Spatial Convergence of US Obesity Rates and Its Determinants

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Abstract

This article quantifies the importance of demographic and food environment variables in determining the convergence rates for obesity incidence across the U.S. Using a spatial autoregressive model with county level data for 2004-2012, a period of rapid spread of obesity in the U.S., to estimate β- and σ-convergence rates; then we estimate a probit model to assess their determinants. Empirical results show β-convergence and σ-convergence occurred in the US and its four regions in 2004-2012. The Northeast and the West have the highest speed of convergence in years 2008-2012. It was also found that β-convergence doesn't occur in counties in metro area in 2004-2012 and 2008-2012. The convergence rate is the largest in completely rural counties and consistently higher for men compared to women. A second-step probit regression shows that states with higher Hispanic proportion, higher availability of fruit and vegetables stores and full-service restaurants are less likely to have β-convergence, while states with higher poverty rates and sex ratio are more likely to have β-convergence. It also shows σ-convergence is more likely to happen in states with a higher proportion of Hispanics and higher availability of fruit and vegetables.

Keywords: Obesity; Overweight; Convergence; Determinant

JEL Codes: I18, J1, R10

1. Introduction

Obesity has become one of the most serious public health problems in the United States, causing more than 160,000 excess deaths and over $100 billion in economic losses annually (National Institute of Health, 2007). Figure 1 shows county-level obesity rates in 2004 (upper) and 2012 (lower), suggesting obesity rapidly increased in the US counties from 2004 to 2012. As a result, until 2014, approximately 34.9% of US adults and 17% of children were obese (Centers for Disease Control and Prevention, 2014).

[Please insert Figure 1 about here]

Since the rapid rise in the increase of obesity rates in the U.S., there has been an immense amount of empirical work devoted to examining the causes of this trend, such as demographics (Baum, 2007), cost of unhealthy food and beverages (Powerll and Chaloupka, 2009; Zhen et al., 2014; Dharmasena and Capps, 2012), food environments (Li and Lopez, 2016), lack of physical activity (Sarma et al., 2014). However, work on the spatial aspects of obesity is lacking. Li and Wang (2015) measure degrees of convergence for U.S. obesity rates using state level data. Stopping at simply measuring convergence rates, however, they leaves many questions, such as whether the spatial effects should be considered in the analysis of convergence? Which factors are mainly responsible for determining obesity convergence? Answers to such questions are important because they could guide policy makers in selecting effective policy instruments.

As Li and Wang (2015) point out, the idea of convergence, originating from literature on economic growth (e.g., Barro, 1991; Baumol, 1986), refers to the drawing together over time of a set of series. Two forms of convergence that dominate the literature are (1) β-convergence, which refers to the processes with higher (lower) initial values experiencing slower (faster) growth than series with lower (higher) initial values, i.e., a pattern of 'catching-up', or even 'leap-frogging'; and (2) σ-convergence, which relates to the spread of cross-sectional distribution of a group of series over time. In essence, if the distribution as measured by the coefficient of variation is seen to narrow, convergence is deemed to be present. The ideas of convergence are widely applied to other fields; for example, Cook and Winfield (2013) investigate the convergence of crime rates across the states over the period 1960-2009, and Sondermann (2014) tests productivity convergence among euro area countries. The objective of this article is to identify and assess the importance of underlying demographic and food environment factors to explain convergence rates of the obesity epidemic in the U.S. The convergence rates are estimated using country-level data and a spatial model of auto-regression. These convergence rates are then regressed on a set of demographics and food environment factors, comprehensively incorporating the determinants of obesity incidence from previous work.

In this article, we analyze convergence of obesity rates (β-convergence and σ-convergence) in following aspects: (1) convergence in US four regions (i.e., the Northeast, the South, the West, and the Mid-West); (2) convergence in rural areas and urban areas; (3) convergence for male and female in four regions; (4) convergence of obesity rates for each states, and (5) factors that potentially affect the convergence. Understanding the convergence of obesity rates can help policy makers better understand spatial pattern of obesity rates in US, and thus make specific policies for some areas. In addition, policy can be more effective if the determinants of obesity convergence are known.

Results show presence of β-convergence and σ-convergence in US and its four regions. The spatial effects are also identified. Although speed of convergence slowed down during 2008-2012 compared to that in 2004-2008, the Northeast and the West still have the highest speed of convergence in year 2008-2012. The disparity of obesity rates is largest in the West and smallest in Northwest. We didn't find that β-convergence in counties in metro area, neither in 2004-2012 nor in 2008-2012, whereas in the completely rural counties, the speed of convergence was the largest. Results also show convergence rate of men are consistently higher than that of women, and men in the Northeast has the largest convergence rate. We also analyze β-convergence and σ-convergence by each state. In order to find out the determinants of the two types convergence, a probit regression model is applied, the results of which show states with SSB higher Hispanic proportion, higher availability of fruit and vegetables stores and full-service restaurants are less likely to have β-convergence, while states with higher poverty rates and sex ratio are more likely to have β-convergence. It also shows σ-convergence is more likely to happen in states with higher proportion of Hispanics, and higher availability of fruit and vegetables. Policy implication is provided at the end of this paper based on these findings.

