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Identifying geographical variations in poverty-obesity relationships: empirical evidence from Taiwan

Tzai-Hung Wen[1], Duan-Rung Chen[2], Meng-Ju Tsai[3]

[1]*Department of Geography, College of Science, National Taiwan University, Taipei, Taiwan;* [2]*Graduate Institute of Health Care Organization Administration, College of Public Health, National Taiwan University, Taipei, Taiwan;* [3]*Taoyuan General Hospital, Taoyuan, Taiwan*

Abstract. There is an increasing interest in the relationship between area-based disadvantage and obesity but the extent to which the poverty-obesity relationship remains constant across geographical areas remains unclear. We examined geographical variations in the relationship between poverty and obesity in Taiwan using geographically weighted regression (GWR). A representative sample of 27,293 Taiwanese adults (21 to 64 years old) from 262 townships was obtained from the 2001 Social Development Trend Survey on Health and Safety (SDSHS) in Taiwan. GWR revealed that there were local variations in the poverty-obesity relationship and that poverty was only significantly associated with obesity in less-developed areas. Significant relationship between poverty and obesity was found only in less-developed areas, suggesting that the impact of poverty on obesity is area-specific.

Keywords: obesity, poverty, socio-economic inequality, geographically weighted regression, Taiwan.

Introduction

Obesity is a rapidly growing global public health problem (WHO, 2000) and is a major risk factor for several important diet-related chronic diseases including type 2 diabetes, cardiovascular disease, hypertension, stroke and certain cancers (Kannel et al., 1996; Alberti and Zimmet, 1998; Carroll, 1998). The WHO defines individuals with a body mass index (BMI) of over 25 kg/m^2 as overweight and those with a BMI over 30 kg/m^2 as obese. However, the prevalence of metabolic co-morbidities such as hypertension, diabetes and hyperuricemia occur at a lower BMI in Taiwan as compared to other countries (Pan et al., 2004). Given the lack of a recognised clinical standard, Taiwanese health officials have adopted a BMI cut-off of 24 for overweight and of 27 for obesity. Based on these definitions, the prevalence of obesity has increased rapidly in the past two decades, especially among children and male adults (Chu, 2001, 2005; Lin et al., 2003; Hsieh and FitzGerald, 2005). Recent reports indicate that the prevalence of overweight in adults in Taiwan is 23.9%, while that of obesity is 13.4% (Chu, 2005).

Economic growth and industrial development in Taiwan are highly concentrated in the north of the country. Socio-economic inequality is associated with geographic inequality (Tsou and Huang, 2003). Economic growth and high-fat dietary lifestyles are assumed to be the main causes of obesity (Popkin, 2001), yet in industrialized countries, disadvantaged socio-economic status (SES) is associated with increased obesity risk (Reidpath et al., 2002). Many studies have shown significant correlations between obesity and contextual measures, such as area-based income inequality, unemployment rate and socio-economic disadvantage, after controlling for individual socio-economic factors

Corresponding author:
Duan-Rung Chen
Graduate Institute of Health Care Organization Administration
R636, Building of Public Health
National Taiwan University, Xu-Zhou Rd. 17, Taipei, 10020 Taiwan
Tel./Fax +886 2 33228066
E-mail: duan@ntu.edu.tw

such as sex, income and education (Pickett and Pearl, 2001; Roux, 2001; Austin et al., 2002; Robinson et al., 2003; Cubbin et al., 2006; Phipps et al., 2006; Zilberberg et al., 2008; Li et al., 2009). Recent studies have also identified geographic associations in the link between poverty and obesity (King et al., 2006; Zhuo et al., 2009; Chen and Wen, 2010). The strength of the relationship between obesity and neighbourhood deprivation is thus well established. However, the majority of studies have modeled the link between obesity and area-based socio-economic measures using a "global" approach which may disguise some interesting local variations in this relationship. Therefore, the mechanism through which geographical variations in SES disadvantage impact on health outcomes is an important topic of research.

