Is Sprawl Unhealthy?

A Multilevel Analysis of the Relationship of Metropolitan Sprawl to the Health of Individuals

Alexia C. Kelly-Schwartz, Jean Stockard, Scott Doyle, & Marc Schlossberg

Abstract

This article addresses the contention that urban sprawl influences general health through physical activity, obesity, and the presence of chronic disease. Data on individual health is obtained from the National Health and Nutrition Examination Survey III study in 29 primary metropolitan statistical areas, and data on sprawl are from Ewing et al. Using hierarchical modeling, the results indicate that even with strong controls for individual variables, residents of areas with more highly accessible and gridded street networks have higher health ratings. At the same time, residents of more densely populated urban areas have lower rated health, net of individual-level measures. Measures of sprawl have no significant relationship to frequency of walking, body mass index, or diagnosis of various chronic diseases. However, among those with chronic conditions, including hypertension, diabetes, and lung disease, those who live in areas with more highly connected street networks have higher rated health.

Keywords: *health; sprawl; physical activity; obesity; sprawl-health chain*

Alexia C. Kelly-Schwartz received her bachelor's degree in planning, public policy, and management from the University of Oregon. She has been working for two small municipalities in South Carolina as an urban planner for the past year. Her

In recent years, a number of authors have commented on the relationship of planning to public health and speculated that sprawling patterns of urban development are harmful to individuals' physical health. Specifically, as shown in Figure 1, it is suggested that the physical structure of sprawling development, by encouraging a greater reliance on automobiles for transportation, discourages walking and other physical activities and also promotes higher levels of air pollution, both of which increase the possibility of various types of physical ailments. As a result, individuals in more sprawling urban settings walk less and are less healthy than they would be if they lived in a more compact environment (e.g., French, Story, and Jeffery 2001; Frank and Engleke 2001; Frumkin 2002; Gillham 2002; Handy et al. 2002; Jackson and Kochtitzky 2002; Kreyling 2001).

A great deal of literature within the medical field supports the linkages within the middle portion of this sprawl-health causal chain. For instance, the relationship of physical activity to obesity is well established, as is the relationship of obesity to a variety of physical ailments such as hypertension, heart disease, and type 2 diabetes (Anspaugh, Hunter, and Dignan 1996; Sallis and Owen 1999; Unger 1995; U.S. Department of Health and Human Services 1996). Similarly, higher levels of air pollution may be related to higher rates of asthma, bronchitis, and other lung disease (Frumkin 2002).

A different body of literature has documented relationships at the beginning of the sprawl-health chain: the relationship of sprawling land-use patterns to physical activity, and especially automobile use and walking. This literature suggests that people are less likely to drive, more often use public transit, and/or are more likely to walk in areas that have better connected and highly accessible street networks, smaller blocks, more compact and dense land-use patterns, ample sidewalks, a rich and varied visual environment, and a strong mix of residential, commercial, and retail activities (e.g., Frank 2000; Frank and Engleke 2001; Ewing, Pendall, and Chen 2002; Craig et al. 2002; Brownson et al. 2001; De Bourdeaudhuif, Sallis, and Saelens 2003; Giles-Corti et al.

Journal of Planning Education and Research 24:184-196
DOI: 10.1177/0739456X04267713

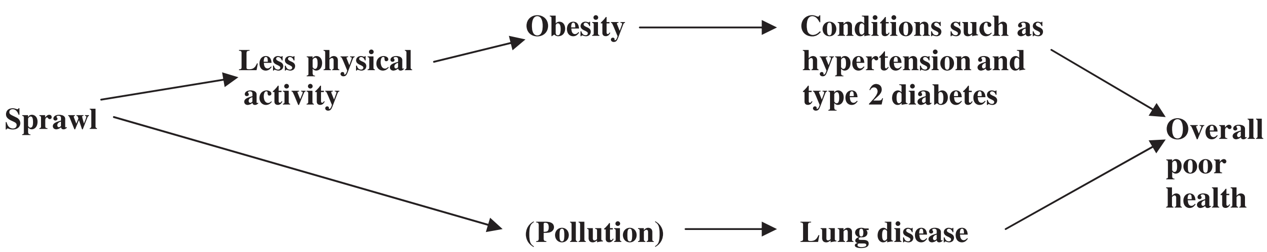

Figure 1. *The hypothesized sprawl-health connection.*

2003; King et al. 2003; Saaleens et al. 2003; Giles-Corti and Donovan 2003). Evidence also suggests that more sprawling metropolitan areas tend to have higher levels of ozone emissions (Ewing, Pendall, and Chen 2002).

We have found only one study that examines several steps within the full length of the sprawl-health chain and directly links measures of sprawl with individual-level measures of health. Using data from telephone interviews conducted by the Behavioral Risk Factor Surveillance System and hierarchical linear modeling (HLM), Ewing and associates (2003) found that, once individual demographic and behavioral characteristics were controlled, residents of counties that were more sprawling (as measured by a global, unidimensional indicator) exercised less, were more likely to be obese, and were more likely to have high blood pressure. No significant relationship was found between sprawl and reporting a diagnosis of diabetes or coronary heart disease. The work of Ewing and associates is a very important addition to the literature and avoids problems endemic to much of the work in the field. The dependent variables related to activity and health are measured at the individual level, the analysis includes individual health-related measures as control factors, and the sample is broad based and includes a widely varying group of geographic areas.

Our analysis replicates and extends the work of Ewing and associates (2003). We examine the sprawl-health connection using a large data set that includes respondents from a number of randomly selected primary metropolitan statistical areas (PMSAs); strong measures of individuals' health and activity, based on both interviews and medical examinations; extensive controls for individual-level variables related to health; and well-validated measures of sprawl. Our analysis differs from Ewing et al.'s in that our data were gathered through in-person interviews and medical examinations rather than a phone survey; we examined variables throughout the entire range of the hypothesized sprawl-health chain, including ratings of overall health; we used PMSAs rather than counties as our geographic unit of analysis; and, perhaps most important, we used a multidimensional conceptualization and measurement of sprawl.

▶ Method

The individual-level data used to test the sprawl-health hypothesis come from the National Health and Nutrition Examination Survey III, 1988-94 (NHANES III). The data on sprawl come from the work of Ewing, Pendall, and Chen (2002).

Sample

The NHANES survey is a nationwide study conducted by the National Center for Health Statistics. The sample was selected using a complex, stratified, multistage probability design, beginning with the selection of individual counties. Mexican Americans and African Americans were oversampled to allow for more accurate comparisons among race-ethnic groups. Data were gathered through personal interviews in respondents' homes and through medical examinations

research interests include the influence of urban form on health and transportation patterns.

