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Local Foods and Community Health: An Exploratory Analysis

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LOCAL FOODS AND COMMUNITY HEALTH:
AN EXPLORATORY ANALYSIS

Abstract

In this exploratory analysis we look for patterns in the relationship between local foods and community health using U.S. nonmetropolitan counties. We take an ecological approach using 2007 Census of Agriculture and "County Health Rankings & Roadmaps" data collected by the University of Wisconsin Population Health Institute program at the U.S. county level. In addition to the central question (are higher concentrations of characteristics of local food systems associated with healthier communities) we address the question of health modeling uncertainty by use a Spatial Bayesian Model Averaging (SBMA). As expected, our findings indicate that higher levels of activities associated with local foods are generally associated with higher levels of community health. Two problems with the analysis are (1) challenges around definitions and measurement of local foods and (2) direction of causation is unclear.

Introduction

The local food movement in the United States emerged over the past decades as a combination of consumer movements promoting increased awareness of the environmental, geographic, and cultural implications of food production and consumption (Martinez et al. 2010, Guptilll and Watkins 2002). Local food systems based strategies are now being promoted at the community and neighborhood level to address a broad range of complex, systemic issues including environmental protection, restoring eco-systems, promoting sustainable economic development, or improving the health and well-being of local residents (e.g., Feenstra 2002, 1997).

In some cases, communities may view food systems strategies as an opportunity to address multiple health, wellness, or agricultural and community vitality issues concurrently. As an example, Dunn (2013) refers to the concurrent farm income crisis and health crisis in terms of the "good food gap." That is, while farmers struggle to remain profitable in supplying the increased consumer demand for local foods, nearly ten percent of the U.S. population or 29.7 million people, live in low-income areas more than one mile from a supermarket (Ver Ploeg 2012). Similarly, rates of both diet-related chronic disease and food insecurity have increased substantially in recent decades (WHO, 2003, Coleman-Jensen, 2013). More than one-third of adults and almost 17 percent of adolescents were obese in 2009-2010 (Ogden, et al, 2012). While the rate of growth of obesity prevalence appears to be leveling off (Flegl, et al 2010; Ogden, et al, 2010), incidence and prevalence of type 2 diabetes continues to rise with nearly 27 percent of the population in the U.S. classified as having diagnosed diabetes in 2010 (CDC, 2011). Meanwhile in 2012 approximately 17.6 million households, or 14.5 percent of the U.S. population are classified as food insecure, meaning they lack assured access to affordable, healthy foods at all times (Coleman-Jensen, et al, 2013).

It is becoming widely argued that the complex nature of food systems issues requires innovative, systems focused and transformative approaches (Clancy 2013). One such argument is the promotion of what is known today as local food systems (e.g., Garnett 2013; Creamer and Dunning 2012). Born and Purcell (2006) have documented that the promotion of local food systems has assert that such systems will promote a healthier society, social or economic justice and/or environmental sustainability. Born and Purcell (2006) further note that, unfortunately, the bulk of the available literature is less than satisfactory in terms of rigor. Indeed, few studies have attempted an empirical analysis of relationships between characteristics of local food systems and public health outcomes (Albrecht et al 2013). The exploratory analysis presented in this paper aims to probe this research gap and follow the lead of Salois (2012). Our primary research question is: do rural communities (nonmetropolitan US counties) with a higher concentration of characteristics associated with local food systems have a positive public health outcome?

A primary and necessary objective of our work was to define a measurement index for both local food systems and public health. While this has been considered by many researchers in the public health realm, our preliminary work in this area indicated that practitioners and researchers might benefit from further consideration of local food indices in particular. Our methods for defining these measures are outlined in the methods section below. Our analysis makes use of 2007 Census of Agricultural data and population health data compiled by the University of Wisconsin Population Health Institute in collaboration with Robert Wood Johnson Foundation and 2010 Census data.

One of the difficulties in modeling health outcomes is that theory suggests that "everything matters" and there are numerous ways to empirically measure individual factors. From an ecological community level, for example, links between poverty and poor health outcomes are numerous, complex and, as expressed by Murray (2006: p923) "inextricably intertwined" (Mansfield and Novick 2012; Montgomery, Kiely and Pappas 1996; Pappas, Queen, Hadden and Fisher 1993). But there are numerous ways to define and measure poverty; which is metric is most consistent with the underlying relationships? Alternatively, is poverty one of the driving factor of health or is poverty a symptom of another underlying cause? For example, the notion of social capital, which is often tied to poverty, is gaining wider interest in the health literature (e.g., Cattell 2001; Szreter and Woolcock 2004; Ziersch 2005). If poverty is a symptom and some elements of social capital are the true underlying causes the policy implications can be tremendous.

These theoretical and empirical challenges can be thought of as modeling uncertainty (Briggs, et. al. 2012; O'Hagan, et. al. 2005). In the presence of modeling uncertainty the problem becomes one of variable selection in statistical modeling. If we wish to identify if a relationship exists between health and local foods related activities we must control for other factors that can influence health. If theory tells us everything matters and we have numerous ways to measure different variables, which variables do we include in our statistical analysis? This is modeling uncertainty. To address this issue we follow the lead of Jackson, Thompson and Sharples (2009) and Negrín and Vázquez-Polo (2008) and use a Bayesian Model Averaging (BMA) approach. Our approach is unique in that we acknowledge the presence of spatial dependency in our data and employ a Spatial Bayesian Model Averaging (SBMA) approach suggested by LeSage and Parent 2007). In addition, as far as we are aware, we are the first to use BMA methods within an ecological health study. The applications of BMA that, again we are aware of, are within medical applications such as in diagnostic or treatment modeling.

Beyond these brief introductory comments, the study is composed of the following additional sections: 1) a review of literature regarding agricultural characteristics and public health outcomes related to local food systems, 2) a description of our modeling approach and specification of the mode including an outline of our measures of local foods and public health, 3) the estimation methods including the Spatial Bayesian Model Averaging and heteroscedastic error spatial lag estimator, 4) the modeling results, and 5) conclusions and policy implications noting the limitations of the work, and future research directions.

Literature Review

Our literature review focuses on understanding known contributors to both public health and local food systems. This includes contributors to public health outcomes (some of which serve as our control variables) and influences on dietary behavior, understanding the food environment as a component of public health, the (limited) existing research on links between local food systems and public health, and known agricultural activities associated with local food systems.

Influences on dietary behavior are numerous, complex, and interrelated, including personal factors (income, age, gender, ethnicity, attitudes and beliefs, self-efficacy, skills, etc.), social networks, physical settings and environments, and policies and social norms (Story, et al, 2008). Diets high in fruits and vegetables are associated with a decreased risk of chronic disease (Hu, et al, 2003, Montonen, et al, 2004, He, et al, 2006, Fung, et al, 2008) and replacing higher energy density foods in the diet with foods of lower energy density, such as fruits and vegetables, can be an effective weight management strategy (Tohill, et al, 2004, Rolls, et al, 2004). Strategies to increase fruit and vegetable consumption are increasingly targeted to improvements to the food environment, particularly focused on access and availability of healthy food choices (Kelly, et al., 2011, Story, et al, 2008, Glanz, et al, 2005.) Further, a growing number of strategies to improve local food environments are tied to local and regional food systems, and include farm to institution or farm to where you are programs, farmers markets, community supported agriculture, and community and home gardens. The underlying rationale being that the direct connection with farmers enhances the perception of the food and willingness of the participant to eat local and regional fruits and vegetables (Centers for Disease Control, 2011).

Despite the growing interest in connecting local food and agriculture strategies, limited research exists on the diet and disease implications of these efforts (McCormack, et al, 2010, Centers for Disease Control, 2011). The WIC Farmers Market Nutrition Program has been most heavily studied for influence on fruit and vegetable intake (McCormack, et al, 2010), with several studies showing increased intake of fruits and vegetables among program participants (Racine, et al, 2010) compared to non-participants (Kropf, et al, 2007, Herman, et al, 2008). Recent evaluation efforts of farmers market based double value incentive programs for SNAP users, however, showed significant changes in shopping behavior among program participants, resulting in increase in fruit and vegetable consumption while using purchasing incentives. The increase in fruit and vegetable consumption remained after the program ended (Wholesome Wave, 2012). Farm-to-school programs may include varying degrees of connectedness with local produce, including local food procurement and inclusion in meal programs, field-trips to local farms, agriculture education, nutrition education, and experiential learning such as garden programs. Roshi, et al (2009) conducted an assessment of farm to school programs and found that 10 of 11 non-peer reviewed evaluation studies confirmed improvements in dietary behavior when fresh, local produce is served in schools. The authors, along with others (Taylor and Johnson, 2013) however, call for additional standardized and more robust evaluation efforts.

A number of food environment measures have been developed to expand the understanding of the relationship between healthy, diet, and disease, and the community nutrition environment (food store, number, type and location), organization nutrition environment (schools, workplaces), and consumer nutrition environment (product availability, information/promotion, accessibility of product) (Glanz, 2005). Caspi and colleagues (2012) conducted a systematic review of local food environment using a slightly expanded framework (Penchanksy and Thomas, 1981) based on the notions of availability (adequacy of healthy food), accessibility (location of food supply, ease of getting to that location), affordability (food prices and personal perception of worth), acceptability (people's attitudes about attributes of the food environment), and accommodation (how well food sources accept and adapt to local resident's needs). Based on this expanded understanding of the food environment we suggest that agricultural activities related to "local foods" might be conceptualized as a component of the food environment in that they can be defined in terms of geographic factors, production (fruits and vegetables versus commodities) , market (farmers market, CSA, institutional) characteristics and economic factors.

