December 11, 2015

FOOD DESERTS AND HEALTH OUTCOMES IN MISSISSIPPI

RESEARCH PROJECT

QMSS 4070
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INTRODUCTION

The objective of this study is to investigate the relationship between food deserts and two health outcomes, obesity and diabetes.

Obesity and diabetes are increasingly cited as major health issues in the United States. Approximately one-third of U.S. adults are obese and one-fourth have diabetes[1]. These health conditions and the resulting increase in chronic disease and other serious conditions cause a high number of preventable deaths; while the reported figures vary according to the measurement technique, it is clear that they are leading causes of death in the United States. The economic costs are also high: $176 billion[2] direct yearly medical costs for diabetes and $190 for obesity[3]. These figures do not include the loss of productivity.

Obesity rates, along with diabetes rates, have begun to sharply increase in the United States in the late 1970s. While unhealthy diets, low physical activity, lack of sleeps, and genetics are widely considered causes of obesity and diabetes, there's less consensus over the causes of the sharp increase. Some scholars have posited the following potential causes for the rise: food-marketing techniques, changing eating habits (in particular, while watching television), changing diets (increase in portion sizes and in consumption of sugary drinks), and an unhealthy food environment. Nevertheless, it remains unclear why the late 1970s marks a change in these patterns.

The increased presence of food deserts – areas with limited availability to fresh fruits and vegetables – provides another explanation for the rise of obesity and diabetes. According to Blanchard (2007), the occurrence of food deserts occurred gradually over the past 40 years. The author explains that the shift from a large number of grocers dispersed across a geographical region to large supermarkets concentrated in very few areas was driven by globalization. Globalization allows supermarket chains to purchase large quantities of food from suppliers in order to sell it at lower prices. The buying power of large retailers has a distinct advantage over the small "mom and pop" stores. Blanchard (2002) shows that the entrance of large supermarkets in an area generates a decline in the small grocers in surrounding areas. Therefore habitants of remote areas have to travel long distances to obtain groceries or rely on convenience stores, which often lack fresh fruit and vegetables.

It is worth noting that the changes in the patterns of obesity and diabetes affect demographic groups differently. Socioeconomic status plays a large role in determining the health outcomes. The rates also vary widely across countries, with the United States displaying the highest prevalence.

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[1] Source: Center for Disease Control and Prevention (CDC) 's website.
[2] Source: American Diabetes Association's website.

[2] Source: American Diabetes Association's website.
[3] Harvard T.H. Chan School of Public Health's website.

However, while initially only an issue of wealthy nations, obesity and diabetes now impacts countries at all economic levels: worldwide the rate of obesity has nearly doubled since the 1980s. The spread of obesity and resulting diseases threatens health systems, economies, and individual lives. Therefore, an improved understanding of the causes of the rise has great relevance for public health in the United States and abroad.

LITERATURE REVIEW

Food deserts have gained the attention of a wide range of disciplines; planning scholars, economists, geographers, public health officials, and community organizations have created maps to better understand disparities in the food environment. However, while the cross-disciplinary attention provides great potential to better understand the problem, there's little consensus among scholars over the roots, solutions, and consequences of food deserts.

The research on food deserts contains many weaknesses. To begin with the construct lacks clarity: accessibility is often interchanged with availability and access to food is interchanged with access to supermarkets (Adams et al, 2010). There's also a lack of consistency in the terms that are used to describe the same problem, which include "supermarket redlining" (Eisenhauer, 2001), "grocery store availability" (Chung and Myers, 1999), "access to food retail" (Clarke, Eyre, and Guy, 2002), and "availability of healthy foods" (Sooman, Macintyre, and Anderson, 1993). The lack of clarity and consistency makes the results between studies difficult to compare.

Another issue with research on food desert is that, while it finds a wide presence and severity of food deserts, it falls short of discussing the causal mechanisms that lead to the problem. In particular, it does not distinguish between demand- and supply-side issues. For example, in Alviola et al (2013), the authors find that areas with higher minority populations were statistically more likely to be food deserts and that rural areas with more vacant housing units faced reduced grocery store access. However, it does not provide an explanation for why this situation arises.

Further, the literature on food deserts displays a particular focus on the urban setting. Therefore, the phenomenon is less understood in rural areas, where the food desert problem likely exhibit a different pattern and might be compounded by a lack of public transportation.

Only a few studies, such as Blanchard (2007), have examined the issue of food deserts within the rural context. Blanchard examined the relationship between food deserts and consumption of fruits and vegetables. In order to address this question, the study employed data on both food retailers and persons from the U.S. Bureau of the Census and the Center for Disease Control Behavioral Risk Factor Surveillance System surveys and used GIS technology to identify the proportion of the population for each country that resided in a food desert. The results show that residents of food deserts are 23.4% less likely to consume five or more servings of fruits and vegetable after adjusting the estimates by age, race, sex, and education. While the study shows that the food deserts correlate with consumption decisions, the direction and mechanism of causality is not clear.

More recently, urban studies have explored the question of whether the introduction of new supermarkets improves nutrition. In an article titled “Giving the Poor Easy Access to Healthy Food Doesn’t Mean They’ll Buy It” (2015), Sanger-Katz provides an overview of recent findings on the topics. The article concludes that increased accessibility does not change food choices; the education-level and income of shoppers is much more predictive of the variations in the food people bought. However, the studies mentioned use small sample sizes. Further, whether this patterns holds in rural areas requires further research.

According to Handbury (2015), while there is agreement among researches that spatial and economic disparities in food exist, the actual effects of healthy food access on food purchases are heavily contested. This study explores the direction of causality in the relationship between nutritional availability and nutritional consumption. To investigate this question, data is used from the Homescan database, which contains transaction-level information on purchases for a representative panel of 114,286 households across the U.S. Households in the panel. The results indicate that the majority of the disparities observed between households across the entire U.S. persist even when we control for access. Therefore, the authors conclude, disparities in access play a minimal role in explaining observed disparities in nutritional consumption.

Beyond food availability, there’s also a concern of food safety in poor and remote areas. Darcey et al (2011) investigates the relationship between socioeconomic status and risk for foodborne illness (FBI). To address this question, the study used food service critical health code violations (CHV) for 10,859 food service facilities in Philadelphia as a proxy for risk for FBI. The results indicate that a greater number of facilities in higher poverty areas were found to have at least one CHV.

In a study on food deserts in Calagary, Canada, Lu et al (2015) explored whether farmers’ markets might be considered potential options for providing relief to food deserts in Calgary. The study investigates whether and to what extent farmers’ markets in Calgary contribute to increased access to healthy and fresh food. To address the question, data was obtained on the locations of grocery stores and farmers markets and population variables and road network information, from Alberta Open Data, City of Calgary’s Open Data Catalogue, University of Calgary Libraries, and DMTI Spatial. The results identify two particular communities with low access and high needs and suggest that farmers’ markets provide surrounding neighborhoods with significant benefits.

