The Impact of Socioeconomic and Spatial Differences on Obesity in West Virginia.

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Abstract. Obesity constitutes an important public policy issue since it causes external costs to society through increased healthcare costs borne by taxpayers. This study employed random and fixed effects estimations and spatial autoregressive approaches under a panel data structure to unravel possible socioeconomic and built environment factors contributing to obesity. Though there is no statistical evidence for time invariant fixed effects, empirical evidence shows that obesity is a spatially non-random event. Educational attainment that raises both human and social capital as well as changes in the built environment could play a vital role in controlling obesity.

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Obesity is reaching epidemic proportions across the U.S., and is an especially serious problem in West Virginia (WV), the study area. In 2000, the economic cost of obesity in the U.S. was estimated at $117 billion, with $61 billion in direct costs such as medical expenditures and $56 billion in indirect costs such as lost wages, disability, or premature deaths (Kuchler and Ballenger 2002). The U.S. Centers for Disease Control and Prevention (CDC) has recently classified obesity as a disease (2003). In states such as WV, the obesity problem is believed to be compounded by poverty and lack of access to healthy foods, and fitness-related amenities.

Obesity prevalence in West Virginia (WV) has been consistently higher than for the U.S. as a whole. Figure 1 shows obesity prevalence trends in WV over the past decade. In 1990, the rate of adult obesity in WV was 15%, compared with a U.S. rate of 12%. By 2000, the rate of obesity in WV had climbed to 23%, compared with 20% nationally. The obesity rate has increased in virtually all WV counties over the past decade, with the highest prevalence found in the southern and western portions of the state, as well as the Eastern Panhandle (WV Dept. of Health and Human Resources 2002). Considering the high prevalence of obesity and other non-communicable diseases (i.e., heart disease and type two diabetes), environmentally diverse natural amenities and recent growing economic development, WV can be a model state for national policymakers to understand and develop viable remedial actions to reverse recent obesity trends. The objectives of this study are to investigate the possible socioeconomic factors, trends and spatial differences of obesity in WV, and to determine the resulting policy implications.

Background and Previous Work

A major policy issue behind obesity is the external cost which creates a welfare loss to society through increased health-care costs. There is a growing literature relevant to obesity from various disciplinary perspectives such as health science, food science, and, more recently, economics; each offers different hypotheses to explain the issue.

Fast food consumption is believed by some to be one of the major contributory factors to obesity. Recent economic and health studies reveal that fast foods, which contain high calories and saturated fats, have a positive impact on gaining body weight (Anderson, Butcher, and Levine 2003; Ebbeling, Dorota and David 2000; French, Harnack, and Jeffery 2001; Binkley, Eales and Jekanowski 2000; Lin and Frazao 2001). Other empirical analyses (Guthrie, Lin and Frazao 2002; McCraken and Brandt 1987; Byrne, Capps, and Saha 1998) show how specific economic and demographic characteristics could influence the demand for food away from home. Both fast food restaurants and full-service restaurants can provide leisure for households, as households are freed from cooking, cleaning and shopping. Along with additional leisure, households with more income tend to buy more variety and other dining amenities. Thus, households with higher incomes tend to spend more on fast food and full service-meals and snacks (McCraken and Brandt 1987; Byrne, Capps, and Saha 1998). Individuals who spend long hours working outside their homes prefer consuming fast foods, if such meals are accessible (Byrne, Capps and Saha 1998). As labor force participation increases, spending on fast foods has been shown to increase (Byrne, Capps, and Saha 1998; Chou, Grossman, and Saffer 2002). However, traveling to and dining at full service restaurants can take the same amount of time as preparing food, eating and cleaning up after a meal at home, thus there is no clear theoretical relationship between a household's demand for food at full-service restaurants and its time constraints (Byrne, Capps, and Saha 1998). In addition, household income and increasing hours of labor force participation, household size, household manager's age and education level, region of residence, race and ethnicity have also been found to contribute to demand for food away from home (Hiemstra and Kim 1995; McCracken and Brandt 1987 and Friddle, Mangraj, and Kinsey 2001). Given the different opportunities to socialize, and to eat out, young and older people choose different establishments for dining out. On balance, empirical studies find that households with younger members tend to spend more money on fast food, while households with older people tend to spend more money on full-service dining (Byrne, Capps, and Saha 1998; Friddle, Mangraj, and Kinsey 2001). Guthrie, Lin,and Frazao (2002) noted that meals and snacks based on food prepared away form home not only contained more calories per eating occasion but they were also higher in fat and saturated fat. In the face of rising incomes and increasingly hectic work schedules, a nearly insatiable demand for convenience will continue to drive fast food sales.

A multivariate analysis of data from the 1994-96 Continuing Survey of Food Intakes by individuals and the 1994-96 Diet and Health Knowledge Survey by Mancino, Lin, and Ballinger (2003), showed that certain behaviors and attitudes are significantly associated with alternative weight outcomes. This study found that individuals who exercise more frequently, watch less television, drink fewer sugary beverages, and eat a higher quality diet are more likely to have a healthy body weight. Mancino and Kinsey (2004) showed that per-meal nutrient demand is a function of food prices, an individual's wage rate, body weight, caloric expenditures, information about health and nutrition, per-meal situational factors that affect one's sensitivity to time delay, and the amount of time spent preparing the meal.

Knutson, Penn, and Boehm (1995) found that poor health leads to poor nutrition, and poor nutrition results in poor health. The authors conclude that poverty, hunger, and poor health foster one another. Many health disparities in the United States are linked to inequalities in education and income. Drewnowski (2003) showed that wealth and poverty have profound effects on diet structure, nutrition and health. The study emphasized that income and the macronutrient composition of diets are linked at the aggregate level and, most likely, also at the individual level. Applying Engel's law to the aggregate level, Drewnowski (2003) showed that the percentage of personal consumption of at-home foods diminishes as per capita gross domestic product rises.

