Many Pathways from Land Use to Health

Associations between Neighborhood Walkability and Active Transportation, Body Mass Index, and Air Quality

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The literature shows single-use, low-density land development and disconnected street networks to be positively associated with auto dependence and negatively associated with walking and transit use. These factors in turn appear to affect health by influencing physical activity, obesity, and emissions of air pollutants. We evaluated the association between a single index of walkability that incorporated land use mix, street connectivity, net residential density, and retail floor area ratios, with health-related outcomes in King County, Washington. We found a 5% increase in walkability to be associated with a per capita 32.1% increase in time spent in physically active travel, a 0.23-point reduction in body mass index, 6.5% fewer vehicle miles traveled, 5.6% fewer grams of oxides of nitrogen (NOx) emitted, and 5.5% fewer grams of volatile organic compounds (VOC) emitted. These results connect development patterns with factors that affect several prevalent chronic diseases.

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Growing evidence documents the adverse health impacts of common land use patterns in the U.S. (Frank & Engelke, 2005; Frumkin, Frank, & Jackson, 2004; Handy, Boarnet, Ewing, & Killingsworth, 2002). Thus, according to some researchers, many zoning and subdivision regulations are doing a poor job of protecting public health, safety, and welfare (Jackson, 2003; Lavizzo-Mourey & McGinnis, 2003; Schilling & Linton, 2005).

Zoning ordinances often require separation between residential and other land uses and restrict mixed-use development capable of supporting local retail and regional transit service (Knaap & Nelson, 1992). Subdivision regulations often favor disconnected cul-de-sac street designs over more connected grid networks. As a result, the distances between places where people live, work, and play are often too great to walk. In the Seattle region, where this study was based, 85.5% of all work trips and 86.0% of all nonwork trips are made in private vehicles (Puget Sound Regional Council, 1999).

Traveling in vehicles rather than on foot can produce adverse health effects through a variety of mechanisms. For example, a survey of 10,898 people in Atlanta, Georgia (Frank, Andresen, & Schmid, 2004), showed that each additional hour spent in a car per day was associated with a 6% increase in the odds of being obese, while each additional kilometer walked per day was associated with a 4.8% reduction in the odds of being obese. Obesity and inactivity are both widespread, and increase the risk of several common chronic diseases (Andersen, 2003; U. S. Department of Health and Human Services, 1996). Increased numbers of vehicle trips and vehicle miles of travel are also associated with higher levels of several air pollutants resulting from vehicle emissions that have adverse respiratory health impacts.

This article examines the following three pathways by which single-use, low-density land use patterns can adversely affect health:

1. If the built environment reduces opportunity for active transportation, this may reduce total physical activity, and potentially increase risk for chronic disease.
2. If the built environment stimulates increased time spent in vehicles, it may reduce physical activity, and both of these may contribute to obesity, potentially increasing risk for chronic disease.

3. If the built environment stimulates increased vehicular travel, this may increase per capita vehicle emissions, and these may increase exposure to pollutants and risk of respiratory and cardiovascular ailments.

We used data from the Neighborhood Quality of Life Study (NQLS), funded by the National Institutes for Health, to study the physical activity and obesity pathways, and data from the King County Land Use, Transportation, Air Quality, and Health Study (LUTAQH) to examine the air quality pathway. Both of these studies were conducted in King County, Washington, and used the same land use measures.

Current Evidence Linking the Built Environment to Physical Activity and Obesity

Recent reviews show consistent associations between neighborhood design and walking and cycling for transportation (Frank, Engelke, & Schmid, 2003; Saelens, Sallis, Black, & Chen, 2003; Sallis, Frank, Saelens, & Kraft, 2004; Transportation Research Board & Institute of Medicine, 2005). People who live in neighborhoods with "traditional" or "walkable" designs report about 30 minutes more walking for transportation each week (Saelens, Sallis, & Frank, 2003) and more total physical activity (Frank, Schmid, Sallis, Chapman, & Saelens, 2005; King et al., 2003; Saelens, Sallis, Black, et al., 2003), compared to those who live in neighborhoods with less walkable "suburban" designs. (For a different approach and result, see also Rodríguez, Khattak, & Evenson in this issue.)

If the built environment affects physical activity, it is reasonable to expect it to affect weight as well. At least five studies demonstrated people were more likely to be heavier, overweight, or obese if they lived in less walkable areas (Ewing, Schmid, Killingsworth, Zlot, & Raudenbush, 2003; Frank, Andresen, & Schmid, 2004; Giles-Corti, Macintyre, Clarkson, Pikora, & Donovan, 2003; Saelens, Sallis, Black, et al., 2003; Lopez, 2004). Moreover, one study related sprawl in metropolitan areas directly to the prevalence of chronic diseases (Sturm & Cohen, 2004). (See also Doyle, Kelly-Schwartz, Schlossberg, & Stockard in this issue.) This body of work links the built environment with physical activity, obesity, and chronic diseases.