In 2009, the United States Department of Agriculture Economic Research Service also released a study analyzing the extent of the problem of limited access and identifies characteristics and causes. To address these question, data was collected on the location of supermarkets, household ownership of a vehicle, household food adequacy, demand for certain nutritious foods, and variations in prices. The findings are: (1) Access to a supermarket or large grocery store is a problem for a small percentage of households, (2) Supermarkets and large grocery stores have lower prices than smaller stores, (3) Low-income households shop where food prices are lower, when they can, (4) Easy access to all food, rather than lack of access to specific healthy foods, may be a more important factor in explaining increases in obesity, (5) Understanding the market conditions that contribute to differences in access to food is critical to the design of policy interventions that may be effective in reducing access limitations, (6) Food has been used as a tool for community development, (7) The current state of research is insufficient to conclusively determine whether some areas with limited access have inadequate access.

Sweeney et al (2015) warns practitioners of the limitations of research on food deserts. The study analyses the methods in scholarly research and web-based food mapping since 2008. To this end, the paper reviews thirty-four journal articles and seventy web-mapping projects. The study reaches multiple findings and concludes with a warning to urban planners on the limitations of GIS mapping and that this tool is better understand as part of a suite of tools—including focus groups, interviews, cognitive mapping, photography, and video—to advance informed community planning and learning.

METHODOLOGY

THE DATA

THE DEPENDENT VARIABLES

I use two dependent variables:

- County-level age-adjusted percentage of people with obesity, and
- County-level age-adjusted percentage of people with diabetes.

I obtained this data from the Center for Disease Control and Prevention (CDC)'s website.

THE INDEPENDENT VARIABLES

I construct a county-level measure for food deserts, as explained later, using the location of grocery stores and tract-level population statistics. I also use county-level poverty statistics as a control in the econometric model.

I obtained the data on grocery stores from the ReferenceUSA dataset, which is available through Columbia's Digital Social Sciences Center. The dataset contains verified and accurate information on 24 million U.S. businesses. Information on each business includes: company name, standard industrial classification codes, employee size, year of establishment, and latitude and longitude. The information is updated monthly and confirmed yearly with one call per business.

An advantage of the ReferenceUSA dataset is that, in addition to data on grocery stores, it also provides data on specialized fruits and vegetables retailers and on farmers markets. This additional information allows distinguishing between grocery stores that provide fresh produce and the ones that do not, with greater precision. Nevertheless, as explained in the following section, some assumptions are still required to make this distinction. A sample of the grocery stores and markets from the dataset is provided in Table 1 below.

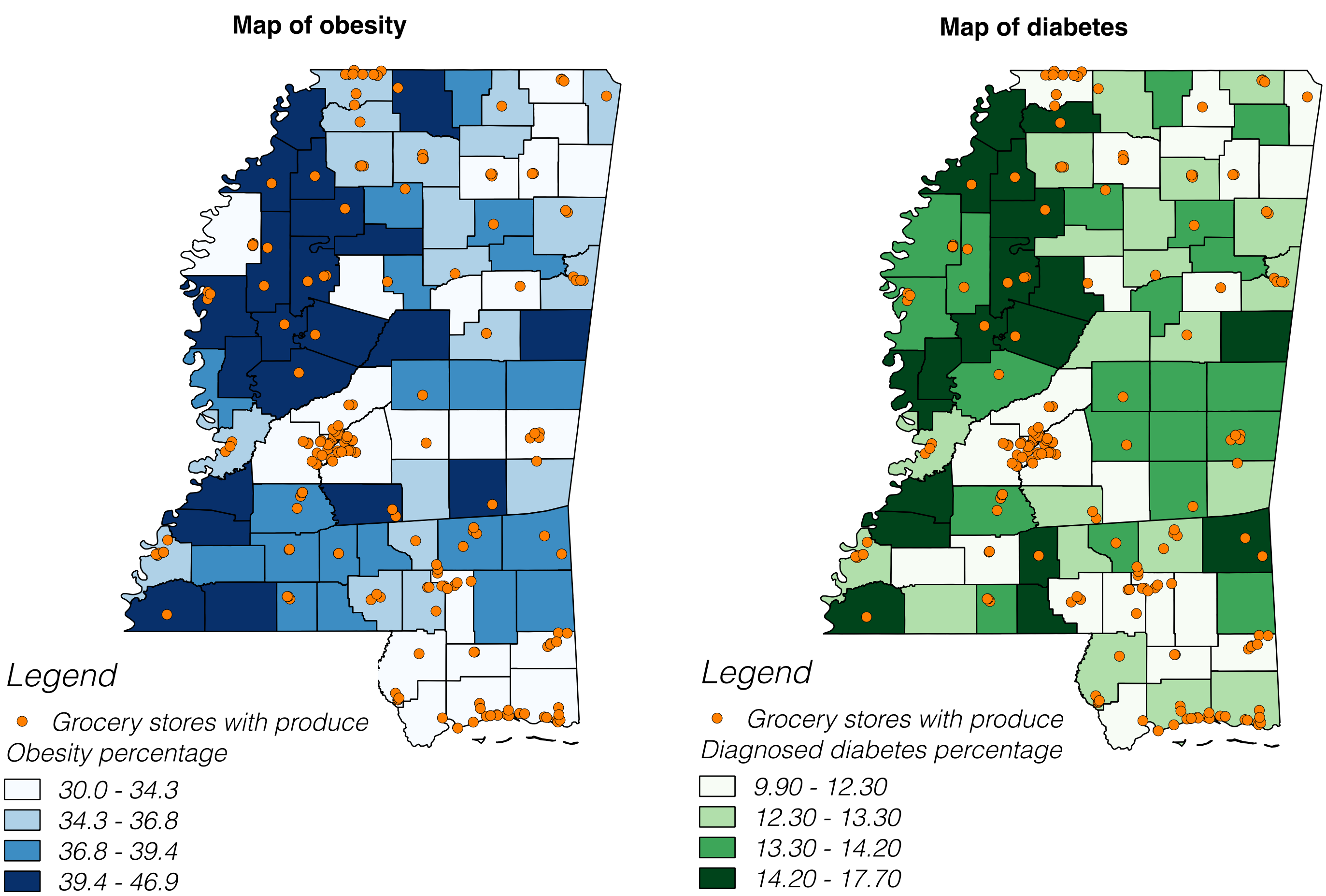
Table 1: Sample of the grocery stores and markets, by industry sub-category

Industry Sub-Categories	Sample of the names
Grocery store: Food retailer	Sunflower Food Store Corner Market
Grocery store: Grocer retail	Roger's Super Market, Supervalu, Food Giant, Kroger, County Market, Piggly Wiggly, etc.
Fruits and vegetables markets: Produce retail	Adams Brothers Produce Church Hill Produce, J & J Produce Co Inc, Yazoo Tomatoes, etc.
Fruits and vegetables markets: Farmers Markets	Natchez Farmers Market, Montilcelo Farmers Market, Farmers Market, etc.