Drewnowski and Specter (2004) find evidence that population groups with the highest poverty rates and the least education have the highest obesity rates. They believe that there is an inverse relation between energy density and energy cost, such that energy-dense foods composed of refined grains, added sugars, or fats are a low cost option to the consumer. Therefore the selection of energy dense foods by food insecure, low-income consumers may represent a deliberate strategy to save money. Also, poverty and food insecurity are associated with lower food expenditures, low fruit and vegetable consumption, and lower-quality diets (Drewnowski and Specter 2004). An analysis of the third National Health and Nutrition Examination Survey (NHNES III) by Basiotis and Lino (2002) showed that women, but not men, in food-insufficient households were more likely to be overweight than food-sufficient women. An investigation of the economic determinants and dietary consequences of food insecurity and hunger in the United States, by Rose (1999), showed that hunger rates decline sharply with rising incomes. Rose (1999) noted that other factors such as food stamp participation, homeowner occupancy, level of education, age of household and ethnicity, also have an impact on food insecurity. However, important policy concerns are the nutrition and health consequences of food poverty, food insecurity and hunger. Even though there is evidence to link food insecurity, hunger, and poverty, their causation of health consequences such as obesity seems to still be a paradox.

The full price of a home-prepared meal includes not only the cost of ingredients bought at the store, but also the travel cost to the store and back, the cost of time spent preparing the food, and information costs related to nutrition knowledge and cooking techniques. A change in any component of the price will change the incentive for consuming that product, as well as its closely related alternatives (Variyam 2005). Foods prices, whether at the store or at a restaurant, have been declining relative to prices of all other items between 1952 and 2003. The ratio of food prices to the price of all other goods has fallen by 12 percent (Variyam 2005).

Theoretical Framework

The household production function framework (Lancaster 1966), the theory of time allocation (Becker 1965), as well as the concept of health capital and the demand for health (Grossman 1972), together underlie the theoretical background for this analysis. Becker and Lancaster (1966) used household production models in which consumers maximize utility derived from desirable attributes of marketed goods combined with household members' labor, subject to budget and time constraints. Grossman (1972) extended this framework to derive the demand for the commodity "good health". Health can be considered a desirable attribute that is produced by a household, entering into its members' utility functions. Gross investments in health capital can be produced by household production functions whose direct inputs include the time of the consumer and market goods such as medical care, diet, exercise, recreation and housing as well as socioeconomic and demographic characteristics (Grossman 1972). In this analysis, it is assumed that a rational consumer allocates time and other resources to produce the commodity "good health" together with other desirable attributes that yield utility or satisfaction. Thus, the utility maximization problem for individual *i* can be represented as:

(1) $$Max U_i = U_i[X, Y, Z, L, L_a, H_i(X, Y, Z, L_a, S)],$$

where X is a numeraire good, Y is fast food, and Z is healthy food (such as fruits and vegetables), L is passive leisure, which includes time spent socializing with family and friends, watching TV, etc., whereas L_a is active leisure, such as time spent at the gym or on other strenuous physical activities that help maintain good health, H_i; S is a vector of socioeconomic and demographic factors that also affect health. It is assumed that some positive marginal utility is derived from consuming the numeraire good, fast food and healthy goods. It is also assumed that better health and passive leisure yield positive marginal utility to the consumer. The impact of active leisure on health can be positive or negative as its impact depends on the individual's subjective preference towards physical activities.

An individual's health production function can be represented as: $H_i(X,Y,Z,L_a,S)$, where the impact of fast food on health is considered to be neutral or negative. The marginal impact of the numeraire good on health is considered indeterminate. The marginal contributions of fruit and vegetable consumption and active leisure are considered to be positive. Utility is maximized subject to a budget constraint:

(2) $$P_z Z + P_Y Y + P_X X + D(H) \leq I + w(T - L - L_a),$$

where $D(H)$ depicts the expenditures on medical services that are assumed to be a function of individual health status, I represents non-wage income, w is the wage and T is total time available, thus, $w(T - L - L_a)$ represents the labor income derived after spending time on both inactive and active leisure activities; P_Y, P_Z, P_X are respective prices of goods Y, Z, and X. Medical expenditures include expenditures on services such as doctors bills, prescription drugs, etc.

Solving the first order conditions for utility maximization, and invoking the implicit function theorem yields the individual demand function for health as well as other goods:

$H_i = f(I, w, P_X, P_Y, P_Z, D_H, S)$. Individual health, indirectly measured by BMI (Body Mass Index), is a function of income other than wages, the wage, prices of marketed goods and the marginal implicit price of health, D_H, i.e., the marginal expenditure incurred by an individual to remain healthy, in addition to socioeconomic and demographic characteristics, *S*.

The equi-marginal principle of optimality states that a rational consumer will allocate his/her resources up to the point where marginal benefits derived from the last dollar spent are equal across all commodities consumed. In this case, the marginal benefits derived from the last dollar spent should not only be equal across commodities consumed but also for the other factors, health and leisure, that also give utility or satisfaction.

Empirical Approach

Panel data analysis is an increasingly popular method of studying a socioeconomic phenomenon that varies across space and time. A panel is a cross-section of a group of people, firms or a geographic entity (such as a county) which has been observed over a defined time frame. It provides a rich environment for the development of estimation techniques and theoretical results for issues that cannot be studied in either cross sectional or time series data alone (Greene 2003; Baltagi 1995). Panel data analysis allows explicit consideration of both random and unobserved time invariant (fixed) effects between geographic entities (Mundlak 1978; Gujarati 2003). Therefore, this study uses random and fixed effects modeling approaches to investigate the county prevalence of obesity.

In this study, county level health status is used to represent an aggregation of each individual's demand for health. Thus county level health status can be represented as $\sum_{j=1}^{n} H_{ij}$, $j = 1, 2, ..., n$ and $i = 1, 2, ..., N$ where *n* is the number of obese individuals in a particular county and

N is number of counties in the study. The proportion of the population considered obese in a county is the dependent variable in the model. Thus, the empirical model can be represented as:

(3) $$H_{it} = \alpha d + \beta x_{it} + \gamma_t + \varepsilon_{it},$$

where H_{it} is the percentage of the population considered obese in county *i* in time period *t.* The vector α represents unobserved county impacts on obesity that may be correlated with the vector of observable explanatory variables, x_{it}, whose effects are of interest with β the associated parameters. The term *d* is a vector of county specific dummy variables relevant to the unobserved fixed effect parameters, α. The scalar γ_t represents the fixed time effects on the model. In order to reduce the large loss of degrees of freedom due to the incidental parameter problem (i.e, larger number of cross sectional units relative to time series), counties are grouped into distinct regions. Baltagi (2002) and Elhorst (2003) state that the fixed effects cannot be estimated consistently if the times series is small relative to the number of cross sectional observations. Therefore, in this analysis, the vector *d* actually represents regional effects instead of county-level effects. Stochastic disturbances, ε_{it}, are assumed to be independently and identically distributed ($\varepsilon_{it} \sim \mathrm{IID}(0,\sigma_{\varepsilon}^{2})$).