To the best of our knowledge, few studies have looked at the impact of characteristics of related to local food systems in the food environment on diet-related disease and health. Salois (2011) examined the association of the built food environment and 'local agriculture' with US county-level prevalence of obesity and diabetes. Total per capita dollar volume of direct farm sales was inversely associated with diabetes and obesity. Specifically, a $100 increase in per capita sales was associated with a 0.80 percent reduction in obesity rate and a 1.2% lower rate of diabetes. The density of farmers markets was also inversely related to the diabetes rate (Salois, 2012). Jilcott, et al (2011) examined associations among obesity and per capita farmers' markets, grocery stores/supermarkets, and supercenters in US counties. Per capita farmers markets were inversely associated with the obesity rate in non-metro counties (Jilcott, et al, 2011).

Modeling Approach and Methods

Or basic model is built on a classical linear model where public health is a function of local foods and a series of other community characteristics within a rural U.S. context. The model can be expressed as:

$$PH = \alpha + \beta LF + \gamma EC + \theta DM + \delta HA + \varphi FA + \vartheta SC + \varepsilon. \quad (1)$$

Where PH is our public health measure, LF is our measures of local foods, EC is a collection of economic characteristics focusing on income, DM is a set of demographic metrics that influence health outcomes such as age and education levels, HA is a set of metrics to reflect access to health care, SC is a set of variables to reflect the social capital of the community, and FA is access to food (other than local foods).

The challenges we face in implementing this model are 1) how to measure health and local foods and 2) what specific variables to include in our set of control variables (economic, demographic, access to health care, access to foods other than local foods, and social capital). One could randomly select a handful of different variables that would capture the essence of the control variables but we would prefer to all the data to identify which variables are most closely tied to the underlying data generating process.

Demographic

- Percent of Population African American
- Percent of Population American Indian/ Alaskan Native
- Percent of Population Asian
- Percent of Population Hispanic
- Percent of Population Not Proficient in English
- Percent of the Population Rural
- Median Age
- Percent of Population Under Age 18
- Percent of Population Over Age 65

Economic

- Percent of Uninsured Adults
- Percent of Uninsured Children
- Percent of Children Eligible for Free lunch
- Unemployed Rate
- Percent of Households Single-Parent
- Percent of those Age 25+ with Less than a 9th Grade Education
- Percent of those Age 25+ with Some High School, No Degree
- Percent of those Age 25+ with Some College, No Degree
- Percent of those Age 25+ with an Associate Degree
- Percent of those Age 25+ with a Bachelor Degree
- Percent of those Age 25+ with a Graduate or Professional Degree
- Poverty Rate for those Under Age 18
- Poverty Rate
- Median Household Income
- Percent Change in Population 2000 to 2010
- Population Density
- GINI Coefficient of Income Equality
- Per Capita Income from Income Maintenance Programs
- Per Capita Unemployment Insurance Benefits

- Per Capita Income from Retirement and Other Sources
- Percent Change in Employment 2000 to 2010
- Population -- Employment Ratio
- 2010 Census Population

Food Access

- Percent of Households Low Income & Low Access to Store
- Percent of Households, No Car & Low Access to Store
- WIC-Authorized Stores/1,000 pop, 2011
- WIC Redemptions/WIC-Authorized Stores/1,000 Pop

Health Care Access

- Number of Health Care and Social Assistance Establishment
- Number of General Hospitals
- Number of Primary Care Physicians
- Number of Health Care and Social Assistance Est/1,000 Pop
- Number of General Hospitals/1,000 Pop
- Number of Primary Care Physicians/1,000 Pop

Social Capital

- Number of Individual and Family Support Est/1,000 Pop
- Number of Vocational and Rehabilitation Est/1,000 Pop
- Number of Child Care Est/1,000 Pop
- Number of Elderly Care Est/1,000 Pop
- Number of Youth Service Est/1,000 Pop
- Number of Community Food Service Est/1,000 Pop
- Number of Community Housing Service Est/1,000 Pop
- Social Capital (Rupasingha and Goetz)

Most of this data is drawn from the USDA Food Atlas, the University of Wisconsin Population Health Institute's "County Health Rankings & Roadmaps", and the Bureau of Economic Analysis Regional Economic Information System. [1] Again, all data are for nonmetropolitan U.S. counties. The Social Capital

[1] USDA Food Atlas: http://www.ers.usda.gov/data-products/food-environment-atlas/go-to-the-atlas.aspx#.UnsImxCiKLI
UW Population Health Institute County Health Rankings: http://www.countyhealthrankings.org/
BEA REIS: http://www.bea.gov/itable/
County Business Patterns: http://www.census.gov/econ/cbp/

(Rupasingha, Goetz) is an index developed by Rupasingha, Goetz and Freshwater (2006), Rupasingha and Goetz (2007) and Goetz and Rupasingha (2006).[2]

An example of the problem is model uncertainty is perhaps most evident with the education measures, where are proxies for human capital. Theory and previous empirical work has suggested that education is a potentially important predictor of health with higher levels of education associated with higher levels of health. But there are multiply ways to measure education ranging from percent of those over age 25 with less than a high school education to those with a graduate or professional degree. Model uncertainty is capture by one simple question: which of these potential measures of education is most appropriate for modeling health?

Approaches to model uncertainty has traditionally consisted of the imposition of some information criteria in order to select a single "best" model regarded as the true model from which variable parameters are estimated. Comparing determination criteria, such as changes in the equation F statistic, $\bar{R}^2$ or Mallows' C_p statistic, are tracked across alternative linear regressions for the purpose of identifying a "best" model. Other criteria include the Amemiya criteria (PC), Akaike Information Criteria (AIC), Sawa Bayesian Information Criterion and/or the Schwarz Bayesian Information Criterion (BIC) as well as the Jeffreys-Bayes posterior odds ratio, among others (see Burnham and Anderson 2004; Judge et al., 1985; Kuha 2004; Posada and Buckley 2004 for formal discussions). Here models with different variable specifications yield some type of selection criteria metric (e.g., F, $\bar{R}^2$, C_p, AIC, BIC, etc.) and the model with the highest (or lowest depending on the criteria metric) is selected as the "correct" model. Or, even more crudely, a process of elimination based on individual variable *t* statistics can be used.

The problem with this approach in the selection of a set of control variables is that it ignores model uncertainty. Analysts typically select a model from some class of models then proceed as if the model generated the data. In addition to problems of vague theoretical foundations for selecting one method over another, critical values of these model selection methods, or rules to follow when methods provide inconsistent results, ignores a component of uncertainty leading to an increase in Type I error and/or over-confident inferences. In the case of a relatively large number of potential variables this can be a very cumbersome and time consuming process.

Within the health literature Bayesian model averaging (BMA) has been introduced to provide a coherent mechanism to account for model uncertainty in terms of what variables should be included in

[2] The social capital index includes religious, civic, social, business, political, professional, labor organizations, bowling centers, physical fitness facilities, public golf courses and sport clubs, managers, and promoters concentrations (number of organizations/associations per 10,000 population), voter turnout, Census response rate and number of non-profit organizations without including those with an international approach. The social capital index is created using principal component analysis with the first principal component considered the index of social capital. The technical documentation and data for the index is available at: http://aese.psu.edu/nercrd/community/tools/social-capital

the final specification of the model (e.g., Jackson, Thompson and Sharples 2009; Negrín and Vázquez-Polo 2008). Suppose that there is a set of models all of which may be "reasonable" based on the theory for estimating θ from a given data set *y*. Suppose further that a particular parameter θ has a common interpretation across all possible models $M_1,\ldots,M_k$. Instead of using one single model for making inferences about θ, Bayesian model averaging constructs $\pi(\theta|y)$, the posterior density of θ given the data and is not conditional on any specific model (M_i).

Following the lead of LeSage and Parent 2007) and Cuaresma, Doppelhofer and Feldkircher (2009) specify the general health model (eq.(1)) as a spatial lag model:

$$y = \alpha\iota_n + \rho W y + X_k\beta_k + \varepsilon \qquad (2)$$

where ι_n is an *n* by 1 vector of ones, $\varepsilon \sim N(0, \sigma^2 I_n)$. The number and identity of variables in X_k is unknown so the columns in X_k are taken to be *k* variables from a larger set (*K*) of potential explanatory variables contained in X_K with $K \geq k$. Any potential model specification is contained in the set of all model possibilities (i.e., $M_k \in \mathcal{M}$). The potential number of possible model combinations is 2^K which can become very large in practice.

Inference on the parameters attached to the variables in X_k can be based on the weighted-average parameter estimates of individual models,

$$p(\beta_j|Y) = \sum_{k=1}^{2^K} p(\beta_j\,|Y, M_k)p(M_k|Y) \qquad (3)$$

with Y denoting the data. The spatial lag vector Wy appears in all models as does the intercept term, leaving only the variable vectors in the matrix X subject to change as we compare alternative models. This approach mirrors the one developed by Fernández, Ley, and Steel (2001a), where the intercept term appears in all models.