Jean Stockard is a professor in the Department of Planning, Public Policy, and Management at the University of Oregon and specializes in social policy and planning.

Scott Doyle, AICP, is a project coordinator for the University of Oregon's Community Service Center, where he works with Oregon communities on natural hazard mitigation and environmental planning projects. He holds a master's degree in community and regional planning (MCRP) from the University of Oregon's Planning, Public Policy and Management Department.

Marc Schlossberg is an assistant professor in the Planning, Public Policy and Management Department at the University of Oregon as well as a research associate for the Mineta Transportation Institute. His research and teaching interests are in geographic information systems (GIS) modeling of pedestrian access, the transportation disadvantaged, participatory GIS, and social planning.

Table 1.
PMSAs (counties) in the analysis and measures of sprawl.

PMSA	*County*	*Density*	*Mix*	*Centers*	*Streets*	n
Riverside–San Bernardino	San Bernardino	93.5	41.5	41.4	80.5	238
West Palm Beach–Boca Raton	Palm Beach	94	54.7	53.9	104.7	227
Ventura	Ventura	103.9	139	55.5	106.5	246
Fort Worth–Arlington	Tarrant	90.3	89.1	73.9	97.5	258
Dallas	Dallas	99.5	83	81.1	90.2	181
Detroit	Oakland and Wayne	97.3	102.5	63	93	458
Jacksonville	Duval	85.6	72.9	102.1	104.6	227
Cleveland–Lorain–Elyria	Cuyahoga	99.7	107.4	100.9	66.8	196
Houston	Harris	95.3	110.1	87	95.6	348
St. Louis	St. Louis	90.3	107.4	76.2	106	241
Cincinnati	Hamilton	88.8	95.8	110.2	85.4	214
Orange County	Orange	128.8	121.5	72.1	136.4	214
Oakland	Alameda	116.6	106.3	57.6	133.4	219
Seattle–Bellevue–Everett	King	103.6	79.4	98	117.1	273
Los Angeles–Long Beach	Los Angeles	151.5	123.1	72.4	123.3	1,245
San Diego	San Diego	113.4	105.4	74.4	106	219
Pittsburgh	Allegheny	90.4	86.8	104.5	124.2	199
San Antonio	Bexar	95	100.6	108.4	103	298
San Jose	Santa Clara	124.8	96.6	93.9	125.2	193
Fresno	Fresno	93.5	130.1	112.6	73	241
Phoenix–Mesa	Maricopa	106.8	116	92.6	107.2	215
Philadelphia	Delaware and Philadelphia	114.7	119.5	95.9	113	341
El Paso	El Paso	100.1	103	119.5	102.3	231
Buffalo–Niagara Falls	Erie	102.1	124.7	135.2	70.6	201
Chicago	Cook	142.9	115.1	85.8	134.9	579
Miami	Dade	129.1	104.7	92.7	136.4	265
Boston	Middlesex	113.6	124.4	109.4	119.1	208
Providence–Fall River–Warwick	Providence	99.1	140.5	140.3	135.9	219
New York	Kings, New York, Queens, Westchester, and Nassau	242.5	129.8	144.6	154.9	1,058
Total (PMSA level)		110.6	104.5	91.6	108.5	29
Total (individual level)		127.6	109.3	93.1	114.9	9,252

Note: Primary metropolitan statistical areas (PMSAs) are ordered from most sprawling to least sprawling on a composite measure of these four dimensions. Higher values on the sprawl measures indicate less sprawling characteristics (e.g., higher density, greater mix of activities, more clearly defined centers, more highly connected street grid).

conducted in a mobile examination center.[1] Information on the county in which respondents live is available for those in areas with a population of 500,000 or more. The PMSAs, associated counties, and number of cases within each PMSA included in the sample are listed in Table 1.[2] We limited our analysis to individuals eighteen years of age and older.

Measures

Our measures of sprawl are taken directly from the analysis of Ewing, Pendall, and Chen (2002). Using factor analytic techniques and data from a variety of sources, they delineated four separate measures, each related to a theoretically distinct characteristic of sprawling metropolitan areas: (1) residential density, which includes measures of population density and average lot size; (2) neighborhood mix, which includes indicators of the mix of work, shopping, and housing within neighborhoods; (3) strength of metropolitan centers, including measures of the extent to which there are identifiable centers within an area; and (4) accessibility of the street network, which measures the extent to which street networks are dense and interconnected. We use the individual factor scores for each of these four dimensions.[3]

The sprawl values for each PMSA in the analysis are shown in Table 1. Higher values on the measures indicate less sprawling areas, that is, metropolitan areas that have higher levels of density, a greater mix of uses within neighborhoods, stronger and more identifiable centers, and a more connected street network. Ewing, Pendall, and Chen (2002) developed their measure on eighty-three metropolitan areas, and all of the PMSAs represented in the NHANES data set were included in their sample. On average, the PMSAs in our data set are somewhat less dense, have a slightly greater mix of activities, and have a more highly connected street grid, but less clearly defined centers, than the metropolitan areas in Ewing et al.'s (2003) full data set.

Table 2.
Measures of health.

Measure	*Source*
Walking frequency: number of times walked at least one mile without stopping in past month, collapsed into never and at least once	Interview
Body mass index (weight in kg)/([height in cm/100]^2)	Exam
Hypertension	
Average systolic and diastolic blood pressure from several measures in home and examination center	Exam
Self-report: ever been told by a health professional that they had high blood pressure (1 = yes, 0 = no)	Interview
Diabetes: ever been told by a health professional that they had diabetes (1 = yes, 0 = no)	Interview
Lung disease: ever been told by a health professional that they had asthma, chronic bronchitis, or emphysema (0 = no, 1 = yes to one or more)	Interview
Summary health ratings from physician and respondent (five-point scale with 1 = excellent and 5 = poor)	Exam and Interview

We use measures from the NHANES data set that were gathered both through personal interviews and medical examinations. As outlined in Table 2, we have nine indicators of the dependent variables included in Figure 1: frequency of walking, indicating whether the respondent had walked a mile or more without stopping in the past month; obesity, measured by the standard body mass index (BMI); hypertension, measured both by self-report and a physician's exam; diagnosis of diabetes; diagnosis of lung disease; and summary health ratings from both respondents and the examiner. Note that the array of dependent variables includes indicators spread throughout the hypothesized sprawl-health chain: the variables that are theoretically most closely related to the built environment (walking and BMI), those in the middle (chronic conditions that are exacerbated by obesity or air pollution, including diabetes, hypertension, and lung disease), and two global, summary measures that are conceptually most distant from the built environment but most indicative of overall health and well-being (both self-reported and physician-reported ratings of health).

