Store)			Model 6 (All Stores)		
Global Moran's I ^a	0.51			0.54			0.87			0.45			0.77			0.70		
Coefficient ^b	OLS (mean)	GWR (min)	GWR (max)	OLS (mean)	GWR (min)	GWR (max)	OLS (mean)	GWR (min)	GWR (max)	OLS (mean)	GWR (min)	GWR (max)	OLS (mean)	GWR (min)	GWR (max)	OLS (mean)	GWR (min)	GWR (max)
Intercept	.2676	.2250	.3315	.2794	.2383	.3450	1.6655	.8433	2.2597	.8977	.7083	1.0862	2.6188	1.9190	3.0983	3.2307	2.3131	4.3246
White Poverty	-.0537	-.0877	-.0426	-.0834	-.1370	-.0503	-.0356	-.1785	.1827	-.1048	-.2643	.0081	-.0219	-.1641	.1953	-.3227	-.9005	.3466
African Poverty	-.0442*	-.0682	-.0241	-.0530†	-.0686	-.0365	-.0437	-.1165	.0596	-.1036	-.1603	-.0455	-.1388	-.2864	-.0058	.1614	-.2085	.3448
Asian Poverty	.0099	.0006	.0233	.0810**	.0681	.1091	.3834**	.2975	.4864	.1145*	.0880	.1837	.4436**	.3871	.6193	.4892*	.3584	.7605
House Value	-.0003**	-.0004	-.0002	-.0004**	-.0004	-.0002	-.0006	-.0008	-.0003	-.0008**	-.0010	-.0006	-.0024**	-.0029	-.0015	-.0022*	-.0035	-.0009
Income	.0004*	.0003	.0004	.0009**	.0007	.0010	.0013	.0010	.0018	.0005	.0002	.0008	.0013	.0007	.0021	.0027	.0012	.0045
Poverty	.0011†	.0008	.0014	.0065**	.0060	.0069	.0332**	.0323	.0345	.0095**	.0087	.0103	.0391**	.0367	.0428	.0087	.0014	.0157
AGE15	-.0048**	-.0080	-.0030	-.0067**	-.0098	-.0051	-.0638**	-.0864	-.0408	-.0251**	-.0266	-.0239	-.0686**	-.0829	-.0598	-.0630**	-.0834	-.0436
AGE64	.0029**	.0015	.0033	.0025	.0005	.0036	-.0198*	-.0322	-.0002	-.0001	-.0047	.0028	-.0133	-.0244	-.0047	-.0142	-.0298	-.0030
Language	-.0008†	-.0019	.0008	.0001	-.0019	.0017	.0106**	.0066	.0142	.0039**	.0016	.0064	-.0106**	-.0186	-.0036	-.0163**	-.0219	-.0105
Vehicle	-.0015*	-.0023	.0007	.0020	.0012	.0037	.0321**	.0250	.0346	.0008	-.0008	.0031	.0220**	.0145	.0266	.0409**	.0358	.0408
Adjusted R ²	.0944	.0945	.1401	.2019	.1869	.2333	.3625	.3450	.3983	.1571	.1303	.1903	.4196	.3905	.4489	.1594	.1262	.2046
Adjusted R ² (mean)	.1067			.1960			.3715			.1903			.4250			.1718		
Condition Index	22.47		29.98	22.49		29.96	20.11		28.95	22.68		29.99	22.75		29.98	21.26		28.11
AIC _c	1,125.81	1,119.29		312.08	302.91		2,240.08	2,132.95		797.19	784.87		2,276.53	2,243.90		2,903.07	2,897.62	
Neighbors	147			147			147			147			147			147		

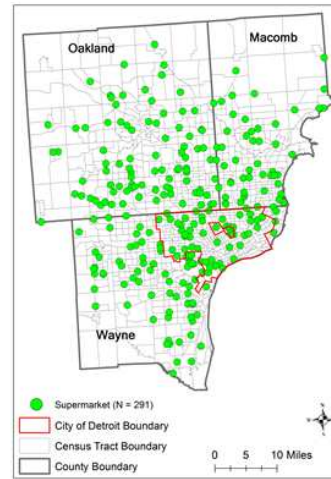
Notes: The sample size for spatial dependence analysis (Global Moran's I) is 1,164 and the sample size for OLS and GWR analysis is 784. AIC_c refers to corrected Akaike's Information Criterion.
 † p > 0.10, * p > 0.05, and ** p > 0.01.