Posterior model probabilities $p(M_k|Y)$ are given by

$$p(M_k|Y) = \frac{p(Y|M_j)p(M_j)}{\sum_{k=1}^{2^K} p(Y|M_k)p(M_k)} \qquad (4)$$

Model weights can be obtained using the marginal likelihood of each individual model after eliciting a prior over the model space. The marginal likelihood of model M_j is given by

$$p(Y|M_j) = \int_0^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} p(Y|\alpha, \beta_k, \rho, \sigma, M_j)p(\alpha, \beta_k, \rho, \sigma|M_j)d\alpha\, d\beta\, d\rho\, d\sigma. \quad (5)$$

Given a model (M_j of dimension *k*) we can use a noninformative prior on α and σ and a g -prior on the β coefficients we have

$$p(\beta_k|\alpha,\rho,\sigma,M_j) \sim N(\beta_k,\sigma^2(gX_k'X_k)^{-1}) \tag{6}$$

with $g = 1/\max\{N, K^2\}$. Fernández, Ley, and Steel (2001) shows that a great deal of computational simplicity can be found by using Zellner's g-prior (Zellner 1986) for the parameters b in the SAR model. In addition to simplifying matters, Fernández, Ley, and Steel (2001) provide a theoretical justification for use of the g-prior as well as Monte Carlo evidence comparing nine alternative approaches to setting the hyperparameter g.

The posterior distributions of the β coefficients for the spatial autoregressive specification are calculated as the β which maximizes the likelihood calculated over a grid of ρ values. Building on the prior work of Raftery, Madigan and Hoeting (1997) as well as Fernandez, Ley and Steel (2001) LeSage and Parent (2007) adopts a Markov Chain Monte Carlo Model Composite (MC^3) method modeling composition approach introduced by Madigan and York (1995). Using a random-walk step in every replication of the MC^3 procedure, one can construct an alternative model to the active one in each step of the chain by adding or removing a regressor from the active model. The chain then moves to the alternative model with probability given the product of Bayes factor and prior odds resulting from the beta-binomial prior distribution. The posterior inference is based on the models visited by the Markov chain instead of on the complete model space which is untraceable given a large *K* (recall the full model space $\mathcal{M}$ is 2^K, if, for example if *K*=10, then the full model space has a dimension of 1,024). We can more formally define a neighborhood $nbd(M)$ for each $M \in \mathcal{M}$ (the set of all possible models). From there we can define a transition matrix *q* by setting $q(M \to M') = 0 \; \forall \; M' \notin nbd(M)$ and $q(M \to M') \neq 0 \; \forall \; M' \in nbd(M)$. If the chain is currently in state *M*, we can proceed by drawing *M'* from $q(M \to M')$. *M'* is accepted with probability

$$\min\{1, \frac{P(M'|y)}{P(M|y)}\}. \tag{7}$$

Otherwise the chain remains in state *M*. Using a Metropolis-Hastings sampling scheme, LeSage and Parent (2007) were able to implement a Markov Chain Monte Carlo routine to move through the modeling space.

There are three ways to use the Spatial Bayesian Model Averaging approach to identify the final set of control variables to include in the general health model (Eq.(1)). First, use the single model $M^* \in \mathcal{M}$ with the highest posterior probability to determine which variables are to be included in the final set of control variables. Second, look at the frequency of variables entering the top ten models ($M^{10} \in \mathcal{M}$) ranked by their posterior probability. If a particular variable appears more than, say seven times, in the top ten models, that variable could be included in the final set of control variables. Finally, examine the posterior probability of individual variables and, if the variable has a posterior probability above some threshold, the variable is included in the final set of control variables. In most cases the three criteria are generally in agreement and the choice of variables is clear. There are, however, a handful of cases where the three methods do not concur and a judgment call is required. For this study we use each of the three criteria: (1) the variable must be contained in the single model $M^* \in \mathcal{M}$ with the highest posterior probability; (2) the variable must be contained in at least eight of the top ten models ($M^{10} \in \mathcal{M}$) ranked by their posterior probability; and (3) the posterior probability of the single variable must be greater than 0.75.

While the use of a Spatial Bayesian Model Averaging is a step above the use of more *ad hoc* criteria metrics (e.g., F, $\bar{R}^2$, C_p, AIC, BIC, etc.) to select the "correct" set of control variables, there are still judgment calls to be made. For example, why is there a threshold of eight of the top ten models, furthermore, why ten models and not twenty or thirty, or why posterior probabilities of a single variable greater than 0.75 and not 0.85 or 0.95? The Spatial Bayesian Model Averaging approach provides a more solid theoretical foundation for model comparisons and variable selection. Specifically, the approach is more theoretically consistent with notions of model uncertainty than the more *ad hoc* criteria metrics.

Once the SBMA approach identifies the set of control variables (X) in the general health model (Eq.(1)), we then introduce the set of local food indices (LF). In essence this is a two-step process: step one, use the SBMA to identify the set of control variables, the step two is to estimate the final model. As outlined in LeSage and Pace (2009) we use a Bayesian heteroscedastic error spatial autoregressive (SAR) model:

$$y = \rho W y + X\beta + \theta LF + \varepsilon \qquad (8)$$

$$\begin{gathered} \varepsilon \backsim N(0, \sigma^2 V) \;\; V = diag(v_1, \dots, v_n) \\ \pi(\beta, \theta) \backsim N(c, N) \\ \pi(r/\, v_i) \backsim IID\; \chi^2(r) \\ \pi(1/\sigma^2) \backsim \Gamma(d, v) \\ \pi(\rho) \backsim \mathrm{U}[0,1] \end{gathered}$$

The set of variance scalars ($v_1, v_2, \ldots, v_n$) are unknown parameters that need to be estimated. We elect to use a heteroscedastic over a homoscedastic error model because prior work on local foods along with health has found clusters of hot and cold spots (see below). If spatial hot and cold spots are present in the data it seems more reasonable to allow for the potential that the variance (σ^2) varies over space ($v_1, \dots, v_n$). From a broader perspective, the heteroscedastic model is a more general form and less restrictive than the homoscedastic error model. The prior distribution for the v_i terms takes the form of an independent $\chi^2(r)/r$ distribution where χ^2 is a single parameter distribution with r as the parameter. By adding the single parameter r this allows the estimation of the n parameters v_i. The prior distributions are indicated using (π), a normal-gamma conjugate prior for σ and a uniform prior for ρ.[3,4]

[3] The Gibbs sampling procedure must be repeated until the values of the estimates converge. For this study we use 100,000 draws with the first 1,000 draws removed in effect acting as a "burn-in" to minimize the likelihood of poor starting values. This is for both the SBMA and Bayesian spatial lag estimators.

[4] Note that we can explicitly capture spatial spillover effects across counties in the SAR model ($y = \rho W y + X\beta + \varepsilon$). Specifically, solving for y, yields $y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1}\varepsilon$. Here we obtain the marginal effects:

The next challenge we face is defining the empirical measures of health and local foods. Salois (2012), for example, models health as adult obesity and diabetes rates with a separate regression model for each. Local food is modeled by the presence of farmers markets and farm direct sales for human consumption. While the Salois (2012) study is very useful, and the motivation for the work reported in this paper, we would prefer to think of health and local foods more broadly. Rather than using a single measure (such as obesity or presence of farmers markets) we use principal component analysis to combine several metrics into a single index of both public health and local foods. By using principal components we not only bring several dimensions or characteristics of health and local foods together, the process of constructing the principal components sheds additional light on which characteristics are most linked to health and local foods from a statistical perspective. Specifically, the loading factors and overall explanatory power provides us with additional insights. Consider first our measure of public health then local foods.

Measuring Public Health Given the complexity of public health issues and limitations of available data, developing a comprehensive metric of public health offers a similar challenge. This study builds on the work of the University of Wisconsin Population Health Institute who, in partnership with the Robert Wood Johnson Foundation, developed the County Health Rankings and Roadmaps program which allows for the construction of detailed population health profiles for every county in the US (University of Wisconsin Population Health Institute, 2013).

The County Health Rankings are based on a model of population health that attempts to account for the many factors that influence health: physical environment, social and economic factors, clinical care, and health behaviors. Together, these factors contribute to overall health outcomes (University of Wisconsin Population Health Institute, 2013). For this exploratory analysis we elected to use five measures of 'public health' encompassing indicators of both health factors and health outcomes, tied closely to diet and nutrition.

Health Factors

- Percent of Adults Obese
- Percent of Adult Diabetic

Health Outcomes

- Low Birth Weight (%)
- Years of Potential Life Lost (Premature Death)
- Percent Fair/Poor Health

$\frac{dy}{dX} = \beta + \rho W(I - \rho W)^{-1}\beta$. This decomposes the total effect of *X* on *y* into two additive parts: the direct effect β and the indirect effect $\rho W(I - \rho W)^{-1}\beta$. The direct effect captures the marginal impact of a change in *X* on the dependent variable in the absence of spatial effects. When $\rho \neq 0$, the indirect effect captures the impact of a marginal change in *X* on *y* due to neighborhood spatial effects.

The measure years of potential life lost (YPLL) attempts to quantify the number of years of life lost due to premature death, defined by a standard cutoff age in a population (Vila, et al, 2006). Heart disease, cancer, stroke, and diabetes, are among the top ten leading causes of death in the US (CDC, 2012). Danaei and colleagues (2009) further substantiate the relative risk of death attributable to chronic disease via estimates suggesting that a number of modifiable risk factors were found to be directly attributable to cardiovascular disease (low fruit and vegetable intake), cancer (overweight-obesity, low fruit and vegetable intake), and diabetes (overweight-obesity) death in both males and females.

Low birth weight is an indicator of current and future morbidity, as well as premature mortality risk, serving as both a maternal and infant health indicator. With regards to maternal health, low birth weight can serve as a proxy for maternal health risk, accounting for both environmental risk as well as modifiable health behaviors. Bailey and colleagues (2007) showed that low birth weight was associated with suboptimal nutrition and maternal overweight. Additional studies have shown that low birth weight and weight status interact later in life leading to increased risk for cardiovascular disease (Rich-Edwards, et al, 2005, Irving, et al, 2000). Percent of the population reporting fair/poor health is a self-reported indicator of overall quality of life. Compared to those with normal body-mass-index, overweight and obese adults were more likely to report their health as fair or poor (Mokdad, et al, 2001).