Finally, we include a number of control variables, all measured at the individual level: age, gender, race-ethnicity, income, education, smoking history, and social support. These variables were chosen because other research has demonstrated that they are highly related to health status. Omitting them from our statistical analysis could produce serious misspecification. In addition, we include measures of how long the respondent had lived in the area to control for the length of time an individual respondent might have been exposed to a PMSA.

Race-ethnicity is measured by dummy variables for Mexican American, African American, and non-Hispanic whites, with the omitted category including all others. Income is measured by the ratio of family income to the poverty level, and education is measured by the highest grade or year of school completed. Smoking history is measured by two dummy variables: currently smoking and used to smoke, with the omitted category indicating that the participant had never smoked. Social support is measured by a composite of standardized scores (z scores) of five variables measuring how frequently participants interacted with others.[4] Both age and length of time at the current address are measured in years. All of these data were obtained in the interviews.

The size of the sample with completed examination data is smaller than that with interview data. Respondents in the interview sample, but not the exam sample, tended to be somewhat older, less healthy, more often non-Hispanic white, and living in less sprawling areas. Because all of these variables are included as controls in our analysis, these differences should not affect our results.

Analysis

To examine the influence of sprawl on measures of health, while controlling for individual-level variables, we used HLM employing SAS PROC MIXED.[5] HLM provides two distinct advantages over ordinary least squares (OLS) regression in testing hypotheses that involve multiple units of analysis: First, and most important, the estimates of the regression equations and standard errors are more accurate with HLM than with OLS. Second, the variance of the dependent variable may be partitioned between the individual and group (PMSA) level, allowing us to obtain estimates of the extent to which the measures of health vary between the PMSAs as well as the extent to which the measures of sprawl, and the control variables, can account for these variations (Raudenbush and Bryk 2002; Singer 1998). With the exception of the measure of income, there were relatively few cases of missing data. Substitution of the mean value was used for missing values on income, and a

Table 3.
Means and standard deviations of dependent and control variables.

	M	SD	n
Dependent variables			
How often walked mile, past month	6.70	12.94	9,229
Ever walked a mile or more in past month	0.47	0.50	9,229
Body mass index	26.83	5.65	8,230
Ever told had high blood pressure	0.26	0.44	9,148
Overall average K1, systolic, blood pressure	123.92	19.33	8,033
Overall average K5, diastolic, blood pressure	73.35	10.82	8,028
Ever told had diabetes	0.08	0.27	9,240
Ever told had lung disease	0.11	0.31	9,249
Poor health, physician rating	2.09	1.05	7,790
Poor health, self-rating	2.74	1.09	9,245
Control variables			
Age	46.80	20.03	9,252
Male	0.48	0.50	9,252
Non-Hispanic white	0.32	0.47	9,252
Non-Hispanic black	0.28	0.45	9,252
Mexican American	0.33	0.47	9,252
Poverty-income ratio	2.44	1.81	8,151
Years of education	10.95	3.96	9,122
Social support	0.00	2.68	9,148
Currently smoke	0.25	0.43	9,252
Used to smoke	0.24	0.43	9,252
Years in area	22.04	18.13	9,068

dummy variable indicating that this had occurred was included.

We first examine the extent to which the PMSAs differ on the dependent variables and the extent to which the measures of sprawl can account for these differences once the individual-level variables are controlled. Then, focusing on the health measures for which the most significant relationships with sprawl appear, we introduce walking and BMI as control variables to test the hypothesis that sprawl influences health through its relationship to physical activity and body mass, as suggested in Figure 1. Finally, in post hoc analyses, we explore the relationship of sprawl to overall health among the subset of individuals who report having a specific chronic condition (hypertension, diabetes, and/or lung disease). We also use the unidimensional measure of sprawl used by Ewing et al. (2003) to compare our results with theirs and to try to better understand why our results differ in some respects.

► Results

Table 3 shows the means and standard deviations of all variables used in the analysis. Slightly less than half of the respondents had walked a mile or more without stopping in the past month. The average BMI for the respondents was almost twenty-seven, a level that is considered within the "overweight, but not yet obese" range.[6] About a quarter of the respondents reported that they had been diagnosed with high blood pressure, and the average levels of measured systolic and diastolic blood pressure were at the high end of the typical normal range. About 8 percent of the sample reported a diagnosis of diabetes, and 11 percent reported a diagnosis of some type of chronic lung disease. In total, about one-third had at least one of these chronic diseases. On average, respondents rated their health as falling between very good and good, although respondents tended to rate their health as somewhat worse than did physicians (t = 43.374, df = 7786, p < .001). All of the dependent variables had sufficient variation for analysis.

Relationship of Sprawl to Measures of Health

Table 4 gives the random coefficient variance estimates for four explanatory models for each of the dependent variables. The first model, the "intercept only" or "unconditional means model," tests the hypothesis that the average health of respondents differs between the PMSAs. This model is equivalent to a one-way analysis of variance with the PMSAs as the factor and the measure of health as the dependent measure. All of the z values associated with the variance estimates for this first model are statistically significant, indicating that the health of respondents varies significantly between the PMSAs in the sample with all of our measures. The intraclass correlation coefficient (ρ) measures the proportion of variance in the dependent variable that is between PMSAs. It is calculated by dividing the covariance estimate associated with the intercept (the between variation) by the sum of the residual and between variation. (For example, for walking, the intraclass correlation = 0.0702/[0.0702 + 0.9975] = .066.) Values of ρ range from a low of .008 (for BMI) to a high of .146 (for physician's rating of health).

The second model in Table 4 (column 2) adds the measures of sprawl (the level 2 or PMSA level measures) as explanatory variables. The z values associated with the random coefficient variance estimates in this column test the hypothesis that the average health of respondents differs across the PMSAs after controlling for the measures of sprawl. This model is equivalent to an analysis of covariance, with the measures of sprawl being covariates. In all cases, the *z* values are significant, indicating that after controlling for the amount of sprawl within the PMSAs, they still differ, on average, on the measures of health. That is, the indicators of sprawl are not sufficient to account for the differences in health that appear between the metropolitan areas.

The proportionate reduction in error (PRE) measures associated with this model indicate the extent to which the variance between the PMSAs has been reduced by adding the measures of sprawl to the model. It is calculated by dividing the difference between the variance estimate in the intercept-only model (model 1) and the estimate for model 2 (including the measures of sprawl) by the variance estimate for model 1. (For instance, for walking and model 2, PRE = [0.0702 – 0.0696]/0.0702 = .009.) The PRE measures indicate, in proportionate form, the extent to which the measures of sprawl can account for the health differences observed between the PMSAs. Some values are negative (for diagnoses of diabetes, hypertension, and lung disease), indicating that the differences between PMSAs actually increase when the sprawl measures are included in the model. Others are quite small (less than .01 for walking and diastolic blood pressure), while those associated with BMI, systolic blood pressure measurement, and the ratings of health are larger (ranging from .07 to .19).