Spatial Autoregressive Approach

Natural amenities impact regional economies through aggregate measures of economic performance such as population, income and/or employment growth, and housing development (Kim, Marcouiller and Deller 2005). Also, there are increasing concerns that the built environment has a substantial influence on people's quality of life and health (Freudenberg et al. 2005; Frumkin 2002). Previous studies using spatial analyses have demonstrated the relationships between human mortality and regional characteristics related to the environment, health-related behavior, and economic and demographic factors (Fukuda et al. 2005; Lin 2003; Fukuda et al. 2004). Rapid suburbanization is hypothesized to be associated with rising obesity, increased physical inactivity, increased social isolation and the breakdown of social capital (Freudenberg, Galea, and Vlahov 2005). Since attributes of the built environment and natural amenities are spatially located, it is reasonable to hypothesize that health disorders like obesity are spatially clustered according socioeconomic, demographic and environmental factors. Thus, this analysis is also extended to test the hypothesis that prevalence of obesity is spatially correlated across counties. In reaching this goal, alternative spatial approaches, a spatial autoregressive (SAR) and a spatial error model (SEM) are considered.

Spatial correlation could be a result of spatial dependence or the spatial heterogeneity of geographic entities. In the event of spatial dependence, OLS estimation produces biased and inconsistent estimates (LeSage et al. 2004). Past studies which used spatial and spatio-temporal samples often relied on dichotomous explanatory variables to control either spatial or temporal effects; however, this method requires interaction with both spatial and temporal dichotomous variables leading to a large number of estimated parameters. Like temporal autoregressive approaches, spatial and spatio-temporal autoregressive processes often provide more parsimonious and better fitting models than those that rely only on dichotomous variables (LeSage et al. 2004).

Spatial dependence can be caused by trans-boundary spillovers among counties in which the activities in one county have a direct influence on activities in other counties. Following Elhorst (2003), the fixed effects model is extended to include spatial lag effects, thus, the SAR model can be represented as:

(4) $$H_{it} = \rho W H_{jt} + \beta X_{it} + \alpha d + \gamma_t + \varepsilon_{it},$$

where $i = 1, 2, ..., N$, $i \neq j$, and $\varepsilon_{it} \sim \left(0, \sigma^2 \mathrm{I}_{NT}\right)$, ρ is a vector of spatial autoregressive coefficients to be estimated which indicate the spatial relationship between counties, and W is a contiguity-based spatial weights matrix, meaning an element in the matrix will be 1 for a contiguous county and 0 if the county does not adjoin the given county.

The degree of spatial autocorrelation can also depend on the potential correlation of the error term across counties. The spatial autocorrelation of the error structure can be incorporated by specifying the error term as $\varepsilon_{it} = \lambda W \varepsilon_{it} + \eta_{it}$, where $\eta_{it} \sim \left(0, \sigma_{\eta}{}^{2} \mathrm{I}_{NT}\right)$, such that the empirical model becomes:

(5) $$H_{it} = \beta X_{it} + \alpha d + \gamma_{t} + \lambda W \varepsilon_{it} + \eta_{it},$$

where λ is the spatial autocorrelation coefficient and the other variables and parameters are as previously defined.

Data

Data used in this analysis were obtained from secondary sources. A description of the variables used in this analysis and their sources are in Tables 1, 2 and 3. Descriptive statistics for the variables are in Tables 4, 5, and 6. Obesity prevalence in WV counties for the periods 1992 and 1997 were obtained from the county health profiles published by the WV Department of Health and Human Resources, Bureau for Public Health (2000). Socioeconomic data relevant to these two time periods were obtained from state and federal agencies including the Appalachian Regional Commission (ARC), WV Bureau of Employment, Natural Resource Analysis Center of West Virginia University, the U.S Census Bureau, and the U.S Department of Agriculture.

County level differences regarding the percentage of the population considered obese were studied using a panel data structure which emphasizes both random and fixed effects. The county prevalence of obesity in the years 1992 and 1997 and the associated data for the explanatory variables relevant for these different time periods were pooled across the 55 counties of WV. In this analysis, the random and fixed effect estimation of county level prevalence of obesity was regressed against county-level socioeconomic, demographic, behavioral risk, built environment and amenity factors.

Both ordinary least squares (OLS) and generalized least squares (GLS) estimates, where the county prevalence of obesity is the dependent variable, are considered. GLS estimates are based on the PROC TRCSREG (time series cross section regression) procedure of SAS which specifies the Fuller and Battese (1974) method of variance component error structure. Population density (PPSM), poverty rate (PR), annual average per capita income (PINC), percentage of the population who have completed a college education (AE), unemployment rate (UR), average annual wage (WAGE), percentage of the population who smokes (PSMOKE), and the percentage of the population which does not have health insurance (PNHINU) are considered as socioeconomic and demographic explanatory variables in the models. The total number of business establishments (TESTB), food stores (FSTOR), eating and drinking places (EDPLA), health care service businesses (HESER), and physical fitness activity places available (PPFAC), per thousand people in a particular county, are explanatory variables representing the built environment, along with TVTRT, which is a measure of mean travel time to work for county residents. Representing fiscal policy measures are social security program beneficiaries per thousand (SSPB), and federal food stamp (PAFSTS) and Medicare benefits (PMCAREB) allocated per thousand people in a county.

Results of the County-level Health Demand Analysis

The results of the random specification, which considers the unobserved latent effects among geographic entities to be a random phenomenon, are presented in Table 7. OLS estimation shows that per capita income (PINC), average college education completed (AE), number of food stores per thousand population (FSTOR), average travel time to work (TVTRT) and average annual wage (WAGE) significantly contribute to county prevalence of obesity. Contrary to expectations, PINC is positively correlated with obesity. Every $1,000 increase in per capita income raises the percentage of obesity by 0.6%. As expected, the prevalence of obesity is negatively and significantly correlated with education level. Results indicate that a 1% increase in the population with a completed college education will decrease the obesity rate by 0.2%. A unit increase in the number of food stores available per thousand population would significantly lower obesity prevalence by 3%. However, a one minute increase in mean commuting time would significantly raise the obesity rate by 0.3%. Similar to per capita income, a $1,000 increase in the average annual wage in a county would raise the obesity prevalence by 0.3%.