Current Evidence Linking the Built Environment to Air Quality

Land use patterns affect travel behavior by altering each mode's relative costs and convenience levels (Boarnet & Crane, 2001a; Cervero & Kockelman, 1997; Frank, 2004; Handy, 1996a). People drive less and walk more in more walkable communities (Ewing & Cervero, 2001). The distance between destinations, which can be affected by the pattern of land development, is positively associated with vehicle miles traveled (Boarnet & Crane, 2001b; Ewing & Cervero, 2001; Holtzclaw, Clear, Dittmar, Goldstein, & Hass, 2002).

In turn, per capita vehicle miles of travel are positively associated with per capita emissions of oxides of nitrogen (NOx) and volatile organic compounds (VOC; Frank, Stone, & Bachman, 2000). These two pollutants react in sunlight and form harmful ground-level ozone (Boubel, Fox, Turner, & Stern, 1994; Frank & Engelke, 2005; Frumkin et al., 2004). High ozone concentrations can trigger shortness of breath and asthma (Bell, McDermott, Zeger, Samet, & Dominici, 2004; Friedman, Powell, Hutwagner, Graham, & Teague, 1998; Gauderman et al., 2004; Hoek, Brunekreef, Goldbohm, Fischer, & van den Brandt, 2002; Nyberg & Pershagen, 2000). Mixed land uses, higher density, and greater street connectivity are associated with significantly lower per capita emissions of NOx and VOC when controlling for income, age, vehicle ownership, and household size (Frank & Engelke, 2005; Frank et al., 2000; Frumkin et al., 2004). We hypothesize that higher per capita emissions of these pollutants lead to increased exposure to ozone and adverse effects on respiratory health, though we do not test this here.[1]

Researchers have studied the effects of the built environment on physical activity and obesity separately from the effects on air quality. The purpose of the present study was to evaluate how an integrated measure of urban form relates to all three pathways in the same region. Conducting the study in a single region controlled for potentially confounding geographic differences, and evaluating effects on several outcomes increased its policy relevance.

The Neighborhood Quality of Life Study (NQLS)

Methods

The purpose of the NQLS was to examine the relationship of urban form to physical activity and obesity. The study was conducted by the authors of this article in

both King County and Seattle, Washington, and in the Baltimore-Washington, DC, region, but only King County data are presented here. We used a "walkability index"[2] as our composite measure of the built environment, computing it by summing z scores for net residential density, intersection density, land use mix, and retail floor area ratio (FAR) for each census block group, giving street connectivity twice the weight of the other three variables. Table 1 summarizes the makeup of the index.

We chose clusters of contiguous block groups (hereafter termed *neighborhoods*) from which to recruit participants for the NQLS. We began by ranking individual block groups by walkability index and median household income deciles. To qualify, block groups had to be in the lowest walkability deciles (deciles 1 through 4) or the highest walkability deciles (deciles 7 through 10) and either a moderately low or moderately high income decile (deciles 2 through 4 or 7 through 9). We considered only block groups that met both of these criteria and had populations of at least 1,000 households, and finalized our determinations following site visits.[3] Approximately 75 adults between the ages of 20 and 65 completed surveys in each of the 16 neighborhoods.[4] Among other measures, participants completed an extensive self-administered survey, from which we have taken demographic covariates[5] and measures of physical activity, weight, and height to use in this analysis. We collected data from approximately May, 2002 through December, 2003, and obtained complete data on the variables described below for a sample of 1,228 adults.

Table 2 characterizes the sample using several sociodemographic covariates as well as the three concepts of interest: walkability, body mass, and physically active travel, which we measured as described below.

Walkability Index. We used the walkability index described previously to characterize the built environment within a 1-kilometer network buffer (measured on the street network) of each respondent's geocoded place of residence.

Body Mass Index (BMI). We converted participants' self-reported heights and weights to meters and kilograms, respectively. We computed BMI as weight in kilograms divided by height in meters, squared.

Transportation-related Physical Activity. We expected neighborhood measures of walkability to relate primarily to active transportation (Saelens, Sallis, & Frank, 2003), and so used the long version of the self-administered International Physical Activity Questionnaire (IPAQ) to assess walking or biking for transportation (Craig et al., 2003). The IPAQ has been evaluated in 14 studies and found to have good test-retest reliability. Previous research found IPAQ results to have a median Spearman correlation of .30 with physical activity measured by accelerometer, which is comparable to other self-reported measures of physical activity (Craig et al., 2003).