The third model in Table 4 includes only the individual-level

Table 4.
Random coefficient variance estimates, four explanatory models and all dependent variables.

	Model			
Dependent Variable	*1. Intercept Only*	*2. Level 2 (Sprawl) Measures Only*	*3. Level 1 (Control) Variables Only*	*4. Levels 1 and 2 (Sprawl and Control) Variables*
Walking				
Intercept	0.0702	0.0696	0.0774	0.0706
z	3.02****	2.77***	2.97****	2.68***
PRE from intercept-only model		.009	–.102	–.006
Residual	.9975			
Intraclass correlation coefficient = .066				
Body mass index				
Intercept	0.269	0.217	0.025	0.001
z	2.47***	2.31***	0.49	0.02
PRE from intercept-only model		.193	.906	.996
Residual	31.665			
Intraclass correlation coefficient = .008				
Average systolic blood pressure				
Intercept	7.857	7.282	2.540	2.335
z	3.19****	3.13****	2.49***	2.46***
PRE from intercept-only model		.073	.677	.703
Residual	366.65			
Intraclass correlation coefficient = .021				
Average diastolic blood pressure				
Intercept	2.029	2.020	1.975	1.900
z	2.97****	2.96****	2.92***	2.93***
PRE from intercept-only model		.004	.027	.064
Residual	115.430			
Intraclass correlation coefficient = .017				
Diabetes diagnosis				
Intercept	0.089	0.106	0.017	0.033
z	2.32***	2.27***	0.79	1.17
PRE from intercept-only model		–.188	.807	.626
Residual	0.9799			
Intraclass correlation coefficient = .083				
Hypertension diagnosis				
Intercept	0.030	0.037	0.003	0.005
z	2.31***	2.26***	0.41	0.58
PRE from intercept-only model		–.216	.903	.834
Residual	0.9959			
Intraclass correlation coefficient = .029				
Lung disease diagnosis				
Intercept	0.033	0.039	0.002	0
z	1.77**	1.78**	0.18	0.00
PRE from intercept-only model		–.196	.953	1.00
Residual	0.9899			
Intraclass correlation coefficient = .032				
Poor health (self-rated)				
Intercept	0.028	0.026	0.004	0.002
z	3.30****	3.24****	1.95**	1.39*
PRE from intercept-only model		.071	.857	.929
Residual	1.158			
Intraclass correlation coefficient = .024				

(continued)

Table 4. (continued)

Dependent Variable	Model: 1. Intercept Only	2. Level 2 (Sprawl) Measures Only	3. Level 1 (Control) Variables Only	4. Levels 1 and 2 (Sprawl and Control) Variables
Poor health (physician rated)				
Intercept	0.168	0.139	0.173	0.138
z	3.69****	3.68****	3.73****	3.70****
PRE from intercept-only model		.173	–.030	.179
Residual	0.984			
Intraclass correlation coefficient = .146				

Note: PRE = proportionate reduction in error. The intercept-only model tests the hypothesis that the primary metropolitan statistical areas (PMSAs) differ on the measure of the dependent variable. The model with only level 2 variables (the measures of sprawl) tests the hypothesis that the PMSAs differ on the measure of health (the dependent measure) once the measures of sprawl are included, and so on. All PRE measures compare the intercept random variance with that in model 1. The residual variance estimate given is only for model 1 and was used to calculate ρ, the intraclass correlation.
*$p < .10$. **$p < .05$. ***$p < .01$. ****$p < .001$.

control variables (the level 1 variables). In several cases (BMI and diagnoses of diabetes, hypertension, and lung disease), including these individual-level variables is sufficient to account for the variations between the PMSAs, as indicated by the nonsignificant z values associated with the random coefficient variance estimates. In other words, for BMI and the three chronic conditions included in our analysis, variations between PMSAs can be totally accounted for by the characteristics of individuals within those settings. With the other variables, however (walking, measured blood pressure, and health ratings), significant differences between the PMSAs remain even when individual-level variables are controlled.

The PRE measures associated with model 3 indicate the reduction in variance from model 1 to model 3, that is, the extent to which differences between PMSAs are reduced by considering the individual-level variables. From two-thirds to more than 90 percent of the variation between PMSAs in BMI; systolic blood pressure readings; diagnoses of diabetes, hypertension, and lung disease; and self-ratings of poor health is accounted for by the individual control variables. In contrast, very little of the variation between PMSAs in diastolic blood pressure is accounted for by these variables, and controlling for only the individual variables actually increases the variation between PMSAs in walking and physicians' ratings of health (as indicated by the negative PRE values).

Finally, column 4 of Table 4 gives the results when both the individual-level control variables and the measures of sprawl are included in the model. The z values test the hypothesis that the average health ratings vary between the PMSAs when both the individual- and PMSA-level variables are controlled and the PRE measures indicate the proportionate reduction in error from model 1. Results with this model are very similar to those with model 3 with the exception of self-ratings of health, where including both the measures of sprawl and individual controls reduces the differences between the PMSAs to a level that is significant at only the .10 level.

Taken together, the results summarized in Table 4 indicate that measures of individuals' health differ significantly between the PMSAs in our sample. Some of these differences—most notably in BMI and diagnoses of chronic conditions—can be accounted for by variations in individual characteristics. The PRE measures associated with model 2 indicate that differences in other characteristics that vary significantly between PMSAs (specifically, walking and diastolic blood pressure readings) cannot be explained by the measures of sprawl. In contrast, both the PRE measures and the intraclass correlations (ρ) suggest that the variation between PMSAs in systolic blood pressure and both self-ratings and physician ratings of health is significant and might be explained, to at least some extent, by the measures of sprawl.

Examination of the coefficients associated with sprawl in model 4 (the model including all individual control variables and the measures of sprawl) indicated that only those associated with the two health ratings reached statistical significance.[7] These coefficients are given in the first column of Table 5. As hypothesized, they indicate that respondents who live in areas with more highly connected street networks are significantly less likely to rate their own health as poor or to have their health rated poor by the examining physician. In addition, and contrary to expectations, those who live in more dense urban environments are significantly more likely to rate their own health as poor.[8]

The coefficients associated with the individual-level control variables are omitted from Table 5 to conserve space. As one would expect, however, many of these individual-level variables have a strong effect on health ratings, usually substantially stronger than that of the measures of sprawl.[9] Still, the influence on health of living within an area with a more highly

Table 5.
Unstandardized coefficients showing the relationship of sprawl, walking, and body mass index (BMI) to self-ratings and physician ratings of poor health.