Figure 1. Spatial Distribution of Food Stores in Study Area

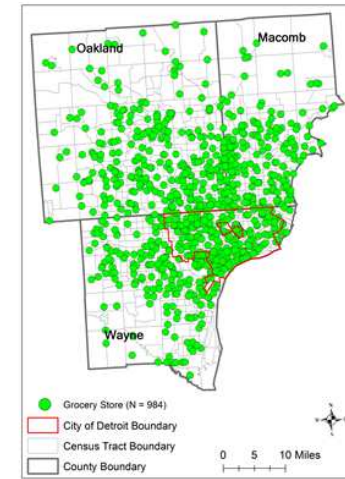
(a) National Chain (n=188)



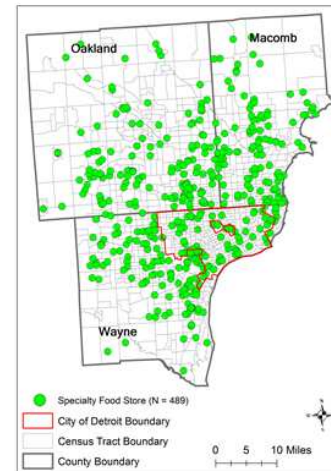
(b) Supermarket (n=291)



(c) Grocery Store (n=984)



(d) Specialty Food Store (n=489)



(e) Convenience Store (n=1,360)