Participants self-reported the following for both walking and biking: (1) the number of days during the past week the respondent walked or biked from place to place for at least 10 minutes at a time, and (2) the number of minutes usually spent on one of those days walking or

Table 1. Walkability index.

Measure	Definition	Data source
Net residential density	Residential units divided by acres in residential use	2000 Census and King County parcel-level land use database
Street connectivity	Intersections per square kilometer	Street centerline file
Land use mix	A/(ln(N)) (see note)	King County parcel-level land use database
Retail floor area ratio (FAR)	Retail building floor area (sq. ft.) divided by retail land area (sq. ft.)	King County parcel-level land use database

Note: Land use mix = $A/(\ln(N))$ where

$A = (b_1/a)*\ln(b_1/a) + (b_2/a)*\ln(b_2/a) + (b_3/a)*\ln(b_3/a) + (b_4/a)*\ln(b_4/a) + (b_5/a)*\ln(b_5/a) + (b_6/a)*\ln(b_6/a)$

a = total square feet of land for all six land uses present in buffer

b_1 = square ft. of building floor area in education uses

b_2 = square ft. of building floor area in entertainment uses

b_3 = square ft. of building floor area in single-family residential uses

b_4 = square ft. of building floor area in multifamily residential uses

b_5 = square ft. of building floor area in retail uses

b_6 = square ft. of building floor area in office uses

N = number of six land uses with FAR > 0

Table 2. Model variables from the Neighborhood Quality of Life Study (*N* = 1,228).

	%	Median	Mean	*SD*	Skewness
Dependent variables					
Body mass index[a]		25.39	26.61	5.48	1.54
Minutes of active transportation[b] last week (not used in regression)		70.00	193.17	384.63	4.50
Log transformed minutes of active transportation[b] last week		1.85	1.49	1.08	−0.38
Independent variables					
Walkability index[c]		−0.75	−0.10	4.16	0.96
Demographic and socioeconomic covariates					
Gender (male)	55.5				
Age in years		44.0			
Education		6.0[d]			
Ethnicity (non-White)	17.4				
Annual household income		7.0[e]			
Children under 18	38.4				

Notes:

a. Weight in kilograms divided by height in meters, squared.

b. Active transportation includes both walking and biking trips.

c. Sum of *z*-scores. The index ranged from −8.13 to 13.26.

d. This corresponds to "completed college or university."

e. This corresponds to $60,000 to $69,999.

biking from place to place. We multiplied these two values for each mode to estimate total minutes of walking and biking during the last 7 days. We then summed these weekly total minutes spent walking and biking for transportation to produce total minutes devoted to active transportation during the past week.

Analysis and Results

We used linear regression to predict BMI and a transformation of minutes devoted to active transportation[6] using the walkability index. In the first step, we entered six demographic covariates often used in studies examining built environment correlates of active transportation (Cervero & Gorham, 1995; Handy, 1992, 1996b; Hess, Vernez Moudon, Snyder, & Stanilov, 1999). We entered the walkability index in the second step in order to assess its contribution to variance in the dependent variables.

Table 3 indicates a strong association between the walkability index and active transportation, consistent with prior findings. All six demographic and socioeconomic covariates together explained 1.4% of the variance in the active transportation variable, while the walkability index explained 8.3% of additional variance in active transportation (based on adjusted R^2 values), which was highly significant. Table 4 shows that the demographic and socio-economic covariates explained 5.6% of variance in the

BMI, and the walkability index explained 1.1% of additional variance, which was significant. In summary, the walkability of neighborhoods around each participant's home was significantly related to both minutes per week devoted to active transportation and BMI. These relationships were in the expected directions, with walkability positively related to active transportation, but negatively related to body mass.

The King County Land Use, Transportation, Air Quality and Health Study (LUTAQH)

Methods

The primary aim of LUTAQH, conducted by the authors of this article, was to assess the effects of land use and transportation network design on travel patterns and per capita vehicle emissions, both of which influence air quality. Our analysis includes complete travel and demographic data from 5,766 King County residents collected as part of the Puget Sound Regional Council's 1999 Travel and Activity Survey. The travel survey instrument differed from that in the NQLS study reported above, and was

Table 3. Regression model predicting log of minutes devoted to active transportation last week, with and without neighborhood walkability index (*N* = 1,228).