2. Methodology

The analysis is implemented in two stages. First, a spatial econometric model is applied to find out the pattern of convergence for each state, and a dichotomous variable is created to denote that. In the second stage, the determinants of convergence are examined with a probit model.

The existence of β-convergence and σ-convergence is examined via a spatial autoregressive model with spatial autoregressive disturbance (SARAR):

$$Y = X\beta + \rho WY + \varepsilon, \tag{1}$$

where

$$Y = \begin{bmatrix} \Delta y_{1t} \\ \Delta y_{2t} \\ \dots \\ \Delta y_{it} \end{bmatrix}, \; X = \begin{bmatrix} y_{10} \\ y_{20} \\ \dots \\ y_{i0} \end{bmatrix}, \; \text{and } \varepsilon = \lambda M \varepsilon + u.$$

Δy_{it} denotes change in the natural logarithmic value of obesity rates in county i over sample period t considered. y_{i0} denotes the natural logarithmic value of the initial level of obesity rates in county i. β is the key parameter. As shown in Barro and Xavier (1992), a negative and significant β $(-1 < \beta < 0)$ indicates the occurrence of convergence.

Spatial-weighting matrices W and M are typically standardized so that the sum of each row equals 1, implying that the spatially lagged dependent variable WY contains the average growth rates of obesity of the neighboring counties. u is an error term, the elements of which are assumed independent. The spatial-weighting matrices W and M are taken to be known and non-stochastic, and in many applications, $W = M$. Equation (1) can be rewritten as follows:

$$Y = (1 - \rho W)^{-1}[X\beta + (1 - \lambda M)^{-1}u], \tag{2}$$

where $(1 - \rho W)^{-1}$ is a spatial multiplier. The spatial multiplier can be written as an infinite power series, $I + \rho W + \rho^2 W^2 + \cdots$, where W contains the neighbors of a county, W^2 denote neighbors of the neighbors, and so forth (Anselin, 2003), indicating that a county's obesity growth rate is not only determined by its own initial obesity rates, but also by this county's location in terms of the average values of X and ε of the neighbors, the neighbors of the neighbors, and so on with decreasing magnitude (Chen et al., 2013).

After estimating the spatial autoregressive model, a dichotomous variable $\varGamma$ is used to denote whether the obesity rate in a state presents a pattern of converge or not, where $\varGamma = 1$ means converge occurs and $\varGamma = 0$ otherwise. A probit model as follows is used:

$$\varGamma^* = Z'\alpha + \eta, \tag{3}$$

where $\varGamma^*$ is a latent variable, vector Z denote the determinants of convergence, α is the vector of the parameters and error term η follows normal distribution. Note that

$$\varGamma = \begin{cases} 1, if\ \varGamma^* > 0 \\ 0, if\ \varGamma^* \leq 0 \end{cases}. \tag{4}$$

The SARAR model is estimated with Quasi-maximum likelihood (QML) estimation. The significance of ρ and λ suggests the existence of spatial spillover effects exist. If spatial spillover effects don't exist, OLS estimation is used instead. Following Drukker, Prucha, and Raciborski (2013), the unconditional log-likelihood function is:

$$lnL(Y|\beta, \sigma^2, \rho, \lambda) = -\frac{n}{2} ln(2\pi) - \frac{n}{2} ln(\sigma^2) + ln\|I - \rho W\| + ln\|I - \lambda M\|$$
$$- \frac{1}{2\sigma^2}\{(I - \rho W)Y - X\beta\}^T (I - \lambda M)^T (I - \lambda M)\{(I - \rho W)Y - X\beta\}, \tag{5}$$

where n is the number of observations, I is the identity matrix, and $\|\cdot\|$ is operator of determinant of a matrix. By maximizing equation above, yielding the maximizers:

$$\hat{\beta}(\rho,\lambda) = \{X^T(I-\lambda M)^T(I-\lambda M)X\}^{-1}X^T(I-\lambda M)^T(I-\lambda M)(I-\rho W)Y \tag{6}$$

$$\hat{\sigma}^2(\rho,\lambda) = (1/n)\{(I-\rho W)Y - X\hat{\beta}(\rho,\lambda)\}^T(I-\lambda M)^T(I-\lambda M)\{(I-\rho W)Y - X\hat{\beta}(\rho,\lambda)\} \tag{7}$$

