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Does Where You Live Make You Fat?

Obesity and Access to Chain Grocers¹

by

Susan Chen, Raymond J.G.M. Florax, and Samantha Snyder

Working Paper #09-11

September 2009

Dept. of Agricultural Economics

Purdue University

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¹ The authors would like to thank Joseph Gibson of the Marion County Health Department for allowing us to use these data. Frank Dooley, Maria Marshall, and William Masters provided very helpful comments on earlier drafts of this paper.

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Working Paper #09-11
September 2009

Abstract

This paper investigates the role that aspects of the physical environment play in determining health outcomes in adults as measured by body mass index (BMI). Using spatial econometric techniques that allow for spatial spillovers and feedback processes, this research specifically examines how differing levels of access to large chain grocers has on individual health outcomes. While other studies have investigated the impact of proximity to food retailers, the point-coordinate data used in this paper is uniquely suited to spatial econometric estimation at the individual level. In addition to modeling spatial dependence and allowing for unobserved neighborhood effects, the flexibility of the model is increased by incorporating potential spatial heterogeneity between wealthier and lower-income neighborhoods. Using survey responses tied to geographic location, demographic, behavioral, and access to chain grocers, this study finds evidence of spatial dependence pointing to locational impacts on BMI. The effect on individual health outcomes of retailer access improvements varies depending on neighborhood characteristics. Our findings suggest structural differences in the variation and sensitivity of BMI dependent jointly on individual and neighborhood characteristics.

Keywords: body mass index, obesity, spatial dependence, obesogenic environments

JEL Codes: C31, D12, I12, I18

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Due to a sharp increase in the prevalence of both overweight and obesity among adults in the United States (US), researchers and policymakers have devoted substantial effort to determining the causes of obesity and subsequent interventions designed to curb the rise in rates of incidence. In addition to individual behavioral characteristics, social and environmental factors have been shown to have strong positive associations with obesity prevalence (Ogden et al. 2006; Mokdad et al. 2003; National Center for Health Statistics 2006; Gallagher 2006). Perhaps more interesting than studying correlates of obesity is looking for the underlying causes. Recently, economists have put forward the theory that obesity is caused by an increase in the real value of time over the last 30 years (Cutler et al. 2003). This increase in the real value of time encourages people to eat at fast food and other restaurants, and increases the consumption of pre-prepared and processed high-caloric foods at home. In this case environmental factors such as the food landscape matter since people will likely prefer the quickest, closest option that is affordable.

It has been suggested that limited access to food retailers, also known as ‘food deserts’, has led to an increase in the prevalence of obesity particularly in urban neighborhoods with low income and/or predominantly minority residents. One reason cited for the decrease in the geographic distribution of food retailers is the consolidation of large grocery chains (Eisenhauer 2001). National chain grocers, who are able to offer the widest range of foods, often at the lowest prices, have left inner city areas in favor of fringe and suburban locations. It has been argued that this exodus has created ‘food deserts’ where disadvantaged residential neighborhoods are left with limited access to food retailers, specifically to those that carry healthy and affordable foods (Cummins and Macintyre 2006).

There is a growing literature on the food environment and the prevalence of obesity in local communities. This literature, however, focuses largely on the consumption of food away from home and not on retail grocers. A notable exception is the series of papers by Morland and colleagues (2002(1); 2002(2)). In the first of two papers, they define an individual's local food environment as the number and type of food retailers within the census tract where the person resides. In Morland et al. 2002(1), they study the effect of access to retail grocers on a resident's intake of fruits and vegetables. They find that for Black Americans in the study, fruit and vegetable consumption increase by 32 percent for each additional supermarket located in their census tract. This association was substantially smaller, although also statistically significant for whites.

In another study using the same data Morland et al. (2002(2)) examined the distribution of food stores and food service places to further highlight that diet choices may be a function of food availability. The study was primarily concerned with possible correlations between store distribution and racial makeup, and store distribution and wealth level. The analysis showed that a larger number of supermarkets and gas station convenience stores are located in wealthier neighborhoods as compared to the poorest neighborhoods. There were also four times as many supermarkets located in neighborhoods classified as white as compared to those classified as black. Fast-food restaurants were most common in the low-to-medium and medium-wealth neighborhoods and less likely to be located in the high-wealth neighborhoods.

There are two main shortcomings of these studies. The first is that census tracts can be fairly large geographic areas with boundaries defined in an ad-hoc manner. As a result, they may not accurately define a person's market for grocery stores since their market may actually be much

smaller and may cross over the boundary of the census tract. The second shortcoming is that these studies do not account for the spatial dependence across observations in a rigorous fashion. The random effect models, which are common in this literature, take into account the correlation of the error terms within a census tract only.