Source: ReferenceUSA

I obtained the data on poverty and population statistics from the American Community Survey's Fact Finder. Map 1 provides an illustration of the data on obesity, diabetes, and location of grocery stores and markets.

Map 1: Obesity Rates, Diabetes Rates, and Grocery Store Locations in Mississippi



Sources: ReferenceUSA and American Community Survey

DEFINING FOOD DESERTS

The literature operationalizes the concept of food deserts in a variety of ways, combining distance from supermarkets and other variables, such as poverty and vehicle ownership. In this paper, I distinguish between availability and access, by defining food deserts in terms of a distance from grocery stores with a produce section. I then use poverty as a control to understand how access mediates the effect between availability of healthy food and health outcomes.

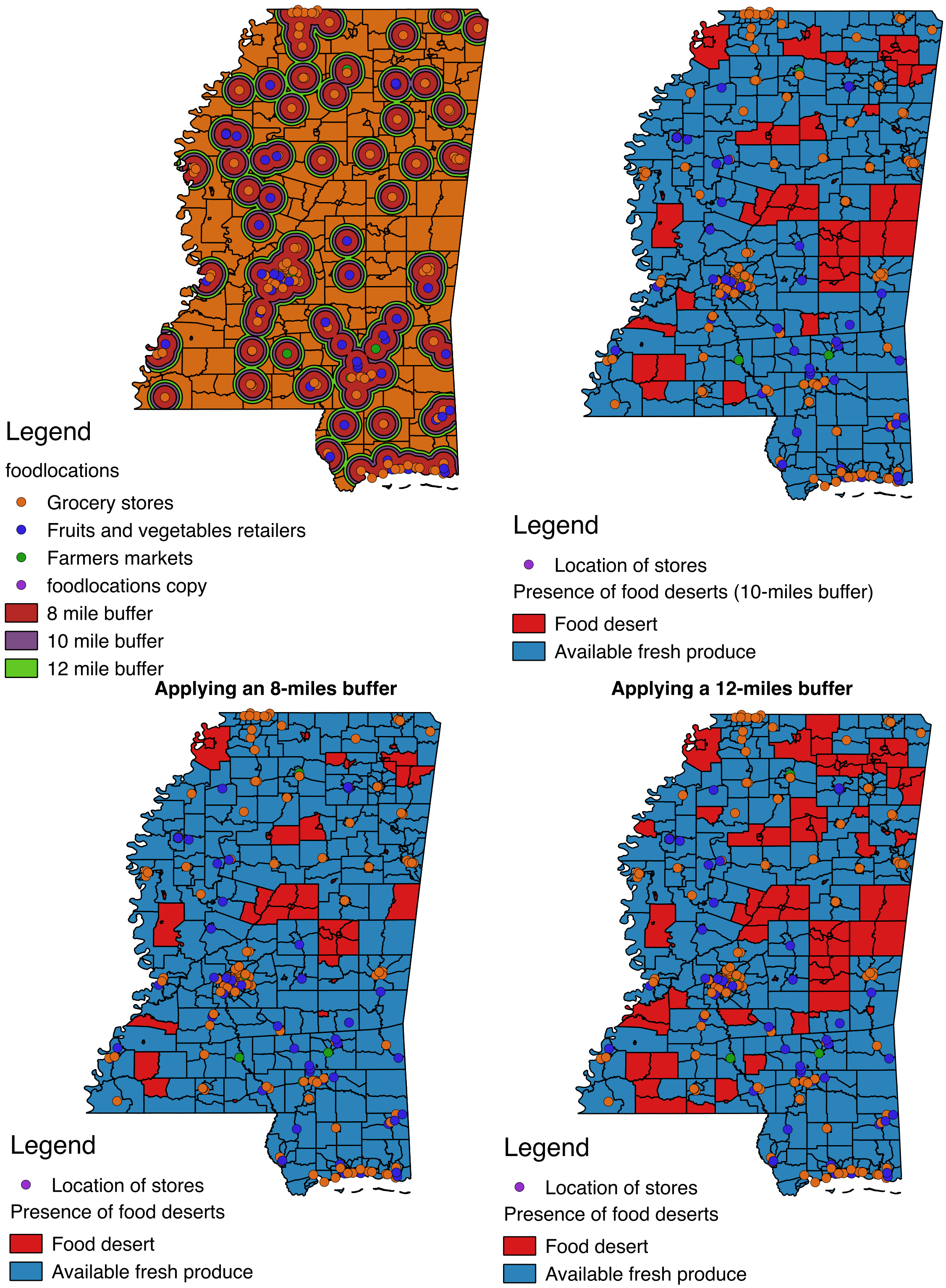
Specifically, I define food deserts as follows: census tracts completely outside a defined radius from grocery stores that have a fresh produce section. I first use a radius of 10 miles as in Blanchard (2007) and then conduct sensitivity analysis using buffers of 8-miles and 12-miles.

The reader should note that the corresponding road-miles are greater than the radius. The actual difference depends on the following factors:

- The shape of the road network. Indirect and windy roads increase the actual-road miles needed to reach a grocery store.
- A person's location within the tract. Given that tracts intersecting the buffer layer are treated as non-deserts, inhabitants of those tracts might actually live outside of the given radius.

Identifying grocery stores that have a fresh produce section requires further assumptions. Given that available data does not directly distinguish between grocery stores with and without fresh produce, I borrow the approach used by the USDA and in Blanchard (2007) to identify grocery stores that are likely to have a fresh produce section. Specifically, I select grocery stores with at least 50 employees. This decision is motivated by the fact that larger grocery stores are more likely to have a fresh produce section. I add to this definition by also including farmers markets and specialized fruit and vegetable retail markets, no matter the size. In the following maps, I color-coded the locations of grocery stores to allow the reader to see the additional grocery stores selected (the blue and green dots).