Substitution of the above expression into (5) yields the concentered log-likelihood function

$$lnL_c(Y|\beta,\sigma^2,\rho,\lambda) = -\frac{n}{2}\{\ln(2\pi)+1)\} - \frac{n}{2}\ln(\sigma^2(\rho,\lambda)) + ln\|I-\rho W\| + ln\|I-\lambda M\| \tag{8}$$

The QML estimates for the autoregressive parameters $\hat{\lambda}$ and $\hat{\rho}$ can now be computed by maximizing the concentrated log-likelihood function. Once we have obtained the QML estimates $\hat{\lambda}$ and $\hat{\rho}$, we can calculate the QLE estimates for β and σ^2as $\hat{\beta} = \hat{\beta}(\hat{\rho},\hat{\lambda})$, and $\hat{\sigma}^2 = \hat{\sigma}^2(\hat{\rho},\hat{\lambda})$. The Stata SE 13.0 is used to estimate the model, where a grid search is conducted to find suitable initial values for ρ and λ.

Coefficient of variation (cv) is computed to examine the existence of σ-convergence for each year:

$$cv_t = \frac{\sigma_t}{u_t}, \tag{9}$$

where σ_t and μ_t are standard deviation and mean of obesity rates at time period t, respectively. The σ-convergence occurs if a decreasing trend of cv presents. Note that we also analyze the determinants of σ-convergence in the second stage with probit regression. Here details are abbreviated for simplicity.

3. Data

The main dataset used in this paper is annual observations of US obesity rates in 3137 US counties in 2004-2012, obtained from CDC, which also provide county-level obesity rates by gender for 2009-2012. This paper segments the sample as four regions based on the definition of United States Census Bureau (USCB). We also partition the counties as four categories: 1) counties in metro area, 2) non-metro counties adjacent to a metro area, 3) non-metro counties not adjacent to metro area, and 4) non-metro counties completely rural, based on the Rural-Urban Continuum Code (US Department of Agriculture, 2003). To obtain indicators of the food environment, we grouped the individual observations by county and matched them with data from the U.S. Bureau of the Census (USBC, County Business Patterns) for 2001-2010, to include the number of establishments in the following industries: fruit and vegetables stores (NAICS 44523), full service restaurants (NAICS 72210), and limited service eating places (NAICS 72211). Following Dunn (2010) and Li and Lopez (2016), we use numbers of food outlets per 1000 persons to approximate availability. Normalizing by population implicitly assumes that food outlets and population are uniformly distributed across a county. Population data is from USCB Population Estimates Program.

Table 1 presents the summary statistics for obesity rates in four US regions in 2004 and 2012. First, obesity rate significantly increased from year 2004 to 2012. Second, compared to other three regions, the obesity problem is most serious in the South. Third, the disparity of obesity rates is largest in the West and smallest in the Mid-West. These pattern are similar with Li and Wang (2015) using state-level data.

[Please insert Table 1 about here]

Figure 2 illustrates the pattern of obesity growth and initial obesity rates at county-level during year 2004-2012, with four U.S. regions (the Northeast, the South, the West, and the Mid-West) in four different colors and shapes.[1] Obesity rates in the South and in the Mid-West are higher than that in the Northeast and in the West. States with higher initial obesity rates are found to be with lower growth of obesity rates, implying the existence of β-convergence. In order to get deep insights and to evaluate the determinants of convergence, the obesity rate data is combined with other datasets such as demographic information (e.g., percentage of bachelor's degree or more, sex ratio, race proportion) from American Community Survey, USCB, poverty rate from Small Area Income and Poverty Estimates, USCB, and Rural-Urban Continuum Code from USDA.

[Please insert Figure 2 about here]

4. Results

Results from estimating equation (1) in the period 2004-2012, 2004-2008, and 2008-2012 for the US and its four regions are reported in Table 2. The estimated βs in 2004-2012 are all negative and between zero and one, which is consistent with our model specification, suggesting convergence is in the US, and the four regions as well. Parameters ρ and λ are significant, indicating the spatial spillover effects exist. The results also show a large degree of variation in the size of the estimated coefficients, with the greatest degree of convergence in the Mid-West, the smallest degree of convergence in the South, indicating obesity spreads faster in the Mid-West. The convergences in the period 2004-2008 and 2008-2012 are also investigated. We find obesity rates in all regions converge in both periods. In addition, β estimates are consistently higher during 2004-2008 than 2008-2012, indicating the speed of convergence slowed during 2008-2012, an exception is the West, where convergence speeded up in the second period. In addition, in 2008-2012, the Northeast and the West, two regions with relatively lower obesity rates, show a higher speed of convergence.