The neighborhood in which a person lives is a key determinant of a person's physical and social environment. In the US, our history of racial segregation has created neighborhoods which are disproportionately black, poor and less educated. These communities are often characterized by high crime and truancy rates, unsafe physical environments and lower investment, both in terms of social institutions and neighborhood amenities (i.e., community facilities, parks, sidewalks, street lighting). Insights from labor economics (see Glasmeier et al. 2007 for a current review of these studies) and the public health literature suggest that these factors correlate positively with poor health, measured in terms of Body Mass Index (BMI) and obesity (Kawachi et al. 2003). Researchers are increasingly finding that there is spatial clustering of obese individuals both at aggregate and disaggregated geographic levels corresponding to these characteristics (The Centers for Disease Control and Prevention 2005; Gallagher 2006; Mobley et al. 2004; Eid et al. 2008). In addition, factors such as the food landscape or high crime rates, segregation or high unemployment may spill over into neighboring communities creating spatial dependence across communities. Potentially these neighborhood effects might also reflect a spatial dimension to an individual's diet, in the sense that differences in accessibility to large-chain grocery stores may induce dietary variation across space.

In this paper we will use spatial econometric methods to account for spatial clustering and spillover effects brought about by the obesogenic environmental factors described above. These

factors are often unobserved to the econometrician but may affect an individual's BMI because of their effect on the level of physical activity and/or eating behavior. Standard models estimated with Ordinary Least Squares (OLS) models do not account for these unobserved spatial processes and may result in inconsistent OLS parameter estimates (Anselin, 2006). We will use a unique data set that contains the geographical location of individuals, their health characteristics and characteristics related to their food environment to examine the relationship between access to grocery retailers and obesity.

The rest of the paper is laid out as follows. The first section provides some background on the use of spatial methods to analyze the obesity epidemic in the United States. Section 2 contains a description of the data that we use for this study, descriptive statistics, and exploratory spatial data analysis. The third section discusses the methods used to estimate the model and the findings. We study this issue in the traditional way using a simple multilevel model with neighborhoods defined at the census tract level. We then move to a model where we fully exploit the geospatial nature of the data to define individual localized neighborhoods. We compare and contrast the effect on health outcomes of using these two measures of neighborhood. In section 4 we discuss the implications of our findings for future research.

1. Background

In fields outside of health, for instance in labor economics, researchers have looked at spatial patterns of labor market outcomes of American households. Mayer (1996) examined trends in spatial segregation by race and income, and assessed the impact of social isolation on economic upward mobility. He showed that location matters in terms of labor market outcomes, often due to practical issues such as lack of transportation and barriers to mobility. These practical issues

may be correlated and endogenous across neighborhoods, and therefore make identifying and isolating neighborhood and societal effects difficult. In addition to the physical environment, there have been studies on the effect neighbors have on each other. Case and Katz (1991) used data from a 1989 National Bureau of Economic Research (NBER) survey of youths living in several low-income neighborhoods in Boston to determine the effects of peers on individual behavior. They found that youth who were surrounded by peers involved in crime and drug and alcohol use were more likely to take up the same activities. Similar results hold for the actions and resulting impacts of family members. More recently, Christakis and Fowler (2007) found that obesity spreads (or is reinforced) by social networks, although a similar follow-up study using a younger cohort of individuals conducted by Cohen-Cole and Fletcher (2008) found no evidence that obesity spreads through social networks.

Although spatial data analysis and formal spatial econometric methods have not been extensively employed in the study of obesity, the discipline is well-suited for this type of analysis. Haining (2003) specifically cites research on the relationship between rates of disease and environmental factors as an area where spatial data analysis can make a meaningful contribution. Similarly, Goodchild et al. (2000) highlight the study of disease prevalence across geographic areas, and especially with respect to proximity to aggravating or mitigating interaction effects call for more integration of spatial techniques in future research. The geographical clustering of obese individuals and obesity related diseases in the US suggests that obesity data is suitable for spatial analysis.

Many recent studies have found that the distribution of high BMIs is not proportional across the adult population in terms of demographic characteristics or geographical location. Rates are

generally highest among minorities, those with less education, and individuals in lower income brackets (Ogden et al. 2006; Mokdad et al. 2003; National Center for Health Statistics 2006). A map of the US shows that rates of obesity are generally highest in the Southeast, extending to the Midwest and into parts of the Northern Plains. States with the lowest rates tend to be clustered in the Northeast and Southwest. Even at lower aggregate scales, such as the neighborhood level, there is clustering of obese individuals (see for example: Gallagher 2006; Liu et al. 2007; Mobley et al. 2004; Eid et al. 2006).

2. *Methodology*

In this research we use disaggregate data on individuals to examine the relationship between BMI and access to grocery stores. We use a combination of OLS, fixed effect, random effect, and spatial econometric models to control for neighborhood effects in a rigorous fashion. BMI was first predicted using an ordinary least squares regression framework. The spatial properties of the model are then explored using a series of diagnostic tests introduced in Anselin et al. (1996). Finally, we estimate models that take into account both spatial dependence and spatial heterogeneity.