Independent variables	Unstandardized coefficients		Standardized coefficients			Partial corr.	Variance explained (%)
	B	*SE*	Beta	*t*	Sig.		
Constant	1.735	.239		7.244	.000		
Gender	−.051	.060	−.024	−.849	.396	−.023	0.05
Age	−.002	.003	−.023	−.789	.430	−.021	0.04
Education	.006	.033	.005	.182	.856	.005	0.00
Ethnicity	.020	.078	.007	.258	.797	.007	0.00
Children under 18	−.005	.029	−.005	−.158	.875	−.004	0.00
Household income	−.016	.011	−.046	−1.486	.138	−.040	0.16
Walkability index	.079	.007	.304	10.659	.000	.289	8.35

	Model without walkability	Full model
*R*²	.135	.319
Adjusted *R*²	.014	.097
*R*² change	.018	.084
F change	3.80	113.61
Significance of change in *F*	.001	.001
df	6, 1221	1, 1220

administered to a different set of respondents, but both employed the same methods to measure walkability.

Households participating in the travel survey were recruited to provide travel and activity data for all members over the age of 5 for two consecutive weekdays between August and November of 1999. The recruitment rate was 45.8% (9,026 households were recruited out of 19,713 eligible contacts) and the completion rate was 66.5% (6,000 surveys were completed from 9,026 households recruited), for an overall response rate of 30.5%. Sample size goals were set based on household size, income, and automobile ownership to ensure representation across a range of household structures and lifestyles. A recruitment interview collected baseline data on the responding household including age, income, household size, gender, educational attainment, vehicle ownership, and ethnicity. Respondents filled out a two-day travel and activity diary recording the address and activities at each destination visited, purpose, day of week, time of day, primary mode of travel, and other persons (if any) accompanying them, and returned this by mail. They were then surveyed by telephone using a computer aided telephone interview (CATI) to verify the written diaries.

Three LUTAQH variables are of interest here: walkability, measured as previously described; vehicle emissions per person; and vehicle miles of travel per person.

Vehicle Emissions. We estimated mean daily grams of oxides of nitrogen (NOx) and volatile organic compounds (VOCs) for each trip reported in the Puget Sound Regional Council's 1999 Travel and Activity Survey data. This required estimating some variables on which we did not have data for individual trips. The U.S. Environmental Protection Agency's emission rate model (MOBILE) is most sensitive to estimates of average speed, environmental conditions, vehicle type, vehicle age, and the time between turning an engine off and restarting it (soak time). Lacking individual data, we made uniform region-wide assumptions about environmental conditions and vehicle age, which means variation in our emission estimates is due only to differences in vehicle use.[7]

Our survey data provided information on trip origins, destinations, modes, and start times. We used origin and destination locations to estimate travel time. The region's travel demand forecasting model defined average operating speeds for major roads in peak and off-peak conditions. We

Table 4. Regression model predicting body mass index, with and without neighborhood walkability index (N = 1,228).

| Independent variables | Unstandardized coefficients | | Standardized coefficients | | | | | |
	B	SE	Beta	t	Sig.	Partial corr.	Variance explained (%)
Constant	28.989	1.241		23.367	.000		
Gender	−.551	.310	−.050	−1.775	.076	−.049	0.24
Age	.073	.014	.146	5.027	.000	.139	1.93
Education	−.539	.172	−.095	−3.140	.002	−.087	0.76
Ethnicity	.172	.406	.012	.425	.671	.012	0.01
Children under 18	.085	.150	.017	.567	.571	.016	0.03
Household income	−.267	.055	−.151	−4.808	.000	−.133	1.77
Walkability index	−.149	.038	−.113	−3.898	.000	−.107	1.14

	Model without walkability	Full model
R^2	.246	.269
Adjusted R^2	.056	.067
R^2 change	.061	.012
F change	13.12	15.19
Significance of change in F	.001	.001
df	6, 1221	1, 1220

estimated trip travel times by defining a shortest network time-path between trip origins and destinations and applying the modeled speed distribution.

Once we had trip start and end times, we were also able to estimate engine soak time. Soak time was the dominant variable in estimating engine start emissions. MOBILE 6.2 allows for 70 different ranges of engine soak time. We created a table of engine start emissions for each soak time and vehicle type (car, bus, etc.) given our assumptions about weather conditions, altitude, and the regional distribution of vehicle model years. We normalized these to emissions per person-trip based on reported vehicle occupancy.

We estimated running exhaust emissions for each road segment traversed in a trip, an approach similar to the one we used to estimate engine start emissions. We used MOBILE 6.2 to generate a Seattle-specific emissions factor lookup table for each pollutant, with a scenario for each possible speed (in 5-mile-per-hour increments) and facility type (freeway, arterial, and local road). We estimated emissions for each trip leg based on these factors and the travel time it required. We again normalized to emissions per person-trip based on reported vehicle occupancy. The

resulting emissions for each subcomponent (engine starts and road segments traversed) were then summed to provide person-trip emissions.