[Please insert Table 2 about here]

Table 3 shows the coefficients of variation in the US and its four regions, where the West has the largest coefficient of variation, the Northwest the smallest, indicating that the disparity of obesity is much

[1] https://www.census.gov/geo/maps-data/maps/pdfs/reference/us_regdiv.pdf. Alaska and Hawaii belongs to division of the West.

larger in the West. In addition, Figure 3 shows that the coefficients of variation in the four regions and the US have a common increasing pattern, quite significant in the South and Mid-West.

[Please insert Table 3 about here]

[Please insert Figure 3 about here]

Table 4 illustrates the β-convergence for rural and urban counties. Here we separate the counties into four categories: metro, non-metro adjacent to a metro area, non-metro not adjacent to a metro area, and completely rural. We find that in 2004-2012, convergence does not occur in metro area counties, while it is found in the other three (i.e., non-metro) counties. We also find that counties completely rural have the highest speed of convergence (-0.181). These findings are consistent with the findings in the relevant literature. For example, Zhao and Kaestner (2010) find a negative association between population density and obesity. Results in 2004-2008 and 2008-2012 show β estimates consistently higher in the earlier period, indicating that obesity spread faster in US counties during 2004-2008 than in 2008-2012. Another finding is that the β estimates for counties in metro areas in 2008-2012 are insignificant, indicating no convergence whereas non-metro counties that are completely rural present the highest convergence speed of obesity rates.

[Please insert Table 4 about here]

Table 5 shows σ-convergence in counties by subcategories. First, the disparity in obesity rates is highest in non-metro counties not adjacent to a metro area, lowest in non-metro counties adjacent to a metro county. Figure 4, which represents the results in Table 5, shows that there is no σ-convergence in US rural and urban areas during 2004-2012. Two interesting findings in Figure 4 are noted here. First, the disparities in obesity rate in counties of all four types are enlarged, and disparities in counties in metro areas and in non-metro counties adjacent to a metro area increase much faster than in other areas. Second, after 2008, the coefficient of variation in four regions significantly increases. This is consistent with Ruhm (2000), who finds that an economic crisis may have intensified the obesity epidemic, particularly among the poor.

[Please insert Table 5 about here]

[Please insert Figure 4 about here]

Table 6 reports the β estimates in the US and its four regions for men and women in 2009-2012. [2] In the Northeast, South and Mid-West, the speed of convergence is much faster for men than for women. The speed of convergence in the Mid-West is highest and lowest in the West. These finding suggest that policy should be aimed more at males, especially in the Mid-West.

[Please insert Table 6 about here]

[2] Due to the availability of county-level obesity rates from CDC, we only have data from 2009-2012.

We also explored whether β-convergence exists within each state. The results based on these regressions are given in Table 7. During 2004-2012, we find there are several states where obesity rates converge, such as Alaska, Arkansas, Georgia, Idaho, Kentucky, and Louisiana. As for the magnitude of the β coefficients, Tennessee has the largest converge rate (-0.644) and Texas the lowest (-0.212), implying that the obesity increased in Tennessee much faster than in Texas. Table 8 presents mean and standard deviations of cv of obesity rates in each state. From the trends of coefficients of variation for each state, we find only a few states present σ-converge (e.g. Delaware, Hawaii, and Massachusetts). Most states show an increasing trend of coefficients of variation, implying that the disparity of obesity rates across the states is enlarged.

[Please insert Table 7 about here]

[Please insert Table 8 about here]

The analysis results in Table 7 and Table 8 are applied in a second-step probit regression to determine the factors which potentially affect the convergence of obesity. In Table 9, we find that the states with higher poverty rates and male to female sex ratio are more likely to exhibit convergence. However, the proportion of Hispanics is found to be positively associated with the probability of convergence. As for the food environment component, we find that states with higher availability of fruit and vegetables stores and full service restaurant are less likely to have converging obesity rates. Table 9 also presents the results of analysis of determinants for σ-convergence. We find that the dispersion of obesity rates in states with a soda tax, higher poverty rate are more likely to decrease. While in states with a higher proportion of Hispanics, it is more likely to be enlarged. States with higher availability of fruit and vegetables stores are more likely to have σ-convergence, while states with higher availability of full-service restaurants are less likely to have σ-convergence.