In comparison to the OLS estimates, the GLS estimation does not indicate that there is a significant contribution of income to obesity. However, GLS estimates show that county level education has a significant negative impact on obesity, with a 1% increase in college education decreasing the obesity rate by about 0.3%. The built environment measures, FSTOR, TVTRT, and TESTB, are significant contributing factors to obesity. The GLS estimates show that, while FSTOR contributes significantly but negatively to county-level obesity, TESTB contributes significantly and positively. This indicates that a one unit increase in the number of business establishments per 1,000 population in a county will raise obesity prevalence by 0.2% whereas a one unit increase in the number of food stores in a county will lower obesity by 2.6%. Again, commuting time is shown to be positively correlated to the county prevalence of obesity.

The adjusted R^2 value of the OLS estimation suggests that about 48% of the variation in the prevalence of obesity across counties is explained by the independent variables included in this regression. Kmenta (1986) noted that 0.20 is a typical R^2 value for various behavioral functions estimated from cross-sectional data. Medical demand models generally have lower values raging from 0.07 to 0.16 (Kenkel 1990). The computed R^2 measure for the GLS estimation shows that 37% of the variation in obesity prevalence is captured by the explanatory variables included in that regression. Hausman specification test of the GLS estimation indicates that there is no statistical evidence to conclude that there are unobserved fixed effects that are correlated with explanatory variables contributing to county obesity rates. The orthogonality of unobserved effects is further confirmed by the Hausman and Breusch-Pagen Lagrange Multiplier tests using the PROCPANEL procedure of SAS, meaning there are no fixed effects.

Regional Differences in Obesity

The incidental parameter problem arises due to the large number of cross sectional units relative to time dimensions, and can be overcome by grouping counties into different regions of the state. Currently, WV epidemiological diseases surveillance is operating under 7 distinct regions. The regional fixed effects are captured by including regional dummy variables in the estimations. Accordingly, regions considered for the analysis were coded as North (N), Northeast (NE), Northwest (NW), Central (C), West (W), Southwest (SW) and Southeast (SE). In order to avoid the dummy variable trap, six regional dummies were included in the estimations leaving the central (C) region out as the base category. In addition, a time dummy is included to capture time effects, with 1997 considered the base category. The estimated regional random and fixed effects are presented in Table 8. Obtained coefficients are Restricted Maximum Likelihood (REML) estimates of the PROCMIXED procedure of SAS.

Similar to GLS estimates, regional random effects show that average college education completed (AE), total number of business establishments per thousand population of a county (TESTB), number of food stores per thousand population (FSTOR), percentage of smokers in a county (PSMOKE), mean travel time to work (TVTRT), and average annual wage (WAGE) have a significant impact on county obesity rates. For example, a 1 % increase in college education completed would decrease the county obesity rate by about 0.2%. While a unit increase in the total number of business establishments has a significant positive impact on county obesity rates, a unit increase in the number of food stores has a significant negative impact on obesity. Results show that a unit increase in TESTB will raise county obesity rates by about 0.2%; however, a unit increase in FSTOR will reduce the county obesity by 3%. A higher percentage of smokers in a county has a significant positive impact on obesity prevalence. As the proportion of smokers in a county increases by 1%, county obesity rates increase by 0.1%. Similarly, a one minute increase in mean travel time to work raises county obesity prevalence by 0.2%. If average annual county wage (WAGE) increases by $1,000 the county obesity rate tends to increase by 0.2%.

In comparison to the regional random effects model, the regional fixed effects estimation shows that average college education completed (AE), total number of establishments per thousand population of a county (TESTB) and number of food stores per thousand population (FSTOR) have significant impacts on county prevalence of obesity. The magnitude and the directional impacts of these variables are quite similar to the regional random effects. In addition, the significant Southwest (SW) regional dummy variable implies that obesity prevalence in that region is significantly higher than the base central region during 1997. However, during 1992, the prevalence of obesity in the Southwest is 0.8% lower than the base central region. The significant time dummy for 1992 implies that obesity prevalence in the base central region during this period was significantly lower than that for 1997.

Spatial Effects of Obesity

Having identified that there are no significant unobserved fixed effects on obesity, this analysis was extended to investigate spatial impacts on the incidence of obesity. The empirical results obtained for a spatial error (SEM) and spatial autoregressive (SAR), or spatial lag, model are presented in Table 9. The significant spatial autocorrelation coefficient (λ) of the SEM implies that county incidence of obesity is spatially correlated. In addition, the SEM shows that county prevalence of poverty (PR), percentage of college education completed (AE), and average annual wage (WAGE) of a county are significant socioeconomic factors affecting obesity. A 1% increase in poverty in a county would raise the county prevalence of obesity by 0.13%. A 1% increase in percentage of the population with a completed college education reduces the county obesity rate by 0.2%. A $1,000 increase in the annual county per capita wage would raise county obesity rate by 0.3%. A unit increase in number of business establishments per thousand population (TESTB) raises the county obesity rate by 0.23%. In contrast, a unit increase in the number of food stores per thousand poulation (FSTOR) would reduce obesity by 3%. A one minute increase in mean travel time to work will raise county incidence of obesity by 0.3%.

In comparison to the SEM, the significant spatial autoregressive coefficient (ρ) of the SAR estimation implies that county prevalence of obesity is not only spatially correlated but also has a significant impact on the incidence of obesity in neighboring counties. The SAR estimation yields quite similar results to the SEM with regard to significant covariates affecting obesity. Having considered spatial random effects, both SEM and SAR are extended to investigate spatial fixed effects. County specific spatial fixed effects are ignored due to the incidental parameter problem of a larger number of cross sectional units relative to the time series; instead, regional spatial fixed effects, which include regional and time dummies, are investigated.

The results obtained for the regional fixed effects spatial error (FSEM) and regional fixed effects (FSAR) approaches are given in the Table 10. As poverty increases by 1%, the county prevalence of obesity decreases by 0.14 %. Similar to previous modeling approaches, the impact of education (AE) is negative and significant; a 1% increase in AE would lower the incidence of obesity by 0.2%. The FESM results indicate that neither travel time nor percentage of the population which smokes have a significant effect on obesity. Significant dummy covariates for time and the northeast, southeast and southwest regions imply that there are significant differences of obesity in these regions in the two time periods. Obesity prevalence in the base central region in 1992 is significantly lower, by 3.0%, than in 1997. Also, during 1997, the prevalence of obesity in all three regions mentioned is significantly higher, by about 2%, compared to the base central region. In addition, the significant value for λ provides evidence of spatial autocorrelation at the county level. In comparison to the FSEM results, the results from the FSAR estimation indicate that only education (AE) total number of business establishments (TESTB), number of food stores (FSTOR) and WAGE are significant variables affecting county-level rates of obesity.