	Model 4	*Model 5*	*Model 6*
Poor health, self-rating			
Centers	–.0009	–.0008	–.0006
Density	.0014***	.0014***	.0012**
Mix	.0007	.0009	.0009
Streets	–.0028***	–.0026***	–.0021**
Walking	—	–.2680****	–.2526****
BMI	—	—	.0151****
Random coefficient variance			
Intercept	.0019	.0010	.0018
z	1.39	0.96	1.28
p	.08	.17	.10
Poor health, physician rating			
Centers	–.0006	–.0006	–.0005
Density	.0045	.0045	.0044
Mix	–.0020	–.0019	–.0018
Streets	–.0107***	–.0107***	–.0104
Walking	—	–.0922****	–.0763****
BMI	—	—	.0428****
Random coefficient variance			
Intercept	.1380	.1364	.1408
z	3.70	3.70	3.71
p	.0001	.0001	.0001

Note: All models control for age, gender, race-ethnicity, income, education, social support, smoking status, time in the area, and missing income. Model 4 includes only the sprawl measures and individual (level 1) controls, model 5 adds the measure of walking, and model 6 adds BMI. These unstandardized coefficients are called fixed effects in the terminology of hierarchical linear modeling and can be interpreted in the same manner as unstandardized regression coefficients in ordinary least squares, showing the expected change in the dependent variable with a one-unit change in the independent variable when all other variables are held constant. Because the two measures of health and the four sprawl measures have the same metric, coefficients may be compared across and within equations.
$^{**}p < .05$. $^{***}p < .01$. $^{****}p < .001$.

gridded street network is not trivial and is similar in magnitude to that of social support. The influence of a more dense environment on poorer health is smaller in magnitude than that of a highly gridded area but is statistically significant at similar levels. Taken together, the results displayed in Tables 4 and 5 support the general notion of the sprawl-health connection with the dimension of sprawl that is related to accessible street networks but contradict the notion with the dimension of sprawl that is related to density.

Effect of Walking and BMI on the Sprawl-Health Connection

To more fully examine the sprawl-health connection outlined in Figure 1, it is important to explore the extent to which the relationship of sprawl to health is modified when measures of walking and BMI are added to the predictive equation. If the model shown in Figure 1 were supported, the coefficients associated with sprawl should decline markedly when these measures are introduced. Models 5 and 6 in Table 5 summarize the results of this analysis. Model 5 adds the measure of walking to the variables included in model 4 (all of the individual-level control variables plus the measures of sprawl), and model 6 adds both walking and BMI.

The results in model 5, which include the measure of walking, are virtually identical to those in model 4. Those who more often walk at least a mile at a time without stopping are less likely to have poorer rated health (either from themselves or the physician), but the coefficients associated with the measures of sprawl are virtually the same as in model 4. In contrast, when both BMI and walking are included in the model (model 6), the influence of the measures of sprawl declines slightly and the significance of the influence of density (for self-rated health only) and streets (for both dependent measures) is somewhat lower (at the .05 rather than the .01 level). These results suggest that while a very small proportion of the influence of sprawl may be related to its influence on obesity (as measured by BMI), sprawl, walking, and body mass all independently influence ratings of health. Put another way, people who live in PMSAs that have highly connected street networks and are less densely populated tend to have higher rated health no matter how much they walk or how much they weigh.

Sprawl and Health for People with Chronic Conditions

Even though there is no indication in our analysis that sprawl is related to a diagnosis of hypertension, diabetes, or lung disease, it is possible that the measures of sprawl may affect the health of people with these conditions. In other words, it is possible that among those with chronic conditions, individuals who live in areas with more connected street networks and lower density will have higher health ratings. To explore this question, we repeated our analysis of health ratings with only those who reported diagnoses of hypertension, diabetes, and/or lung disease (about one-third of the sample).

As noted in Table 6, the rated health of those with chronic diseases differs significantly between the PMSAs (see the random coefficient variance for the intercept for the intercept-only models). For self-rated health, this difference declines to nonsignificance with the addition of the measures of sprawl and the individual-level controls (model 4). For physicians' ratings, the differences remain significant throughout all the models. These findings parallel those for the total group (see Table 5). Coefficients in model 4 are also similar to those with the total group, with respondents having higher rated health when they live in PMSAs with more highly gridded street networks. The relationship of lower density to better self-rated health is similar in direction to that with the total group but not strong enough to reach statistical significance ($t = 1.54$, $p = .123$). The results in model 5, when walking is added to the model, are very similar to those in model 4, except that the relationship of density with self-rated health becomes significant at the .10 level. Finally, when both walking and BMI are added to the model (model 6), the influence of a highly accessible street pattern remains significant for physicians' ratings of health but declines somewhat and is below traditional levels of significance for self-ratings of health ($t = -1.33$, $p = .18$). In general, the results with the subgroup of respondents who have a chronic condition replicate the findings with the total sample regarding the relationship of street connectivity to health. Even with strong controls for individual characteristics, people who live in PMSAs with a more connected and accessible street network have higher ratings of health from both themselves and medical examiners.

Table 6.
Unstandardized coefficients showing the relationship of sprawl, walking, and body mass index (BMI) to self-ratings and physician ratings of poor health in respondents with a chronic disease.

	Model 4	*Model 5*	*Model 6*
Poor health, self-rating[a]			
Centers	–.0009	–.0008	–.0004
Density	.0011	.0012*	.0007
Mix	.0001	.0006	.0004
Streets	–.0028**	–.0026**	–.0018
Walking	—	–.3882****	–.3500****
BMI	—	—	.0114****
Random coefficient variance			
Intercept	.00117	.0000	.00171
z	0.39	—	.51
p	.35	—	.31
PRE from model 1	.928	1.00	.895
Poor health, physician rating[b]			
Centers	–.0003	.0001	–.0002
Density	.0037	.0036	.0035
Mix	–.0030	–.0028	–.0026
Streets	–.0086**	–.0084**	–.0081**
Walking	—	–.1757****	–.1442****
BMI	—	—	.0407****
Random coefficient variance			
Intercept	.1162	.1116	.1144
z	3.42	3.41	3.44
p	.0003	.0003	.0003
PRE from model 1	.108	.144	.122

Note: PRE = proportion reduction in error. All models control for age, gender, race-ethnicity, income, education, social support, smoking status, time in the area, and missing income. Model 4 includes only the sprawl measures and controls, model 5 adds the measure of walking, and model 6 adds BMI. Coefficients may be compared to those in Table 5.
a. Random coefficient variance, intercept, intercept-only model (model 1) = .01627, $z = 2.15$, $p = .0159$; residual random coefficient variance, intercept-only model = 1.1409; $\rho = .014$.
b. Random coefficient variance, intercept, intercept-only model (model 1) = 0.1303, $z = 3.38$, $p = 0.0004$; residual random coefficient variance, intercept-only model = 1.1131; $\rho = .105$.
*$p < .10$. **$p < .05$. ****$p < .001$.