The use of a global estimate of regression parameters may obscure interesting or potentially complex geographical phenomena. Geographic variation (heterogeneity) is a lack of uniformity across space with locations varying in different ways, including size, shape, population and level of economic development (Anselin, 1988; LeSage and Krivelyova, 1999). Regression models with spatially varying coefficients were developed to capture these local variations in associations by exhibiting a non-constant mean and variance across the whole study area (Besag et al., 1991; Brunsdon et al., 1996; Gelfand et al., 2003). In other words, local statistical parameters change with location and are thus not uniformly distributed. These methods are useful for the identification of the nature of local variations in relationships over different locations. One of these spatially-varying coefficient methods, geographically weighted regression (GWR), is widely used in geographical analysis as an exploratory tool to examine geographical variation in associations between dependent and explanatory variables (Fotheringham et al., 2002). GWR uses a local weights matrix, W_i, that is calculated from a kernel-weighted function, placing more weight on locations that are closer in space to the calibration location than those that are more distant in space. It takes into account the strength of spatial dependence in a continuous spatial framework (Fotheringham et al., 2002). GWR builds local regression models at each location and uses a weighting scheme to include neighbouring locations in the construction of each local model.

The objectives of this study were to examine the extent of geographic variation in the relationship between poverty and obesity using GWR, and to compare poverty-obesity relationships of populations in economically developed areas to those in disadvantaged areas. An understanding of geographical variation in the relationship between poverty and obesity is essential for identifying high-risk areas that may require more intervention.

Materials and methods

Data

Data were obtained from the 2002 Social Development Survey on Health and Safety (SHDSH) conducted by the Statistics Bureau, Executive Yuan, Taiwan. The SHDSH is a two-stage stratified sample of all registered households in Taiwan. A total of 13,066 households were sampled, and every family member aged 15 years or older was interviewed, resulting in a sample size of 50,354. Respondents who were current students, younger than 21 years old or older than 65 years were excluded in order to focus the analysis on working-age subjects. As a result, our analysis included a total of 29,273 respondents from 11,763 households in 262 townships. The data were weighted to correct for sample selection probabilities and non-response, resulting in a weighted sample that approximated the demographic distribution of the adult population in Taiwan.

Definition of poverty and obesity at the individual level

Poverty was defined as a personal monthly income lower than 20,000 New Taiwan Dollars

(NTD, currently equivalent to 597 US$). This cut-off was selected for two reasons: firstly, according to minimum-wage legislation in Taiwan, the minimum legal monthly wage is 17,280 NTD (equivalent to 520 US$) (Tsou and Huang, 2003). This wage is also the lowest at which workers may sell their labor. Secondly, due to the limited ordinal data format of the income variable, precise information for personal income was not available. The first category of the income variable was 20,000 NTD or below.

Obesity was defined as a BMI greater than 27 (Chu, 2005).

Township-level variables

The spatial unit in the statistical analysis was the township. The township-level measures included poverty and obesity rates. The poverty rate was calculated as the ratio of individuals with poverty to all individuals surveyed in the township and represented the explanatory variable in the study. The rate of obesity was the ratio of individuals with obesity to all individuals and represented the health outcome variable in the study.

Statistical methods: GWR modeling

Consider a general linear regression model with one predictor variable:

$$y = \beta_0 + \beta_1 x_1 + \varepsilon, \quad \text{(Eq. 1)}$$

where y is the dependent variable (e.g. the obesity rate), x_1 the independent variable (e.g. the poverty rate), β_0 and β_1 the parameters to be estimated, and ε a random error term assumed to be normally distributed. Using ordinary least squares (OLS) estimation, the parameters for a linear regression model can be obtained by solving:

$$\beta = (X^T X)^{-1} X^T Y \quad \text{(Eq. 2)}$$

The assumption is that the values of β_0 and β_1 are constant across the study area. This means that if there is any geographic variation in the relationship then it must be confined to the error term. GWR permits the parameter estimates to vary locally so we can rewrite the model in a slightly different form (Fotheringham et al., 2002):

$$y(g) = \beta_0 (g) + \beta_1 (\mathrm{g})\, x_1 + \varepsilon, \quad \text{(Eq. 3)}$$

where (g) indicates that the parameters are to be estimated at a location whose coordinates are given by the vector g (e.g. the townships in this study).