To operationalize the model we estimate BMI as a function of demographic, behavioral, and environmental factors. In this case, the model takes the form:

$$Y_i = X_{1i}\beta_1 + X_{2i}\beta_2 + \mu_i \quad (1)$$

where the subscript i denotes an individual respondent, Y_i is the dependent variable defined as BMI, X_1 is the vector of individual demographic and behavioral characteristics such as age, gender, race, education, income and employment status, and smoking behavior, X_2 is a vector of environmental variables such as access to grocery retailers, and μ_i is an error term.

If individuals' BMIs are not independent of their neighbors' BMIs, or there is clustering of BMI because of environmental factors that affect BMI but they are not observed by the econometrician (and therefore not included in the model specification), the standard assumptions of OLS are violated. To deal with this issue, researchers have moved to multilevel models that take into account correlation within neighborhood entities. In general, these models use random effects methods to control for correlation within neighborhood where neighborhoods are defined at the census tract level. While random effects models are an improvement over the naïve OLS model, they do not take into account potential spatial correlation in the error structure.

Moving to matrix notation, an alternative specification which takes into account the spatial correlation in the error terms is:

$$y = \rho W y + X \beta + \mu \quad (2)$$

where W is an $(n \times n)$ weights matrix defining who is a neighbor of whom by means of values of either 0 or 1 defining non-neighbors and neighbors, respectively, and μ is the independently distributed error term.

Written another way, the spatial lag model can also be expressed as:

$$y = (I - \rho W)^{-1}[X\beta + \mu] \quad (3)$$

This specification shows that equation (2) allows for spatial spillover and feedback effects with changes in the values of the independent variables as well as for spatially autoregressive errors. In this way, neighborhood and potential peer effects are captured by the model. The term $(I - \rho W)^{-1}$ serves as a spatially defined multiplier on the estimated parameters that provides additional insight into the spillover and feedback effects present in the spatial system. Termed the spatial multiplier (Anselin 2003), it allows that an individual's BMI is jointly determined by his or her own explanatory variables, as well as the average of the values observed for his or her neighbors. Additionally, the spatial multiplier also acts on the error term and thereby allows for spatially correlated omitted variables, which intuitively can be described as potential shared neighborhood characteristics that remain unobserved but might exert influence on the BMI of neighbors similarly.

Effect of Food Access in High and Low Income Neighborhoods

Low-income and high-income neighborhoods and their residents differ in many unobservable individual and neighborhood level characteristics. For poor individuals who live in poor neighborhoods, factors such as inadequate transportation, unsafe streets, or built environments that are not conducive to walking can mean that the effect of access is very different from their

wealthier counterparts in richer neighborhoods. We therefore allow the effect of access to chain grocers to differ for people who live in poor versus not poor neighborhoods. To incorporate this flexibility into Equation (3), we define two regimes (not poor and poor neighborhoods) and the parameters for access to chain grocers are allowed to differ across the different regimes, thereby capturing any structural differences in individual behavior due to location.

3. *Data*

The two main data sources for our analysis are the Marion County Health Department (MCHD) Obesity Needs Assessment Survey and the MCHD health inspection database. The MCHD Obesity survey was fielded in 2005 and contains self-reported information on weight along with geographic identifiers of a person's home address for each individual in the sample. Our sample consists of 3,550 individuals.

Information on chain grocers came from the Marion County Health Department's health safety inspection records. These data include name, type, and location of all food retailers in Marion County. Information on chain grocers were geocoded and linked to the individuals in our study using GIS techniques. We then created a 1 mile buffer around each individual's residence and counted the number of chain grocery stores within this buffer. These buffers represent the individual level markets for food. In order to compare our localized approach with the more aggregate analysis that has been done in the past, we also geocode individual location information into census tracts and merge in census tract level information from the US Census Bureau.²

² Information on the spatial distribution of individuals and the manipulation of data are available in a technical appendix available upon request from the authors.

The descriptive statistics are laid out in Table 1. The dependent variable is BMI.³ Self reported height and weight were used to calculate BMI. The average BMI for the individuals in the sample used in the following analysis was approximately 27.7 indicating that the majority of the individuals are overweight. Approximately 25.5 percent of our sample was overweight and 27 percent was obese. These findings are close to estimates from the Selected Metropolitan Micropolitan Area Risk Trends (SMART) from the Behavioral Risk Factor Surveillance Survey conducted in 2005. This survey reports rates of overweight and obesity within Marion County of 35 and 29.5 percent for overweight and obese individuals.

In terms of demographic variables, the individuals in the sample were predominantly female, white and educated. The average age of the respondents was just over 47 years old. Almost 21 percent lived in a household that earned an annual income of less than 200 percent of the Federal Poverty Level (FPL) in 2003.⁴ The behavioral variables that influence BMI are a combination of physical activity and smoking behavior. Just over 41 percent of the respondents reported that their job keeps them physically active. More than one quarter of the individuals in the sample currently smoke.