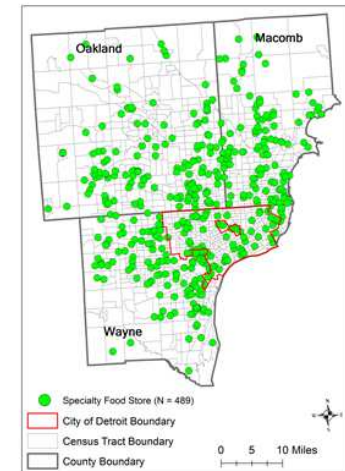


Figure 2. Spatial Clustering of Food Store Establishments

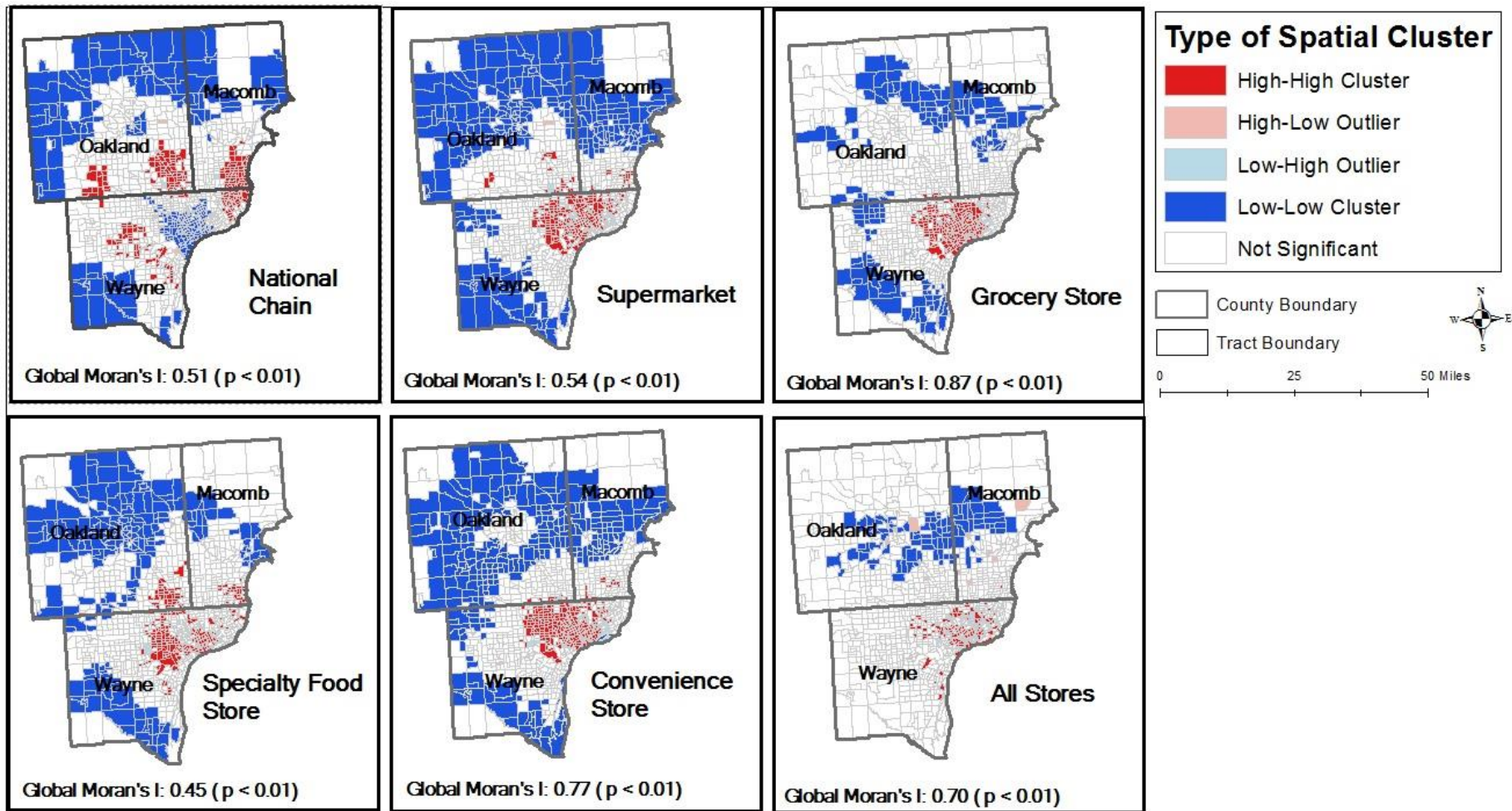


Figure 3. Spatial Distribution of Local Coefficients (National Chain)

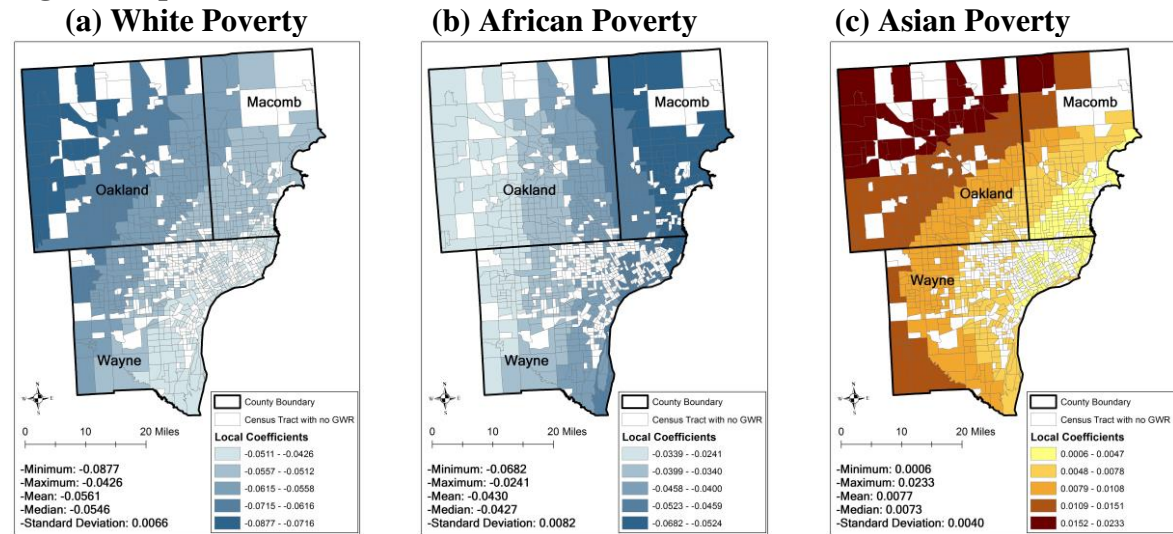


Figure 4. Spatial Distribution of Local Coefficients (Supermarket)