Unidimensional Conception of Sprawl at the County Level and Health

As noted above, the only other study that has examined relationships along the entire sprawl-health connection (Ewing et al. 2003) used a unidimensional measure of sprawl; counties as the geographic, or level 2, unit of analysis; and data gathered through a phone survey.[10] Four of the dependent variables used by Ewing and his associates (2003) were very similar to our own: walking, BMI, and reported diagnoses of diabetes and hypertension.[11] As noted above, we found no

Table 7.
Relationship between unidimensional, county-level, sprawl measure and health measures, NHANES and BRFSS data.

	NHANES			*BRFSS*		
Dependent Variable	*Coefficient*	t	p	*Coefficient*	t	p
Walking	.0036	3.51	.0013	.000872	1.94	.052
Diabetes	.0014	1.46	.1535	–.00059	–1.32	.19
Hypertension	–.0001	–0.21	.8381	–.00119	–2.37	.018
Body mass index	–.00313	–1.93	.0532	–.00344	–2.84	.005
Poor health, physician rating	–.0002	–0.10	.9167	—	—	—
Poor health, self-rating	.00004	0.13	.8959	—	—	—

Note: NHANES = National Health and Nutrition Examination; BRFSS = Behavioral Risk Factor Surveillance System. All models with NHANES data control for age, gender, race-ethnicity, income, education, social support, smoking status, time in the area, and missing income. All models with the BRFSS data control for age, gender, race-ethnicity, education, smoking status, and, for body mass index and diabetes, fruit and vegetable consumption. Results for the BRFSS come from Ewing et al. (2003, 53-54).

significant relationship between the four indicators of sprawl and these dependent variables, while Ewing and associates found significant relationships between their unidimensional measure of sprawl and three of these four variables (all but diabetes). In a post hoc analysis designed to help understand these differences, we used Ewing et al.'s county-level measure of sprawl and counties as the level 2 unit of analysis and repeated our analysis using the four dependent measures that are common between our study and that of Ewing et al. as well as the two summary health ratings.

Results from our analysis, as well as the comparable coefficients from Ewing et al. (2003), are in Table 7.[12] Replicating the results of the Behavioral Risk Factor Surveillance System (BRFSS) data, the results of our NHANES data indicate that residents of less sprawling counties tend to walk more and to have lower BMIs. The size of the coefficient associated with walking is markedly higher with the NHANES data than with the BRFSS data, perhaps reflecting the differences in this measure between the two data sets (see note 11), while the coefficients associated with BMI are virtually identical.[13] In contrast to the results of the BRFSS, the analysis of the NHANES data indicates no relationship between the unidimensional measure of sprawl and hypertension. In addition, as shown in the bottom two rows of Table 7, the unidimensional measure of sprawl has no significant relationship to the overall health ratings.

▶ Summary and Discussion

Our results provide evidence to support the general hypothesis that sprawl is related to health, but the relationship appears to be more complex than diagrammed in Figure 1 and than suggested by the results of Ewing and associates (2003). First, our results suggest that the various dimensions of sprawl affect health in different, and even contradictory, ways. Among the four aspects of sprawl delineated by Ewing, Pendall, and Chen (2002; density, mix, centralization, and streets), having a more accessible and highly gridded street network appears to promote significantly better health ratings, while living in a more densely populated urban environment promotes significantly poorer health ratings (self-reports only). The influence of the street network was expected and reflects, we suspect, the way in which such designs promote activity, by making walking more accessible and attractive than alternative means of transit. The lack of significance associated with the measures of mixed uses and strongly defined centers suggests that connectivity of streets may be a more important design element in promoting health.

Even though our finding that more dense urban environments are related to poorer health once other variables were controlled was unexpected, inspection of the underlying correlation matrix provides clues as to why it occurred. The measures of density and streets are highly correlated ($r = .788$, $r^2 = .62$), reflecting the fact that many highly gridded urban areas also tend to be relatively dense. We hypothesize that once environments are theoretically equal in terms of "walkability," as measured by the nature of street layout and design, a more dense environment may be less inviting and more stressful. A growing literature documents the relationship of stress to health on an individual level (e.g., Lovallo 1997; Rice 1992), and our results may provide some support for this conclusion on a more macro level.

We suggest that our analyses with the county-level, unidimensional measure used by Ewing et al. (2003) may provide further support for this conclusion. Because the unidimensional measure of sprawl focuses on smaller units of analysis than the four-dimensional measure does (counties vs. PMSAs), it probably provides a more precise measure of the built environment. We suspect that the significant relationship that we found between the unidimensional measure of sprawl and walking and BMI reflects the greater exercise and activity that residents of more highly connected and dense areas can experience. This became apparent only when smaller geographic units were analyzed with a more precise measure of the built environment.[14] At the same time, the unidimensional measure of sprawl confounds the aspects of density and streets by combining them into one index. We suggest that our failure to find a significant relationship between the unidimensional sprawl measure and overall measures of health reflects the different elements of this measure. Street connectivity may promote walking and overall health, but greater density is detrimental. Because the unidimensional measure combines these two elements, this more complex relationship is masked.[15]

To illustrate the different influences of street connectivity and density, consider that once individual-level variables are controlled, the healthiest PMSA within our sample is Providence–Fall River–Warwick, Rhode Island, followed by Pittsburgh. The New York City PMSA, which is actually less sprawling overall, is less healthy. As shown in Table 1, both Providence and Pittsburgh have well-defined networks of streets relative to other PMSAs yet below average density. New York City has a value on the street factor that is higher than that of Providence or Pittsburgh, but a density level that is about 2.5 times as great. It does not take a great deal of imagination to compare the experience of living in Providence or Pittsburgh with that of New York in terms of accessibility for walking (where New York has a slight advantage) countered by the stress that can come from a highly dense environment (where Providence and Pittsburgh have an advantage).

These differences are not substantively trivial. The expected difference in physician-rated health for residents of Providence and New York City, once individual characteristics are equalized, is .46 on a five-point scale, almost half a rating point. At the same time, residents of both Providence and New York are healthier, controlling for individual characteristics, than those of Riverside, the most sprawling PMSA in our sample. The predicted difference in physician-rated health for residents of Providence and Riverside is .82.[16] Even though residents of New York City may not be as healthy as those in Providence or Pittsburgh, once individual characteristics are equalized, they are rated far healthier than those in Riverside and other very sprawling PMSAs.

