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A Spatial Analysis of Linkages between Health Care Expenditures, Physical Inactivity, Obesity and Recreation Supply

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Rates of physical inactivity and obesity in the United States have reached epidemic proportions. This study estimates the linkages between health care expenditures for treatments of circulatory problems, physical inactivity, obesity, and the supply of recreation opportunities in West Virginia. Estimation of a spatial econometric model shows that rates of physical inactivity for counties are positively related to expenditures on health care treatments of diseases and disorders of the circulatory system. Results also show that quantities of variously measured recreation opportunities are negatively related to rates of physical inactivity, but not to obesity. The recursive nature of our model demonstrates that physical inactivity explains spatial patterns of obesity, but not vice versa. Therefore, increasing recreation opportunities have the potential to decrease health care expenditures and rates of obesity through increasing rates of physical activity.

KEYWORDS: *Health care expenditures, obesity, physical inactivity, recreation supply, spatial analysis.*

Introduction

The overall health of the United States improved throughout the 20th Century (U.S. Department of Health and Human Services, 2001). The ten greatest public health achievements in the United States from 1900 to 1999

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included improvements in the areas of vaccinations; motor vehicle safety; safer workplaces; control of infectious diseases; reduced deaths from coronary heart disease and stroke; safer and healthier foods; healthier mothers and babies; family planning; fluoridation of drinking water; and recognition of tobacco as a health hazard (Centers for Disease Control and Prevention, 2001a). The nation faces other health challenges in the 21st Century, including the noninfectious diseases of overweight and obesity. These diseases have reached epidemic proportions (U.S. Department of Health and Human Services, 2001). The prevalence of obesity increased from 12.0% in 1991 to 17.9% in 1998 (Mokdad, et al., 1999), and continued to increase to 19.8% in 2000 (Mokdad, et al., 2001), reaching 20.9% in 2001 (Mokdad, Stroup, & Giles, 2003).

Overweight and obesity are associated with increased health risks for certain chronic diseases, including coronary heart disease, type 2 (non-insulin dependent) diabetes, various cancers (e.g., endometrial, breast, and colon cancers), among other diseases and disorders (Mokdad, et al., 2003; Must, et al., 1999; Thompson, Edelsberg, Colditz, Bird, & Oster, 1999). The top five chronic disease killers, which include heart disease, cancer, stroke, chronic obstructive pulmonary disease, and diabetes, accounted for 68% of all deaths in the United States in 1999 (U.S. Department of Health and Human Services, 2002). Obesity has been estimated to lead to the death of 300,000 adults in the United States each year (Allison, Fontaine, Manson, Stevens, & VanItallie, 1999).

In addition, overweight and obesity impose substantial costs on the United States' health care system (Roux & Donaldson, 2004; U.S. Department of Health and Human Services, 2001). Direct health care costs of overweight and obesity include preventive, diagnostic, and treatment services (such as physician visits and hospital care). Indirect health care costs of overweight and obesity include lost wages due to an inability to function properly, and the value of future earnings due to premature death. Wolf and Colditz (1998) estimated the total costs of obesity to be $99 billion in 1995. Wolf (2001) estimated the total cost of obesity to be $117 billion in 2000, including $61 billion in direct costs and $56 billion in indirect costs. The costs of obesity are primarily due to its contribution to incidences of coronary heart disease, type 2 diabetes, and hypertension (Wolf, 1998).

Pronk, Goodman, O'Connor, and Martinson (1999) estimated a 1.9% increase in medical charges for every one-unit increase in body mass index (BMI). Thompson et al. (1999) estimated lifetime medical care costs are at least $10,000 higher for moderately obese (BMI of 32.5 kg/m^2) as compared to non-obese (BMI of 22.5 kg/m^2) 45-54 year old men in 1996. Severely obese (BMI 37.5 kg/m^2) men in the same age group could expect $17,000 higher lifetime medical care costs as compared to non-obese men in 1996. Nearly half of their estimated lifetime medical care costs, regardless of degree of obesity, were due to coronary heart disease. They also reported similar results across other age groups and for women (Thompson et al., 1999).

The relative magnitudes of excess lifetime medical care costs associated with increasing degrees of obesity were similar to estimates for smoking (Thompson et al., 1999).

Chronic diseases, including overweight and obesity, are not only the most prevalent and costly of all health problems, but they are also among the most preventable (U.S. Department of Health and Human Services, 2002). Many chronic diseases are a function of people's daily choices. The lack of physical activity and poor dietary habits are second only to tobacco use as leading causes of preventable death in the United States (McGinnis & Foege, 1993; U.S. Department of Health and Human Services, 2002). Further, physical inactivity is estimated to account for about 22% of colon cancer, 18% of osteoporotic fractures, 12% of diabetes and hypertension, and 5% of breast cancer or about $24 billion of total United States' health care costs each year (Colditz, 1999). Pratt, Macera, and Wang (2000) estimated that $29.2 billion to $76.6 billion (in 2000 dollars) in national health care costs could be reduced annually if the 88 million inactive Americans over the age of 15 increased their participation in moderate-intensity physical activity.