The spatial distribution of obesity in WV for the two specific time periods (1992 and 1997) are mapped in Figures 2 and 3. These spatial patterns show that obesity existed in relatively higher proportions in almost all counties in 1997 compared to 1992. However, the empirical findings do not support the proposition that there are unobserved fixed effects contributing to the spatial patterns.

Almost all the empirical specifications in this analysis indicate county educational level has a significant and negative impact on county prevalence of obesity. This finding is similar to that of Nayga (2000), who found that knowledge is inversely related to the probability of a person being obese. Kenkel (1991) shows that schooling improves the choice of health inputs by improving one's health knowledge to choose healthier life styles. Other economic studies also conjectured that schooling improves the efficiency of household production of health (Grossman 1972; Berger and Leigh 1989). Halverson et al. (2004) stated that despite the improvement of educational attainment across WV counties, the relative differences appear to persist over time. Although counties with higher percentages of adults with at least a college degree appear to be more evenly distributed across the state, the counties in the southern part of the state continue to exhibit a lower percentage of college graduates (Halverson et al. 2004). This pattern is further explained to a certain extent by the geographic distribution of education and obesity given in Figures 4 and 5.

Conclusions and Policy Implications

This study attempts to integrate both theoretical and empirical insights and information to facilitate understanding of the current obesity problem in WV. In meeting this objective, this study employed different econometric specifications under a panel data structure to unravel possible socioeconomic and built environment factors contributing to obesity. Of the considered empirical specifications, GLS (generalized least squares), SEM (spatial error model) and SAR (spatial autoregressive approach) seem to be the better fitting models for explaining county prevalence of obesity. The empirical estimations suggest that there are no time invariant unobserved county or regional fixed effects impacting county obesity rates. Though there is no evidence for unobserved fixed effects or for serial correlation, empirical investigations provide evidence for obesity to be a spatially non-random event. The spatial investigation shows that obesity tends to cluster among certain geographic locations. There is a tendency for obesity to cluster around the southern and northeastern parts of the state near concentrated business environments.

Similar to findings of previous studies, the county poverty rate (PR), and average percentage of the population who have completed a college education (AE) are significant socioeconomic determinants of obesity. While poverty positively contributes to obesity, education has a negative impact. In addition, the county annual per capita wage (WAGE) also positively and significantly contributes to obesity. Total number of business establishments (TESTB) and total number of food stores per thousand population (FSTOR) as well as mean travel time to work (TVTRT) are significant built environment determinants of county-level obesity. While TVTRT and TESTB positively contribute to obesity, FSTOR reduces obesity. The impacts of per capita income (PINC) and the percentage of smokers (PSMOKE) in a county are not consistent; their impacts cannot be explained precisely and should be further investigated.

Average wage is a fairly consistent socioeconomic variable contributing to obesity. Empirical results suggest that as wage increases the county prevalence of obesity increases. As economic theory suggests wage is a proxy for opportunity cost of time or price of leisure and the higher opportunity costs of time prevent people from substituting leisure for work. It should also be noted that the U.S. economy is becoming more service oriented and people are paid to work rather than to have leisure. As Philipson and Posner (2003) suggest, obesity is accompanied by technological change in developed nations and has resulted in cheaper calories while exercise has become relatively more expensive. Thus, an unintended consequence of increased labor force participation in advanced economies has resulted in unintended public health consequences like obesity. This economic reasoning seems to be quite applicable for WV’s high prevalence of obesity. Mean annual wage for WV counties for the period 1992 to 1997 ranges from $16,839 to

$24,991. This wage premium may not be high enough for average WV residents to meet their needs. Thus, economic incentives may induce WV residents to work more, perhaps in sedentary environments and also to engage in less leisure time physical actives, at the expense of their own health outcomes.

As the results of this study suggest, in addition to socioeconomic factors, built environment factors are also significant determinants of county prevalence of obesity. Therefore, the current obesity epidemic is not only due to individual behavior, but can also be interpreted as an unintended consequence of current land use planning; hence, economic agents and policy makers must be held partly responsible. Because poverty is a contributing factor to the current obesity epidemic, especially in a rural state like WV, it might be necessary to implement poverty alleviation programs in the state. As this study suggests, a higher number of food stores per one thousand population results in a lower prevalence of obesity, at least in WV, meaning land use planners and economic developers need to focus special attention on local food accessibility and availability. Frank, Anderson and Schmid (2004) pointed out that the likelihood of obesity apparently declines with increases in mixed land use, but rises with the time spent per day in a car, as confirmed by the adverse impact on obesity of mean commute time (TVTRT) found in this study.

Lastly, this study indicates that educational attainment in a county has a significant and negative impact on county prevalence of obesity. Previous health and economic studies (Grossman 1972; Kenkel 1991; Farrel and Fuchs 1972; Variyam, Blaylock, and Smallwood 1996; Adler and Ostrove 1999; Nayga 2000) also show that educational attainment has a powerful impact on lifestyles as well as health. At the same time, level of education is a remedial factor for other pressing socioeconomic problems like poverty and unemployment. Education, one of the key determinants of human capital, not only provides an economic return, increasing both employment rates and earnings, but also improves health, well-being and parenting (OECD 2001). Therefore, interventions which enhance educational attainment could also play a vital role in preventing obesity. This may be especially true of childhood obesity, a growing problem in WV. The results presented in this study may be of use to researchers and policy makers to better understand the problem and to better prioritize resource allocation among WV counties. Allocation of physical and financial resources to improve community intervention strategies through educational programs as well as better built environment planning strategies would be helpful in promoting healthier communities and also in stimulating economic development in WV.