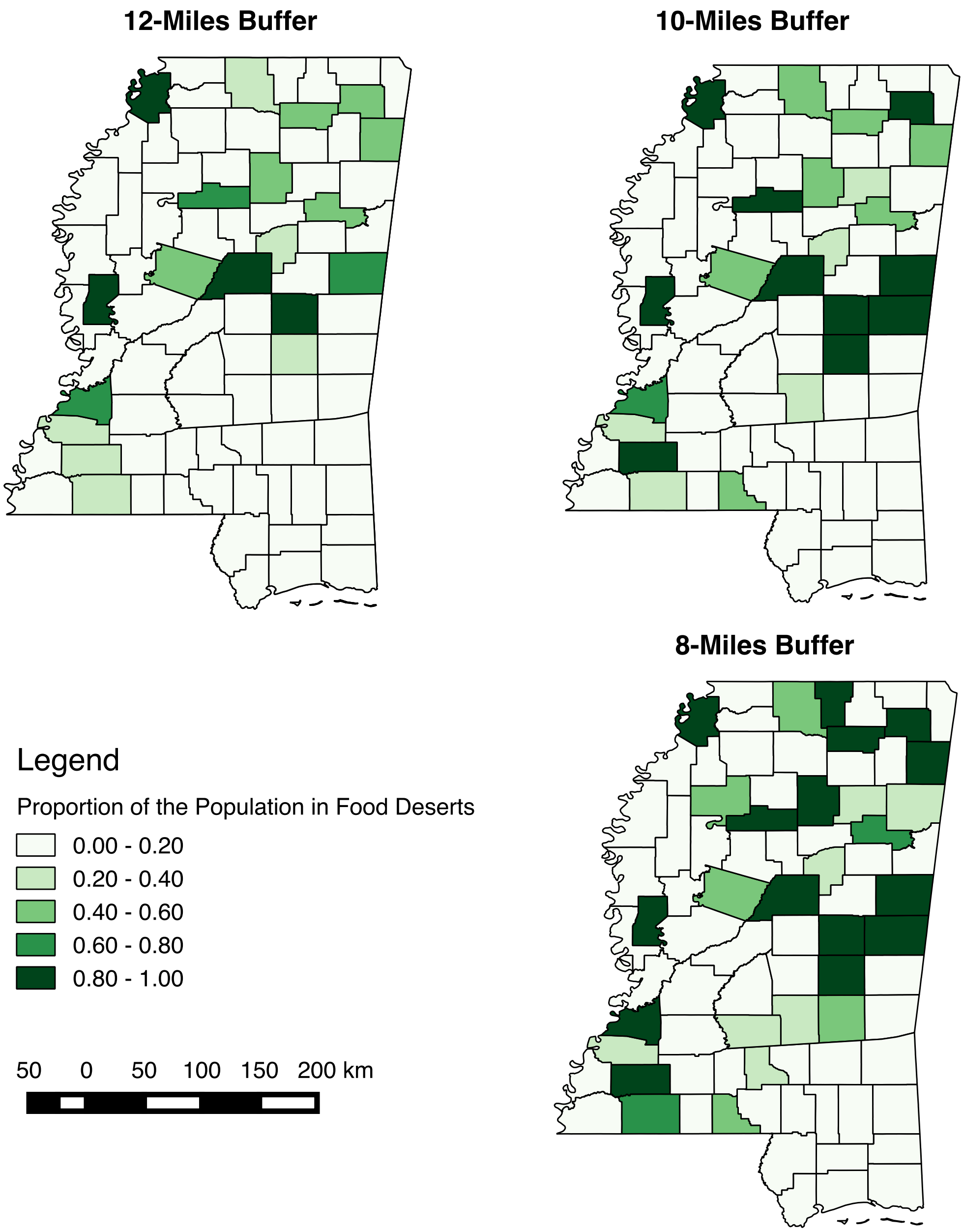
Map 2: Tract-Level Food Deserts in Mississippi Using Multiple Buffers



Constructing a County-Level Measure of Food Deserts

Given that the dependent variables - obesity and diabetes rates - are available at the county-level only, I construct a county-level measure of food deserts. For each county, I take the number of people living in food deserts tracts (according to above criteria) and divide the result by the county's population, obtaining a fraction between 0 and 1. This proportion is the main independent variable. Map 3 illustrates variations of this proportion on a map.

Map 3: County-level Measures of Food Deserts

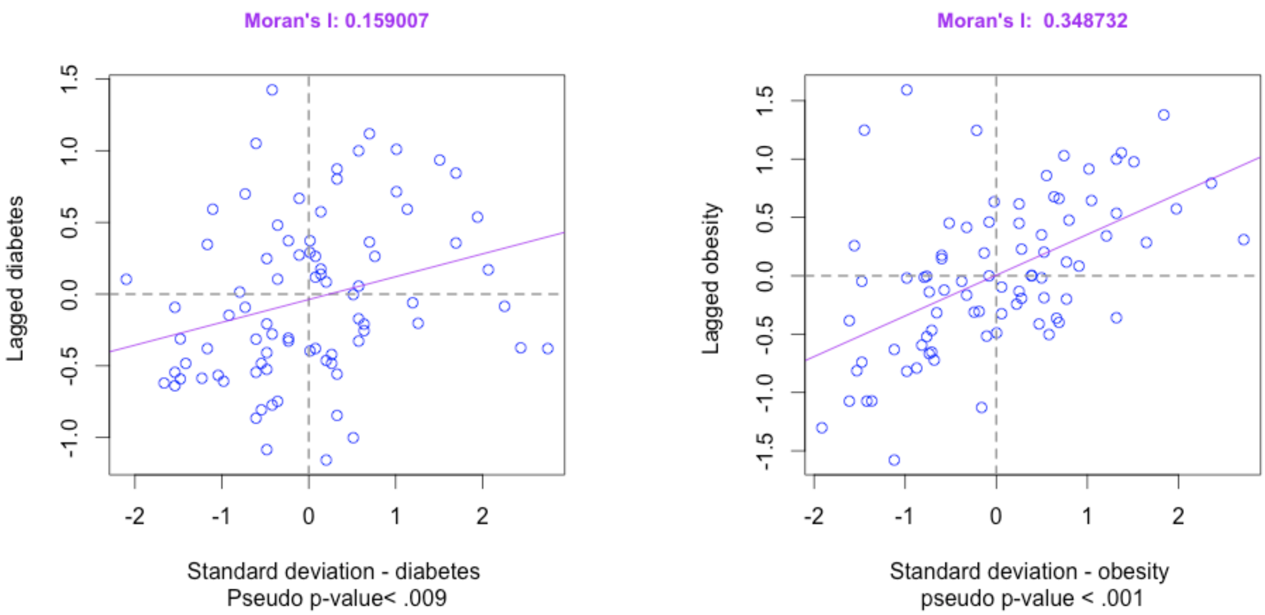


Spatial Dependence

To test for spatial dependence, I use the Moran's I statistic and rely on the traditional statistical alpha of .05 as the threshold to make decisions about spatial dependence. As illustrated in the scatterplots below, the Moran's I statistic for obesity rates and the associated pseudo p-value are 0.348732 and .001, respectively. The Moran's I statistic and the pseudo p-value associated with diabetes rates are 0.159007 and .009, respectively. Map 4 and 5 illustrate the spatial clusters of obesity rates and diabetes rates, respectively.