Emphasis on research that links behavioral choices, in particular regular physical activity, with health outcomes was initiated in 1992 (Dunn & Blair, 2002). Sustained activity levels are recommended for long-term health benefits, including moderate-intensity physical activity ($\geq$ five times per week for $\geq$30 minutes each time) and vigorous-intensity physical activity ($\geq$3 times per week for $\geq$20 minutes each time), the latter level being necessary for cardio-respiratory fitness (Centers for Disease Control and Prevention, 2001b; Pate et al., 1995).

In 1996, the director of the Centers for Disease Control and Prevention appointed the non-Federal Task Force on Community Preventive Services (Task Force). The Task Force reviewed and assessed scientific evidence on the effectiveness of community preventive health services and provided several recommendations to help improve the health state of the nation (Pappaioanou & Evans, 1998). The Task Force's review of scientific studies measuring the effectiveness of intervention programs, physical activity, and health found that regular physical activity is associated with improved health, including aerobic capacity, muscular strength, body agility and coordination, and metabolic functioning (Task Force on Community Preventive Services, 2002). Regular physical activity helps reduce risks of cardiovascular disease, stroke, type 2 diabetes, some cancers, and other diseases (Task Force on Community Preventive Services, 2002). There is also evidence that physical activity has an important role in improving self-confidence, self-esteem, and general feelings of well-being (Coleman & Iso-Ahola, 1993; Fletcher et al., 1996; Ponde & Santana, 2000). Therefore, eating healthy and engaging in regular physical activity are two behavioral changes people can make to help prevent obesity and reduce the risks of heart disease, hypertension, diabetes, colon cancer, and premature mortality (U.S. Department of Health and Human Services, 1996).

The dose-response function relating increases in physical activity with health benefits is generally positive and linear in shape (Bouchard, 2001). Small increases in activity for inactive people result in significant health gains. Pronk et al. (1999) estimated medical care costs to be 4.7% lower for people who were physically active for only one day per week as compared to people with no days of physical activity. The Task Force notes that "the largest public health benefit of physical activity interventions is a result of increased activity among sedentary populations, rather than increased activity among already active people" (Task Force on Community Preventive Services, 2002, 71-72). However, despite scientific evidence and health education campaigns, leisure time physical activity rates have remained relatively unchanged (Centers for Disease Control and Prevention, 2001b) while rates of overweight and obesity have continued to increase (Mokdad et al., 1999, 2001, 2003) from 1990 to 1998. Only about 25% of the United States' adult population engaged in leisure time physical activity at or above the recommended levels. Nearly half of the adult population (45%), while physically active in their leisure time pursuits, is active at an insufficient level for long-term health benefits. About 30% of the adult population in the United States gets no physical activity in their leisure time (Centers for Disease Control and Prevention, 2001b). The rates for leisure time physical inactivity were slightly lower in 2000 (27%) and in 2001 (26%) (Centers for Disease Control and Prevention, 2003).

The Task Force also evaluated 94 published studies on the effectiveness of various approaches for increasing physical activity (Kahn et al., 2002). They classified the physical activity intervention studies as (1) informational approaches; (2) behavioral and social approaches; or (3) environmental and policy approaches. Based on the evidence, the Task Force recommended six interventions for increasing physical activity: two informational approaches that include communitywide campaigns and point-of-decision prompts to encourage using stairs; three behavioral and social approaches that include school-based physical education, social support interventions in community settings, and individually adapted health behavior change; and one environmental and policy approach that includes creation of or enhanced access to places for physical activity combined with informational outreach activities (Task Force on Community Preventive Services, 2002). The environmental and policy intervention recommendation is broader than the others; it targets entire populations through enhancing physical and organizational structures.

This study focuses on the environmental and policy approach recommendation, which includes interventions to change the local environment to create opportunities for physical activity. The Task Force notes the importance of developing access to places for physical activity, including building or improving trails or facilities. Evidence shows that "neighborhood and environmental characteristics such as safety lighting, weather, and air pollution also affect physical activity levels, regardless of individual motivations and knowledge" (Task Force on Community Preventive Services, 2002, p.

71). We hypothesize that the uneven distributions of natural amenities (e.g., parks, waterways, hiking trails) and urban facilities (e.g., ball fields, tennis courts, health clubs, etc.) result in comparative health advantages for communities high in natural amenities and urban facilities.

We estimate a model of the relationship between health care expenditures for treating diseases and disorders of the circulatory system, rates of physical inactivity, rates of obesity, and measures of recreation supply using a spatial econometric method. West Virginia was selected as our case study. West Virginia's rates for behavioral risk factors, including obesity and physical inactivity, are among the highest in the United States. According to the Centers for Disease Control and Prevention's Behavioral Risk Factor Surveillance System (BRFSS) data, West Virginia had the sixth highest rate for no leisure time physical activity (31.3% of the adult population) in the nation (25.7% of the adult population) in 2001 (Centers for Disease Control and Prevention, 2003). Based on the same dataset, West Virginia had the second highest rate for obesity (24.6% of the adult population) in the nation (21.0% of the adult population) (Mokdad et al., 2003) in 2001. According to the U.S. Department of Health and Human Services (2002), West Virginia had the third highest proportion (70.7%) of total deaths due to the five leading chronic disease killers (diseases of the heart, all cancers, stroke, chronic obstructive pulmonary disease, and diabetes) in 1999. West Virginia had the second highest rate of death due to heart disease in 1999 (U.S. Department of Health and Human Services, 2002). The health profile for West Virginia is, thus, a major concern for state legislators as they emphasize the need to "begin addressing obesity and laziness because the state can't afford the costs associated with unhealthy lifestyles" (Bundy, 2002).