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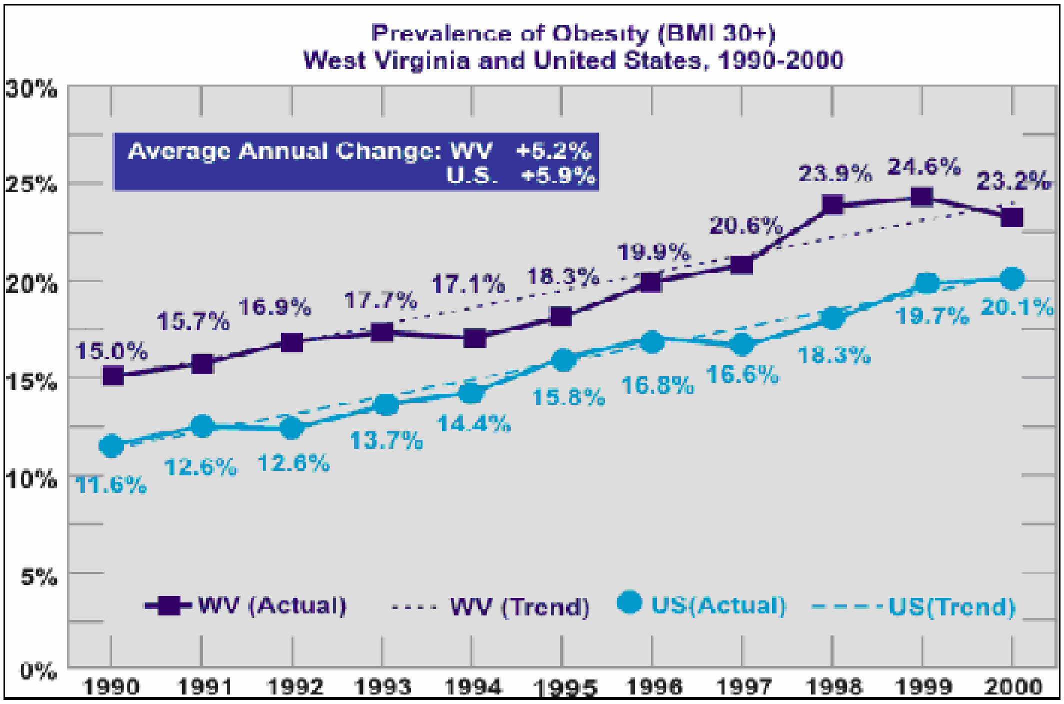
Figure 1. Obesity Prevalence in West Virginia and the United States



Source: West Virginia Department of Health and Human Resources.

Figure 2. Obesity Prevalence in WV (1992)

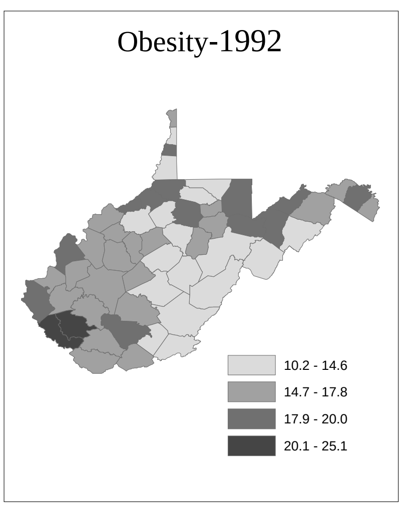


Figure 3. Obesity Prevalence in WV (1997)

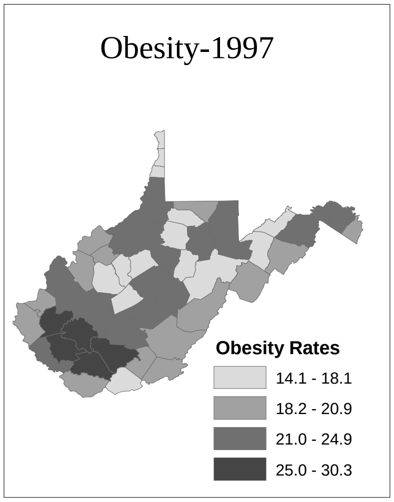


Figure 4. Obesity and Average College Education Completed (1992)

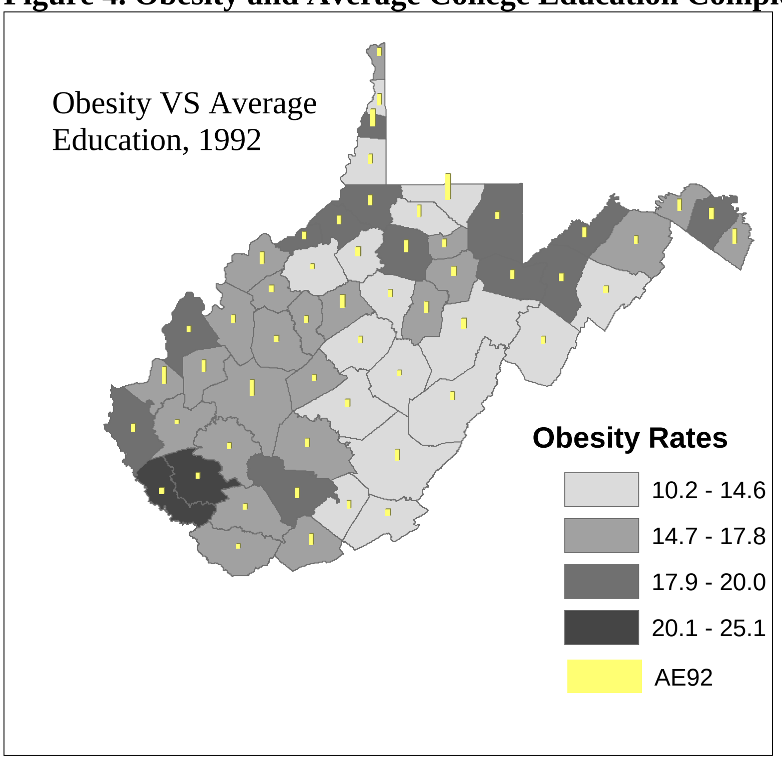


Figure 5. Obesity and Average College Education Completed (1997)