Vehicle Miles of Travel (VMT). We also analyzed VMT as an outcome. We estimated vehicle trip distances based on a shortest time-path network distance between reported origins and destinations. We then divided total vehicle trip distance by the number of vehicle occupants for each trip and summed trip distances for each individual for each survey day.

Distance to Transit. We used street network distance from the place of residence to the nearest bus stop as a surrogate for transit level of service.

Analysis and Results

We again used linear regression, this time to predict VMT and two emissions variables (NOx and VOC) using a model that included the walkability index and sociodemographic covariates. In the first step we simultaneously entered four demographic covariates[8] often correlated with the outcome variables (and, in the VMT model only, we also added transit access), then entered the walkability index in the second step to assess the independent variance accounted for by

the built environment, as with the NQLS data. We again conducted the regression using log transformations of all of the dependent variables to meet assumptions of normality.

Table 5 shows that the sample size was between 5,718 and 5,766 depending upon the variable. The sample was well balanced by gender, educated, had a median household income between $55,000 and $74,999, and median vehicle ownership of 2 per household. The mean distance to the nearest bus stop was just over 1/3 of a mile. The mean value for walkability was 0.0, with a large standard deviation of 3.53. The average participant traveled about 29 miles per day in a car and generated about 25 grams of NOx and 13 grams of VOC. Skewness was under 2 for all dependent variables.

Table 6 shows the results for a regression model predicting VMT based on 5,710 observations. The entire set of covariates explained 8.8% of the variance, and the walkability index explained an additional 1.8% of the variance. All of the variables in the model were significant at the .01 level or better. Only educational attainment explained more of the variation in VMT than walkability.

Table 7 shows a regression model predicting per capita NOx, and Table 8 a model predicting VOC. Collectively, the covariates of gender, educational attainment, income, and vehicle ownership explained about 14% of the variance in mean grams of NOx and VOC emitted per person per day. Walkability explained about 1.7% of additional variance in both types of emissions. Walkability was the most significant explanatory variable in the model after educational attainment for NOx and after educational attainment and vehicle ownership for VOC.

Implications of the Model Results

After obtaining these results, we performed a test to assess the change in each of the four components of the walkability index associated with changes in outcomes: minutes devoted to active transport, BMI, VMT, and per capita emissions of NOx and VOC. We based these determinations on the LUTAQH sample and range of walkability values (about 31 points) because the regional household travel and activity survey sampled the entire Seattle region, unlike the NQLS. We calculated mean values for intersection density (52.28), net residential density (3.63), our measure of land use mix (0.31), and retail floor area ratio (0.25) for the LUTAQH sample, then calculated the walkability index (summed z scores) for these mean values as 0.02. Doing the same at 120% of these mean values yielded a walkability index of 1.53. Such an increase of 1.51 in the walkability index represents about 5% of the total range of walkability index values associated with LUTAQH responses.

Holding all of the other covariates in the model constant, this 5% increase in the walkability of residential

Table 5. Model variables from the King County Land Use, Transportation, Air Quality and Health study ($N = 5,718$ to 5,766).

	%	Median	Mean	SD	Skewness
Dependent variables					
Mean daily VMT per person[a]			28.88	24.27	1.86
Log transformed mean daily VMT per person			1.30	0.43	−0.87
Mean daily grams of NOx per person[a]			25.37	19.89	1.49
Log transformed mean daily grams of NOx per person			1.25	0.41	−0.88
Mean daily grams of VOC per person[a]			12.97	8.82	1.15
Log transformed mean daily grams of VOC per person			0.98	0.43	−1.55
Independent variables					
Walkability index[b]			0.00	3.53	1.06
Demographic and other covariates					
Gender (male)	48.5				
Education		3.0[c]			
Annual household income		7.0[d]			
Vehicles per household		2.0			
Miles to nearest bus stop (VMT model only)			0.39	0.66	

Notes:

a. Not used in regression.

b. Sum of z-scores. The index ranged from −7.15 to 23.66.

c. This corresponds to "some college."

d. This corresponds to $55,000–$74,999.

Table 6. Regression model predicting vehicle miles of travel, with and without neighborhood walkability index ($N = 5,710$).