Methods

Data Sources

Table 1 lists the sources from which the data used in this analysis were compiled. Health care expenditures, health status, health care availability, the number of recreation facilities, and county-level socio-demographics were provided by West Virginia's state agencies, including the Health Care Authority, Department of Health and Human Resources, West Virginia University, and the Bureau of Employment Programs. The remaining data were provided by federal agencies including socio-demographic data and journey-to-work data from the U.S. Census Bureau, and land use allocation data and metropolitan status data from the U.S. Department of Agriculture.

Model Conceptualization and Testing

Estimation of the effect of physical inactivity on health care expenditure and the effect of recreation supply on the prevalence of physical inactivity and obesity is based on a three equation system. The first equation in the system models the dependence of health care expenditures (*HCE*) on phys-

TABLE 1
Variable Descriptions, West Virginia Counties

Variable	Description	Source
DEPENDENT VARIABLES		
Health Care Expenditures (Circ. System)	Per capita hospital charges in 1999 by county of residence in West Virginia hospitals for treatment of diseases and disorders of the heart (dollars)	A
Physical Inactivity Prevalence	Proportion of county adult population with a behavioral prevalence for physical inactivity, 1997	B
Obesity Prevalence	Proportion of county adult population with a behavioral prevalence for obesity, 1997	B
HEALTH CARE AVAILABILITY		
Cardiovascular Physician	Dummy variable; 1 = presence of cardiovascular physician, 1990	C
Cardiac Rehabilitation Center	Dummy variable; 1 = presence of a cardiac rehabilitation unit, 1993	C
Hospital Beds	Per capita hospital beds, 1999 (per 10,000)	D
SOCIO-DEMOGRAPHICS		
Population Over 65	Proportion of population over 65 years of age, 2000	E
Education Level	Proportion of adults over 25 years of age with a high school diploma, 2000	E
Median Age	Median age, 2000	D
Income	Per capita personal income, 1998 (in $1,000s)	D
Population Density	Population density, 2000 (per square mile)	D
Metro	Dummy variable; 1 = metropolitan designated county, 1993	F
Work Out-of-State	Proportion of total number of employed county residents who work outside West Virginia, 2000	G
RECREATION SUPPLY		
Municipal Land	Total county acres managed by municipalities, 1997 (1,000s)	H
Public Land	Total county acres managed by public agencies, 1997 (1,000s)	H
Recreation Water	Total county acres devoted to water-based recreation, 1997 (1,000s)	H
Recreation Facilities	Total number of indoor and outdoor recreation facilities including ball diamonds, basketball and tennis courts, swimming pools, country clubs, golf courses, parks and playgrounds, 2000	D
Parks & Recreation Department	Dummy variable; 1 = county has a parks & recreation department, 1997	I

TABLE 1
(Continued)

Source Code	Source
A	West Virginia Health Care Authority, Hospital Data
B	West Virginia Department of Health and Human Resources, Bureau for Public Health, Office of Epidemiology and Health Promotion, Health Statistics Center, individual county profiles
C	West Virginia University, Health Sciences Center, Prevention Research Center: *Heart Disease in Appalachia: An Atlas of County Economic Conditions, Mortality and Medical Care Resources*
D	West Virginia Bureau of Employment Programs, Research, Information and Analysis, individual county profiles
E	U.S. Census Bureau, Census of Population
F	U.S. Department of Agriculture, Economic Research Service, Rural/Urban Continuum Codes
G	U.S. Census Bureau, Journey to Work and Place of Work, 2000 County-to-County Worker Flow Files
H	U.S. Department of Agriculture, Natural Resource Conservation Service, National Resources Inventory, 1997
I	U.S. Department of Agriculture, Forest Service, Southern Research Station, National Outdoor Recreation Supply Information System, 1997

ical inactivity (*PI*), controlling for other factors affecting health care expenditures including the availability of health care (*HCA*) and socio-demographic characteristics (*SD*):

$$HCE = f(PI, HCA, SD). \tag{1}$$

The second and third equations model the dependence of physical inactivity (*PI*) and obesity (*OB*) on the supply of recreation opportunities (*RO*), while controlling for socio-demographic characteristics (*SD*):

$$PI = f(OB, RO, SD) \tag{2}$$

$$OB = f(PI, RO, SD). \tag{3}$$

Cyclically, physical inactivity tends to promote obesity, and obesity tends to promote physical inactivity. Therefore, physical inactivity and obesity are likely simultaneously determined in Equations 2 and 3. Not accounting for simultaneity in the regressors leads to inconsistent and biased Ordinary Least Squares estimators. Simultaneity arises when a regressor is endogenous to the system and is, therefore, likely correlated with the error term. If physical inactivity and obesity are in fact endogenous to the system, then an alternative to the Ordinary Least Squares estimator is required (e.g., Two-Stage Least Squares) in order to produce unbiased, consistent, and efficient estimators.