We use two measures to define neighborhoods. By the first definition, a census tract is defined as poor if the median family income is at or below the mean median family income for all Census tracts in Marion County. About 53 percent of the sample lives in poor neighborhoods under this definition (see Figure 1). The advantage of using this measure is that it is more homogeneously distributed across space, because the stratification variable is defined at a higher

³ BMI is calculated by dividing an individual's weight, in kilograms, by height squared, in meters. A BMI of 18.5 through 24.9 is considered normal. Overweight is classified as a BMI between 25 and 29.9. A BMI of 30 or greater is considered indicative of obesity.

⁴ All figures reported here correspond to a family of 4. More detailed information on the FPL is contained in the technical Appendix, Table A1.

spatial level of aggregation. Using the census tract as our neighborhood definition, access to chain grocers is defined as the count of the number of chain grocers within the census tract where people reside. Based on this definition the mean number of groceries in poor census tracts is 0.44 compared to richer census tracts that have a mean number of groceries of 0.59.

The second measure is more localized and based on looking at proximate individuals and defining neighborhoods based on the income of an individual's first-order neighbors. In order to construct these neighbor definitions, Thiessen polygons were constructed around each individual in the sample based on their point location. Thiessen polygons are described by assigning pieces of area to the individual's in the sample based on proximity. In this way, each individual is assigned the area of the county for which their residential location is the one closest. First-order neighbors are those whose Thiessen polygons share a boundary. Under this definition, a person is defined as living in a poor neighborhood if more than 20% of their proximate neighbors are poor. About 43 percent of the sample lives in a poor neighborhood based on this definition (see Figure 2). Compared to the previous definition, this definition results in a stratification of neighborhood that are spatially rather scattered around Marion county. The number of chain grocers within 1 mile of an individual's residence is approximately the same for both poor and not poor neighborhoods, and equals approximately 1.

4. Empirical Analysis

For the respondent data, it was necessary to ascertain whether there was spatial autocorrelation (evidenced as clustering) of BMI values. A second-order queen contiguity weights matrix was used to compute the value of Moran's I (plot shown in technical Appendix, Figure A1) and confirms that there is a very small amount of significant positive spatial

correlation in BMI values. Moran's I, which can be viewed as a spatial correlation coefficient, is 0.0189. Randomization techniques were used to test the Moran's I value against repeated random permutations of the respondent BMIs over the sample space. These results collectively indicate that to some small degree, respondent BMI is positively correlated with neighbors' BMIs, giving the data the property of spatial clustering. This supports our hypothesis that there may be some characteristic about an individual's geographic location that influences his or her BMI. Additional preliminary diagnostic tools used to detect spatial clustering suggest that spatial econometric techniques could aid in further analysis of the study of BMI and help to identify the presence of a spatial process.

Spatial diagnostics on the regression residuals are reported in Table 2. The Moran's I value was small 0.007652 with a *p*-value of 0.114. The LM and the Wald tests all point to lag dependence although at a relatively low level of significance of about 10%. Despite this, we use a rather cautious approach and take it into account because failing to control for a spatial lag process (if it exists) creates bias and inconsistency.

The parameter estimates are presented in Table 2. In our first specification we used census tract level measures of access and neighborhoods. We estimated both a naïve OLS model and a random effects model that allows the errors terms within census tracts to be correlated. These results are presented in Table 2, columns 1-3. The OLS and random effects specification were almost identical in this case so we will restrict our discussion to the random effects model only. For the random effects model, the effect of increasing access to chain grocers in poor neighborhoods was positive and insignificant. The only significant association was for living in a poor neighborhood. Living in a poor neighborhood increased BMI by 1. A Chow test of

structural stability fails to reject the null hypothesis that the parameter estimates are the same in poor and not poor neighborhoods.

In columns 5-7 we report our results that use a localized definition of access and neighborhood. We also report results for a naïve OLS model and a spatial lag specification. A Chow test of structural stability of the food access parameters rejects the null that they are identical. In poor neighborhoods, the effect of increasing access to chain grocers within 1 mile of an individual's residence is negatively associated with BMI. In not poor neighborhoods the association is positive, but statistically insignificant.

Unlike OLS, the parameter estimates for the spatial lag model cannot be interpreted as marginal effects because of the spillover effects represented by the spatial multiplier in equation (3). The changes in BMI resulting from an increase in access to chain grocers are presented in Figure 3 and Figure 4. In Figure 3 the improvement in food access is administered to the poor neighborhoods while in Figure 4 the improvement in food access is administered to the neighborhoods that are not poor. This type of representation allows us to display changes in BMI for each of the individuals in our study. It is clear from both maps that the change in policy has a different effect on each person based on how far they live from the neighborhood where there is a change in food access. The effect of marginal changes in access to chain grocers will have ripple effects across space and will thereby affect the BMI of individuals living in neighboring locations.