Independent variables	Unstandardized coefficients		Standardized coefficients				
	B	SE	Beta	t	Sig.	Partial corr.	Variance explained (%)
Constant	.988	.029		33.621	.000		
Gender	−.043	.011	−.050	−3.985	.000	−.050	0.25
Education	.057	.003	.253	19.787	.000	.248	6.13
Household income	.018	.003	.072	5.327	.000	.067	0.44
Vehicles per household	.022	.006	.054	3.906	.000	.049	0.24
Miles to nearest bus stop	.029	.009	.045	3.164	.002	.040	
Walkability index	−.019	.002	−.157	−10.740	.000	−.134	1.81

	Model without walkability	Full model
R^2	.298	.327
Adjusted R^2	.088	.106
R^2 change	.089	.018
F change	111.590	115.358
Significance of change in F	.001	.001
df	5, 5499	1, 5498

neighborhoods was associated with 32.1% more minutes devoted to physically active travel, about a one-quarter point lower BMI (0.228), 6.5% fewer VMT per capita, 5.6% percent fewer grams of NOx emitted per capita, and 5.5% fewer grams of VOC emitted per capita.

Discussion

Recent articles from the Centers for Disease Control and Prevention (Dannenberg et al., 2003) and the National Institute for Environmental Health Sciences (Srinivasan, Dearry, & O'Fallon, 2003) described research agendas for investigating how the built environment is related to a wide range of outcomes related to health, including air pollution, respiratory diseases, physical activity, obesity, unintentional injuries, cardiovascular disease, diabetes, mental health, and quality of life. Although these outcomes have been studied in the past (Frumkin et al., 2004), each has been studied separately, and each literature is isolated. This makes them difficult to compare. Moreover, it is difficult to present policymakers with comprehensive information on the full impacts of land use patterns on health. Our study begins to remedy this. We used comparable

methods to discover that people living in more walkable neighborhoods (characterized by mixed use, connected streets, high residential density, and pedestrian-oriented retail) did more walking and biking for transportation, had lower BMIs, drove less, and produced less air pollution than people living in less walkable neighborhoods.

In the analysis of NQLS data, we found the walkability index to be significantly related to both active transportation and BMI among adults, after accounting for sociodemographic variables. Physical activity (Dishman, Washburn, & Heath, 2004) and obesity (Andersen, 2003) are high priorities in public health because they are risk factors for several common chronic diseases, including cardiovascular disease and some cancers. Walkability was associated more strongly with active transportation than with BMI. We expected this because our walkability index seeks to measure how conducive an area is to walking and biking. Walkability was also more important to active transportation than were sociodemographic variables, which made a minor contribution. The well known sociodemographic factors associated with BMI (Andersen, 2003) were confirmed in our study. The significant association we found between walkability and BMI was consistent with recent studies (Ewing et al., 2003; Frank et al., 2004; Saelens, Sallis,

Table 7. Regression models predicting log transformed grams of transportation-related NOx emissions per capita, with and without neighborhood walkability index ($N = 5,718$).

Independent variables	Unstandardized coefficients		Standardized coefficients			Partial corr.	Variance explained (%)
	B	SE	Beta	t	Sig.		
Constant	.847	.027		30.845	.000		
Gender	−.036	.010	−.043	−3.543	.000	−.043	0.18
Education	.077	.003	.354	28.550	.000	.346	11.98
Household income	.014	.003	.058	4.490	.000	.054	0.30
Vehicles per household	.046	.005	.119	8.807	.000	.107	1.14
Walkability index	−.016	.002	−.140	−10.841	.000	−.131	1.73

	Model without walkability	Full model
R^2	.378	.400
Adjusted R^2	.142	.160
R^2 change	.143	.017
F change	238.429	117.526
Significance of change in F	.001	.001
df	4, 5508	1, 5507

Black, et al., 2003), though the variance we explained was modest. However, genetics, physiology, diet, and physical activity all contribute to BMI, so this is not surprising.

Our results also indicated that the walkability index was significantly related to emissions that cause the formation of ozone, which impacts respiratory health (Bell et al., 2004). We assume that increased per capita emissions would increase concentrations of ozone and would likely increase exposure as well. While we have not demonstrated causal linkages between walkability and exposure to ozone, the potential exists for this to be yet another pathway by which patterns of land development could affect health.

Use of the same walkability index in two studies in one region allowed us to compare the strength of association across multiple outcomes. After controlling for potential demographic influences, the walkability index accounted for 8.3% of the variability in minutes of active transportation. This amount of explained variance could be a powerful impetus for policy change. For BMI and the two air pollution outcomes, walkability explained 1.1 to 1.7% of the variance. However, walkability was statistically significant in all of the models and was among the strongest single-variable correlates in all models. Even small amounts of variance could indicate important public health effects,

because we would expect the walkability of a neighborhood to affect all people living there, and to have lasting effects.