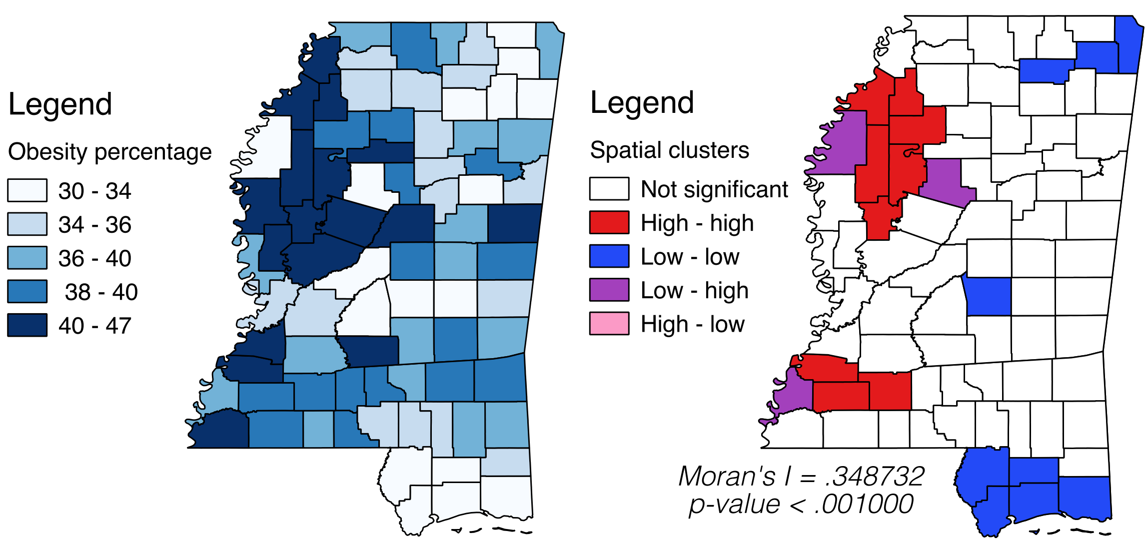
Further, after running a classic OLS regression, I noted that both spatial lag and spatial error are present. However, neither the robust spatial lag nor spatial error is statistically significant.

Scatterplot 1: Testing Spatial Dependence of the Dependent Variables

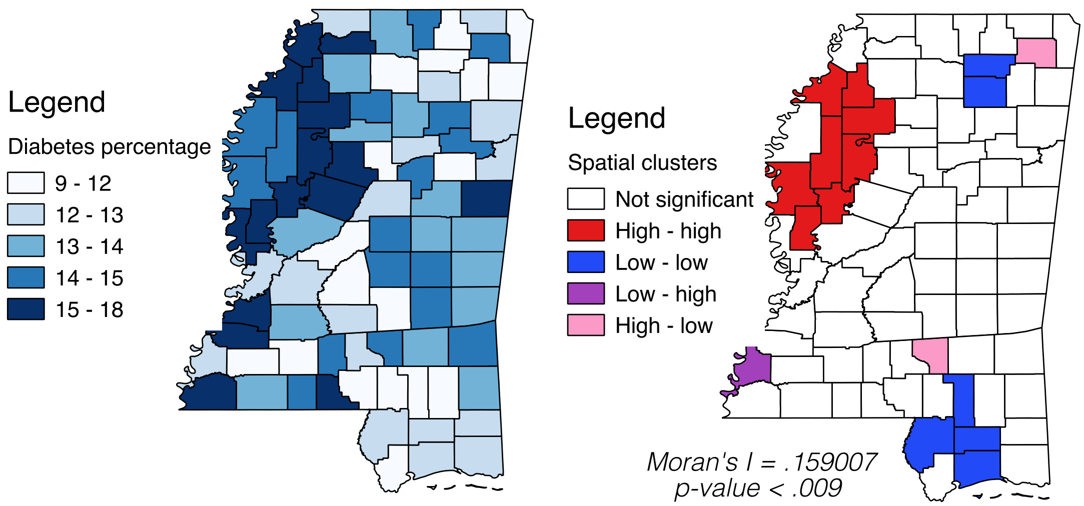


Source: Author's calculations

Map 4: Spatial Distribution and Locations of Significant Spatial Clusters of Obesity Rates



Map 5: Spatial Distribution and Locations of Significant Spatial Clusters of Diabetes Rates



I also tested the independent variable for spatial dependence and noted that the Moran's I statistic is not significant at conventional levels, as reported in the table below.

Table 2: Spatial dependence statistics for the county-level proportion of food deserts.

Variable	Moran's I	Pseudo p-value
Food desert proportion (using 8 miles buffer)	- 0.0291342	0.443
Food desert proportion (using 10 miles buffer	- 0.0111159	0.451
Food desert proportion (using 12 miles buffer)	- 0.0759135	0.156

Source: Author's calculations

Spatially-weighted Regression

To control for the spatial dependence described above, I add a spatial parameter to the regression model. The preliminary model is as following.

$$y_i = \alpha + \beta x_i + \rho W_y + \epsilon$$

Where:

- y_i is the health outcome (I use both obesity and diabetes).
- x_i is the proportion of food deserts in the county.
- W_y is the spatial weight matrix.

In later steps, I add a control, and conduct sensitivity analysis.

Controls

After running a spatially weighted regression, I added a control: percentage of households in the county with income below the poverty line. Further, note that the health outcomes are already age-adjusted.

RESULTS

PRELIMINARY RESULTS

The regression results for the proportion of food deserts on obesity rates are reported in Table 3 below. In the first model, I applied a simple bivariate regression. I then added a spatial parameter in the second model and then a control – poverty rate – in the third. The results indicate that the association between food deserts and obesity is positive and statistically significant (even though the association is partially mediated by the control). More precisely, an increase in the proportion of food deserts of .1 (a 10% increase) is associated on average with a .1792% increase in the number of people with obesity, after controlling for spatial dependency and poverty[4].

Table 3: Regression Results for Obesity Model

	Dependent variable:		
	Obesity rates		
	(1)	(2)	(3)
Proportion of food deserts (10 mile buffer)	2.257*	2.213**	1.792**
	(1.161)	(0.980)	(0.784)
Percentage below poverty line			0.323***
			(0.048)
Spatial parameter		2.978***	1.216**
		(0.515)	(0.486)
Constant	36.549***	36.543***	29.978***
	(0.456)	(0.385)	(1.015)
Observations	82	82	82
R^2	0.045	0.329	0.578
Adjusted R^2	0.033	0.312	0.562
Note:	*p<0.1; **p<0.05; ***p<0.01		

The pattern is similar for diabetes rates, as shown in Table 4. While the additional control and spatial parameter reduce the association between food deserts and diabetes rates, the association continues to be positive and statistically significant. A 10% increase in the proportion of food deserts is associated on average with a .1020% increase in the number of people with diabetes, after controlling for spatial dependency and poverty rates.

[4] The food desert measure is expressed in proportions and can take a value between 0 and 1. Instead obesity rates are expressed as percentages and can take a value between 0 and 100%.