Another statistical issue that should be addressed is the inherent spatial dependence of many types of data. The data used in this analysis contain spatial aspects based on the arbitrary delineation of the spatial units (county boundaries), the spatial distribution of the supply of recreation opportunities and health care, and the inherent mobility of county residents as they seek places for health care, employment, and recreation opportunities beyond the boundaries of their respective counties. The location aspects of our data lead to two potential problems in estimation: (1) spatial dependence among observations in the data; and (2) spatial heterogeneity in the relationships being modeled (LeSage, 1999). Both spatial dependence and spatial heterogeneity are violations of assumptions underlying unbiased, consistent, and efficient Least Squares estimators. Our focus will be on the potential spatial dependence associated with our data. Bateman et al. (2002) paraphrase Irwin and Geoghegan's (2001) argument "that analyzing a problem that is essentially location based while ignoring the potential of spatial interactions among observations is analogous to analyzing a time series problem without knowing the chronological order of the observations considered" (pg 221).

Spatial dependence in the data can be modeled using a generic spatial autoregressive model of the form:

$$HCE_i = \rho W\, HCE_{i-1} + \beta PI_i + \beta HCA_i + \beta SD_i + u_i, \qquad u_i = \lambda u_{i-1} + \varepsilon_i; \quad (4)$$

$$PI_i = \rho W\, PI_{i-1} + \beta OB_i + \beta RO_i + \beta SD_i + u_i, \qquad u_i = \lambda u_{i-1} + \varepsilon_i; \quad (5)$$

$$OB_i = \rho W\, OB_{i-1} + \beta PI_i + \beta RO_i + \beta SD_i + u_i, \qquad u_i = \lambda u_{i-1} + \varepsilon_i. \quad (6)$$

The two forms of spatial dependence are incorporated in the generic spatial autoregressive model (LeSage, 1999). First, spatial dependence may arise based on interdependence among the observations, similar to serial correlation in time-series models. If this interdependence among observations is not accounted for, then Least Squares estimators will be inefficient. The expanded error term (u_i) in the generic spatial autoregressive model accounts for the relationship between the errors for observation i and its spatially lagged neighbor $i-1$. Second, spatial dependence may arise based on an error-in-variable measurement or omitted variable, similar to the simultaneity problem. If this error-in-variables or omitted variable problem is not accounted for, then Least Squares estimators are biased and inconsistent. The first term on the right hand side consists of an autocorrelation parameter (ρ) and a weighting scheme (W) that accounts for the relative spatial interaction between observations i and their defined spatial lags ($i-1$). If $\rho = 0$ in Equations 4-6, then a spatial error form is estimated to account for spatial dependence of the first type. If, however, $\lambda = 0$ in Equations 4-6, then a spatial lag form is estimated to account for spatial dependence of the second type.

An important aspect in spatial analysis is the quantification of location (Anselin, 1988; LeSage, 1999). There are two sources of locational information: (1) latitude and longitude coordinates in Cartesian space that allow calculation of distances from any point in space; and (2) contiguity, or the relative position of observations with regard to each other in space (LeSage, 1999). We use the Queen Contiguity procedure for defining and measuring the relative location of observations with each other in the weight matrix, *W*. The Queen Contiguity procedure identifies the first-order contiguous region as observations (in our case, counties) that share a common side or vortex. Therefore, the weight matrix for county *i* includes all other counties *j* that share a common side or point with county *i* and is standardized so that the contiguous county weights for county *i* sum to one.

Model Specification

Data were collected for all 55 counties in West Virginia. While the theoretical model directed data collection, data availability was a significant factor in the empirical specifications of the models. Table 1 provides variable definitions and data sources. Table 2 provides summary statistics for each variable. The dependent variables in the models include per capita health care expenditures in West Virginia hospitals for treatments of diseases and disorders of the circulatory system. Expenditures are measured by county of residence, not location of treatment. The broad classification of diseases and disorders of the circulatory system was selected based on the linkages between physical inactivity, obesity and cardio fitness (Task Force on Community Preventive Services, 2002). Prevalence measures for physical inactivity

TABLE 2
Summary Statistics (n = 55)

Variable	Mean	Std. Dev.	Min	Max
Health Care Expenditures (Circ. System)	284.57	127.24	50.8	663.1
Physical Inactivity Prevalence	45.01	8.69	22.4	63.2
Obesity Prevalence	21.31	3.94	14.1	30.3
Cardiovascular Physician	0.34	0.48	0	1
Cardiac Rehabilitation Center	0.34	0.48	0	1
Hospital Beds	46.44	41.90	0	190.2
Population Over 65	15.44	1.90	10.7	19.9
Education Level	62.84	7.71	42.3	75.4
Median Age	39.29	1.93	30.4	43.4
Income	17.99	3.33	12.7	26.4
Population Density	94.71	100.14	9.7	446.6
Metro	0.22	0.42	0	1
Work Out-of-State	11.50	13.02	0.8	46.3
Municipal Land	0.78	1.52	0	6.8
Public Land	28.57	57.94	0	343.6
Recreation Water	2.61	1.93	0.3	8.6
Recreation Facilities	58.80	53.30	11	343
Parks & Recreation Department	0.42	0.50	0	1

and obesity in the adult population for each county were derived from the Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS is a cross-sectional, population-based, random digit dial telephone survey of adults (18 years of age and older) conducted by the Centers for Disease Control and Prevention and state health departments for the purpose of tracking health risks in the United States (Mokdad, Stroup & Giles, 1998).