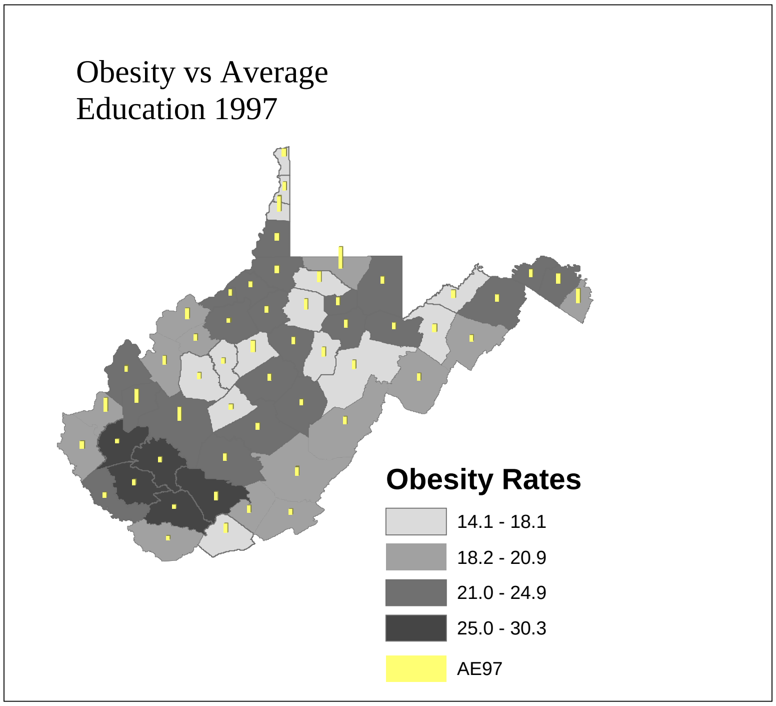


Table 1. Socioeconomic and Demographic Variables

Variable	Definition	Source
Dependent variable		
OBESITY	% of obesity 1992 and 1997	A
Socioeconomic and Demographic factors		
POPUL	Population 1990 and /2000	B
PPSM	Population Density (Persons/Square mile) 1990 and 2000	B
PR	% of population below poverty line	B
AE	% of population who completed college	B
UR	% of unemployment	B
SSPB	Social Security program beneficiaries per 1000 population	C
WAGE	Average annual wage 1992/1998	C
PINC	Average per capita income 1990-94 and 1995-99	C
PAFSTS	Food stamp benefits per thousand population in $1000 1992 and 1997	C
PMCAREB	Medicare Benefits per thousand population in $1000 1992 and 1997	C

A: Department of Health and Human Resources, West Virginia Health statistics, Bureau of Public Health; http://www.wvdhhr.org/bph/oehp

B: Online Resource Center, Appalachian Regional Commission; http://www.arc.gov

C: Bureau of economic Analysis, U.S. Department of commerce; http://www.bea.gov

D: U.S. Census Bureau Economic Census 1992 and 1997

E: U.S. Census Bureau 1990 and 2000

Table 2. Built-environment Factors

Variable	Definition	Source
TESTB	Total number of establishments per 1000 population 1992 and 1997	D
FSTOR	Total Number of Food Stores per 1000 population 1992 and 1997	D
EDPLA	Eating and Drinking places per 1000 population 1992 and 2002	D
PPFAC	Physical Fitness Activity places per 1000 population 1992 and 1997	D
HESER	Health Care Services per 1000 population 1992 and 1997	D
TVTRT	Average Travel Time to work 1990 and 2000	E

D: U.S. Census Bureau Economic Census 1992 and 1997

E: U.S. Census Bureau 1990 and 2000

Table 3. Behavioral Factors and Dummy Variables

Variable	Definition	Source
PHEART	% of population with heart disease 1992 and 1997	A
PNUSBT	% of population not using seat belt 1992 and 1997	A
PSMOKE	% of population who smoke 1992 and 1997	A
PNSTU	% of people using smokeless tobacco 1992 and 1997	A
PBDRINK	% of people who participate in binge drinking 1992 and 1997	A
PNHINU	% of people with no health insurance 1992 and 1997	A
PDSDC	% of people who can't afford to see a doctor 1992 and 1997	A
DT	Dummy Time (1= 1997 and 0= 1992)	*
DN	Dummy North	*
DNE	Dummy Northeast	*
DSE	Dummy Southeast	*
DSW	Dummy Southwest	*
DWT	Dummy West	*
DC	Dummy Central	*
DNW	Dummy Northwest	*
DLIN	Dummy Lower Income group (PINC < $12000)	*
DMIN	Dummy Median Income group ($12000 < PINC<$20000)	*
DHIN	Dummy High Income group (>$20000)	*

A: Department of Health and Human Resources, West Virginia Bureau Health Statistics
* Created by the author using information from WV department of Health and Human Resource and per capita income data from the Bureau of economic Analysis, U.S. Department of commerce; http://www.bea.gov.

Table 4. County Level Definitions and Descriptive Statistics

Variable	**Mean**	**Std Dev**
OBESITY	18.92	4.20
POPUL	32743.83	32430.43
PPSM	94.66	101.17
PR	20.32	6.36
AE	11.10	4.57
UR	7.57	3.03
SSPB	211.83	30.37
FPCEXP	3860.91	776.72
WAGE	21472.64	4161.66
PINC	15438.23	3006.40
PAFSTS	142.07	51.89
PMCAREB	3862.56	19021.40

Table 5. Built-environment Factors Descriptive Statistics

Variable	Mean	Std dev
TESTB	743.65	933.16
FSTOR	26.66	22.78
EDPLA	51.71	65.89
HESER	57.45	87.01
PPFAC	1.10	1.76
TVTRT	26.12	5.77

Table 6. Behavioral and Dummy Variable Descriptive Statistics

Variable	Mean	Std dev
PHEART	26.96	4.02
PSMOKE	26.01	4.82
PNSTU	10.16	3.57
PBDRINK	9.17	3.64
PNHINU	23.23	5.60
PDSDC	16.76	3.83
DT	0.50	0.50
DN	0.11	0.31
DNE	0.16	0.37
DSE	0.15	0.35
DSW	0.13	0.33
DWT	0.15	0.35
DC	0.20	0.40
DNW	0.11	0.31
DLIN	0.12	0.32
DMIN	0.81	0.38
DHIN	0.06	0.24

Table 7. Model 1 OLS & GLS estimates of Random Effects of Obesity in WV (Dependent Variable % of Obesity in Counties)

	OLS			GLS		
Variable	Coeff.	Pr>|t|		Coeff.	Pr>|t|	
CONSTANT	-7.4813600	0.082	*	1.6880730	0.796	
PPSM	-0.0064700	0.248		-0.0035200	0.536	
PR	0.1404500	0.111		0.1379060	0.110	
PINC	0.0006043	0.045	**	0.0003530	0.272	
AE	-0.2155500	0.062	*	-0.2551100	0.027	**
UR	0.0128000	0.939		0.0429100	0.796	
TESTB	0.1944600	0.166		0.2409910	0.086	*
FSTOR	-2.7632300	0.055	*	-2.6419800	0.061	*
PEDPLA	-0.1785900	0.829		-0.5216400	0.530	
PHESER	-0.2132600	0.819		-0.3432700	0.708	
PPPFAC	-2.0643900	0.624		-1.4130400	0.733	
PSMOKE	0.1012400	0.202		0.1473910	0.072	*
PNHINU	-0.0243300	0.733		-0.0677400	0.357	
TVTRT	0.3191200	0.001	***	0.2072600	0.050	**
SSPB	-0.0007431	0.951		-0.0075000	0.544	
AWAGE	0.0003049	0.010	***	0.0002520	0.033	**
PAFSTS	-0.0024400	0.835		-0.0056500	0.625	
PMCAREB	-0.0000150	0.403		-0.0000200	0.292	

Number of cross sections 55, Length of the time series 2, Number of observations 110.
*/**/*** mean significant at 10%, 5%, 1% or higher level, respectively.