Table 4: Regression Results for Diabetes Model

	Dependent variable:		
	Diabetes rates		
	(1)	(2)	(3)
Proportion of food deserts (10 mile buffer)	1.090**	1.011**	1.020**
	(0.509)	(0.494)	(0.422)
Percentage below poverty line			0.209***
			(0.038)
Spatial parameter		0.746**	0.134
		(0.297)	(0.277)
Constant	13.065***	13.109***	10.370***
	(0.200)	(0.194)	(0.523)
Observations	82	82	82
R^2	0.054	0.124	0.370
Adjusted R^2	0.042	0.102	0.346
Note:	*p<0.1; **p<0.05; ***p<0.01		

Sensitivity Analysis

Sensitivity analysis using different buffers for the measurement of food deserts (Table 5) indicates that the relationship is robust across the different buffers used in the measurements of food deserts.

Table 5: Sensitivity Analysis Using Different Buffers

	Dependent variable:			
	Obesity rates		Diabetes rates	
	(1)	(2)	(3)	(4)
Proportion of food deserts (8 mile buffer)	1.814**		0.744**	
	(0.696)		(0.357)	
Proportion of food deserts (12 mile buffer)		2.421**		0.937*
		(0.990)		(0.507)
Percentage below poverty line	0.322***	0.314***	0.151***	0.149***
	(0.047)	(0.048)	(0.023)	(0.023)
Spatial parameter for obesity	1.241**	1.233**		
	(0.482)	(0.484)		
Spatial parameter for diabetes			-0.006	-0.023
			(0.268)	(0.269)
Constant	29.882***	30.190***	9.970***	10.086***
	(1.008)	(1.008)	(0.497)	(0.497)
Observations	82	82	82	82
R^2	0.586	0.582	0.439	0.433
Adjusted R^2	0.570	0.566	0.418	0.411
Note:	*p<0.1; **p<0.05; ***p<0.01			

However, sensitivity analysis using different income levels (Tables 6 and 7) shows that some measures of income fully mediate the relationship between food deserts and health outcomes. The income levels that mediate the effect are the same for obesity and diabetes: percentage of households with income of less than 25,000; 35,000; and 50,000. Interestingly, these measures also mediate the spatial parameter for diabetes.

Table 6: Sensitivity Analysis Using Different Income Levels

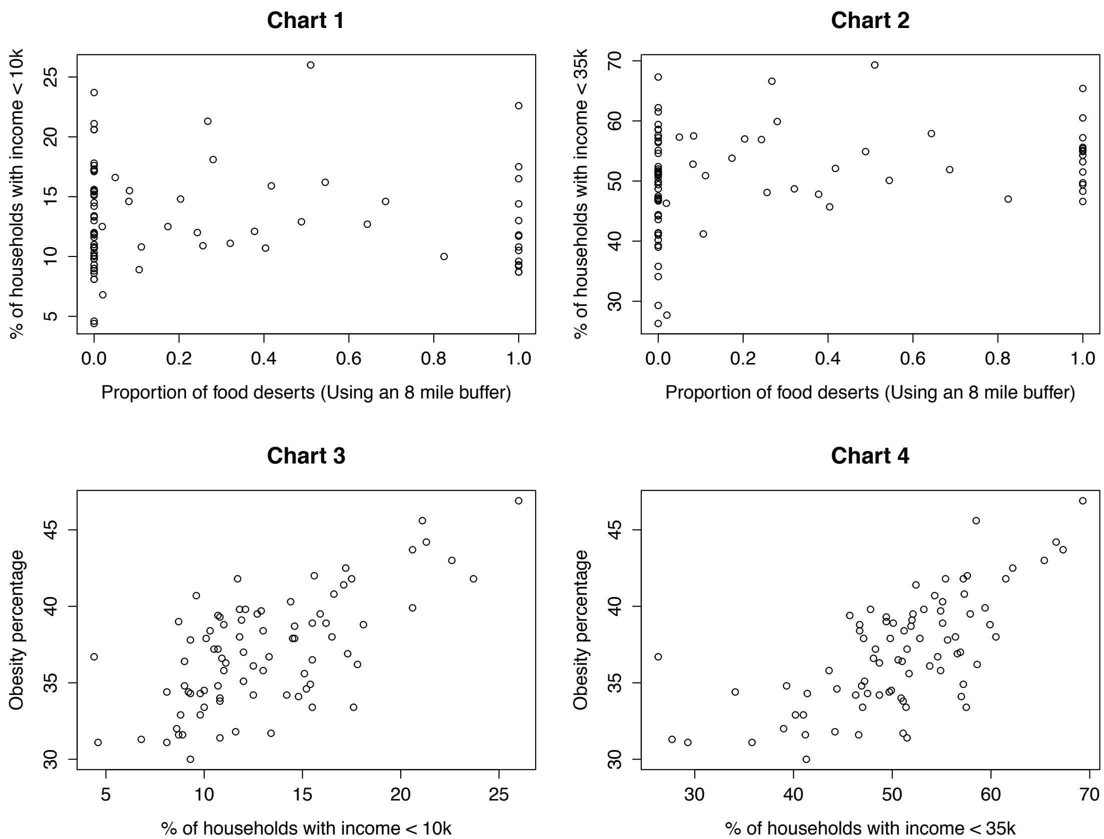
	Dependent variable:				
	Obesity rates				
	(1)	(2)	(3)	(4)	(5)
Proportion of food deserts (10 mile buffer)	2.111**	1.718**	1.131	1.005	0.855
	(0.819)	(0.815)	(0.814)	(0.841)	(0.845)
Percentage: household income < 10K	0.451***				
	(0.076)				
Percentage: household income < 15K		0.336***			
		(0.055)			
Percentage: household income < 25K			0.275***		
			(0.043)		
Percentage: household income < 35K				0.236***	
				(0.040)	
Percentage: household income < 50K					0.242***
					(0.040)
Spatial parameter	1.632***	1.555***	1.467***	1.626***	1.864***
	(0.487)	(0.486)	(0.480)	(0.485)	(0.466)
Constant	30.698***	29.141***	26.308***	24.794***	21.126***
	(1.038)	(1.251)	(1.618)	(1.990)	(2.575)
Observations	82	82	82	82	82
R^2	0.537	0.546	0.562	0.540	0.542
Adjusted R^2	0.519	0.529	0.545	0.522	0.525
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 7: Sensitivity Analysis Using Different Income Levels