We include maps of both not poor and poor neighborhoods to show the spatial spillover and feedback process, the magnitude of the marginal effects and the different ways in which the impact of increasing access differs across space in poor versus not poor neighborhoods. These

maps also make clear the idea that where a particular change occurs (i.e., where we improve access to chain grocers) matters and has very different spatial trajectories. The spatial heterogeneity of the partial effects and the policy diffusion process that occurs is evident from the shading patterns in Figures 3 and 4.

In Table 2 column 8 we report the averages of the marginal effects for all the variables in our model. The averages for chain grocers are the average of the marginal effects displayed in Figures 3 and 4. They show that increasing access to a chain grocer will decrease BMI by an average of 0.3 (averaged over all residents in Marion County). Living in a not poor neighborhood had a positive effect on BMI and was associated with an increased BMI of 0.2.

For all models, the results for the individual level demographic and behavioral variables conform to previous studies and they are presented in Table 3.⁵ Most effects of the covariates were highly significant and moved BMI in the expected direction. As individuals grow older, BMI tends to increase, non-whites were associated with a significantly higher BMI. Individuals with a lower income (less than 200 percent of the FPL) had a higher BMI than their wealthier counterparts. Similarly, individuals with less education had significantly higher BMIs than the reference category of holding more than a high school diploma. Smokers tended to have lower BMIs than non-smokers; again, this is a finding consistent with other studies of weight and behavioral variables. Not surprisingly, having a job that required regular physical activity was significant in lowering BMI.

⁵ Available in a technical appendix available from the authors upon request.

5. Summary and Conclusion

Ultimately, this study reinforces previous work in the field showing that demographic and behavioral variables exert a strong influence on BMI. For some of the behavioral variables, the relationship between habit and health seems obvious. For the demographic variables, it is less clear why it is that minorities and those with lower incomes and lower educational attainment seem so strongly linked with poor health outcomes. It is at this juncture that the contribution of spatial econometric techniques becomes valuable. Because American cities, and Indianapolis as an example, are so highly geographically segregated on characteristics such as income, it is natural to wonder about the impact that geographical location could be having on health.

Our results provide some additional insight into how an individual's market for food while controlling for other environmental effects may affect his or her health. Evidence of clusters of higher and lower BMIs, especially noticeable in areas characterized by segregation based on income, initially pointed to possible environmental effects on health. Using a spatial lag model which accounts for possible spatial dependence and calculating marginal effects for subgroups of the population based both on individual and neighborhood income characteristics revealed that changes in access to chain grocers had differing impacts depending on location. Segmenting the sample based on neighborhood income characteristics highlighted the discrepant responsiveness of BMI to food access. The addition of one chain grocery store to a respondent's food landscape, defined as a buffer with one-mile radius centered on a person's home, in a poor neighborhood decreased his or her BMI by approximately 0.3.

It is also important to note that this research started with a specific and descriptive set of geographical data for the survey respondents. In the previous studies cited at the beginning of

this paper, the researchers were not privy to individual location at the address level. In most cases, the highest level of specificity was the census tract. The boundaries of census tracts are, however, purely administrative and arbitrary. Performing counts and analyses based solely on the characteristics of an individual's census tract could feasibly yield different results from those originating from actual coordinates.

The possibilities for analysis offered by this unique dataset hold potential in revealing both the power of spatial econometric techniques as well as important advances in explaining the obesity epidemic in this country. While the results thus far provide a strong indication for a spatial process at work across the geographic space and data, additional analysis should be conducted in other geographic areas to verify that these spatial processes are at work and that geographic aspects of a community can impact the health of its residents. In particular, future work in this area should try to take into account the effect of both access to the good food and the bad food, i.e., chain grocers and fast food establishments.

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Table 1. Summary Statistics

Variable	Poor Neighborhood	Not Poor Neighborhood	Total
Body Mass Index	28.1953	27.2837	27.675
No. of chain grocers within 1 mile	1.0269	0.9808	1
Nonwhite	41.40%	21.96%	30.31%
Female	56.69%	59.43%	58.25%
Age	46.9193	47.0805	47.0113
More than high school	50.92%	74.73%	64.51%
Physically demanding job	43.90%	39.29%	41.27%
Smoker	33.14%	20.43%	25.89%
Less than 200% of the FPL	31.43%	12.59%	20.68%
Percent who live in poor nghd - local nghds	42.93%	57.07%	
Percent who live in poor nghd - census tracts			53.13%