The parameter estimates for GWR can be solved using a weighting scheme:

$$\beta(g)= (X^T\, W(g)X)^{-1}\, X^T\, W(g)\; Y \quad \text{(Eq. 4)}$$

The weights are chosen such that those observations near the point in space of the desired parameter estimates have more influence on the result than observations that are further away. In the case of the Gaussian weighting scheme, the weight function for the i^{th} observation is:

$$w_i(g) = exp\ (-d/h)^2, \quad \text{(Eq. 5)}$$

where d is the Euclidean distance between the location of observation I and location g, while h is a quantity known as the bandwidth. The weighting factor is used to show the distance-decay property (Fotheringham et al., 2002).

Since the GWR model allows a separate estimate of the parameters to be made at each data point, the resulting parameter estimates may be mapped in order to examine local variations in the parameter estimates. The value of t–statistics at each data point is calculated by dividing each local estimate by the corresponding local standard error of the estimate. However, these t–statistics values represent a relatively *ad hoc* inference, and not a formal statistical estimate (Waller et al., 2007). They are often used in an exploratory role to highlight local areas which appear to show potentially interesting relationships. The Akaike information criterion (AIC) is widely used as a diagnostic measure for model fitting (Fotheringham et al., 2002). Since the obesity rate was analysed as a continuous variable in this study and the goodness-of-fit test indicated no statistically significant deviation from a normal distribution (Chi-square statistic = 10, P = 0.867), a Gaussian GWR model was used to estimate the local poverty rate parameters. The software GWR 3.0 developed by Fotheringham was used in this study and provides convenient linkage to geographical information systems (GIS) software for mapping local variations in regression parameters. The software ArcGIS 9.3 (ESRI, Redlands, CA, USA) was used for data mapping.

Results

The study analyzed 29,273 working adults aged between 21 and 65 years of age living in 262 townships. The mean age of study subjects was 40.8 years (Table 1). About one quarter (25.9%) of the subjects had an elementary level of education or below, and almost one quarter (23.5%) had a college education or above. Figure 1 shows a scatter plot of the association between poverty and obesity. The analysis was limited to respondents in the workforce by excluding subjects who were younger than 21, older than 65 years or current students. The use of OLS revealed a statistically significant relationship between poverty and obesity. However, the R-square was only 0.04 (Table 2), indicating that only 4.3% of the variation in obesity could be explained by poverty. Examination of the OLS residuals revealed that the they were spatially clustered (Moran's *I* was 0.62 and Z(I) = 4.91). The spatial clustering and spatial autocorrelation of the residuals was statistically significant (P <0.01), suggesting a violation of the assumptions of OLS regression. In order to incorporate geographic inequalities in our models of the poverty-obesity relationship, GWR was used to analyze the sample data.

Table 1. Socio-demographic characteristics of the study sample (n = 29,273).

Variables		N	%/(SD)
Age		40.8	(11.6)
Gender			
	Men	14,778	50.5%
	Women	14,495	49.5%
Education			
	<6 years	7,569	25.9%
	7-9 years	5,434	18.5%
	10-12 years	9,383	32.1%
	>13 years	6,887	23.5%
Personal income (in US$)			
	<597	12,195	41.6%
	597-895	5,023	17.2%
	895-1194	4,475	15.3%
	1194-1791	4,215	14.4%
	1791-2388	2,027	6.9%
	>2388	1,338	4.6%