[Please insert Table 9 about here]

5. Concluding remarks

Applying spatial analysis of convergence to the trends of US obesity rates at the county level over 3 periods (2004-2008, 2008-2012, and 2004-2012), we find β-convergence and σ-convergence in the US and its four regions in 2004-2012. Although the speed of convergence slows during 2008-2012 compared to that in 2004-2008, the Northeast and the West still have the highest speed of convergence in the later period. The disparity in obesity rates is largest in the West and smallest in the Northwest. Results show that β-convergence doesn't exist in counties in metro areas, in 2004-2012 and 2008-2012. In the completely rural counties, the speed of convergence is the largest. The β-convergence for males and females is also examined. Results show that the men in the Northwest have the largest convergence rate, and the convergence rate for men is consistently higher than that for women. We also analyze the determinants of β-convergence and σ-convergence with a probit regression in the second step, the results of which show that states with SSB tax, higher education level, higher GDP per capita, and higher Hispanic proportion are less likely to have β-convergence. It also show that β-convergence is likely to happen in the state with higher proportion of Whites. However, we find σ- convergence is more likely to happen in relatively poor states, and in states with higher proportion of Hispanics. Additionally, states with higher availability of fruit and vegetables stores and full service restaurant are less likely to have β-convergence. States with higher availability of fruit and vegetables stores are more likely to have σ-convergence, while states with higher availability of full-service restaurants are less likely to have σ-convergence.

This paper contributes to the literature of health economics, particularly, obesity, by applying spatial analysis to discover the pattern of obesity rates in US region. This findings provide policy implications for obesity intervention. First, more policy intervention should be placed in the Northeast and the West, as well as the counties completely rural. Second, policy makers should focus on specific group of people, for example, the male in the Mid-West. At last, SSB tax and education, to some extent, slow down the sprawling of obesity, which can be two tools to fight against obesity.

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Table 1. Summary statistics of county-level obesity rates for US regions in year 2004 and year 2012

Year	Region	Mean	Std. Dev	Min	Max
2004	NE	0.228	0.031	0.138	0.306
	South	0.267	0.028	0.170	0.380
	West	0.215	0.037	0.123	0.339
	Mid-West	0.255	0.017	0.189	0.372
2012	NE	0.279	0.039	0.147	0.362
	South	0.325	0.041	0.169	0.466
	West	0.260	0.047	0.107	0.367
	Mid-West	0.315	0.029	0.210	0.445

Table 2. β-convergence in US and four regions in 2004-2012, 2004-2008, 2008-2012

	2004-2012	2004-2008	2008-2012
US	-0.114***	-0.197***	-0.128***
	(0.016)	(0.014)	(0.015)
NE	-0.215***	-0.264***	-0.143***
	(0.055)	(0.044)	(0.049)
South	-0.120***	-0.231***	-0.130***
	(0.027)	(0.026)	(0.025)
West	-0.122***	-0.119***	-0.188***
	(0.033)	(0.036)	(0.028)
Mid-West	-0.316***	-0.428***	-0.132***
	(0.043)	(0.023)	(0.043)

Table 3. Test for σ convergence: coefficient of variation during 2004-2012 for US and four regions

Year	Northeast	South	West	Mid-West	U.S.
2004	0.136	0.106	0.173	0.065	0.128
2005	0.123	0.108	0.184	0.063	0.130
2006	0.117	0.111	0.185	0.058	0.130
2007	0.121	0.110	0.189	0.060	0.128
2008	0.124	0.111	0.187	0.061	0.128
2009	0.135	0.116	0.173	0.092	0.137
2010	0.135	0.119	0.170	0.092	0.139
2011	0.141	0.122	0.174	0.094	0.141
2012	0.141	0.127	0.179	0.091	0.144

Table 4. β-convergence in counties by subcategories in 2004-2012, 2004-2008, 2008-2012, respectively

	2004-2012	2004-2008	2008-2012
County in metro area	-0.036	-0.142***	-0.038
	(0.023)	(0.018)	(0.023)
Non-metro county adjacent to a metro area	-0.171***	-0.198***	-0.091***
	(0.027)	(0.020)	(0.025)
Non-metro county not adjacent to a metro area	-0.114***	-0.140***	-0.094***
	(0.030)	(0.029)	(0.033)
Non-metro county completely rural	-0.181***	-0.161***	-0.152***
	(0.026)	(0.020)	(0.026)

Table 5. σ-convergence in counties by subcategories: coefficient of variation during 2004-2012

Year	Metro	NM-AD	NM-NAD	NM-R	U.S.
2004	0.130	0.112	0.144	0.126	0.128
2005	0.131	0.113	0.143	0.131	0.130
2006	0.133	0.113	0.145	0.128	0.130
2007	0.132	0.110	0.143	0.126	0.128
2008	0.132	0.110	0.147	0.122	0.128
2009	0.144	0.118	0.151	0.130	0.137
2010	0.147	0.120	0.150	0.130	0.139
2011	0.149	0.125	0.151	0.130	0.141
2012	0.154	0.127	0.153	0.131	0.144