Table 2. Effect of Access to Chain Grocer on BMI

	Census Tract Level Analysis		Localized Neighborhoods		
	OLS	RE	OLS	Spatial Lag	Average Marginal Effect Spatial Model
No. of chain grocers within 1 mile -- poor neighborhood	0.017 (0.159)	0.020 (0.164)	-0.2871** (0.1325)	-0.273** (0.133)	-0.295
No. of chain grocers within 1 mile – not poor neighborhood	0.027 (0.166)	0.032 (0.175)	0.1836* (0.1054)	0.179* (0.105)	0.194
Poor neighborhood	0.996*** (0.248)	1.020*** (0.258)	1.0775** (0.2770)	1.002*** (0.281)	1.084
Constant	26.322*** (0.503)	26.276*** (0.508)	26.3841** (0.5021)	24.325*** (1.403)	26.312
Rho (<i>p</i> -value)				0.076	
R-squared	0.037		0.036	0.119	
LM test for spatial lag dependence			2.607 [0.1064]		
Chow test	0.00		7.76		
F(1, 3539)	(0.9510)		[0.0054]		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All models adjust for age, race, education, etc. These effects are reported in Table 3.

Chow test of the structural stability of the coefficient on the number of chain grocers in not poor and poor neighborhoods.

p-values are in square brackets and standard errors are in parentheses.

Table 3. Effect of Other Variables on BMI

	Census Tract Level Analysis		Localized Neighborhoods		
	OLS	RE	OLS	Spatial Lag	Average Marginal Effect Spatial Model
Nonwhite	0.814*** (0.233)	0.806*** (0.236)	0.8724** (0.2312)	0.838*** (0.281)	0.907
Female	-0.256 (0.206)	-0.255 (0.206)	-0.2093 (0.2067)	-0.212 (0.206)	-0.229
Age	0.032*** (0.007)	0.032*** (0.007)	0.0319** (0.0073)	0.032*** (0.007)	0.034
More than high school	-0.553** (0.229)	-0.536** (0.229)	-0.5974** (0.2297)	-0.577** (0.229)	-0.624
Physically Demanding Job	-0.707*** (0.213)	-0.709*** (0.213)	-0.6949** (0.2129)	-0.693*** (0.212)	-0.750
Smoker	-1.259*** (0.236)	-1.263*** (0.236)	-1.2495** (0.2367)	-1.260*** (0.236)	-1.363
Less than 200% of the FPL	0.902*** (0.271)	0.896*** (0.271)	0.9938** (0.2701)	0.990*** (0.270)	1.071