Health care expenditures in hospitals for treatments of diseases and disorders of the circulatory system are hypothesized to be positively related to rates of physical inactivity based on empirical evidence. However, physical inactivity is not the only factor that contributes to expenditures on health care. Therefore, two broad classifications of factors are controlled for in the regression analysis: the availability of health care and socio-demographics (Equation 4). The presence of a cardiovascular physician and a cardiac rehabilitation center measures the health care industry's supply response to the demand for specialized health care. It is expected that specialized physicians and centers will locate where the demand for their services is high. The number of hospital beds per 10,000 people measures the location and size of hospitals where expenditures are being measured.

Variability in the socio-demographic characteristics of county residents also may contribute to rates of expenditure on health care, physical inactivity, obesity, and the demand for recreation opportunities. For example, the older a county's population the higher we would expect health care expenditures for circulatory system diseases and disorders, holding all else constant. Socio-demographic differences are controlled by including measures of the proportion of total county population over the age of 65 years, education level, median age, and per capita income in the equation. Urban areas are expected to have a greater supply of recreation facilities due to larger and denser populations. Therefore, counties classified as metropolitan are quantified along with the population density of each county.

The prevalence of physical inactivity and obesity (Equations 5 and 6) are hypothesized to be negatively related to the availability of recreation opportunities, controlling for socio-demographic differences across counties. Recreation opportunities at the county-scale are difficult to measure. In this study, we assume availability is equivalent to accessibility. Data of a higher resolution would be required to measure the accessibility of recreation sites and facilities for a given population. We measure recreation opportunities as the total county acres managed by municipalities, which provide urban recreation opportunities and the total county acres that are managed by public agencies. Public lands are typically available to a local population free of charge or for a minimal fee. Water resources in a county also may be significant contributors to the supply of recreation opportunities. We use the total county acres devoted to water-based recreation as measured by the U.S. Department of Agriculture's Natural Resource Conservation Service's (NRCS) National Resource Inventory. Recreation facilities are measured as the number of indoor and outdoor recreation facilities, including baseball fields, basketball and tennis courts, swimming pools, country clubs, golf courses, parks, and playgrounds. A final measure of the supply of recreation opportunities is the presence of a parks and recreation department in the county. Less than half of the counties in West Virginia have a parks and recreation department (Table 2).

The variable, Work Out-of-State, is important for two reasons. Potential measurement errors in health care expenditures, health care availability and recreation supply exist due to the spatial nature of the data and how they were collected. Health care expenditures are expenditures that occur in West Virginia hospitals and measured based on county of residence. It is likely that residents of counties on or near the state line may seek health care outside of West Virginia, especially if adequate or better health care is available outside the state, but within commuting distance. The likelihood that residents of state line counties will seek health care outside of their state of residence is greater if those residents also work outside the state. People that work out-of-state may have health care insurance that is fully available in the state in which they are employed. A similar argument can be made regarding the availability of recreation sites and facilities. Recreation opportunities outside the state of West Virginia are most accessible to residents of counties on the state line. Therefore, the variable Work Out-of-State serves as a proxy for access to health care and recreation opportunities. The proportion of a county's workers that work out of state is directly related to distance from the state boundary.

Results

Diagnostic Tests

Several econometric issues need to be investigated before fully specifying the equations and choosing efficient and unbiased estimators. Table 3 provides the results of diagnostic tests for spatial dependence, heteroskedasticity, and simultaneity/endogeneity. The statistics used to evaluate the presence of spatial dependence in the data are Lagrange Multiplier (LM) statistics, distributed as a χ^2 with one degree of freedom. These LM statistics are robust to the presence of spatially lagged correlation in the dependent variable when testing for spatial correlation in the error term and vice versa. The null hypothesis for these tests is no spatial autocorrelation, or the case of $\rho = 0$ or $\lambda = 0$.

Both test results for the health care expenditure equation (Equation 4) reject the null hypothesis in favor of the presence of spatial autocorrelation in both the spatially lagged dependent variable and the spatial error term (both $\rho \neq 0$ and $\lambda \neq 0$). Anselin (1995) states that given the LM tests are robust to spatial autocorrelation misspecification, it is best to choose the one (spatial lag model or spatial error model) with the most significant test statistic. In our case, we favor a spatial lag model specification given the LM for ρ is the most significant of the two LM statistics. The LM tests for the physical inactivity equation (Equation 5) and the obesity equation (Equation 6) are definitive. The null hypothesis that $\lambda = 0$ is not rejected, but the null

TABLE 3
Diagnostic Tests for West Virginia Data (n = 55)