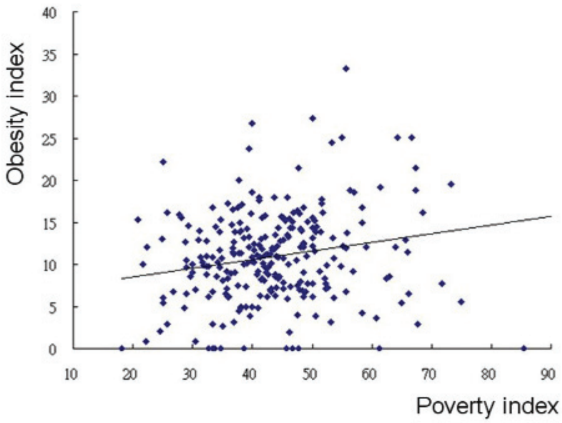

Fig. 1. Scatterplot of the poverty-obesity relationship. The poverty rate (X-axis) refers to the ratio of individuals in poverty to the total population in a township (%). Poverty is defined as a personal monthly income of less than 20,000 NTD (597 US$) per month. The obesity rate (Y-axis) refers to the ratio of individuals with obesity to the population in a township (%). Obesity was defined as BMI greater than 27.

Table 2. Results of the OLS model of the poverty-obesity relationship.

Regression coefficients		R-square	P-value
Intercept (β_0)	Poverty rate (β_1)		
6.45	0.102	0.043	0.001

Dependent variable = obesity rate; OLS = ordinary least squares.

The GWR model

In the GWR model, the R-square increased from 0.04 (OLS) to 0.14 (GWR) (Table 3), demonstrating that GWR had a better explanatory ability than OLS. The F-test rejected the null hypothesis (P <0.001), suggesting that the improvement to model fit using GWR was statistically significant. The results refute a simple linear relationship between poverty and obesity rates in townships.

Table 3 summarizes the estimates derived from the OLS and GWR models. If the inter-quartile range of the local estimates was greater than that of the global OLS parameter estimation ± 1 standard deviation (SD), the relationship between the two variables may be non-stationary (Brunsdon et al., 1996; King et al., 2006). For the intercept coefficient (β_0), the inter-quartile range of 5.4-8.5 of the GWR local parameter estimates exceeded the range of 5.1-7.8 ± 1 SD of the OLS parameter estimate. Similarly, for the slope coefficient (β_1), the inter-quartile range of 0.05-0.16 of the GWR local parameter estimates exceeded the range of 0.07-0.13 ± 1 SD of the OLS parameter estimate (Table 3). Therefore, the model parameters in Eqn. no. 4 clearly varied between townships.

Table 3. Parameter estimates using OLS and GWR models.

	β_0 (estimate)	β_1 (estimate)	R-square
OLS model			0.04
Estimates	6.45	0.102	
Standard error	1.35	0.03	
β ± 1 SD	5.1-7.8	0.07-0.13	
GWR model			0.14
25% quartile	5.39	0.05	
50% quartile (median)	7.47	0.072	
75% quartile	8.50	0.16	

OLS = ordinary least squares; GWR = geographically weighted regression.

Table 4. Results of linear regression models for two specific areas.

Model	Regression coefficients		R-square	P-value
	Intercept (β_0)	Poverty rate (β_1)		
Northern Taiwan	11.41	0.002	<0.001	0.980
Hua-Lien and Tai-Tung areas	0.89	0.28	0.45	0.005

Spatial mapping of coefficients in the GWR model

Figure 2 shows the continuous smooth surface of the estimated local intercept coefficient (β_0) and slope coefficient (β_1) interpolated by the inverse distance weighting method. Fig. 2a shows that the estimates of the local intercept coefficients (β_0) ranged from 0.05 to 9.27. The largest coefficients were concentrated in northern Taiwan and in these areas, variations in the rate of obesity could not be explained by variations in poverty as shown in Fig 3a and Table 4. Figure 2b shows that the estimates of the local slope coefficients (β_1) ranged from 0.03 to 0.26. The largest values were located in eastern Taiwan (Hua-Lien, and Tai-Tung Areas), where a linear relationship existed between the rate of poverty and obesity (R-square = 0.45 in Figure 3b and Table 4).