p<0.10, ** p<0.05, *** p<0.01

Figure 1. Poor and Not Poor Neighborhoods by Census Tract

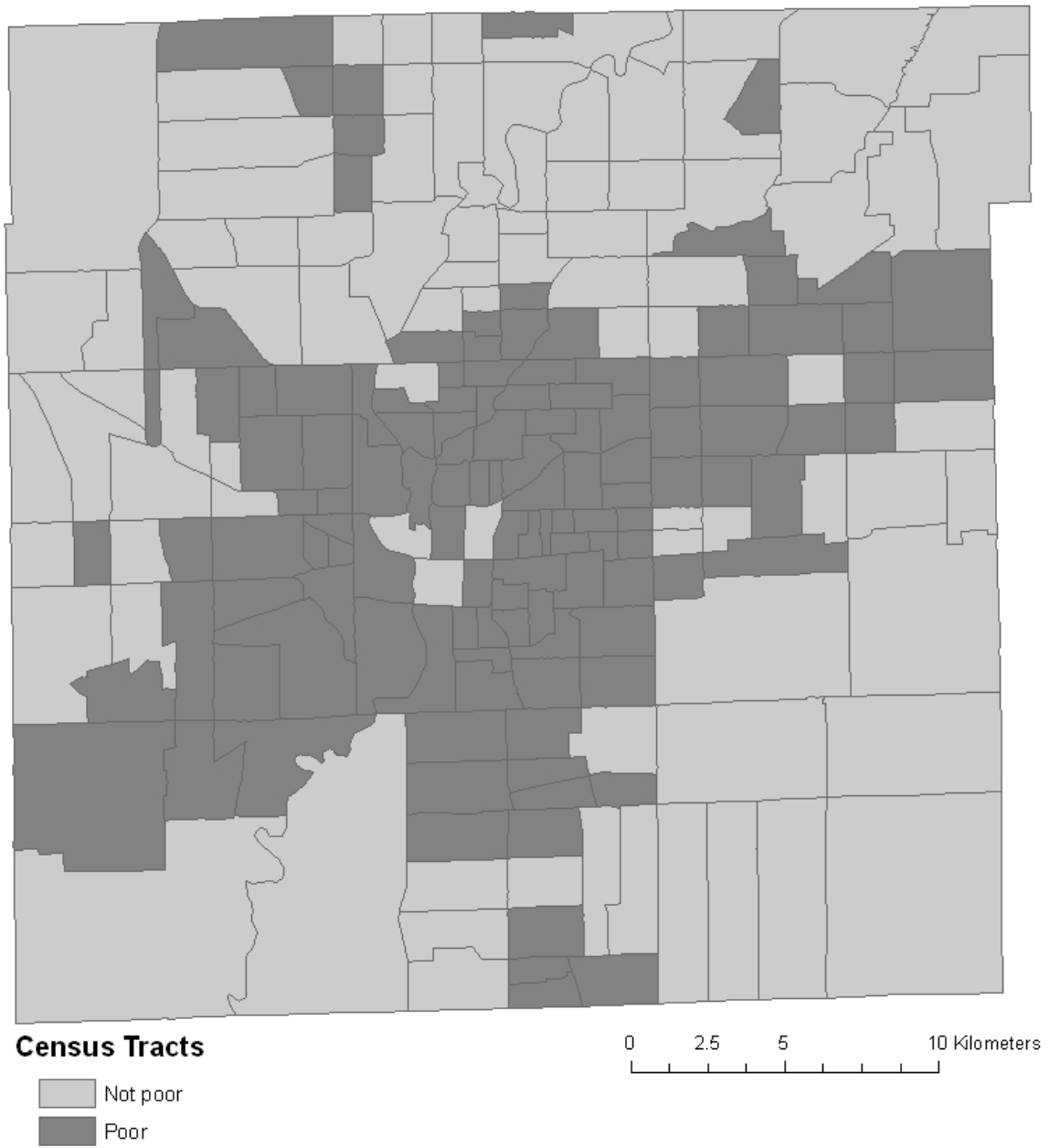
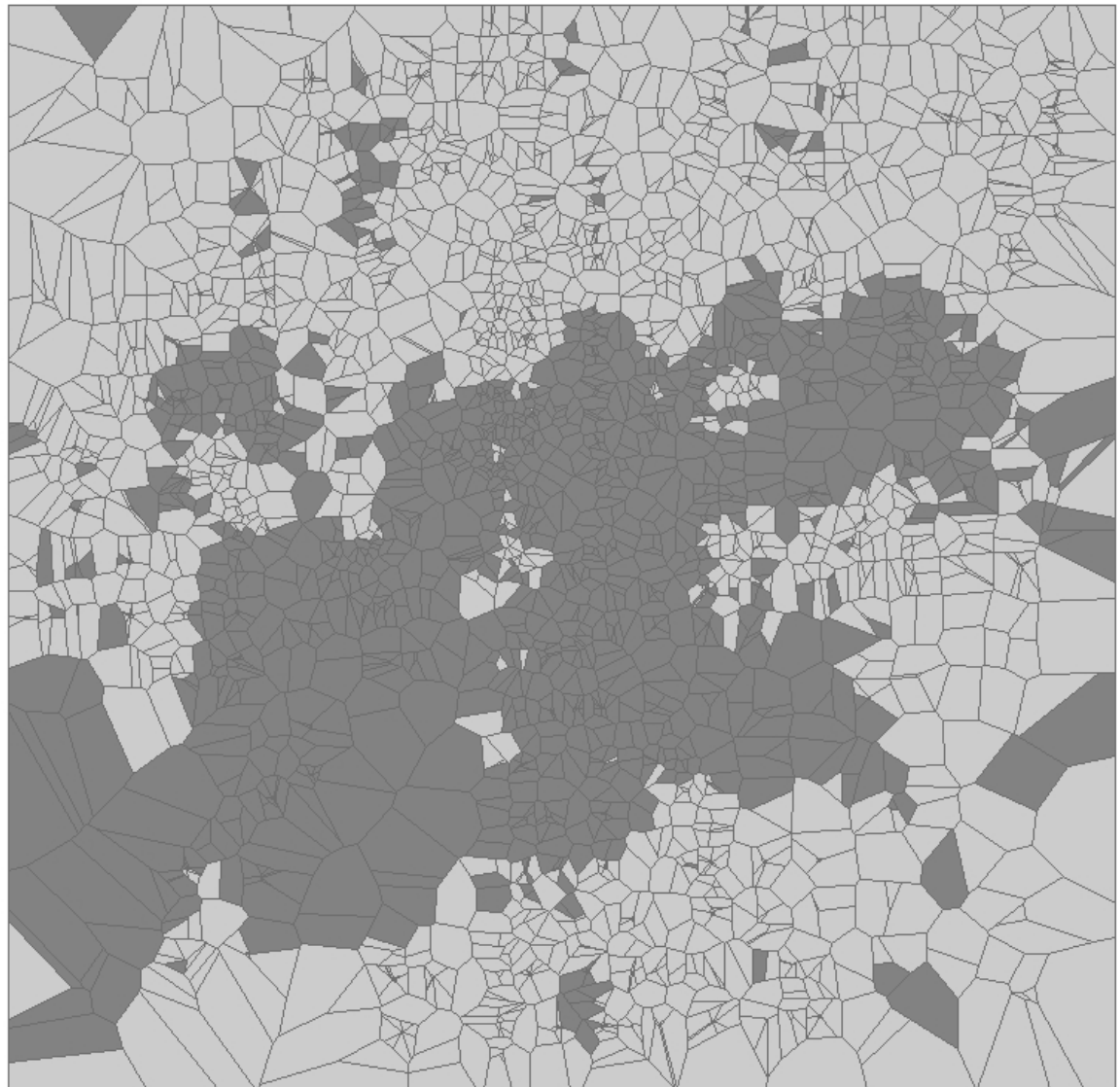