Our estimates of the change in each outcome measure associated with increases in walkability could inform policymakers who are considering changes in land use and development regulations or investments in existing neighborhoods to increase walkability. The actual amount of change in the outcomes is modest, but the combined effects on public health could be considerable. And greater improvements in walkability should lead to larger effects. Calculations such as these could be used to estimate the cost effectiveness of changes resulting from increased interest in creating walkable communities (Lavizzo-Mourey & McGinnis, 2003).

It may be that the marginal effect will diminish once the demand for more walkable environments is met. People preferring an auto-oriented lifestyle may not change their behavior much, even if they live in a walkable environment. Alternatively, the creation of a critical mass of walkable environments may produce even more significant changes than our findings suggest. Perhaps residents of an entire region must have walkable neighborhoods before transit becomes truly viable, allowing vehicle ownership to decline. A critical mass of "walkable urbanity" (Leinberger,

Table 8. Regression models predicting log transformed grams of transportation-related VOC emissions per capita, with and without neighborhood walkability index ($N = 5{,}718$).

Independent variables	Unstandardized coefficients		Standardized coefficients			Partial corr.	Variance explained (%)
	B	SE	Beta	t	Sig.		
Constant	.544	.027		19.867	.000		
Gender	−.024	.010	−.029	−2.401	.016	−.029	0.085
Education	.072	.003	.332	26.646	.000	.324	10.499
Household income	.016	.003	.064	4.926	.000	.060	0.359
Vehicles per household	.056	.005	.146	10.841	.000	.132	1.738
Walkability index	−.016	.002	−.139	−10.750	.000	−.131	1.709

	Model without walkability	Full model
R^2	.372	.394
Adjusted R^2	.138	.155
R^2 change	.138	.017
F change	229.233	115.570
Significance of change in F	.001	.001
df	4, 5508	1, 5507

2005) in a region might allow it to attract new residents that prefer a less auto-oriented lifestyle. In order to make accurate predictions at the regional level, we will need to better understand how underlying preferences shape residential location choice and travel patterns (Transportation Research Board & Institute of Medicine, 2005), and how transit use and vehicle ownership affect active transportation.

Examining any single outcome may underestimate the overall consequences for health, or miss important tradeoffs associated with changes in walkability. Thus we recommend further study to examine a wider range of potential health-related consequences of land use (Dannenberg et al., 2003; Srinivasan et al., 2003). It may be feasible to estimate walkability's impact on mortality, morbidity, or health care costs.

Although we found walkability to be associated with beneficial outcomes, it does not necessarily follow that all consequences will be positive. For example, greater concentrations of small particulate matter (smaller than 2.5 microns), which have been linked to cardiovascular disease risk in some groups, have been found in walkable central-city locations (Pope et al., 2000). Therefore, while promoting walkable communities for their multiple benefits, we also advocate mitigating negative effects (Frank & Engelke,

2005). And while this research documents associations between walkability and per capita vehicle emissions, additional research is required to assess associations between pollutant exposure levels and urban form.

Major limitations of this study included relying on self-reported physical activity, BMI, and travel behavior, and modeled emissions estimates. Physical activity is routinely over-reported (Rzewnicki, Vanden Auweele, & De Bourdeaudhuij, 2003), although there is no strong evidence of systematic bias (for example, by gender, activity level, or socioeconomic status) that could lead to corrected estimates. The NQLS also measured physical activity objectively. Each participant was asked to wear an accelerometer (Manufacturing Technology Incorporated's activity monitor model 256) during waking hours for 7 consecutive days. From these data we totaled the number of minutes of moderate and vigorous activity for each individual, giving us a continuous, objective measure of physical activity for 1,175 of the NQLS participants. Our analysis shows that objectively measured physical activity was more closely related to sociodemographic factors than self-reported minutes of active transportation. Collectively, gender, age, education, ethnicity, and income explained 8.4% of the

variance in the average level of moderate and vigorous activity per day. Each of these variables was significant at the .05 level. Walkability explained an additional 2.1% of the variation in objectively measured physical activity after controlling for sociodemographic factors. A 5% increase in walkability was associated with a 4.7% increase in minutes devoted to moderate and vigorous activity on average per day compared with a 32.1% increase in minutes of active transportation. It is not surprising that walkability is a better predictor of active transportation than of overall physical activity. These results show that measures of active transportation should not substitute for more precise and complete measures of physical activity, and challenge the accuracy of self-reported travel data. Self-reported active transportation was unrelated to demographic factors once the walkability measure was introduced into the model. The large increase in self-reported minutes of active transportation per day in association with walkability was due in part to the fact that a significant share of the sample reported no walking at all.