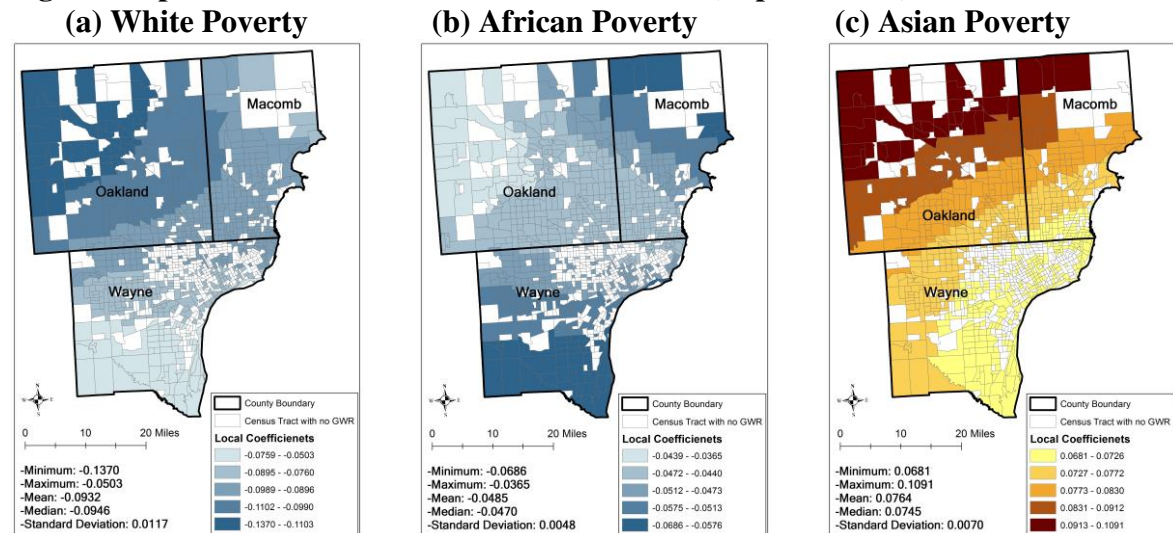


Figure 5. Spatial Distribution of Local Coefficients (Grocery Store)

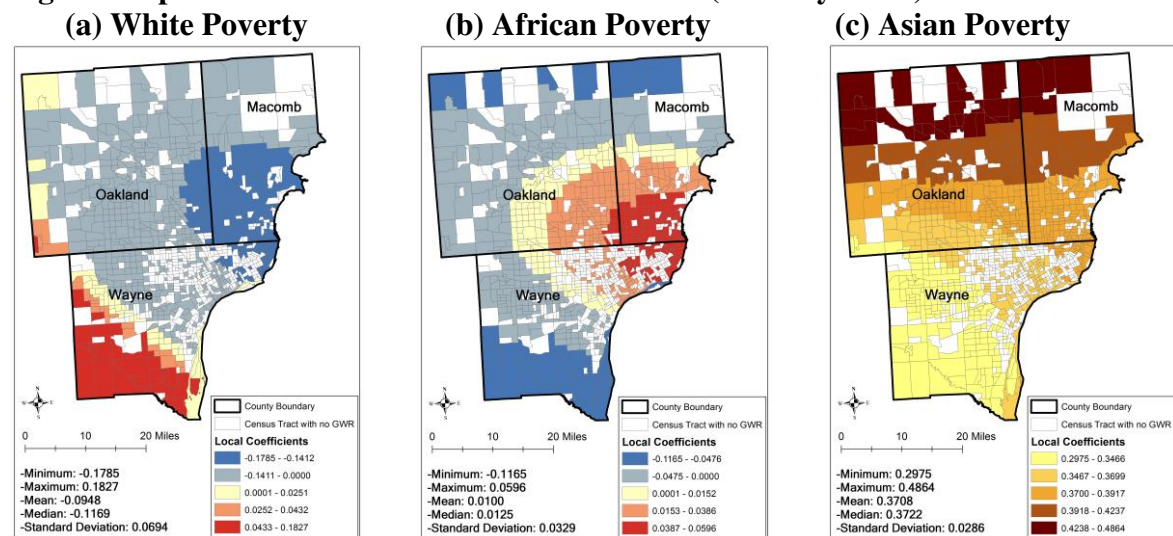


Figure 6. Spatial Distribution of Local Coefficients (Specialty Food Store)