Note: Metro--Counties in Metro area; NM-AD-- Non-metro counties adjacent to a metro area; NM-NAD--Non-metro counties not adjacent to a metro area; NM-R-- Non-metro counties completely rural

Table 6. β-convergence in US and four regions for men and women in 2009-2012

	Men	Women
US	-0.266***	-0.251***
	(0.015)	(0.013)
NE	-0.230***	-0.212***
	(0.046)	(0.040)
South	-0.335***	-0.279***
	(0.024)	(0.020)
West	-0.098***	-0.119***
	(0.032)	(0.027)
Mid-West	-0.498***	-0.464***
	(0.028)	(0.026)

Table 7. β-convergence for US states

State	β	Convergence	State	β	Convergence
Alabama	-0.106(0.081)	No	Montana	-0.265(0.067)	Yes
Alaska	-0.348(0.171)	Yes	Nebraska	-0.537(0.213)	Yes
Arizona*	-0.012(0.178)	NA	Nevada*	-0.303(0.184)	No
Arkansas	-0.245(0.104)	Yes	New Hampshire*	-0.271(0.308)	No
California	0.032(0.137)	No	New Jersey	0.102(0.058)	No
Colorado	0.057(0.151)	No	New Mexico	-0.032(0.102)	No
Connecticut*	0.017(0.263)	No	New York	-0.134(0.095)	No
Delaware*	-0.057(0.128)	No	North Carolina	-0.067(0.068)	No
D.C.	NA	NA	North Dakota	-0.233(0.097)	Yes
Florida	0.347(0.146)	NA	Ohio	-0.400(0.216)	Yes
Georgia	-0.245(0.084)	Yes	Oklahoma	-0.403(0.131)	Yes
Hawaii*	NA	NA	Oregon	-0.162(0.124)	No
Idaho	-0.352(0.110)	Yes	Pennsylvania	-0.585(0.128)	Yes
Illinois	-0.267(0.194)	No	Rhode Island*	0.076(0.383)	No
Indiana	-0.256(0.231)	No	South Carolina	0.127(0.085)	No
Iowa	-0.185(0.169)	No	South Dakota	-0.251(0.073)	Yes
Kansas	-0.127(0.135)	No	Tennessee	-0.644(0.162)	Yes
Kentucky	-0.406(0.137)	Yes	Texas	-0.212(0.102)	Yes
Louisiana	-0.290(0.133)	Yes	Utah	0.166(0.099)	No
Maine*	-0.064(0.189)	No	Vermont*	-0.071(0.240)	No
Maryland	0.121(0.187)	No	Virginia	0.009(0.097)	No
Massachusetts*	-0.144(0.143)	No	Washington	0.064(0.062)	No
Michigan	-0.124(0.184)	No	West Virginia	-0.356(0.155)	Yes
Minnesota	-0.054(0.202)	No	Wisconsin	-0.301(0.197)	No
Mississippi	-0.287(0.089)	Yes	Wyoming	0.071(0.156)	No
Missouri	-0.395(0.176)	Yes	**United States**	**-0.114(0.016)**	**Yes**

Table 8. σ–convergence for US states

State	c.v. (s.d.)	Convergence	State	c.v. (s.d.)	Convergence
Alabama	0.110(0.010)	No	Montana	0.150(0.007)	No
Alaska	0.102(0.006)	Yes	Nebraska	0.060(0.022)	No
Arizona	0.155(0.011)	No	Nevada	0.124(0.012)	Yes
Yes	0.085(0.008)	No	New Hampshire	0.081(0.006)	No
California	0.136(0.019)	No	New Jersey	0.128(0.012)	No
Colorado	0.155(0.024)	No	New Mexico	0.176(0.009)	No
Connecticut	0.117(0.023)	Yes	New York	0.105(0.012)	No
Delaware	0.100(0.015)	Yes	North Carolina	0.126(0.007)	Yes
D.C.	NA	NA	North Dakota	0.085(0.010)	Yes
Florida	0.150(0.027)	No	Ohio	0.057(0.025)	No
Georgia	0.088(0.009)	No	Oklahoma	0.062(0.011)	No
Hawaii	0.065(0.012)	Yes	Oregon	0.113(0.005)	Yes
Idaho	0.115(0.004)	Yes	Pennsylvania	0.084(0.008)	No
Illinois	0.050(0.019)	No	Rhode Island	0.118(0.019)	No
Indiana	0.060(0.025)	No	South Carolina	0.123(0.011)	No
Iowa	0.057(0.021)	No	South Dakota	0.124(0.008)	Yes
Kansas	0.061(0.018)	No	Tennessee	0.068(0.010)	No
Kentucky	0.073(0.012)	No	Texas	0.056(0.011)	No
Louisiana	0.073(0.008)	No	Utah	0.129(0.009)	Yes
Maine	0.124(0.008)	No	Vermont	0.098(0.011)	No
Maryland	0.131(0.009)	No	Virginia	0.098(0.016)	No
Massachusetts	0.124(0.014)	Yes	Washington	0.131(0.010)	Yes
Michigan	0.068(0.023)	No	West Virginia	0.070(0.008)	Yes
Minnesota	0.055(0.022)	No	Wisconsin	0.065(0.021)	No
Mississippi	0.095(0.006)	Yes	Wyoming	0.148(0.011)	No
Missouri	0.051(0.021)	No	**United States**	**0.134(0.006)**	**No**