Higher values of each of these metrics in the public health index are associated with poorer overall levels of health. One of the limitations to the public health data is that the data are not available for all counties for every year. This means that data values may be missing for smaller, more rural counties. The selection of these particular metrics could be viewed as arbitrary as minimizing the problem of missing data was a consideration. Given the multifaceted influences on health outcomes, and dietary behavior, we then constructed indices for our control metrics: demographics, access to health care, and access to food (other than local foods). The selection of these components is in line with the County Health Rankings Framework.

Measuring Public Health In the vast food systems literature there is significant variation in terms of how local foods are defined. This has led to difficulties in both defining and measuring local food systems (Martinez et al 2010). Durham, et al., (2009), for example, found that many consumers disagree that food produced beyond a 100-mile designation could be considered local foods. In a study of food retailers Dunne, et al. (2011) found that grocers' perceptions of local food varied significantly from one another. Martinez and his colleagues (2010) find that opinions of what defines local also varied by the agricultural product being considered. In our review of existing literature we found that local foods is characterized: from the consumer or intermediated consumer perspective (Dunne, 2010, Zapeda, 2006), in terms of proximity- distance, drive time, food-miles (Dunne, 2010, Darby 2008, King, 2010, Zapeda, 2006), by geo-political boundaries such as states (Darby, 2008), by ownership structure (local or non local) of farm (Low, 2011), relationship to place (Marsden, 2000), production techniques used, marketing channels used (Low, 2011), size/scale, (Low, 2011), products grown, quality relationships /supply chain (Marsden, 2000, King, 2010), or integration of the related supply chain (Marsden, 2000).

As described in our literature review, these factors are consistent with a food environment model that considers the following characteristics of agriculture as one component of the overall food environment. These data are drawn from the USDA Food Environment Atlas and the USDA 2007 Census of Agriculture.

Local Food Characteristics

- Number of Farms with Sales Below $100K per 1K Persons
- Number of Vegetables Farms per 1K Persons
- Number of Orchard Farms per 1K Persons
- Number of Fruit, Nut or Berry Farms per 1K Persons
- Number of Organic Farms per 1K Persons
- Number of Farms with Value Added Activities per 1K Persons
- Number of CSA Farms per 1K Persons
- Number of Orchard, Fruit, Vegetable and Berry Farms per 1K Persons
- Direct Sales for Human Consumption per Capita
- Number of Farmers Markets per 1K Persons

Low and Vogel (2011) found that of all farm selling local foods, local food sales account for 65 percent of sales for fruit, vegetable and nut farms on average and only 37 percent for livestock farms. Vegetable fruit and nut farms also accounted for 40 percent of all farmers using direct to consumer marketing channels exclusively and 60% of all farms using for direct to consumer and intermediated marketing channels. While the study additionally notes farms participating in local (direct or intermediated markets) operate fewer acres and grow higher value commodities, this metric was sufficient to represent the overall profile of these farms in our index.

The “Number of Farms with Direct Sales per 1K Population 2007” and “Sales Per Capita, Direct Sales 2007” metrics represent the number and sales of farms in a county that sell directly to consumers including sales from roadside stands, farmers markets, pick-your-own, door-to-door, among others. It does not include sales of craft items or processed products, such as jellies, sausages, and hams. It is important to recognize that while farms with direct sales may be located in a particular county; their primary market area may be outside of the county.

The measures of "Number of Orchard, Fruit, Vegetable and Berry Farms per 1K Population 2007” are data from the US Census of agriculture based on types of products produced by the farm. Low and Vogel (2011) found that of all farm selling local foods, local food sales account for 65% of sales for fruit, vegetable and nut farms on average and only 37% for livestock farms. Vegetable fruit and nut farms also accounted for 40% of all farmers using direct to consumer marketing channels exclusively and 60% of all farms using for direct to consumer and intermediated marketing channels. While the study additionally notes farms participating in local (direct or intermediated markets) operate fewer acres and grow higher value commodities, this metric was sufficient to represent the overall profile of these farms in our index.

The “Number Farmers' Markets per 1K Population” is anther metric of markets in the food environment and is compiled by the Agricultural marketing Service. A farmer's market is a retail outlet in which two or more vendors sell agricultural products directly to customers through a common marketing channel and at least 51 percent of retail sales are direct to consumers. As mentioned before, farmers markets has become the “face” of the local foods movement. A complement to farmers markets are community support farms (CSAs) where consumers buy shares of a farms products which can be harvested by the consumer at the farm themselves or take delivery of products at a predetermined location. Many farms that are part of a local foods system also tend to be organic. While there is a debate within the industry as to whether or not USDA organic certification is a good thing or not and not all organic farms are part of the local foods system, we suggest that organic operations tend to a common characteristics of farms producing for the local foods market. Low and Vogel (2011) also found that the predominance of farms that sell for direct human consumption, whether that is through farmers markets, CSAs, or other local outlets tend to be of modest size. Thus we include the “Number of Farms with Sales less than $100K per 1K Population” to reflect the tendency of these farms to be of smaller size. If there is a higher concentration of these smaller farms, the likelihood of there being a stronger local foods oriented market is higher. Our final metric to be included in the local foods index is “Number of Farms with Value Added Production per 1K Population”. Many farmers that sell into the local foods markets have modest value added production activities associated with their farms ranging from jellies, sausages and prepared meats to dried fruits and pickled vegetables. Unfortunately, the Census of Agriculture reports out a simple “yes/no” as to whether or not value added production is present on the farm, scale of that production, if present, is not reported.

The results of the principal component analysis (based on the correlation matrix) are provided in Table 1. Of the five different health metrics, the adult diabetic rate comes in the highest (eigenvector weight of 0.4889) and low birth weight comes in the lowest (eigenvector weight of 0.3900). As such one could conclude that many of these individual health metrics tend to move in unison with no one metric dominating. The final principal component index accounts for or explains 63.66 percent of the variation in the correlation matrix of the individual metrics. By construction, higher values of our health index are associated with lower levels of overall health. This is important in interpreting the statistical modeling results below.

The results for the local foods index are also provided in Table 1. Because we introduce more individual metrics into the local foods index than the health index it is not surprising that the performance of the index appears weaker. In essence, the greater the number of metrics entered into a principal component the greater the potential overall variation that the index is required to explain. As such the lower variation explained (33.38 percent) is not unexpected. Based on the eigenvector weighting, the number of orchards, fruit, vegetable and berry farms per 1,000 persons tends to contribute the most to the final index. The three traditional metrics of local foods, CSA and farmers markets concentration and direct sales for human consumption appear to be less important in our measure. Indeed, the “face” of local foods, farmers markets, has the lowest eigenvector weight (0.0850).

A simple mapping and cluster analysis (Getis-Ord Gi*) of the nonmetropolitan or rural focused health and local foods indices (Maps 1 and 2, respectively) suggests that there are some unique spatial patterns to the data. For the health index the highest values of the index (poor health) appear to be in the south-eastern U.S. and in small pockets of the Great Plains and southwestern U.S. These latter two appear to coincide with the location of Native American reservations. The spatial clustering analysis (i.e., Getis-Ord Gi*) suggests that there is a strong "hot-spot" of poor public health throughout the southern states through the traditional Appalachian region. This pattern is not unique to our index and its consistency with other ecological studies of public health lends some credibility to our index. The simple mapping of our local food index (Map 2a) is not as easy to interpret, but the spatial clustering analysis (Map 2b) reveals several patterns. There appears to be several hot spots of local foods related activities in the Pacific Northwest, parts of the Upper Midwest, Northern New England, parts of Oklahoma/Texas as well as New Mexico/Arizona and southern Florida. Perhaps more interesting is the cluster of little local foods related activity as we have defined it in much of the southern states and Appalachia. A simple overlapping of the health and local foods indices clusters suggest that there is a strong pattern in the southern and Appalachia region: poor levels of health and limited local foods activity. In addition to the insights gained by the mapping and spatial cluster analysis, the "easily" identifiable hot and cold spots suggest that the error structure of the model may indeed be heteroscedastic. This is yet another justification for using the more general Bayesian heteroscedastic estimator outlined in eq(8).[5]

Empirical Results

Recall that our analysis could be considered a two-step process: step one is to use the Spatial Bayesian Model Averaging estimator to determine the set of control variables and step two is to introduce the local foods index into the health model and estimate the parameters. For this paper we elect to discuss the results on the full health index. We estimated the full models for each of the individual elements that make up the health index, and we include some of those results in an appendix, a full discussion of all the health metrics is beyond this scope of this particular paper.

Of the 50 potential control variables that are introduced into the SBMA estimator 15 are identified as being most consistent with the underlying data generating process (Table 2):

- Percent of Population African American
- Percent of Population American Indian/ Alaskan Native
- Percent of Population Hispanic
- Percent of Children Eligible for Free lunch
- Percent of Population Under Age 18
- Percent of those Age 25+ with an Associate Degree

[5] One potential short coming of using a heteroscedastic error structure in the second step of our analysis is that the Spatial Bayesian Model Averaging (SBMA) assumes a homoscedastic error structure. Development of a heteroscedastic SBMA estimator is far beyond the scope of this research.