	Dependent variable:				
	Diabetes rates				
	(1)	(2)	(3)	(4)	(5)
Proportion of food deserts (10 mile buffer)	1.020**	0.832**	0.565	0.521	0.424
	(0.422)	(0.412)	(0.413)	(0.433)	(0.432)
Percentage: household income < 10K	0.209***				
	(0.038)				
Percentage: household income < 15K		0.159***			
		(0.026)			
Percentage: household income < 25K			0.127***		
			(0.020)		
Percentage: household income < 35K				0.105***	
				(0.019)	
Percentage: household income < 50K					0.111***
					(0.020)
Spatial parameter	0.134	0.135	0.161	0.239	0.322
	(0.277)	(0.267)	(0.262)	(0.272)	(0.263)
Constant	10.370***	9.567***	8.362***	7.875***	5.984***
	(0.523)	(0.608)	(0.778)	(0.979)	(1.273)
Observations	82	82	82	82	82
R^2	0.370	0.403	0.415	0.364	0.378
Adjusted R^2	0.346	0.380	0.393	0.340	0.354
Note:					*p<0.1; **p<0.05; ***p<0.01

The following charts help explain this effect. The charts illustrate that low household income using either the $10,000 (Chart 3) or $35,000 (Chart 4) thresholds is positively associated with obesity. However, the relationship between food deserts and income is stronger using the $35,000-threshold. As can be seen in Charts 1 and 2, when the proportion of food deserts is zero, the percentage of households below a certain income takes a wide range of values. However, when there's at least a food desert in the county, the points become less dispersed and on average higher. The $35,000-threshold simply captures a higher proportion of the households as compared to the lower threshold and therefore can show a positive relationship.

Scatterplot 2: Relationship between Poverty, Food Deserts, and Health Outcomes



Source: Author's calculations

Comparison Between Models

A comparison between models using the Akaike information criterion (AIC) – Table 8 - indicate that the model that best fits the data uses the 8 mile buffer and the poverty line as the threshold for the poverty measures. In this model, the food desert measure is only partially mediated by poverty. It is therefore possible that both income and the presence of food deserts affect health outcomes.[5] However, the results are not conclusive.

Table 8: AIC scores for selected models

	Independent Variables			Dependent Variables	
Model #	**Control for Spatial Dependence**	**Food Desert Buffer**	**Poverty Measure**	**Obesity**	**Diabetes**
1	✔	8 miles	BPL	381.7563	272.2055
2	✔	10 miles	BPL	383.2876	281.7321
3	✔	12 miles	BPL	382.5368	273.1424
4	✔	8 miles	Less than 35K	390.5549	283.3325
5	✔	10 miles	Less than 35K	390.3435	282.5015
6	✔	12 miles	Less than 35K	388.1010	282.0173

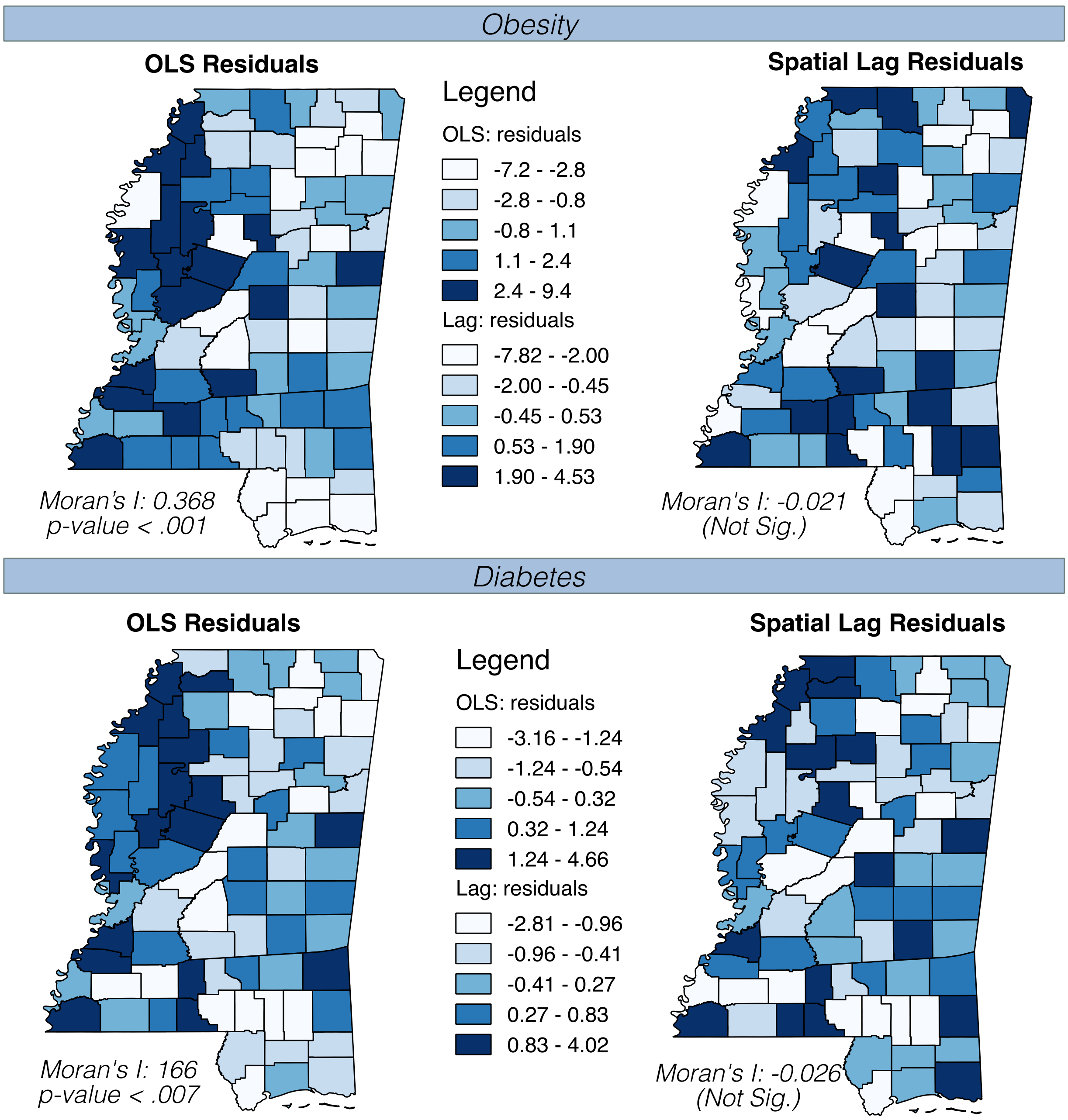
Source: author's calculations

[5] Also, a reason why income may have mediated the effect between food deserts and outcomes is that the income variable is more granular.

Maps of Residuals

Map 6 compares the residuals in the OLS bivariate model with the residual in the spatial lag model (model number 1 in table 8). It is clear that, for both obesity and diabetes, the residuals in the OLS model display spatial dependence. On the other hand, the residuals in the spatial lag model appear to be randomly distributed across space.