Table 9. Determinants for β-convergence and σ–convergence

Dependent variables	β-convergence	σ-convergence
SSB tax	-0.705	-1.677**
	(0.94)	(0.66)
Poverty rate	67.63**	-51.324***
	(33.02)	(15.65)
Education	-0.098	0.037
	(0.08)	(0.09)
GDP per capita	93.391	-71.006
	(99.07)	(55.48)
White	3.638	0.396
	(3.013)	(1.884)
Hispanic	-30.050***	11.174***
	(-10.98)	(2.89)
Sex ratio	64.870***	2.465
	(19.32)	(14.36)
Fruit and vegetables stores	-236.535***	124.434**
	(80.14)	(54.68)
Full-service restaurants	-4.892**	-12.837***
	(2.40)	(4.82)
Limited-serv. rest.	-4.608	5.286
	(5.05)	(3.50)
Constant	17.819	8.973
	(13.23)	(14.78)

Note: region fixed effects are included. Robust standard errors clustered at the county level are reported in the parenthesis. *, **, *** represent the 10%, 5%, 1% significance levels, respectively.

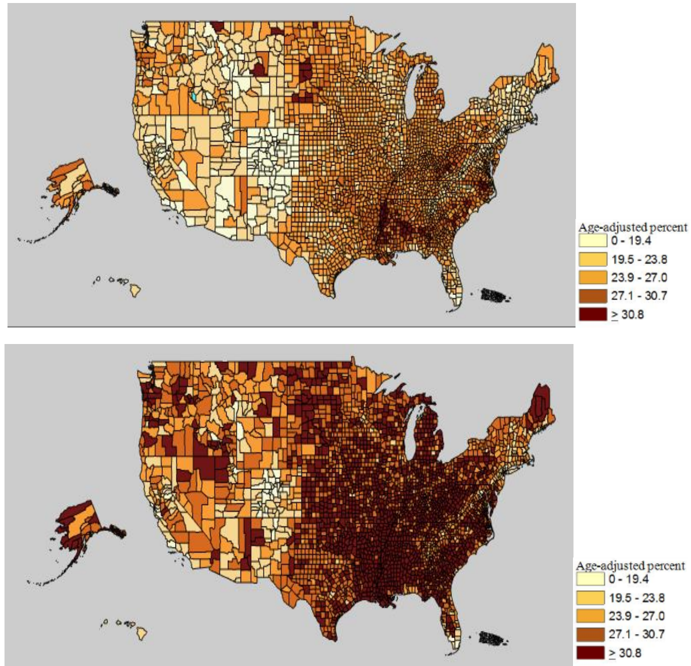

Figure 1. The county-level change of obesity rates in US in year 2004 (upper) and year 2012 (lower).

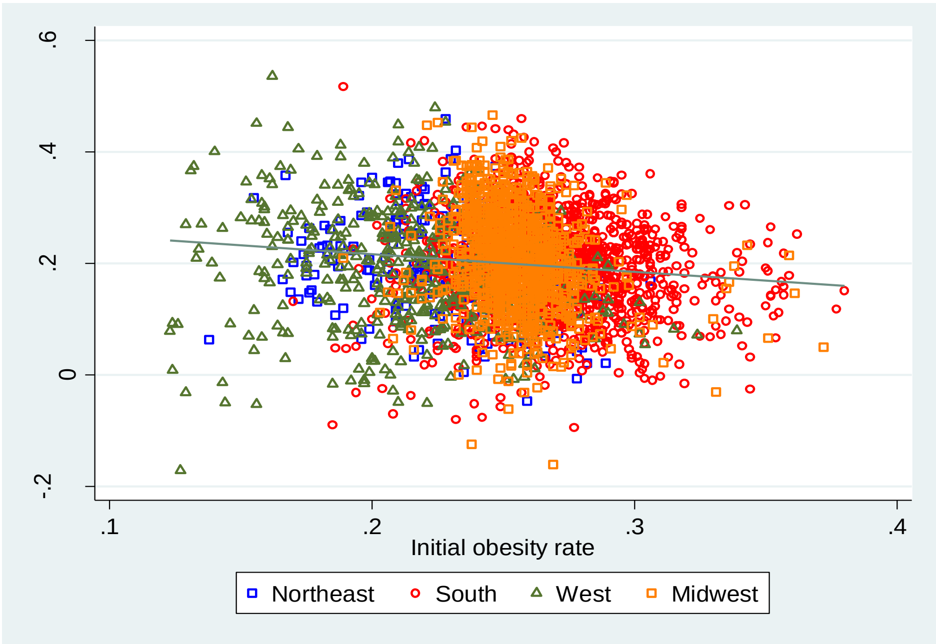

Figure 2. Trends of obesity rates for US regions: Northeast, South, West, and Mid-West: 2004-2012.