- Percent of those Age 25+ with a Bachelor Degree
- Percent of those Age 25+ with a Graduate or Professional Degree
- Percent Change in Population 2000 to 2010
- Per Capita Income from Income Maintenance Programs
- Per Capita Unemployment Insurance Benefits
- Per Capita Income from Retirement and Other Sources
- WIC Redemptions/WIC-Authorized Stores/1,000 Pop
- Number of Elderly Care Est/1,000 Pop
- Social Capital (Rupasingha and Goetz)

The selection of these variables to help explain the variation in our health index provides valuable insights into the underlying factors associated with public health. Notice that the overall poverty rate, a popular control variable in ecological studies of public health, does not help us in understanding our health index. Rather, two other measures of poverty are found to be more robust: percent of children eligible for free lunch and per capita income from income maintenance programs. This suggests that the overall poverty rate may be too gross of a measure to capture the subtleties between poverty and health. Also note that higher levels of education, as opposed to lower levels of education, are more consistent with the underlying data generating process.

Now turn attention to the second step of the analysis, the estimation of the final health model with local foods included in the analysis (Table 3). We estimate two version of the model, one with the control variables identified via the SBMA process and local foods, and a second with the control variables, local foods, and local foods squared. We introduce the squared local foods term to examine any potential non-linearities in the local foods and health relationship. We also report out the overall Bayesian posterior estimates along with the direct, indirect and total effects (see footnote 4). Consider the simple linear local food results then the results with local foods squared. The spatial parameter ρ is significant in both the linear and non-linear (local foods squared) models and the R^2 is above 0.84 for both models. For a cross sectional analysis, an R^2 suggesting that the model explains 84 percent of the variance in our public health measure is very high lending further confidence to our results.

Higher concentrations of African Americans and Native Americas are associated with poorer levels of public health, but higher share of Latinos (Hispanics) is associated with better levels of public health. This apparent inconsistency has been widely studied (e.g., Abriado-Lanza, Chao and Florez 2005; Viruell-Fuentes and Schulz 2009). A common hypothesis explaining this pattern is the strong family and social ties within the Latino community.[6] The higher the rate of child free lunch eligibility the lower the overall level of public health which is as expected. A younger population is also associated with lower overall levels of health but this relationship is statistical weak despite the SBMA results. Higher levels of

[6] Perhaps a more interesting "paradox" is the significant difference between recent Latino migrants and those that have been in the U.S. for a longer period of time: more recent migrants tend to have lower mortality than those that have been in the U.S. longer.

education across the board are associated with better levels of public health. Counties that are experiencing population growth also tend to have better levels of public health. This could be that people are drawn to healthier communities. Consistent with the free lunch eligibility result immediately above, the higher the dependency on income maintenance programs, the lower the level of public health. These two results taken together is consistent with the poverty and poor health hypothesis. Higher dependency on unemployment insurance payments, expectedly, is associated with higher levels of public health. It may be that this variable is more reflective of the Great Recession and perhaps long-term unemployment would be a better measure. Dependency on retirement income does not appear to be statistically significant in the full model. Access to WIC redemption and authorized stores appears to improve public health (this could be interpreted within the context of food deserts) and a higher concentration of elderly care establishments is also associated with higher levels of health. Finally the Rupasingha and Goetz social capital measure is also associated with higher levels of public health. This latter result is as expected.

We notice that across the board, the direct, indirect and total effects complement each other. Given the rural nature of our analysis, the spatial spillovers are particularly important. Unlike many metropolitan counties that could be "self-contained" rural residents often must travel outside of their home counties for employment, access to health care, and making major purchases. This consistency in direct and indirect results suggests that these factors not only influence within county (direct) but also across county (indirect) health. When comparing the results on the control variables for the linear and non-linear (local foods squared) models there is remarkable stability in results. The strong R^2, consistency of results from a direct and indirect perspective, and across the linear and non-linear specification lends confidence to our overall results.

The focal point results for our analysis is on local foods and we find that higher concentrations of local foods related activities is associated with higher levels of public health. But the coefficient on the local foods squared term is positive and statistically significant suggesting that as the concentration of local foods related activity becomes larger, the positive impact on health becomes weaker. Using the posterior estimates the numerical minimum of that convex relationship is about 5.8 which is much higher than the mean value of the local food index (mean=0 variance=3.3). Of the 1,518 counties in the analysis, only 26 counties have a local food index greater than 5.8. Regardless of where the approximate location of the minimum of the convex relationship, the policy implications are clear: higher concentrations of local foods related activities, the higher the level of public health, but that relationship is declining in the scale or intensity of local foods.

Conclusions and Implications

In this study we have explored the relationship between local foods related activities and public health across rural America. We follow the lead of Salois (2012) and use county level (nonmetropolitan in our case) data to examine local foods and health from an ecological perspective. Unlike Salis we use principal component analysis to construct indices of both public health and local foods related activities. In addition, we acknowledge the problem of model uncertainty in estimating ecological models of public health. Model uncertainty is said to exist if the theory is unclear on what should be controlled for in statistical analysis and/or there are numerous ways to measure a particular characteristic. Model uncertainty can also exist if theory tells us "everything matters". We address model uncertainty by using a Bayesian Model Averaging approach that has been specifically tailored to take into consideration spatial dependency in the data.

Of the 50 potential control variables, there are 15 that are identified via the Spatial Bayesian Model Averaging (SBMA) method as most consistent with the underlying data generating process. We find that at least one variable for each of the five broad classification of control variables (demographics, economics, access to health care, access to foods and social capital) is an important determinant of public health. We find that using the SBMA gives us unique insights into factors that influence public health. For example, overall poverty rates are inferior to more subtle measures such as percent of children eligible for free school means and levels of higher education are more robust then measures of lower education.

Most important we find that higher concentrations of local foods related activities are associated with higher levels of public health. We also find that the relationship between local foods and public health is non-linear and follows a convex relationship: as local food concentrations increase the positive impact on public health diminishes. The policy implication suggests that if public health is a primary targeted outcome, investing limited public resources may have the largest impacts in rural regions with the lowest levels of local food activities. Investing these same resources in rural communities that already have viable local foods related activity will have less of an impact on public health.

There is one major short-coming to this work: the direction of causation between local foods and public health is not clear. Does access to local foods related activity "cause" healthier outcomes or do people who tend to be healthier demand higher levels of local foods? The analysis presented in this study cannot provide a definitive answer to that question. At best we can conclude that a relationship does exist and is in need of further exploration.

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Table 1: Health and Local Foods Indices (Principal Components)

	Weights
Low Birth Weight (%)	0.3900
Percent of Adults Obese	0.4344
% Adult diabetic	0.4889
Years of Potential Life Lost (Premature Death)	0.4627
Percent Fair/Poor Health	0.4540
Variance Explained	0.6366
Number of Farms with Sales Below $100K per 1K Persons	0.2179
Number of Vegetables Farms per 1K Persons	0.2601
Number of Orchard Farms per 1K Persons	0.4244
Number of Fruit, Nut or Berry Farms per 1K Persons	0.4295
Number of Organic Farms per 1K Persons	0.2857
Number of Farms with Value Added Activities per 1K Persons	0.2449
Number of CSA Farms per 1K Persons	0.2534
Number of Orchard, Fruit, Vegetable and Berry Farms per 1K Persons	0.4849
Direct Sales for Human Consumption per Capita	0.2686
Number of Farmers Markets per 1K Persons	0.0850
Variance Explained	0.3338

