A Spatial Analysis of County-level Obesity Prevalence in Michigan

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Obesity Epidemic

- Obesity and its co-morbidities including diabetes and hypertension are major threats to public health all around the world.
- Globally, in 2008 (WHO, 2010; WFP, 2010);

1.5 billion People with Overweight or Obese **925 million** People in Undernourishment

• Obesity is measured by a Body Mass Index (BMI) which is calculated by dividing one's weight in kilogram by one's height square in meter.

BMI <18.5	18.5 - 24.9	25 - 29.9	30 -	
Underweight	Healthy	Overweight	Obese	

Obesity in the US

- Adults obesity prevalence has doubled in the past two decades; 12% in 1991 → 27% in 2009 (Mokdad et al., 2001; Flegal, 2002; Chou, 2004; CDC, 2010).
- In Michigan, 30.9% (95% CI: 29.6-32.3) of Michiganders were obese in 2009, compared with 22.5% (95% CI: 20.7-24.3) in 2000 (MDCH, 2009).
- It is interesting that there is a substantial variability in obesity prevalence across counties in the US.

Obesity in the US



-		
26	з-	27.7
27	.8 -	29.1
29	2-	30.8
≥3	0.9	

Source: CDC Website (MMWR 58:1259-1263, 2009)

Obesity Rates in Michigan



Created by the author using 2008 NDSS

The Obesity Literature

an individual's BMI or Obesity

Demographic

Age, Dietary Habit, Races, Marital Status, # of Children, Smoking, ...

<u>Socioeconomic</u>

Education, Income, Jobs,...

Environmental

Urban sprawl, Mixed land-use planning, Commute time, Transit use, Accessibility to groceries, Crime, ...

→ Most previous studies have analyzed the association between an individual's obesity status and risk factors.

Why County-level Study?

- 1. There are noticeable health disparities across US counties (Joins et al, 2003; Soobader et al., 2006; Sparks et al, 2010)
- There are only a handful of studies on the county-level obesity prevalence and risk-factors (Amarasinghe et al., 2006; Chen et al., 2009).
- 3. Spatial dependence/autocorelation problems (Anselin, 1988; LeSage, 1998; LeSage & Pace, 2008).
- 4. Recent progresses in spatial modeling
- → This study aims to examine <u>what makes the variability in</u> <u>obesity prevalence among Michigan counties</u> and to discuss subsequent policy implications.

Methodology

• OLS
$$O = \beta X + \varepsilon$$

• SAR
$$\begin{split} O &= \rho WO + X\beta + \epsilon \\ \epsilon &\sim N \left(0, \ \sigma^2 I_n \ \right) \end{split}$$

O: county level obesity prevalence in Michigan

X: a set of independent variables

β: parameters

ε: error term

p: the parameter of the spatially lagged variable

W: a spatial weight matrix

Methodology

• SEM
$$\begin{split} O &= \beta X + \mu \\ \mu &= \lambda W \mu + \epsilon \\ \epsilon &\sim N \left(0, \ \sigma^2 I_n \right) \end{split}$$

• SAC
$$\begin{split} O &= \rho W_1 O + X\beta + \mu \\ \mu &= \lambda W_2 \mu + \epsilon \\ \epsilon &\sim N\left(0, \ \sigma_{\epsilon}^2 I_n \right) \end{split}$$

 λ : the coefficients of spatial errors $W_1 \& W_2$: spatial weight matrices

Methodology

• Data Sources:

(1) Obesity rates: 2008 National Diabetes Surveillance System (NDSS) from CDC

(2) Contextual data: 2000 Census, 2002 Economic Census, 2008 Michigan Incident Crime Reporting

- Software: ArcGIS 9.3 (ESRI, 2008), SAS 9.2 (SAS Institute, 2008), Matlab 7 (MathWorks, 2010)
- Variables: VIF (Variance Inflation Factor) & CI (Condition Indices) checked for multicollinearity, z-scores for normalization



Classification	Variables	Explanation	Mean	SD	Expectation
Dependent	ODECITY	County-level	20.42	1.50	
Variable	OBESITY	Obesity Prevalence	30.42	1.58	
Independent	Demographic				
Variables	INCOME	Median Household Income	\$38,493	\$7,735	-
	% BLACK	% Blacks	3.92	5.98	+
	% FOREIGN	% Foreign-born Population	2.23	1.93	-
	% UNIV	% College Graduates	16.37	7.25	-
	Environmental				
	COMMUTE	Daily Travel Time to Work	23.03	3.93	+
	HOMEOWN	% Homeownership	79.56	5.97	-
	% POVERTY	% People under Federal Poverty Line	14.75	3.8	+
	CRIME	Crime Incidence Rate	8716.73	3148.43	+
		(per 100,000 people)			
	FOORSTR	Rate of Food and Beverage Stores	71.86	189.49	-
		(per 100,000 people)			

Results

	OLS		Spatial Models					
			SA	SAR		SEM		SAC
Variables	Coefficient	Pr> t	Coefficient	Pr> t	Coefficient	Pr> t	Coefficient	Pr> t
CONSTANT	0.0000		0.0175		0.3040		0.1094	
Demographic								
INCOME	-0.0403		-0.0727		-0.1031		-0.1282	
% BLACK	0.6341	***	0.6472	***	0.7477	***	0.6913	***
% FOREIGN	-0.4720	***	-0.3710	***	-0.3577	**	-0.1743	
% UNIV	-0.4496	***	-0.4210	***	-0.4371	***	-0.2260	**
Environmental								
COMMUTE	0.1121		0.0602		0.0118		-0.0342	
HOMEOWN	-0.2695	*	-0.2020		-0.1549		0.0102	
POVERTY	-0.1272		-0.1593		-0.1467		-0.1715	
CRIME	0.0615		0.0803		0.1295		0.1907	**
FOODSTR	-0.1146		-0.1436		-0.2755	**	-0.3021	**
ρ (rho)			0.6610	***			3.5670	***
λ (lambda)					0.7970	***	1.3660	***
Adj R-square	0.5221		0.4792		0.6353		0.7749	
σ^2	0.4779		0.3462		0.3208		0.1980	
Log-Likelihood			-47.5182		-45.9766		-50.9665	

***p<.01 **p<.05 *p<.1

Results

- Better model explanation in two spatial models (SAC & SEM), compared to OLS model
- Impacts from *demographic variables* are consistent with previous studies: %BLACK, %UNIV
- Stronger effects from *environmental variables*: CRIME, FOODSTR
- Positive spatial dependence in Michigan's countylevel obesity rates: significant values of ρ & λ

Policy Implications

- 1. Preventing crime
- 2. Enhancing food environment in terms of the numbers of stores
- 3. Educating higher risk population or counties
- 4. Understanding the effect from spatial dependence or autocorrelation

Limitations

- 1. Which 'neighborhood' level of study is best?
- 2. Data collected at different time
- 3. Inconsistency with spatial autocorrelation statistical tests and spatial model
- → Statistically insignificant Moran's I yet significant values of $\rho \& \lambda$



- 1. More advanced spatial models or Bayesian modeling should be applied.
- 2. Different scales needed: e.g. zip code, census tract, census subdivisions, inter-state, or international levels.
- 3. More environmental variables should be investigated.



Thank You! kohkeums@msu.edu