In general, our results suggest that once individual-level variables related to health, such as age, race-ethnicity, and gender, are controlled, areas that are accessible and have highly connected street systems (that theoretically encourage walking) yet are relatively less dense (and theoretically less stressful) tend to promote higher levels of general health among residents of metropolitan areas. In other words, some aspects of sprawl (the lack of accessible places to walk) are harmful to health, while others (the relatively less-dense environment) may promote better health. It is, we believe, noteworthy that the strongest relationships appear with the overall measures of health because these measures, whether from the respondent or the physician, provide a global assessment of well-being and functioning.

Our results provide only limited support for the hypothesized chain of influence between sprawl and health that is diagrammed in Figure 1. When PMSAs were the geographic unit of analysis, we found no strong direct influence of measures of sprawl on frequency of walking, obesity, or the presence of chronic disease, although there was an influence on walking and obesity when counties were the geographic unit. While both frequency of walking and body weight influence overall health, the measures of sprawl appear to affect health ratings independently and jointly with these measures. More important, our results suggest that the influence of sprawl on health is both positive and negative, with greater street connectivity promoting better health but greater density related to poorer overall health ratings.

Although we did not find that the measures of sprawl were significantly related to measures of blood pressure or diagnoses of hypertension, diabetes, or lung disease, it is important to emphasize that the measure of street connectivity was related to the health of individuals with these diagnoses. Among people with these chronic conditions, those in areas with more connected street networks were healthier, even after individual factors were controlled. In addition, the relationship of walking with the rated health of chronic patients is substantially larger than that observed for the total population (compare coefficients for walking in models 5 and 6 between Tables 6 and 7). This could suggest that environments that promote exercise could be even more important for those with chronic conditions than for the general public, a hypothesis that could be tested in future work.

While we examined measures of each element of the sprawl-health model in Figure 1, it is possible that at least some of our measures were less than optimal. Most important, our measure of walking may not have tapped the casual type of exercise that is common in less sprawling areas. Respondents were asked how often, within the past month, they had walked a mile without stopping. While this may tap the people who regularly exercise for health reasons or who might walk a fair distance to work or from a transit stop, it may not capture much of the everyday walking that occurs within compact settings. In these environments, people may walk several times a day for different lengths and periods. It may well be this cumulative pattern of walking, rather than specific extended periods of exercise, that contributes to the better health of participants in more compact settings.

The work reported in this article represents a very conservative test of the sprawl-health connection. We looked at very broad geographic areas, used very strong individual control measures, and used well-validated measures of health gathered from both self-reports and medical examinations. Even with such stringent controls and broad-based measures of sprawl, the relationship between environmental characteristics and ratings of health is statistically significant and substantively strong. Future studies could examine the relationship of the built environment to health using smaller geographic areas as the unit of analysis. Given the conservative nature of the present test, we would expect examinations at these more proximate locations to produce even stronger results, an expectation supported, to some extent, by our post hoc analysis using county-level measures. It would also be important in future studies to examine the specific aspects of the built environment that influence health, especially what components of street patterns and density contribute to better (or worse) outcomes. It is also possible that other control variables—whether behavioral, demographic, or ecological—could be included. Most important, future studies should attempt, as this work has done, to use well-developed and validated measures of health, strong individual-level controls, and analysis techniques that are appropriate for multilevel data.

The association between the built environment and health presented in this article supports the idea that it may be beneficial for planners and public health officials to collaborate and explore ways to address public health issues. While much research is still needed to fully explore and understand the sprawl-health connection, our results suggest that the relationship of the built environment to public health should not be ignored. At the same time, planners and public health officials should remember that the impact of sprawl on health is potentially complex and multidimensional, with some aspects of compact development, such as street connectivity, promoting better health and other aspects, such as higher density, potentially detracting from better health.

Authors' Note: *We thank Judith Hibbard, Michael Hibbard, and Ken Hudson for their comments on this work. Any errors are solely the responsibility of the authors.*

▶ Notes

1. Very elderly respondents were examined in their homes with a shorter battery.

2. All counties in the sample except Nassau County, New York, correspond to primary metropolitan statistical areas (PMSAs) for which Ewing and associates (2003) calculated measures of sprawl. Nassau County is part of the Nassau-Suffolk PMSA, while other counties in the sample from the greater New York area are part of the New York PMSA. Nassau County is part of the greater New York–Northern New Jersey–Long Island consolidated metropolitan statistical area, as are the other counties in the greater New York area. Thus, residents of Nassau County were assigned the sprawl measures of others within this greater New York area.

3. Due to data availability, the measures we use are for 2000, but Ewing et al. (2003, 45) note in their discussion of validation of the measures that "the sprawl measures for 1990 are entirely consistent with measures for 2000."

4. The scale includes measures regarding talking on the phone with family, friends, and neighbors; getting together with friends and relatives; visiting with neighbors; attending religious services; and attending meetings of clubs or organizations. Standardized alpha was .39. All items are positively correlated, but, as would be expected, some are less highly correlated than others. Highest correlations are between talking on the phone and visiting friends and relatives ($r = .21$), between visiting friends and relatives and visiting neighbors ($r = .29$), and attending church and clubs or organizations ($r = .23$). We chose to combine the items into a scale even though the alpha is relatively low because all the items are positively correlated, they all relate to the concept we are concerned with, and the somewhat lower correlations (e.g., between attending religious services and talking on the phone) are not surprising.

5. For the dichotomous dependent variables (the measures of walking and the self-reports of hypertension, diabetes, and lung disease), we used hierarchical generalized linear models (Raudenbush and Bryk 2002, 291-309), employing a glimmix procedure within SAS to obtain the appropriate estimates.

6. Obesity is commonly defined as having a body mass index (BMI) greater than or equal to 30; overweight is defined as having a BMI measure between 25 and 29.9.

7. Even in model 2, with only the level 2 variables, none of the measures of sprawl are significantly associated with systolic blood pressure. In addition, most of the individual-level variables (especially age, gender, race-ethnicity, income, and smoking status) have a very strong relationship with measures of systolic blood pressure, and when these are controlled, the relationship of sprawl to systolic blood pressure declines dramatically.

8. The coefficient is in the same direction for physician rating of health and is substantively larger. However, a larger standard error is associated with this coefficient, and the resulting t value (1.39) is not statistically significant at the standard levels.