Figure 1a: Health Index

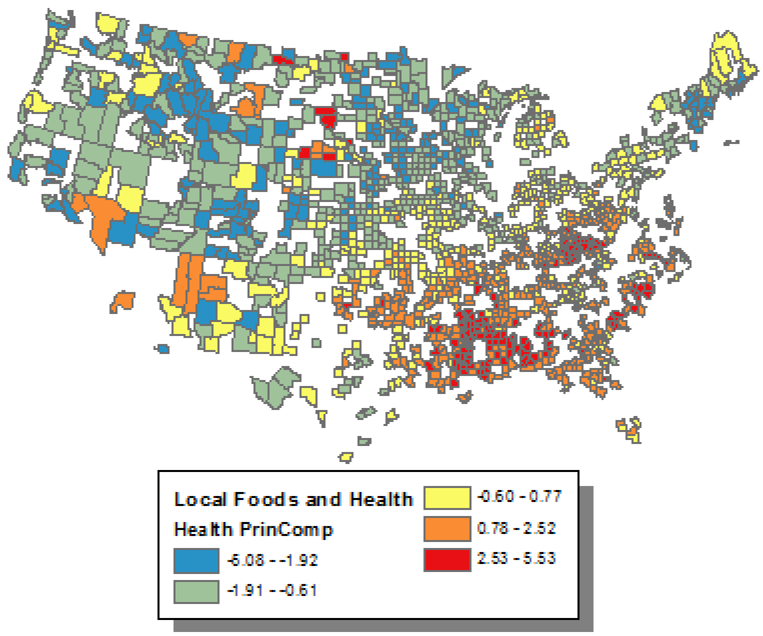

Figure 1b: Health Index Getis-Ord Gi*

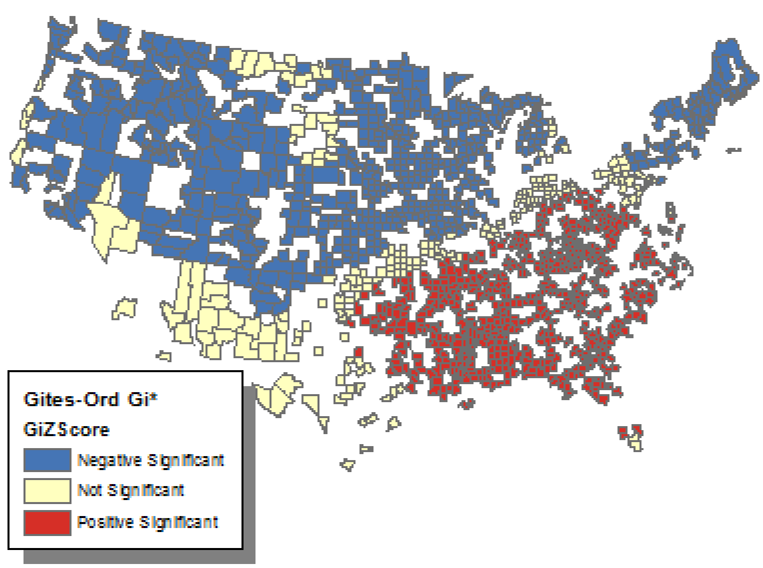

Figure 2a: Local Foods Index

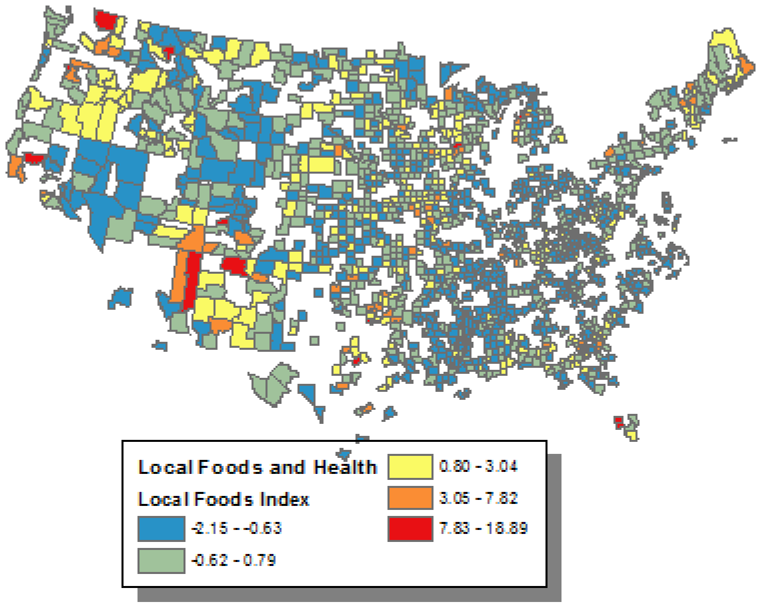

Figure 2b: Local Foods Index Getis-Ord Gi*

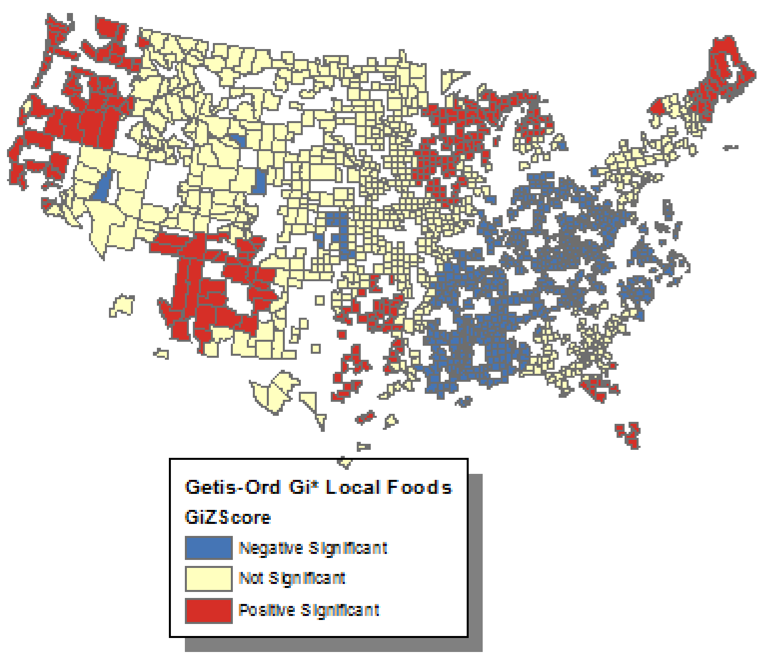

Table 2: Spatial Bayesian Modeling Average Health Index

MCMC draws = 100,000	m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	Probs
Percent of Population African American	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9584***
Percent of Population American Indian/ Alaskan Native	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9795***
Percent of Population Asian	0	0	0	0	0	0	0	0	0	0	0.1641
Percent of Population Hispanic	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9599***
Percent of Population Not Proficient in English	0	0	0	0	0	0	0	0	0	0	0.0472
Percent of the Population Rural	0	0	0	0	0	0	0	0	0	0	0.1765
Percent of Uninsured Adults	1	0	1	1	1	0	1	0	1	0	0.3738
Percent of Uninsured Children	1	0	1	1	1	0	1	0	1	0	0.4564
Percent of Children Eligible for Free lunch	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9014***
Unemployed Rate	0	0	0	0	0	0	0	0	0	0	0.0930
Percent of Households Single-Parent	0	0	0	0	0	0	0	0	0	0	0.0369
Median Age	0	0	0	0	0	0	0	0	0	0	0.0388
Percent of Population Under Age 18	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9431***
Percent of Population Over Age 65	0	0	0	0	0	0	0	0	0	0	0.1687
Percent of those Age 25+ with Less than a 9th Grade Education	0	0	0	0	0	0	0	0	0	0	0.0360
Percent of those Age 25+ wit Some High School, No Degree	0	0	0	0	0	0	0	0	0	1	0.5000
Percent of those Age 25+ with Some College, No Degree	0	0	0	0	0	0	0	0	0	0	0.0366
Percent of those Age 25+ with an Associate Degree	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.7856***
Percent of those Age 25+ with a Bachelor Degree	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9600***
Percent of those Age 25+ with a Graduate or Professional Degree	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.6646***
Poverty Rate for those Under Age 18	0	0	0	0	0	0	0	0	0	0	0.0467
Poverty Rate	0	0	0	0	0	0	0	0	0	0	0.0489
Median Household Inocme	0	0	0	1	0	0	1	0	0	0	0.1085
Percent Change in Population 2000 to 2010	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.8121***
Population Density	0	1	0	1	0	1	0	1	0	0	0.2912
GINI Coefficient of Income Equality	0	0	0	0	0	0	0	0	0	0	0.0400
Per Capita Income from Income Maintenance Programs	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9578***
Per Capita Unemployment Insurance Benefits	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9211***
Per Capita Income from Retirement and Other Sources	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9599***
Percent Change in Employment 2000 to 2010	0	0	0	0	0	0	0	0	0	0	0.0442
Population -- Employment Ratio	1	0	0	0	0	1	0	0	0	0	0.3008
2010 Census Population	0	0	0	0	0	0	0	0	0	0	0.0629
Percemt of Households Low Income & Low Access to Store	0	1	1	0	1	0	0	0	0	0	0.1989
Percent of Households, No Car & Low Access to Store	0	0	0	0	0	0	0	0	0	0	0.0520
WIC-Authorized Stores/1,000 pop, 2011	0	0	0	0	0	0	0	0	0	0	0.0356
WIC Redemptions/WIC-Authorized Stores/1,000 Pop	***1***	***1***	***1***	***1***	***0***	***1***	***1***	***1***	***1***	***1***	***0.3751***
Number of Health Care and Social Assistance Establishment	0	0	0	0	0	0	0	0	0	0	0.0538
Number of General Hospitals	0	0	0	0	0	0	0	0	0	0	0.0395
Number of Primary Care Physicians	0	1	0	1	0	1	0	1	0	0	0.1962
Number of Health Care and Social Assistance Est/1,000 Pop	0	0	0	0	0	1	0	0	0	0	0.1163
Number of General Hospitals/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0519
Number of Primary Care Physicians/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0480
Number of Individual and Family Support Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0320
Number of Vocational and Rehabilitation Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0385
Number of Child Care Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0310
Number of Elderly Care Est/1,000 Pop	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9249***
Number of Youth Service Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0552
Number of Community Food Service Est/1,000 Pop	1	1	1	1	1	0	1	1	1	1	0.6558
Number of Community Housing Service Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0393
Social Capital (Rupasingha and Goetz)	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9337***

Table 3: Results Health Index

MCMC draws = 100000	Posterior Estimates	Direct	Indirect	Total
Percent of Population African American	0.0089	0.0092	0.0062	0.0154
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population American Indian/ Alaskan Native	0.0234	0.0243	0.0163	0.0406
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Hispanic	-0.0174	-0.0180	-0.0121	-0.0302
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Children Eligible for Free lunch	0.0134	0.0139	0.0093	0.0232
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Under Age 18	0.0055	0.0057	0.0039	0.0096
	(0.0964)	(0.1928)	(0.1964)	(0.1935)
Percent of those Age 25+ with an Associate Degree	-0.0374	-0.0388	-0.0261	-0.0649
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of those Age 25+ with a Bachelor Degree	-0.0664	-0.0689	-0.0463	-0.1153
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of those Age 25+ with a Graduate or Professional Degree	-0.0494	-0.0512	-0.0344	-0.0856
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent Change in Population 2000 to 2010	-0.0119	-0.0123	-0.0083	-0.0206
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Per Capita Income from Income Maintenance Programs	0.0009	0.0010	0.0007	0.0016
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Per Capita Unemployment Insurance Benefits	-0.0005	-0.0005	-0.0003	-0.0009
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Per Capita Income from Retirement and Other Sources	0.0001	0.0001	0.0001	0.0002
	(0.4779)	(0.9562)	(0.9562)	(0.9562)
WIC Redemptions/WIC-Authorized Stores/1,000 Pop	-0.3944	-0.4091	-0.2750	-0.6841
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Number of Elderly Care Est/1,000 Pop	-0.5236	-0.5431	-0.3652	-0.9083
	(0.0018)	(0.0032)	(0.0042)	(0.0033)
Social Capital (Rupasingha and Goetz)	-0.0588	-0.0610	-0.0410	-0.1021
	(0.0047)	(0.0100)	(0.0116)	(0.0102)
Local Food Index	***-0.0472***	***-0.0489***	***-0.0329***	***-0.0818***
	(0.0001)	***(0.0001)***	***(0.0001)***	***(0.0001)***
Local Foods Index Square	---	---	---	---
Rho	0.4229	---	---	---
	(0.0001)			
R^2	0.8455	---	---	---

Marginal significance value in parentheses.