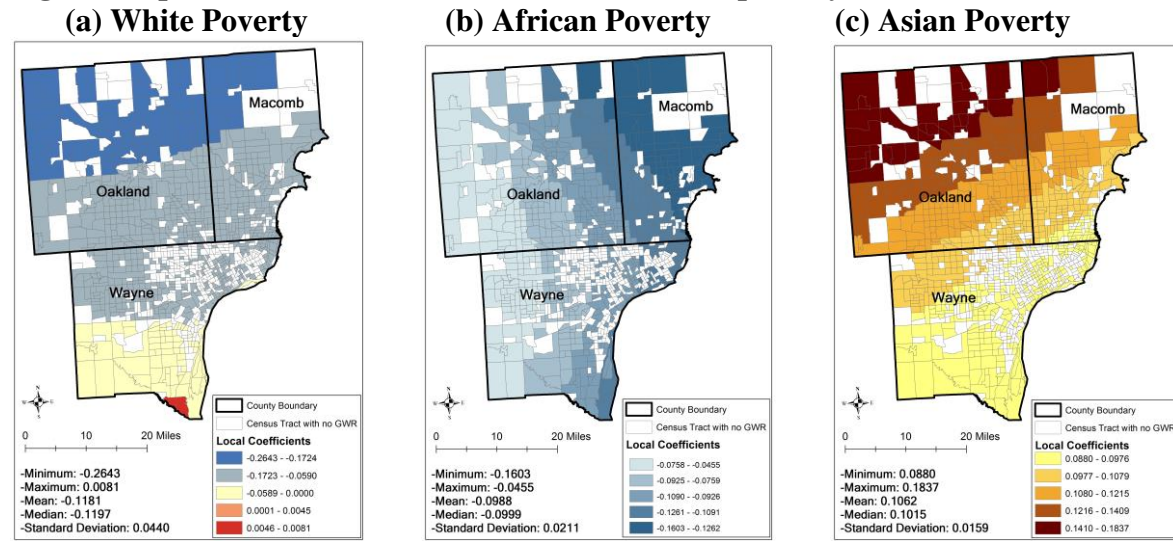


Figure 7. Spatial Distribution of Local Coefficients (Convenience Store)

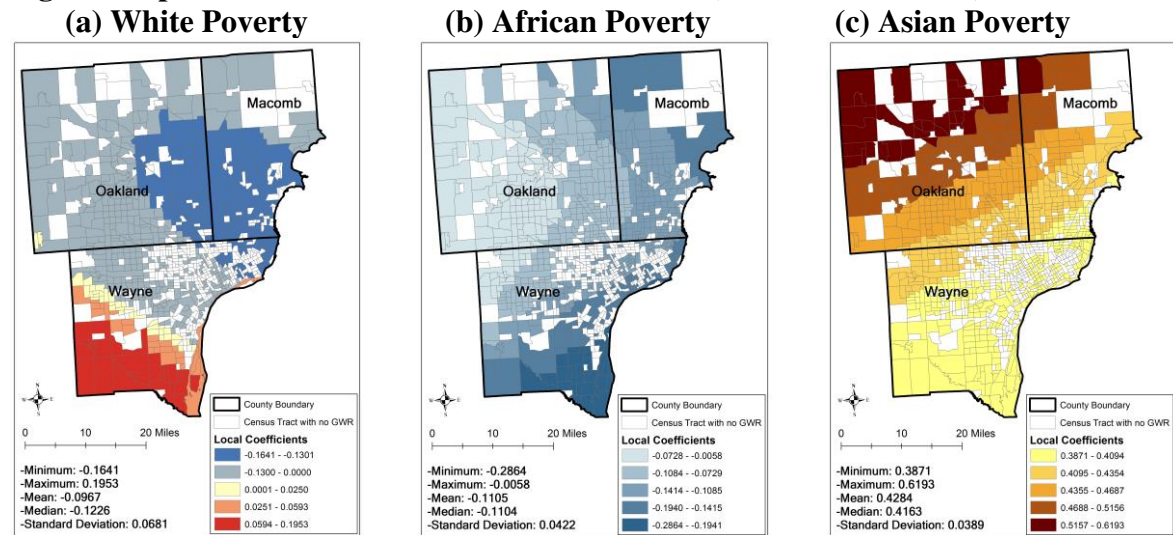


Figure 8. Spatial Distribution of Local Coefficients (All Stores)