Discussion

Analysis based on GWR revealed geographical inequality in poverty rates. In areas with the highest rate of poverty (eastern Taiwan, including Hua-Lien and Tai-Tung) which contributes to less than 3% of total yearly national revenue (Tsou and Huang, 2003), the prevalence of poverty was a significant predictor of obesity. Our findings imply that poverty is associated with lower food expenditures, lower fruit and vegetable consumption and lower-quality diets, resulting in an increased prevalence of obesity (Drewnowski, 2009). These findings add to the existing literature which indicates strong associations between area-level variables, such as income inequality and neighborhood deprivation, and the likelihood of obesity (Kahn et al., 1999; Sampson et

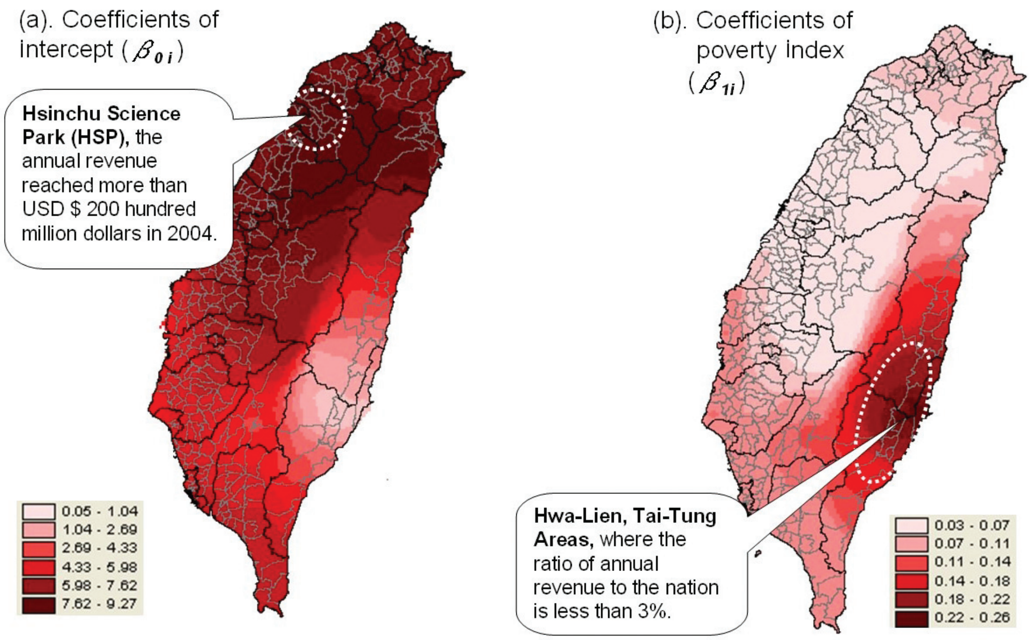

Fig. 2. Spatial mapping of the coefficients from geographically weighted regression (GWR) modeling.

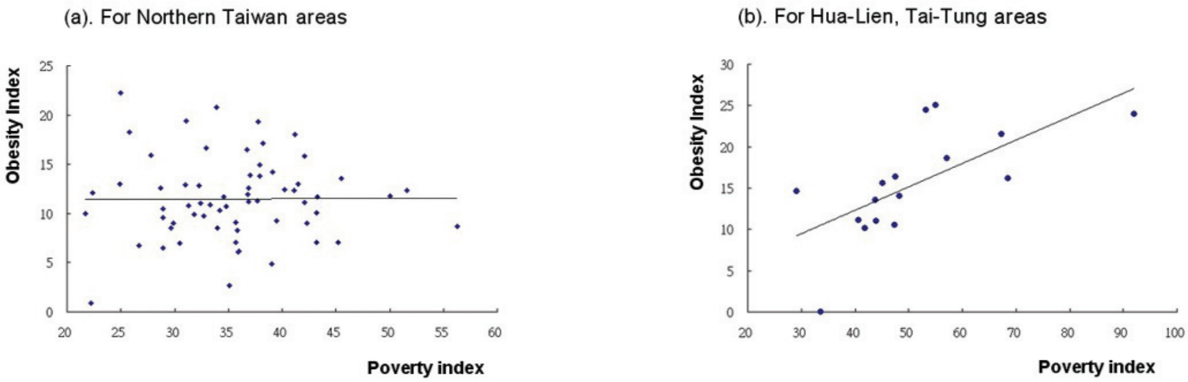

Fig. 3. Scatterplot of poverty-obesity relationships in northern Taiwan (a), and in Hua-Lien and Tai-Tung (b). The poverty rate (X-axis) refers to the ratio of individuals in poverty to the total population in a township (%). Poverty was defined as a personal monthly income of less than 20,000 NTD (597 USD) per month. The obesity rate (Y-axis) refers to the ratio of individuals with obesity to the total population in a township (%). Obesity was defined as BMI of greater than 27.