Equation	Test Statistic	Value	*P*-Value
Spatial Autoregressive Model			
H_0: $\rho = 0$ (lag) or $\lambda = 0$ (error)			
Eq (4): Health Care Expenditures (Circ. System)	Robust LM (on ρ)	12.84	0.0003
	Robust LM (on λ)	8.78	0.003
Eq (5): Physical Inactivity Prevalence	Robust LM (on ρ)	5.31	0.02
	Robust LM (on λ)	0.98	0.32
Eq (6): Obesity Prevalence	Robust LM (on ρ)	1.98	0.16
	Robust LM (on λ)	0.30	0.58
Heteroskedasticity			
H_0: Homoskedastic			
Eq (4): Health Care Expenditures (Circ. System)	Koenker-Bassett	5.57	0.78
Eq (5): Physical Inactivity Prevalence	Breusch-Pagan	5.81	0.83
Eq (6): Obesity Prevalence	Breusch-Pagan	14.21	0.22
Simultaneity/Endogeneity			
H_0: Not simultaneous/Exogenous			
PI = f(OB)	Pindyck & Rubin/ Hausmann	4.22	0.0001
OB = f(PI)	Pindyck & Rubin/ Hausmann	0.28	0.80

hypothesis that $\rho = 0$ is rejected. Therefore, all three equations will be specified as spatial lag models.

Table 3 also reports the diagnostic test outcomes for heteroskedasticity. The null hypothesis for these tests is a homoskedastic error processes. Although parameter estimates are unbiased and consistent in the presence of heteroskedasticity, they are inefficient and may lead to incorrect inferences regarding model fit and covariate significance. However, all three test statistics fail to reject the null hypothesis in favor of no heteroskedasticity. The health care expenditure equation (Equation 4) used a Koenker-Bassett test for heteroskedasticity given the error term was not normally distributed. The error terms in Equations 5 and 6 were found to be normally distributed, and therefore the Breusch-Pagan heteroskedasticity test was used.

As we mentioned earlier, we can intuitively argue that Equations 5 and 6 are simultaneously determined and that the prevalence of physical inactivity and the prevalence of obesity are endogenous to each other and to the system. When two variables are jointly determined, then Ordinary Least Squares estimators are inconsistent due to the correlation between one of the endogenous variables and the error term. Table 3 also reports the diagnostic tests for simultaneity and endogeneity between measures of physical inactivity and obesity. The results suggest that the prevalence of obesity is endogenous to the system and jointly determined with the prevalence of physical inactivity if entered as an explanatory variable, but that the prevalence of physical inactivity is exogenously determined from the prevalence of obesity. Therefore, our system of equations model does not exhibit simultaneity and can be structured as a recursive or causal system.[1] The structure of the recursive system of equations model is depicted in Figure 1. The solid arrows define the direction of statistical causality. The dashed lines illustrate the possibility of feedback from improved health conditions on the demand for recreation opportunities. In the fully simultaneous system of equations (Equations 5 and 6), the uni-directional arrow linking physical activity and obesity would be bi-directional; i.e., a simultaneous interaction between the two variables. In the recursive system, causality is defined in a single direction. Therefore, the measure of physical inactivity is specified as an explanatory variable in the obesity equation, but not the reverse.

Empirical Models

Table 4 provides the estimated spatial lag models for the system of equations.[2] The estimated health care expenditures equation had a log-likelihood of -320 and a pseudo-R^2 of 0.57. All of the signs on the variables were as expected. Four of the variables were statistically significant at the 0.10 level or better. The prevalence of physical inactivity is statistically significant and positively related with health care expenditures for treatments of diseases and disorders of the circulatory system. A one percent increase in physically inactive adults increased health care expenditures on hospital treatments of diseases and disorders of the circulatory by $3.42 per capita. The presence of a cardiac rehabilitation center was the only health care availability measure statistically significant. The presence of a cardiac rehabilitation center was associated with a $74.43 increase in hospital charges for treatments of diseases and disorders of the circulatory system.

The proportion of the total population that is over the age of 65 years was statistically significant and positively related with health care expenditures. For every one percent increase in a population over the age of 65, per capita hospital expenditures for treatments of diseases and disorders of the

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[1]Implied causality is in a statistical sense (Granger, 1969); physical inactivity precedes or causes obesity. Medical studies indicate that this form of causality may also be in a physical sense. According to Blair and Brodney (1999), physical inactivity is the primary cause of morbidity and mortality when compared with obesity. They also provide evidence that suggests physically active obese people have lower morbidity and mortality risks than normal weight, sedentary people. In addition, several studies document that, of all the behavioral risk factors, physical inactivity has the greatest impact on health status and is the best predictor of cardiovascular diseases and overall mortality (Johansson & Sundquist, 1999; Myers et al., 2002).

[2]All models were estimated using SpaceStat software and James P. LeSage's spatial econometrics toolbox for MatLab (http://www.spatial-econometrics.com/). Both software packages resulted in similar estimated parameters. The estimated models reported in this paper are the results from the SpaceStat application.