Table 3 (continued): Results Health Index

MCMC draws = 100000	Posterior Estimates	Direct	Indirect	Total
Percent of Population African American	0.0088	0.0091	0.0059	0.0150
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population American Indian/ Alaskan Native	0.0227	0.0235	0.0152	0.0388
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Hispanic	-0.0184	-0.0191	-0.0124	-0.0315
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Children Eligible for Free lunch	0.0141	0.0146	0.0095	0.0241
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Under Age 18	0.0049	0.0051	0.0033	0.0084
	(0.1232)	(0.2466)	(0.2500)	(0.2472)
Percent of those Age 25+ with an Associate Degree	-0.0378	-0.0392	-0.0254	-0.0645
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of those Age 25+ with a Bachelor Degree	-0.0684	-0.0708	-0.0459	-0.1168
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of those Age 25+ with a Graduate or Professional Degree	-0.0502	-0.0520	-0.0337	-0.0858
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent Change in Population 2000 to 2010	-0.0119	-0.0124	-0.0080	-0.0204
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Per Capita Income from Income Maintenance Programs	0.0009	0.0010	0.0006	0.0016
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Per Capita Unemployment Insurance Benefits	-0.0005	-0.0005	-0.0004	-0.0009
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Per Capita Income from Retirement and Other Sources	0.0003	0.0003	0.0002	0.0005
	(0.4363)	(0.8715)	(0.8714)	(0.8714)
WIC Redemptions/WIC-Authorized Stores/1,000 Pop	-0.3729	-0.3861	-0.2503	-0.6364
	(0.0001)	(0.0002)	(0.0004)	(0.0003)
Number of Elderly Care Est/1,000 Pop	-0.5153	-0.5336	-0.3460	-0.8797
	(0.0020)	(0.0039)	(0.0050)	(0.0041)
Social Capital (Rupasingha and Goetz)	-0.0528	-0.0547	-0.0354	-0.0901
	(0.0090)	(0.0201)	(0.0224)	(0.0204)
Local Food Index	***-0.0941***	***-0.0974***	***-0.0632***	***-0.1606***
	(0.0001)	***(0.0001)***	***(0.0001)***	***(0.0001)***
Local Foods Index Square	***0.0081***	***0.0084***	***0.0054***	***0.0138***
	(0.0001)	***(0.0001)***	***(0.0001)***	***(0.0001)***
Rho	0.4135	---	---	---
	(0.0001)			
R^2	0.8480	---	---	---

Marginal significance value in parentheses.

Appendices: Results for Selected Individual Components of the Health Index

Table A1: Spatial Bayesian Modeling Average Percent Adults Obese

MCMC draws = 100000	m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	Probs
Percent of Population African American	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9416***
Percent of Population American Indian/ Alaskan Native	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9404***
Percent of Population Asian	0	0	0	0	0	0	0	0	0	0	0.0283
Percent of Population Hispanic	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9317***
Percent of Population Not Proficient in English	1	1	1	1	1	1	1	1	1	1	0.6952
Percent of the Population Rural	0	0	0	0	0	0	0	0	0	0	0.0287
Percent of Uninsured Adults	0	0	0	0	0	0	0	0	0	0	0.0363
Percent of Uninsured Children	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9416***
Percent of Children Eligible for Free lunch	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.6824***
Unemployed Rate	0	0	0	0	0	0	0	1	1	0	0.3968
Percent of Households Single-Parent	0	0	0	0	0	0	0	0	0	0	0.0265
Median Age	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9410***
Percent of Population Under Age 18	0	0	0	0	0	0	0	0	0	0	0.0376
Percent of Population Over Age 65	0	0	0	0	0	0	0	0	0	0	0.0433
Percent of those Age 25+ with Less than a 9th Grade Educati	0	0	0	0	0	0	0	0	0	0	0.0297
Percent of those Age 25+ wit Some High School, No Degree	0	1	1	1	0	1	1	1	1	1	0.4688
Percent of those Age 25+ with Some College, No Degree	0	0	0	0	0	0	0	0	0	0	0.0336
Percent of those Age 25+ with an Associate Degree	0	0	0	0	0	0	0	0	0	0	0.0605
Percent of those Age 25+ with a Bachelor Degree	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9708***
Percent of those Age 25+ with a Graduate or Professional De	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9421***
Poverty Rate for those Under Age 18	0	0	0	1	1	1	0	0	0	0	0.1256
Poverty Rate	0	0	0	0	0	0	0	0	0	0	0.0469
Median Household Inocme	0	0	0	0	0	0	0	0	0	0	0.0409
Percent Change in Population 2000 to 2010	1	1	0	0	1	1	1	0	0	0	0.3548
Population Density	0	0	0	0	0	0	0	0	0	0	0.0575
GINI Coefficient of Income Equality	0	0	0	0	0	0	0	0	0	0	0.0305
Per Capita Income from Income Maintenance Programs	0	0	0	1	0	0	0	0	0	0	0.1057
Per Capita Unemployment Insurance Benefits	1	1	1	1	1	1	1	0	0	1	0.5647
Per Capita Income from Retirement and Other Sources	0	1	1	1	1	1	0	1	1	1	0.5743
Percent Change in Employment 2000 to 2010	0	0	0	0	0	0	0	0	0	0	0.0333
Population -- Employment Ratio	0	0	0	0	0	0	0	0	0	0	0.0345
2010 Census Population	0	0	0	0	0	0	0	0	0	0	0.0587
Percemt of Households Low Income & Low Access to Store	0	0	0	0	0	0	0	0	0	0	0.0244
Percent of Households, No Car & Low Access to Store	0	0	0	0	0	0	0	0	0	0	0.0293
WIC-Authorized Stores/1,000 pop, 2011	0	0	0	0	0	0	0	0	0	0	0.0319
WIC Redemptions/WIC-Authorized Stores/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0276
Number of Health Care and Social Assistance Establishment	0	0	0	0	0	0	0	0	0	0	0.0352
Number of General Hospitals	0	0	0	0	0	0	0	0	0	0	0.0384
Number of Primary Care Physicians	0	0	0	0	0	0	0	0	0	0	0.0350
Number of Health Care and Social Assistance Est/1,000 Pop	0	1	1	0	0	0	0	1	0	0	0.1001
Number of General Hospitals/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0413
Number of Primary Care Physicians/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0541
Number of Individual and Family Support Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0347
Number of Vocational and Rehabilitation Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0269
Number of Child Care Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0310
Number of Elderly Care Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0259
Number of Youth Service Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0313
Number of Community Food Service Est/1,000 Pop	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.8924***
Number of Community Housing Service Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0227
Social Capital (Rupasingha and Goetz)	0	0	0	0	0	0	0	0	0	0	0.0222

Table A2: Results Percent Adults Obese

MCMC draws = 100000	Posterior Estimates	Direct	Indirect	Total
Percent of Population African American	0.0241	0.0297	0.0976	0.1273
	(0.0001)	(0.0003)	(0.0006)	(0.0005)
Percent of Population American Indian/ Alaskan Native	0.1052	0.1297	0.4262	0.5559
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Hispanic	0.0108	0.0134	0.0439	0.0573
	(0.0860)	(0.1727)	(0.1780)	(0.1760)
Percent of Uninsured Children	-0.0728	-0.0898	-0.2948	-0.3846
	(0.0002)	(0.0003)	(0.0007)	(0.0006)
Percent of Children Eligible for Free lunch	0.0405	0.0500	0.1642	0.2142
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Median Age	0.1260	0.1553	0.5104	0.6658
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of those Age 25+ with a Bachelor Degree	-0.0508	-0.0626	-0.2057	-0.2683
	(0.0188)	(0.0373)	(0.0423)	(0.0405)
Percent of those Age 25+ with a Graduate or Professional De	-0.0895	-0.1103	-0.3627	-0.4730
	(0.0070)	(0.0133)	(0.0168)	(0.0155)
Number of Community Food Service Est/1,000 Pop	0.8853	1.0916	3.5885	4.6801
	(0.0924)	(0.1897)	(0.1954)	(0.1933)
Local Food Index	***-0.1231***	***-0.1518***	***-0.4989***	***-0.6507***
	(0.0010)	***(0.0018)***	***(0.0030)***	***(0.0025)***
Local Foods Index Square				
Rho	0.8096			
	(0.0001)			
R^2	0.2050			

Marginal significance value in parentheses.