Table 8. Regional Random and Fixed Effects

	Random Effects			Fixed Effects		
Variable	Estimate	Pr>|t|		Estimate	Pr>|t|	
CONSTANT	0.812700	0.918		4.803000	0.517	
PPSM	-0.003820	0.502		-0.003020	0.633	
PR	0.138000	0.112		0.125400	0.210	
PINC	0.000379	0.237		0.000305	0.388	
AE	-0.250600	0.031	**	-0.231900	0.079	*
UR	0.041440	0.804		0.088610	0.646	
TESTB	0.237900	0.090	*	0.292700	0.051	**
FSTOR	-2.657000	0.062	*	-2.852600	0.099	*
EDPLA	-0.482300	0.562		-0.513000	0.575	
HESER	-0.350100	0.704		-0.913000	0.384	
PPFAC	-1.496600	0.718		-1.828800	0.670	
PSMOKE	0.141100	0.085	*	0.107600	0.251	
PNHINU	-0.062420	0.396		-0.046250	0.573	
TVTRT	0.217000	0.038	**	0.148600	0.214	
SSPB	-0.006810	0.582		-0.008100	0.551	
WAGE	0.000255	0.031	**	0.000206	0.102	
PAFSTS	-0.005170	0.657		-0.001410	0.917	
PMCAREB	-0.000020	0.303		-0.000020	0.329	
C	-0.057190	0.746		-	-	
N	0.018330	0.918		1.416400	0.271	
NE	0.013520	0.939		1.735400	0.252	
NW	-0.001060	0.995		1.386600	0.362	
SE	0.011950	0.946		1.753000	0.177	
SW	0.038120	0.830		2.338000	0.084	*
W	-0.023660	0.894		0.704900	0.605	
1992	-1.045600	0.430		-3.120100	0.026	**
1997	1.045600	0.430		-	-	

Number of cross sections 55, Length of the time series 2, Number of observations 110.
*/**/*** mean significant at 10%, 5%, 1% or higher level, respectively.

Table 9. Random Effects Spatial Error (SEM) and Spatial Autoregressive (SAR) Estimation Results

	SEM			SAR		
Variable	Coeff.	Pr>|z|		Coeff.	Pr>|z|	
CONSTANT	-2.12763	0.633		4.46105	0.416	
PPSM	-0.00405	0.410		-0.00215	0.674	
PR	0.13452	0.073	*	0.14016	0.068	*
PINC	0.00040	0.142		0.00024	0.415	
AE	-0.24738	0.012	***	-0.27919	0.007	***
UR	0.11080	0.449		0.06090	0.681	
TESTB	0.23983	0.050	**	0.26033	0.037	**
FSTOR	-2.90923	0.016	***	-2.56161	0.041	**
EDPLA	-0.09428	0.895		-0.57729	0.436	
HESER	-0.39789	0.632		-0.36532	0.656	
PPFAC	-3.70153	0.314		-1.28640	0.729	
PSMOKE	0.07546	0.309		0.15212	0.035	**
PNHINU	-0.02761	0.680		-0.07957	0.224	
TVTRT	0.30803	0.000	***	0.16616	0.079	*
SSPB	-0.00366	0.739		-0.01122	0.317	
WAGE	0.00026	0.010	***	0.00022	0.036	***
PAFSTS	-0.01040	0.308		-0.00822	0.429	
PMCAREB	-0.00001	0.695		-0.00002	0.244	
λ	0.61000	0.000	***			
ρ				0.15400	0.003	***

Number of cross sections 55, Length of the time series 2, Number of observations 110.
*/**/*** mean significant at 10%, 5%, 1% or higher level, respectively.

Table 10. Fixed Effects Spatial Error (FSEM) and Spatial Autoregressive (FSAR) Estimation Results

	Fixed SEM			Fixed SAR		
Variable	Coeff.	Pr>|z|		Coeff.	Pr>|z|	
CONSTANT	7.002524	0.267		-1.173769	0.866	
PPSM	-0.002231	0.679		-0.002466	0.648	
PR	0.140892	0.089	*	0.138022	0.105	
PINC	0.000167	0.571		0.000260	0.389	
AE	-0.228564	0.034	**	-0.253478	0.024	**
UR	0.134895	0.392		0.112935	0.494	
TESTB	0.311200	0.012	***	0.297258	0.019	***
FSTOR	-3.378136	0.018	***	-2.908835	0.048	***
EDPLA	-0.256930	0.729		-0.323029	0.680	
HESER	-1.001809	0.254		-0.830886	0.355	
PPFAC	-3.567365	0.329		-2.282894	0.534	
PSMOKE	0.073505	0.373		0.091165	0.254	
PNHINU	-0.035378	0.612		-0.037041	0.598	
TVTRT	0.158643	0.119		0.155526	0.127	
SSPB	-0.007866	0.497		-0.010933	0.350	
WAGE	0.000198	0.057	*	0.000197	0.065	*
PAFSTS	-0.005400	0.634		-0.004016	0.729	
PMCAREB	-0.000012	0.416		-0.000015	0.341	
DT	-3.362627	0.011	**	4.085395	0.240	
DN	1.111596	0.332		1.379088	0.209	
DNE	2.288043	0.087	*	1.756787	0.175	
DSE	1.963887	0.086	*	1.616045	0.146	
DSW	2.201709	0.078	*	1.772235	0.131	
DWT	1.193585	0.318		0.649354	0.579	
DNW	1.858562	0.162		1.370587	0.293	
λ	0.508968	0.001	***			
ρ				0.34499	0.027	**

Number of cross sections 55, Length of the time series 2, Number of observations 110.
*/**/*** mean significant at 10%, 5%, 1% or higher level, respectively.