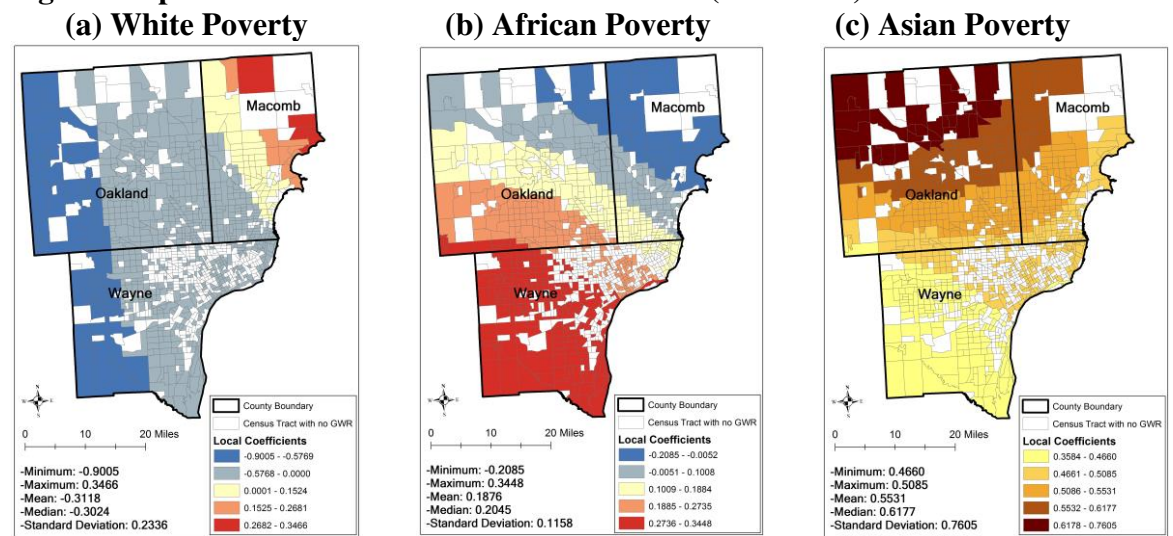


Figure 9. Spatial Distribution of Local R^2 by Type of Food Store

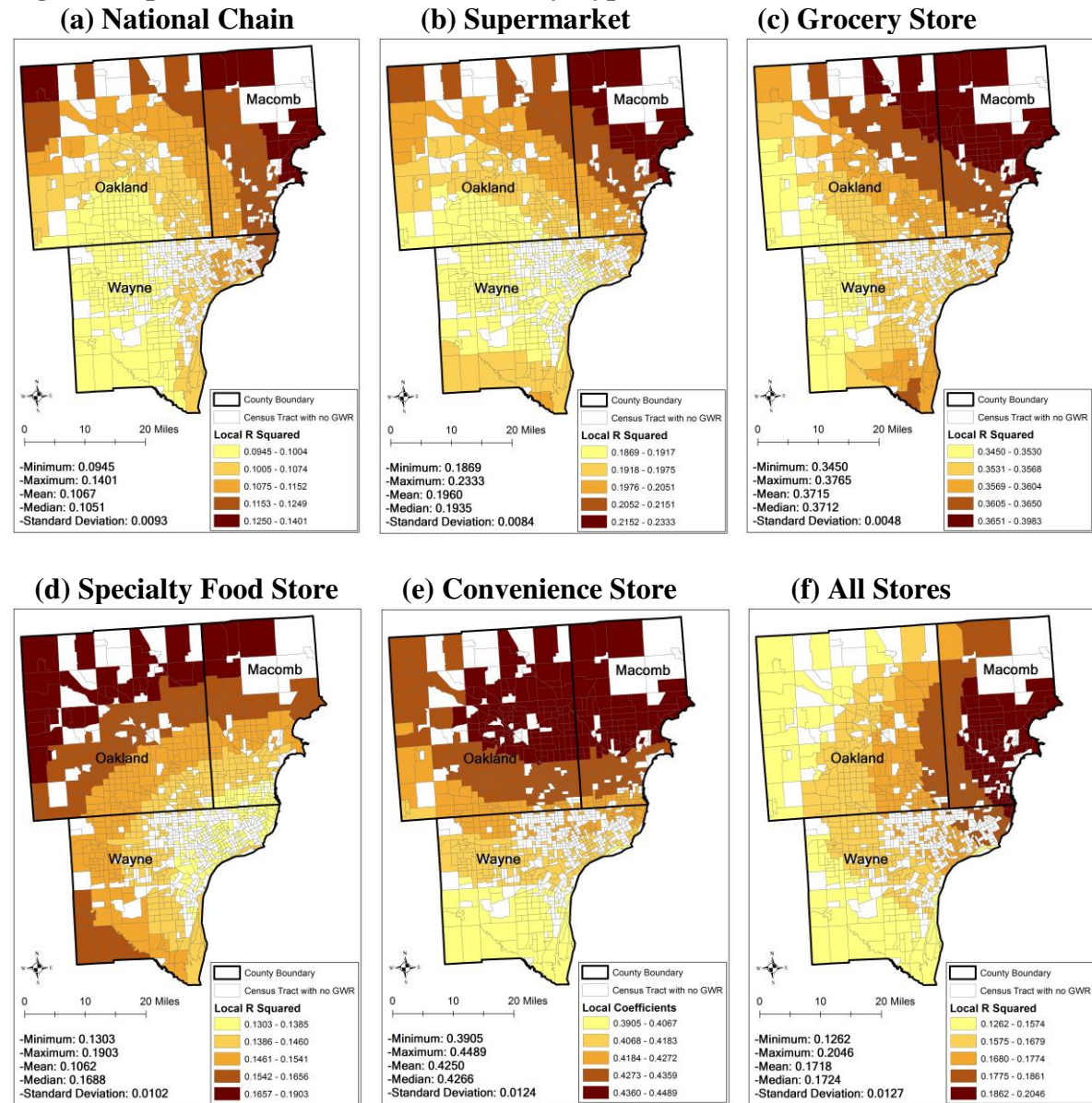