9. The individual-level health-related control variables (age, gender, race-ethnicity, income, education, social support, and smoking status) are strongly related to the measures of health. For virtually all of the dependent measures, older, female, and non-Hispanic black respondents have less favorable health outcomes, net of other variables. Income, education, social support, and history of smoking are also significantly related to a number of the dependent measures including frequency of walking and health ratings. Smoking status is most highly related to BMI (with current smokers weighing less and past smokers weighing more) as well as, for both groups, a greater likelihood of having lung disease and poorer ratings of health. A complete listing of coefficients is available from the authors on request.

10. This unidimensional measure included four indicators of density and two of street connectedness but no measures of mix or centeredness. Higher values indicate greater density and higher levels of street connectivity.

11. The measures of BMI and reported diagnoses of diabetes and hypertension are identical in the two studies. Our measure of walking from the National Health and Nutrition Examination Survey data set is a dichotomy indicating if the respondent ever walked

a mile or more without stopping within the past month. The Behavioral Risk Factor Surveillance System (BRFSS) item is also a dichotomy but indicates whether participants engaged in the recommended levels of physical activity in the past month. The recommended level is thirty minutes of moderately intense physical activity at least five days per week and/or twenty minutes of vigorously intense physical activity at least three days per week.

12. The coefficients can be directly compared because the dependent measures are identical and the coefficients are unstandardized coefficients.

13. The higher level of significance for BMI with the BRFSS sample results from the much larger sample size in that data set.

14. As shown in Table 1, three of the PMSAs in our sample had more than one county within the sample: Detroit, New York, and Philadelphia. Counties within these PMSAs often differed substantially in their scores on the unidimensional sprawl measure, from 106 to 123 for the Detroit counties, from 128 to 352 for the New York City counties, and from 125 to 188 for the Philadelphia counties.

15. We are unsure why we did not find a significant relationship of the unidimensional measure of sprawl with a diagnosis of hypertension, while Ewing et al. (2003) did when using the BRFSS data. One possibility is that our model was better specified in that it included several more individual-level control variables including income and social support. Our analyses with the four-dimensional measure of sprawl indicated that the individual-level measures in our model were sufficient to account for differences in hypertension across PMSAs.

16. These figures were calculated using the coefficients for physician-rated health in model 4 in Table 5. The coefficients were multiplied by the sprawl scores given in Table 1, summed, and compared.

▶ References

Anspaugh, David J., Susan Hunter, and Mark Dignan. 1996. Risk factors for cardiovascular disease among exercising versus nonexercising women. *American Journal of Health Promotion* 10:171-74.

Brownson, Ross C., Elizabeth A. Baker, Robyn A. Housemann, Laura K. Brennan, and Stephen J. Bacak. 2001. Environmental and policy determinants of physical activity in the United States. *American Journal of Public Health* 91:1995-2003.

Craig, Cora L., Ross C. Brownson, Sue E. Cragg, and Andrea L. Dunn. 2002. Exploring the effect of the environment on physical activity: A study examining walking to work. *American Journal of Preventive Medicine* 23:36-43.

De Bourdeaudhuif, Ilse, James F. Sallis, and Brian E. Saelens. 2003. Environmental correlates of physical activity in a sample of Belgian adults. *American Journal of Health Promotion* 18:83-92.

Ewing, Reid, Rolf Pendall, and Don Chen. 2002. *Measuring sprawl and its impact: Technical report*. Washington, DC: Smart Growth America.

Ewing, Reid, Tom Schmid, Richard Killingsworth, Amy Zlot, and Stephen Raudenbush. 2003. Relationship between urban sprawl and physical activity, obesity, and morbidity. *American Journal of Health Promotion* 18:47-57.

French, Simone A., Mary Story, and Robert W. Jeffery. 2001. Environmental influences on eating and physical activity. *Annual Review of Public Health* 22:309-35.

Frank, Lawrence D. 2000. Land use and transportation interaction: Implications on public health and quality of life. *Journal of Planning Education and Research* 20:6-22.

Frank, Lawrence D., and Peter O. Engleke. 2001. The built environment and human activity patterns: Exploring the impacts of urban form on public health. *Journal of Planning Literature* 16:202-81.

Frumkin, Howard. 2002. Urban sprawl and public health. *Public Health Reports* 117:201-17.

Giles-Corti, Billie, and Robert J. Donovan. 2003. Relative influences of individual, social environmental, and physical environmental correlates of walking. *American Journal of Public Health* 93:1583-89.

Giles-Corti, Billie, Sally Macintyre, Johanna P. Clarkson, Terro Pikora, and Robert J. Donovan. 2003. Environmental and lifestyle factors associated with overweight and obesity in Perth, Australia. *American Journal of Health Promotion* 18:93-102.

Gillham, Oliver. 2002. *The limitless city: A primer on the urban sprawl debate*. Washington, DC: Island Press.

Handy, Susan L., Marlon G. Boarnet, Reid Ewing, and Richard E. Killingsworth. 2002. How the built environment affects physical activity: Views from urban planning. *American Journal of Preventive Medicine* 23:64-73.

Jackson, Richard J., and Chris Kochtitzky. 2002. *Creating a healthy environment: The impact of the built environment on public health*. Washington, DC: Sprawl Watch Clearinghouse.

King, Wendy C., Jennifer S. Brach, Steven Belle, Richard Killingsworth, Mark Fenton, and Andrea M. Kriska. 2003. The relationship between convenience of destinations and walking levels in older women. *American Journal of Health Promotion* 18:74-82.

Kreyling, Christine. 2001. Fat city: Are we building sick communities? *Planning* 2001 (June): 4-9.

Lovallo, William R. 1997. *Stress and health: Biological and psychological interactions*. Thousand Oaks, CA: Sage.

Raudenbush, Stephen W., and Anthony S. Bryk. 2002. *Hierarchical linear models: Applications and data analysis methods*. Thousand Oaks, CA: Sage.

Rice, Phillip L. 1992. *Stress and health*, 2nd ed. Pacific Grove, CA: Brooks/Cole.

Saalens, Brian E., James F. Sallis, Jennifer B. Black, and Diana Chen. 2003. Neighborhood-based differences in physical activity: An environment scale evaluation. *American Journal of Public Health* 93:1552-58.

Sallis, James F., and Neville Owen. 1999. *Physical activity and behavioral medicine*. Thousand Oaks, CA: Sage.

Singer, Judith D. 1998. Using SAS PROC MIXED to fit multilevel models, hierarchical models, and individual growth models. *Journal of Educational and Behavioral Statistics* 24:323-55.

Unger, Jennifer B. 1995. Sedentary lifestyle as a risk factor for self-reported poor physical and mental health. *American Journal of Health Promotion* 10:15-17.

U.S. Department of Health and Human Services. 1996. *Physical activity and health: A report of the surgeon general*. Atlanta, GA: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Chronic Disease Prevention and Health Promotion.