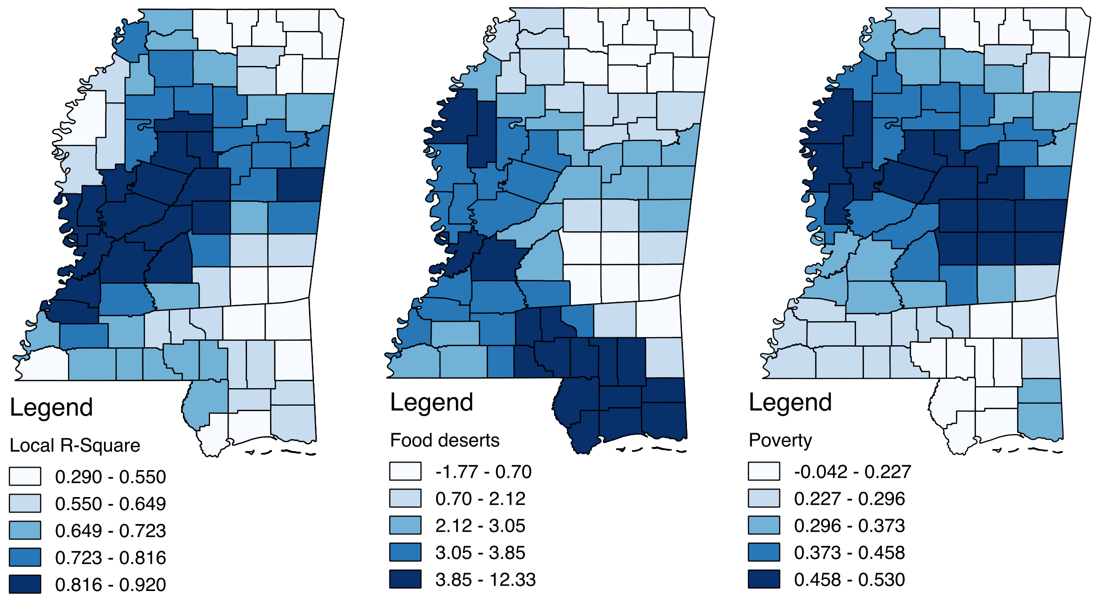
Map 6: Regression Residual Comparison: OLS versus Spatial Lag Results



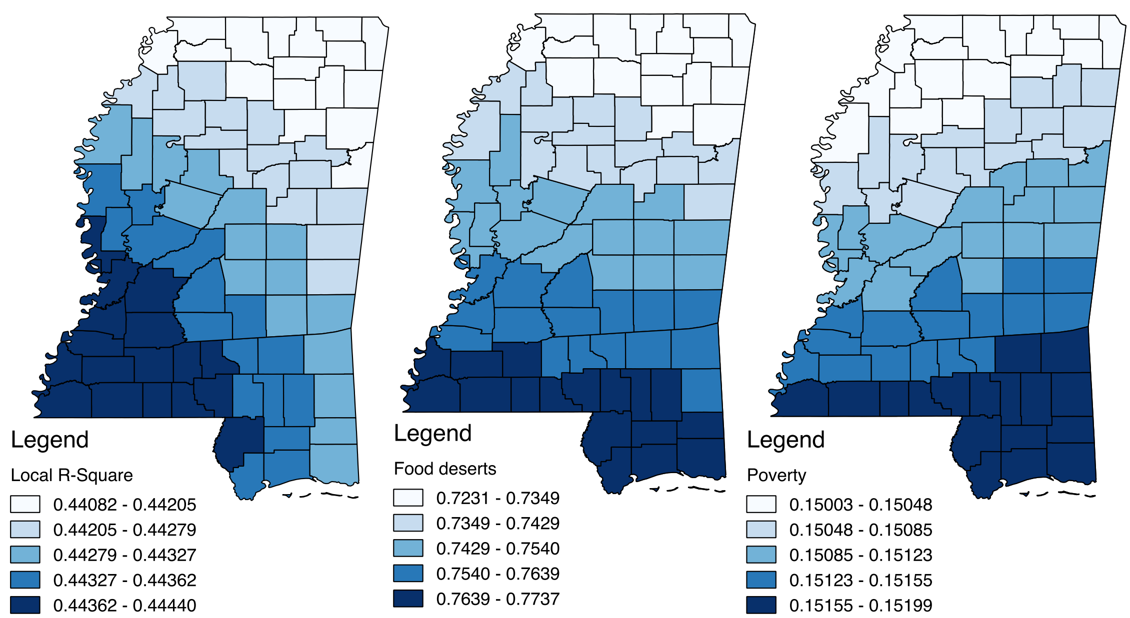
Geographically Weighted Regression

Maps 7 and 8 display the geographically weighted local variations in food deserts and poverty. The patterns in variations point to potential non-stationarity in the relationship between food deserts, poverty, and the health outcomes.

Map 7: Geographically Weighted Local Variations in the Predictors of Obesity



Map 8: Geographically Weighted Local Variations in the Predictors of Diabetes



FINAL DISCUSSION

Consistent with the results in Blanchard (2007), I find that food deserts are positively associated with negative health outcomes[6]. However, after conducting sensitivity analysis, I find that certain measures of income completely mediate the effect. Nevertheless in the model with the lowest AIC score, food deserts and poverty are both statistically significant predictors of health outcomes. It is possible that income appears to fully mediate the relationship between food deserts and health outcomes in some of the models (with the higher AIC score) because of its greater granularity.

Further research should identify a more precise measurement of food deserts that exhibits more granularity. For example, at the tract-level, the food deserts variable could take multiple values depending on the severity (distance from a supermarket), instead of being a binary variable as in this and other research studies. Also, for tracts that are partially within a given radius from a supermarket, the food deserts variable could be designed to reflect the proportion of the tract that is within the radius, instead of completely including the tract in the non-desert area.

Further, tract-level data for obesity and diabetes, rather than county-level, should be used and regressed on the tract-level food desert variable. However, this approach was not possible in this study because I did not have access to tract level data for obesity and diabetes. Instead, I had to construct a county-level measure of food deserts. Nevertheless, further research may be able to obtain access to this data from the Center for Disease Control and Prevention.

A limitation of this study is that it does not identify the causal mechanism between food deserts and health outcomes. A possible explanation for the positive association is that the lack of availability of fresh fruit and vegetables lowers the quality of food consumptions, resulting in higher diabetes and obesity rates. However, there are other possible rival explanations. For example, food desert areas may also be characterized by low demand for healthy food options, causing supermarkets in the area to go out of business. To distinguish between supply and demand side issues, further research could use a difference in differences approach.

Further, research could take advantage of the numerous policies that were recently implemented to address the low supply of healthy food options. By treating the increase in supply resulting from the introduction a state policy as exogenous, any accompanying decrease in obesity and diabetes rates can be viewed as a consequence of the change.

While further investigation is needed to better understand the patterns and causal mechanism of food deserts, it appears that food deserts are tied to obesity and diabetes outcomes. Therefore, addressing these leading public health concerns requires further attention on food deserts.

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[6] Blanchard (2007) investigated the relationship to food consumption rather than diabetes and obesity.

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