Table A2 (continued): Results Percent Adults Obese

MCMC draws = 100000	Posterior Estimates	Direct	Indirect	Total
Percent of Population African American	0.0234	0.0287	0.0948	0.1234
	(0.0002)	(0.0004)	(0.0008)	(0.0006)
Percent of Population American Indian/ Alaskan Native	0.1036	0.1273	0.4204	0.5476
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Hispanic	0.0097	0.0119	0.0392	0.0510
	(0.1134)	(0.2292)	(0.2340)	(0.2322)
Percent of Uninsured Children	-0.0709	-0.0871	-0.2875	-0.3746
	(0.0001)	(0.0005)	(0.0010)	(0.0008)
Percent of Children Eligible for Free lunch	0.0406	0.0499	0.1647	0.2146
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Median Age	0.1255	0.1542	0.5093	0.6635
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of those Age 25+ with a Bachelor Degree	-0.0511	-0.0627	-0.2072	-0.2699
	(0.0179)	(0.0361)	(0.0408)	(0.0390)
Percent of those Age 25+ with a Graduate or Professional De	-0.0935	-0.1149	-0.3797	-0.4945
	(0.0045)	(0.0099)	(0.0129)	(0.0118)
Number of Community Food Service Est/1,000 Pop	0.9412	1.1562	3.8203	4.9765
	(0.0787)	(0.1628)	(0.1690)	(0.1668)
Local Food Index	***-0.1852***	***-0.2275***	***-0.7516***	***-0.9790***
	(0.0007)	***(0.0014)***	***(0.0025)***	***(0.0020)***
Local Foods Index Square	***0.0124***	***0.0152***	***0.0503***	***0.0655***
	(0.0678)	***(0.1342)***	***(0.1404)***	***(0.1381)***
Rho	0.8096			
	(0.0001)			
R^2	0.2019			

Marginal significance value in parentheses.

Table A3: Spatial Bayesian Modeling Average Years of Potential Life Lost (YPLL)

MCMC draws = 100000	m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	Probs
Percent of Population African American	0	0	0	0	0	0	0	0	0	0	0.0328
Percent of Population American Indian/ Alaskan Native	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9741***
Percent of Population Asian	0	0	0	0	0	0	0	0	0	0	0.0346
Percent of Population Hispanic	1	1	0	1	0	1	1	0	0	0	0.1620
Percent of Population Not Proficient in English	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9413***
Percent of the Population Rural	0	0	0	0	0	0	0	0	0	0	0.0359
Percent of Uninsured Adults	1	0	1	0	1	1	1	0	0	1	0.3622
Percent of Uninsured Children	0	1	0	0	0	0	0	0	0	0	0.0631
Percent of Children Eligible for Free lunch	0	1	0	1	0	1	0	0	1	0	0.2755
Unemployed Rate	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9154***
Percent of Households Single-Parent	0	0	0	0	0	0	0	0	0	0	0.0487
Median Age	0	0	0	0	0	0	0	0	0	0	0.0370
Percent of Population Under Age 18	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9358***
Percent of Population Over Age 65	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.2810***
Percent of those Age 25+ with Less than a 9th Grade Education	1	0	0	0	1	0	0	0	0	0	0.1623
Percent of those Age 25+ wit Some High School, No Degree	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9486***
Percent of those Age 25+ with Some College, No Degree	1	1	1	1	1	1	1	1	1	1	0.8502
Percent of those Age 25+ with an Associate Degree	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9063***
Percent of those Age 25+ with a Bachelor Degree	0	0	0	0	0	0	0	0	0	0	0.1015
Percent of those Age 25+ with a Graduate or Professional Degree	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.5772***
Poverty Rate for those Under Age 18	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.8904***
Poverty Rate	0	0	0	0	0	0	0	0	0	0	0.0784
Median Household Inocme	0	0	0	0	0	0	0	0	0	0	0.0946
Percent Change in Population 2000 to 2010	0	0	1	0	0	0	0	0	0	0	0.1586
Population Density	0	0	0	0	0	0	0	0	0	0	0.0345
GINI Coefficient of Income Equality	0	0	0	0	0	0	0	0	0	0	0.0292
Per Capita Income from Income Maintenance Programs	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9222***
Per Capita Unemployment Insurance Benefits	0	0	0	0	0	0	0	0	0	0	0.0774
Per Capita Income from Retirement and Other Sources	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9483***
Percent Change in Employment 2000 to 2010	0	0	0	0	0	0	0	0	0	0	0.0487
Population -- Employment Ratio	0	0	0	0	0	0	0	0	0	0	0.0250
2010 Census Population	0	0	0	0	0	0	0	0	0	0	0.0348
Percemt of Households Low Income & Low Access to Store	0	0	0	0	0	0	0	0	0	0	0.0286
Percent of Households, No Car & Low Access to Store	0	0	0	0	0	0	0	0	0	0	0.0233
WIC-Authorized Stores/1,000 pop, 2011	0	0	0	0	0	0	0	0	0	0	0.0354
WIC Redemptions/WIC-Authorized Stores/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0407
Number of Health Care and Social Assistance Establishment	0	0	0	0	0	0	0	0	0	0	0.0313
Number of General Hospitals	0	0	0	0	0	0	0	0	0	0	0.0283
Number of Primary Care Physicians	0	0	0	0	0	0	0	0	0	0	0.0456
Number of Health Care and Social Assistance Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0563
Number of General Hospitals/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0325
Number of Primary Care Physicians/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.1373
Number of Individual and Family Support Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0312
Number of Vocational and Rehabilitation Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0302
Number of Child Care Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0314
Number of Elderly Care Est/1,000 Pop	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.9475***
Number of Youth Service Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0259
Number of Community Food Service Est/1,000 Pop	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***1***	***0.6192***
Number of Community Housing Service Est/1,000 Pop	0	0	0	0	0	0	0	0	0	0	0.0330
Social Capital (Rupasingha and Goetz)	0	0	0	0	0	0	0	0	0	0	0.1246

Table A4: Results Years of Potential Life Lost (YPLL)

MCMC draws = 100000	Posterior Estimates	Direct	Indirect	Total
Percent of Population American Indian/ Alaskan Native	61.8405	63.0939	28.3390	91.4329
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Not Proficient in English	-111.4965	-113.7588	-51.1333	-164.8922
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Unemployed Rate	-62.2273	-63.4899	-28.5368	-92.0266
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Under Age 18	90.1498	91.9783	41.3337	133.3120
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Over Age 65	-43.2414	-44.1175	-19.8105	-63.9279
	(0.0007)	(0.0015)	(0.0024)	(0.0016)
Percent of those Age 25+ wit Some High School, No Degree	100.9891	103.0374	46.3014	149.3388
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of those Age 25+ with an Associate Degree	-68.6750	-70.0671	-31.4756	-101.5427
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of those Age 25+ with a Graduate or Professional De	-56.2013	-57.3412	-25.7684	-83.1096
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Poverty Rate for those Under Age 18	53.7903	54.8811	24.6600	79.5412
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Per Capita Income from Income Maintenance Programs	0.5685	0.5800	0.2608	0.8408
	(0.0002)	(0.0007)	(0.0015)	(0.0008)
Per Capita Income from Retirement and Other Sources	0.3795	0.3872	0.1740	0.5612
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Number of Elderly Care Est/1,000 Pop	-1383.6480	-1411.7070	-634.3096	-2046.0166
	(0.0000)	(0.0001)	(0.0002)	(0.0001)
Number of Community Food Service Est/1,000 Pop	913.5145	932.0518	418.9660	1351.0178
	(0.0025)	(0.0042)	(0.0062)	(0.0044)
Local Food Index	***-37.3333***	***-38.0894***	***-17.0995***	***-55.1888***
	(0.0143)	***(0.0299)***	***(0.0341)***	***(0.0303)***
Local Foods Index Square				
Rho	0.3230			
	(0.0001)			
R^2	0.7061			

Marginal significance value in parentheses.

Table A4 (continue): Results Years of Potential Life Lost (YPLL)

MCMC draws = 100000	Posterior Estimates	Direct	Indirect	Total
Percent of Population American Indian/ Alaskan Native	61.5261	62.7111	27.2146	89.9257
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Not Proficient in English	-121.3490	-123.6880	-53.7020	-177.3900
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Unemployed Rate	-66.4950	-67.7770	-29.4316	-97.2086
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Under Age 18	91.7877	93.5568	40.6194	134.1763
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of Population Over Age 65	-39.5614	-40.3230	-17.4936	-57.8166
	(0.0016)	(0.0035)	(0.0051)	(0.0036)
Percent of those Age 25+ wit Some High School, No Degree	102.2963	104.2679	45.2687	149.5366
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of those Age 25+ with an Associate Degree	-69.4053	-70.7425	-30.7064	-101.4489
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Percent of those Age 25+ with a Graduate or Professional De	-57.8539	-58.9691	-25.6047	-84.5738
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Poverty Rate for those Under Age 18	55.6139	56.6855	24.6068	81.2924
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Per Capita Income from Income Maintenance Programs	0.5695	0.5804	0.2521	0.8326
	(0.0003)	(0.0006)	(0.0014)	(0.0007)
Per Capita Income from Retirement and Other Sources	0.3717	0.3789	0.1645	0.5434
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Number of Elderly Care Est/1,000 Pop	-1380.9500	-1407.5548	-610.9445	-2018.4992
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Number of Community Food Service Est/1,000 Pop	935.2942	953.3353	414.1157	1367.4511
	(0.0020)	(0.0034)	(0.0053)	(0.0036)
Local Food Index	***-86.0945***	***-87.7521***	***-38.0739***	***-125.8260***
	(0.0002)	***(0.0007)***	***(0.0013)***	***(0.0007)***
Local Foods Index Square	***7.1232***	***7.2604***	***3.1510***	***10.4114***
	(0.0046)	***(0.0120)***	***(0.0153)***	***(0.0123)***
Rho	0.3152			
	(0.0001)			
R^2	0.7085			

Marginal significance value in parentheses.