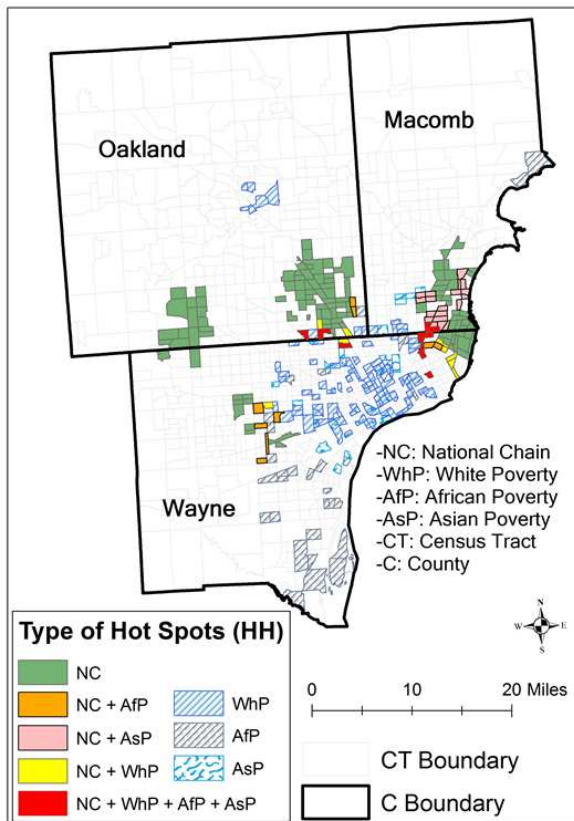


Figure 10. Spatial Distribution of Hot Spots of Intersectionality and Food Stores

(a) National Chain



(b) Supermarket