Figure 2. Poor and Not Poor Neighborhoods Using Local Definition



Type of neighborhood

Not poor

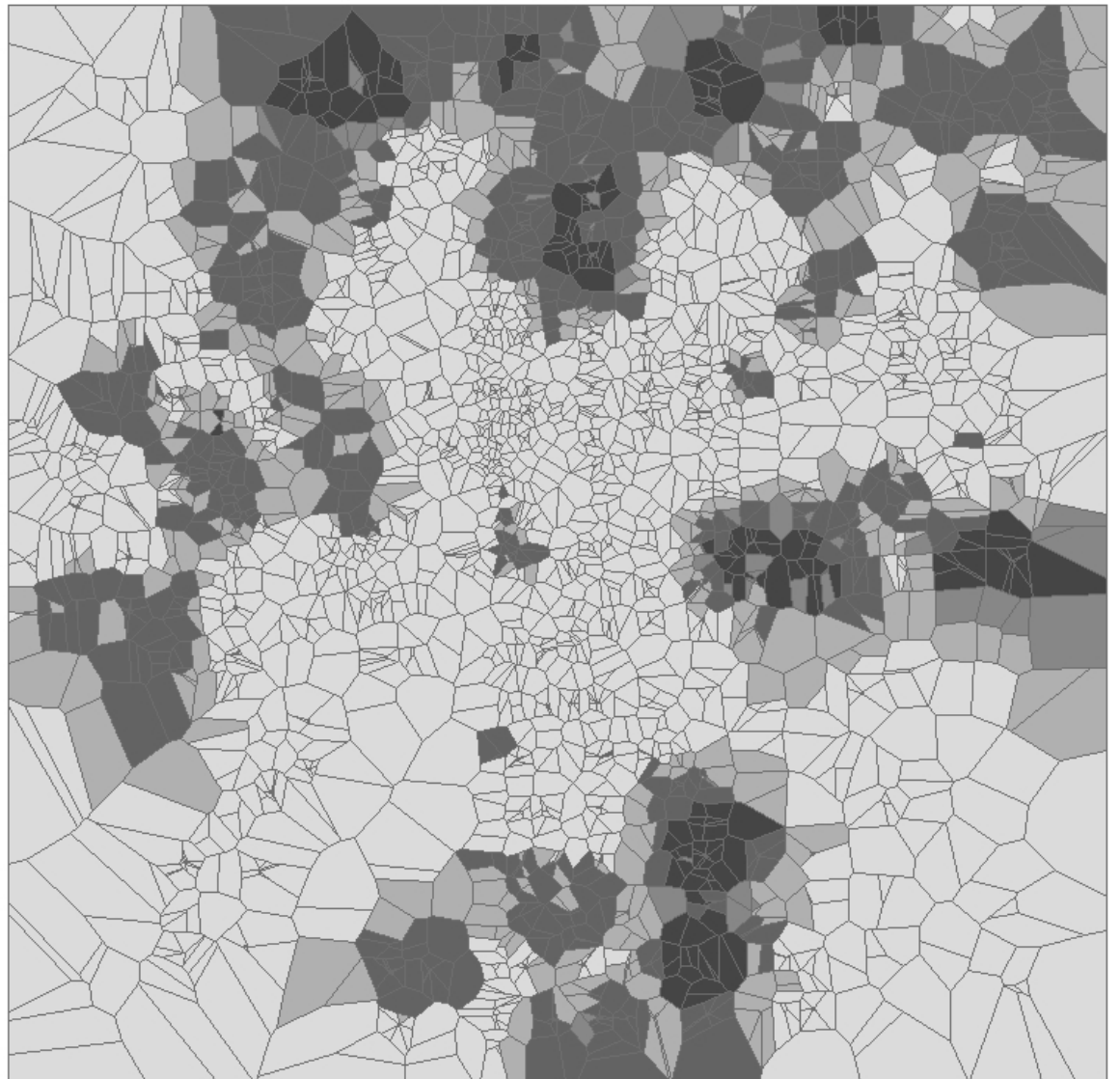
Poor

0 2.5 5 10 Kilometers

Figure 3. Marginal Effects of Change in Poor Neighborhood



Figure 4. Marginal Effects of Change in Not Poor Neighborhood



Not poor neighborhood

Marginal effects

0.000 - 0.005

0.005 - 0.018

0.018 - 0.060

0.060 - 0.397

0.397 - 1.314

0 2.5 5 10 Kilometers