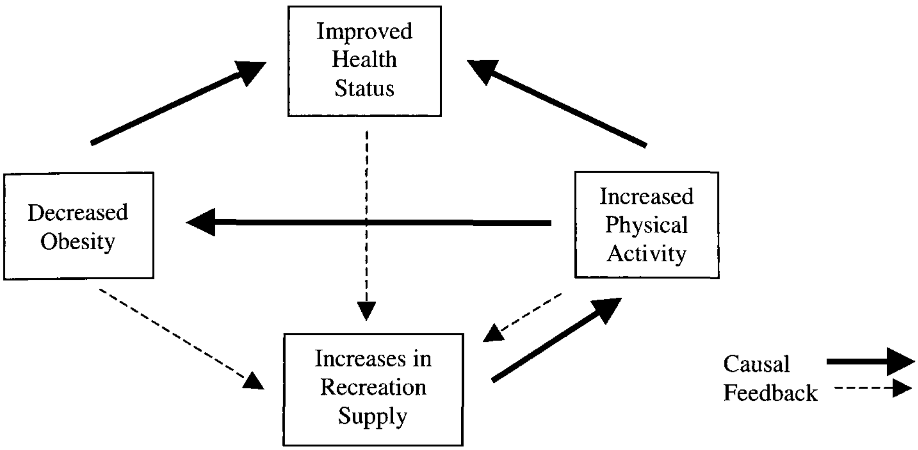

Figure 1. Recursive model of the relationship between recreation supply, physical activity, obesity and health status.

circulatory system increased by $16.51 per capita. The proportion of workers in a county with jobs outside the state was statistically significant and negatively associated with health care expenditures. This suggests that many residents of counties on the state line seek health care outside their state of residence. For every one percent increase in workers with jobs outside the state, per capita health care expenditures for treatments of diseases and disorders of the circulatory system declined by $2.82.

The estimated physical inactivity equation had a log-likelihood of -165 and a pseudo-R^2 of 0.67 (Table 4). All of the signs on the variables were as expected. Four of the variables were statistically significant at the 0.10 level or better. The supply of recreation opportunities was hypothesized to be negatively related to the prevalence of physical inactivity among the adult population for each county. Total county acres managed by public agencies and total county acres devoted to water-based recreation were statistically significant. For every 1,000 acres of public land or surface area devoted to water-based recreation, rates of physical inactivity declined by 0.04 and 0.66, respectively. Every 1,000 acres of land managed by municipalities reduced physical inactivity by 0.04.

Socio-demographic factors also may contribute to rates of physical inactivity. Education level, as the proportion of adults over the age of 25 with high school diplomas, was significantly and negatively associated with physical inactivity rates. The proportion of employed adults in a county that work outside of the state was statistically significant and negatively associated with physical inactivity rates. This variable served as a proxy for access to recreation opportunities out-of-state for counties on the state line.

The estimated obesity equation had a log-likelihood of -135 and a pseudo-R^2 of 0.47 (Table 4). The only variable that was statistically significant

TABLE 4
Spatial Lag Model Results for West Virginia (n = 55)

Variable	Parameter Estimates (Std. Dev.) Health Care Expenditures (Equation 4)	Physical Inactivity (Equation 5)	Obesity (Equation 6)
Health Care Expenditures (Circulatory System)	Dep. Var.	—	—
Physical Inactivity Prevalence	3.421*	Dep. Var.	0.215***
	(1.86)		(0.07)
Obesity Prevalence	—	—	Dep. Var.
Cardiovascular Physician	7.204	—	—
	(35.26)		
Cardiac Rehabilitation Center	74.434**	—	—
	(33.10)		
Hospital Beds	0.476	—	—
	(0.45)		
Population Over 65	16.51**	—	—
	(6.69)		
Education Level	−2.784	−0.453***	−0.067
	(2.35)	(0.12)	(0.08)
Median Age†	—	6.326	0.822
		(5.36)	(3.14)
Income	5.248	—	—
	(6.521)		
Population Density†	−0.068	0.555	0.730
	(0.22)	(1.31)	(0.77)
Metro	—	−2.919	−0.816
		(2.40)	(1.39)
Work Out-of-State†	−2.818***	−1.131*	0.559
	(1.06)	(0.63)	(0.37)
Municipal Land	—	−0.403	−0.280
		(0.49)	(0.29)
Public Land	—	−0.036***	0.004
		(0.01)	(0.008)
Recreation Water	—	−0.657*	0.127
		(0.36)	(0.22)
Recreation Facilities	—	−0.012	0.015
		(0.02)	(0.01)
Parks & Recreation Department	—	−0.396	−0.146
		(1.86)	(1.08)
Constant	−150.096	38.054	1.825
	(256.51)	(25.89)	(15.46)
ρ	0.326**	0.345***	0.310**
	(0.14)	(0.12)	(0.14)
Log-likelihood	−320.11	−165.02	−134.82
Pseudo-R^2	0.57	0.67	0.47
LM Test for Spatial Error	6.76***	0.02	0.02

†Variables are in natural logarithmic form for the Physical Inactivity and Obesity models.
*, ** and *** mean significant at the 0.10, 0.05 and 0.01 critical levels, respectively.

(with the exception of the spatial autocorrelation parameter) was the prevalence of physical inactivity. Physical inactivity was statistically significant and positively associated with rates of obesity; for every one point increase in the rate of physical inactivity, obesity rates increased by 0.22 points.

Rho (ρ) is the spatial lag coefficient and was significant and positive in all of the equations. If the model does not account for the spatially lagged dependence in the data, the estimated parameters would have been biased and inconsistent. The test statistic derived from a robust LM test for spatial error showed spatial dependence, in the form of interdependence among observations in the data, was not fully corrected in the spatially-lagged health care expenditures equation. Therefore, while the parameter estimates are unbiased and consistent in the health care expenditures equation, they are not efficient. The physical inactivity and obesity equations' robust LM test for spatial error show no spatial interdependence among the data are present. Therefore, for the physical inactivity and obesity equations, the estimated parameters are unbiased, consistent, and efficient.