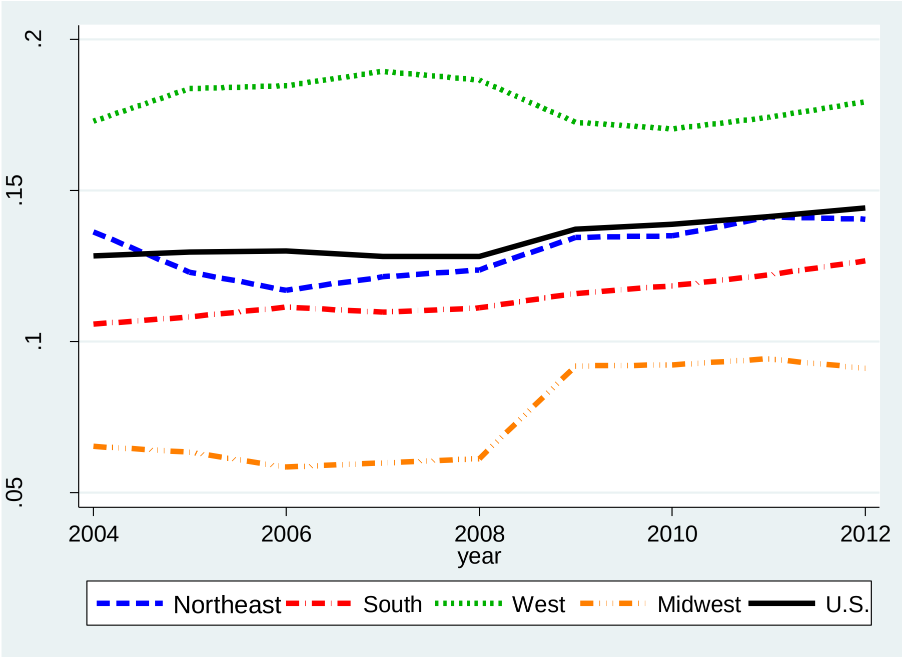

Figure 3. Trends of coefficient of variation for obesity in US and four regions: 2004-2012

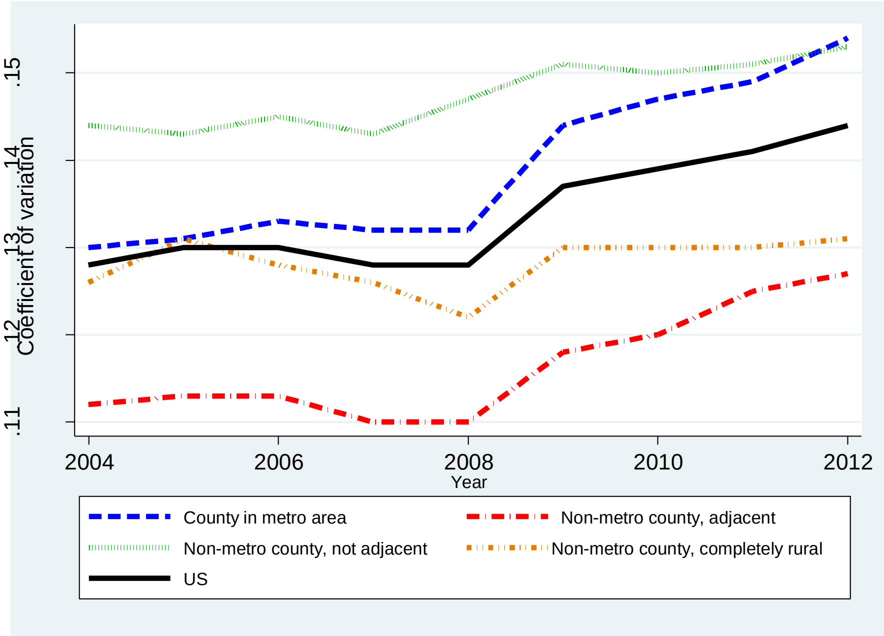

Figure 4. Trends of coefficient of variation for obesity in US rural and urban areas: 2004-2012