We also did not take vehicle type into account for each household, and it is possible that household members switched vehicles between trips, which would impact the accuracy of our estimates of cold start emissions. Our estimates of emissions have wide confidence bands, meaning the true values may have differed substantially from what we report. However, our methods were similar to those used in other studies, and our emissions estimates came from the MOBILE 6.2 model sanctioned by the U.S. Environmental Protection Agency.

As would be expected, the explained variance was modest for any single outcome. Adding minutes of active transportation to the BMI model and VMT to the emissions models significantly increased the overall explained variance, but this approach confounded relationships between walkability and these outcomes. We did not examine more complex links between walkability and health, such as considering the interactions between the different pathways. For example, time spent in physically active transportation could result in increased exposure to air pollution. Future research should explore such potentially offsetting effects.

A wide range of zoning, development, and transportation regulations and guidelines favor less walkable land use patterns (Schilling & Linton, 2005). Our findings are consistent with literature suggesting current laws and regulations are producing negative health outcomes (Frumkin et al., 2004; Hirschhorn, 2004), and support assessing the health impacts of actions that shape the built environment (Cole, Shimkhada, Fielding, Kominski, & Morgenstern, 2005).

Notes

1. Concentrations of certain harmful air pollutants including air toxics, carbon monoxide, and particulates can be higher where activities are concentrated in urban centers or where truck traffic or traffic congestion are greatest. Levels of concentration also depend upon seasonal weather patterns and land formations that help to shape regional airflow patterns.

2. This index is similar to those reported elsewhere (Frank et al., 2004; Frank, Schmidt, et al., 2005), except that those did not include the retail FAR variable.

3. More detail on the neighborhood selection methods and characteristics of study neighborhoods can be found elsewhere (Frank, Sallis, et al., 2005).

4. Individual participants were randomly selected from households. The sample was drawn from all households with listed telephone numbers, and was recruited by mail and telephone. The recruitment rate was 40.2% (1,495 individuals consented out of 3,723 eligible contacts), data completion rate was 86.5% (1,294 surveys were completed out of 1,495 individuals who consented to be surveyed), and the overall response rate was 34.7% (1,294 surveys were completed out of 3,723 eligible contacts).

5. The demographic covariates were (a) gender, coded as male = 1 and female = 2; (b) age, reported in years; (c) highest level of education, with 1 = less than 7th grade, 2 = junior high/middle school, 3 = some high school, 4 = completed high school, 5 = some college or vocational training, 6 = completed college or university, 7 = completed graduate degree; (d) ethnicity, coded as White = 1 and non-White = 0; (e) household income, coded as 1 = less than $10,000, 2 = $10,000–$19,999, 3 = $20,000–$29,999, 4 = $30,000–$39,999, 5 = $40,000–$49,999, 6 = $50,000–$59,999, 7 = $60,000–$69,999, 8 = $70,000–$79,999, 9 = $80,000–$89,999, 10 = $90,000–$99,999, and 11 = $100,000 or more; and (f) number of children in the household.

6. Among the NQLS participants ($N = 1,228$), 31% reported zero minutes of active transportation (walking or biking for transportation) during the past week. Because this measure of active transportation was not normally distributed, we transformed this variable in the regression analyses to the log of minutes devoted to active transportation to create a more nearly normal distribution, and added 1 to avoid problems with the log of zero. We transformed the results back to minutes in order to interpret them. For example, to illustrate the dependent variable change associated with a change in a single independent variable, raise 10 to the power of the product of the dependent variable coefficient times the change, subtract 1, and multiply by 100 or $(((10^{\text{(dependent variable coefficient*change in dependent variable)}}) - 1) \times 100)$. We recognize that this procedure fails to correct for potential problems in retransformation. For example, it creates geometric rather than arithmetic means, and heteroscedasticity of the error term (Manning, 1998).

7. The four demographic covariates entered simultaneously in the first step of the regression analyses included (a) gender, coded as male = 1 and female = 2; (b) education, coded as less than high school = 1, high school graduate = 2, some college = 3, vocational/technical = 4, undergraduate/ bachelors degree = 5, graduate/post-graduate degree = 6; (c) household income, coded as 1 = less than $10,000, 2 = $10,000–$14,999, 3 = $15,000–$24,999, 4 = $25,000–$34,999, 5 = $35,000–$44,999, 6 = $45,000–$54,999, 7 = $55,000–$74,999, 8 = $75,000 or more; and (d) vehicles per household, reported as the number of working vehicles owned and operated by the participant's household.

8. The model was run assuming that the trips took place in July 1999, that an inspection and maintenance program was being conducted for odd model year vehicles, and that the national distribution of vehicle model years correctly represented Seattle.

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