Conclusions

We estimated three equations in a system of equations model that relates county-level measures of health care expenditures in hospitals for treatments of diseases and disorders of the circulatory system, rates of physical inactivity and obesity, and recreation opportunities for West Virginia. The equations were specified as spatial lag models and were estimated using maximum likelihood estimators. The equation also controlled for the effects of health care availability and socio-demographic differences across the counties. The estimated health care expenditure equation showed higher rates of physical inactivity among adults in each county were associated with higher hospital expenditures for treatments of diseases and disorders of the circulatory system. The estimated physical inactivity equation showed negative relationships between the quantity of various recreation opportunities and the rate of physical inactivity among the counties. The estimated obesity equation showed no statistically significant relationships between the quantity of various recreation opportunities and rates of obesity among the counties. In the system, however, the measures of recreation opportunities were negatively associated with health care expenditures and rates of obesity indirectly through their direct effect on physical inactivity. Rates of physical inactivity were statistically significant and positively associated with rates of obesity and health care expenditures across the counties.

We also tested the system for simultaneity and endogeneity problems between physical inactivity and obesity. Obesity was found to be endogenous to the system and simultaneously determined with physical inactivity. However, physical inactivity was not found to be simultaneously determined with obesity. This outcome resulted in our specification of the system as a recursive one; physical activity was a contributing factor to rates of obesity, but not vice versa. This result is supported in the literature. For example, Blair and

Brodney (1999), in a review of the literature on the relationship between physical inactivity and obesity, conclude that physical inactivity is the primary cause of morbidity and mortality as compared with obesity. They cite additional evidence that physically active obese people have lower morbidity and mortality risks than normal weight but sedentary people. This evidence is consistent with our results. However, the causality identified in our study is a statistical one. Our results should not be confused with a dose-response relationship for individuals. In aggregate, we do find that more physically active counties are (1) associated with counties with higher quantities of recreation opportunities; (2) associated with counties with lower health care expenditures; and (3) are associated with counties with lower rates of obesity.

The results of this research may aid policy makers advocating healthier lifestyles by providing a framework that links physical inactivity to the supply of recreation opportunities. Recreation, leisure time and health status are interrelated. Policy makers have the means to significantly affect the supply of recreation facilities as opportunities for physical activities, including budget allocations and promoting better health. Our results suggest that there is a positive relationship between rates of physical inactivity and the demand for health care. Evidence also supports the hypothesis that populations with more opportunities for recreating are more physically active than those populations with limited recreation opportunities. Therefore, targeting issues of physical inactivity through educational campaigns and increasing the accessibility to recreation sites and facilities would serve a dual purpose. Increased rates of physical activity not only would directly reduce the rate of obesity and health care burdens, but also indirectly through decreased health burdens due to high incidences of obesity.

Extensions of this research should focus on expanding the variability in the data. There are three dimensions in the data that should be investigated. First, the current analysis is a cross-sectional study. We cannot discern directions or magnitudes of changes that may be occurring in people's health states with regard to recreation opportunities. Do areas high in natural amenities and recreation opportunities have a comparative advantage in attracting healthier migrating populations over areas without these attributes? Or is the uneven distribution of healthy people and recreation opportunities a simultaneous system of cause and effect? Expanding this analysis temporally is one way of addressing these questions. Temporal analyses of landscape changes, migration patterns, and investments in recreation sites and facilities would enable estimation of an aggregate dose-response function between recreation opportunities and changes in behavioral risk factors.

A second dimension for expanding the data is geographically. Expanding the scope of the analysis to include other regions of the United States would introduce variability in recreation opportunities and access to these opportunities based on climatological and topographical variation. Weather can be a significant determinant of people's participation in and availability of certain outdoor recreation activities. For example, snow-based activities are not locally available in regions with temperate climates. Land ownership patterns could be significant constraints on the ability to provide dispersed land-based recreation opportunities such as hiking trails, backcountry experiences, etc. The lack of these types of experiences locally is a function of the lack of public land in certain regions. However, recreation opportunities on private land may compensate for the lack of public land.

A third dimension for expanding the data is the measurement of key variables and the resolution of the data. The health care expenditure data are for charges incurred in hospitals for the treatment of diseases and disorders of the circulatory system. Other factors can contribute to the level of health care expenditure, including genetics and age. Similarly, physical inactivity and obesity can contribute to other types of diseases and disorders. By using an all-inclusive measure of health care expenditure, we also have included expenditures for preventive health care and screening (annual check-ups). Higher resolution in the health care expenditure data could lead to the estimation of the marginal contributions of physical activity to reductions of the health care burden. In a similar fashion, measures of recreation opportunities could be improved. Higher resolution of recreation opportunity data including spatial locations, accessibility and use by local communities would enable estimation of the marginal contributions of different types of recreation opportunities to overall improvements in physical activity levels. The supply of and accessibility to recreation opportunities is likely to vary from region to region.

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