al., 1999). Many of the people living in eastern Taiwan are Taiwanese Aborigines. Racial and ethnic segregation has been regarded as another possible structural area-based risk factor for obesity. Chang (2006) demonstrated that racial isolation is related to the prevalence of obesity among African American residents in the US (Chang, 2006). In Taiwan, Lin et al. (2003) found that those residing in the mountainous regions (where Aborigines are the majority population) are prone to obesity (Lin et al., 2003). The poor socio-economic status of many Taiwanese Aborigines and their isolation in these particular regions may be related to obesity. Our results indicate that the prevalence of obesity in eastern Taiwan could be improved by reducing poverty.

In contrast, the prevalence of obesity could not be explained by the prevalence of poverty in northern Taiwan. The North is the center of socio-economic and industrial development in Taiwan, especially the Hsinchu Science Park (HSP) region (encircled in Fig. 2a) where the annual revenue reached more than two hundred million USD in 2004 (Chen, 2005). Residence in high-income areas may be negatively associated with obesity risk according to some reports (Byrne et al., 1998; Mancino and Kinsey, 2004). However, as this study was focused only on the prevalence of obesity in populations experiencing poverty, health-related conditions and other related geo-referenced variables of individuals whose monthly incomes exceed 20,000 NTD (equivalent to 597 US$) were not analyzed. Therefore, the importance of the SES-obesity relationship in dense high-tech industrial parks and metropolitan areas could not be determined. The effect of high income on obesity or related health conditions warrants further study.

Methodologically speaking, spatially-varying coefficient models, including GWR, have become important statistical methods for identifying local variations in relationships between outcome and explanatory variables (Assuncao, 2003; Gelfand et al., 2003; Waller et al., 2007). However, as relatively *ad hoc* inferences limits the statistical explanatory capability of GWR, it has only been used as an exploratory tool in this study. On the other hand, Bayesian approaches, such as spatial random effect models, provide model-based estimation and inferences by using Markov chain Monte Carlo (MCMC) algorithms to fit complex hierarchical models (Waller et al., 2007). However, currently MCMC algorithms require intensive and complicated computation. Therefore, the development of flexible and robust computational frameworks for spatially-varying coefficient models for model-based inferences would be greatly beneficial for researchers who are interested in identifying spatial variations in relationships.

As populations in disadvantaged areas of developed countries have the highest risk of obesity (McLaren, 2007), and as adult obesity is more common in high-income groups in developing countries (Popkin, 2001), determining the relationships between socio-economic status (SES) and obesity may be considered as a way of distinguishing between developed and developing countries (Monteiro et al., 2004). As opposed to national-level SES comparisons, our results further highlight the spatial variations in the poverty-obesity relationship in Taiwan.

In conclusion, our findings suggest that the prevalence of poverty is significantly associated with the prevalence of obesity only in certain less-developed areas. In the highly socio-economically developed or dense high-tech industrial areas, factors other than poverty appear to be contributing to variations in obesity. The life-style of shift work and SES differs greatly between dense high-tech industrial areas and other areas of Taiwan (Chen, 2003). This study has distinguished between these areas by analyzing the geographic correlations between obesity and poverty.

The use of a GWR model allowed for the adjustment of spatial heterogeneity when exploring poverty-obesity relationships by local area. The geographical visualization provided by the GWR model can provide policy-makers with important information about potential risk factors for health problems. Given the strong relationship between poverty and obesity in less-developed areas, the poverty-obesity relationship warrants further study.

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