Integrating Walkability into Planning Practice

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This study used data from www.walkscore.com to assess walking behavior in four U.S. cities. Walk scores measuring the so-called walkability of neighborhoods are ubiquitous, and although the relationship between walk scores and real estate values has been established, the relationship between walk scores and walking has not. In this research three models were developed to understand the correlation between walk scores (as indicators of walkability; i.e., opportunity to walk) and walking. The models looked at walk scores and walk mode share for different trip types. What changes should be expected with changing walk scores along different parts of the walk score spectrum are illustrated. Results suggest that walk scores may be used as a reasonable heuristic to assist with assessing trip impacts for individual projects. With the universal availability of such data, planners can establish a consistent, cost-effective tool for assessing walking behavior with robust and transferable results.

Ample research has linked urban form with walking—demonstrating that a variety of features, including density, land use mix, and pedestrian facilities are important in affecting mode choice (*1–4*). Because this research has relied, historically, on expensive site-specific data collection, it has been difficult to generalize to different environments. Thus practice lags in incorporating these results in traffic and environmental impact analyses. Instead, the majority of industry standard tools for assessing travel behavior remain automobile focused. Planning analyses such as environmental impact assessments rely almost exclusively on traffic engineering methods and legal precedent, which overwhelmingly presume use of the automobile. Frequently these studies ignore other travel options. Reliance on the Institute for Transportation Engineers' automobile-focused *Trip Generation* and *Parking Generation* books is the primary method by which planners and engineers estimate travel effects of proposed developments. There are no parallel references by which planners can develop estimates of non-walking mode use. Generally, the failure to incorporate walking research findings leads to more automobile infrastructure than may be required, which leads in turn to increased auto dependency (*5, 6*). Ironically, the least expensive and most widely available mode of transportation, walking, is perhaps the least likely to be assessed in a robust manner for small projects. Providing a convenient method for assessing walking is the primary aim of this research.

In recent years, several nationally scoped databases describing "walkability" on the basis of density of amenities, land use mix, and other features of the built environment have become available [for a review, see Manaugh and El-Geneidy (*7*)]. The availability of walkability metrics has created a potential source of data that can be easily compared across urban environments. Walkability measures the opportunity to walk, rather than actual walking behavior, and although there are some limitations to walkability measures, which are outlined below, there is reason to believe that walkability measures can be parlayed into robust planning tools. In this study, the relationship between walkability and actual walking behavior is investigated; how practicing planners and traffic engineers can estimate walk mode share is demonstrated with data from walkscore.com, an easily accessed Internet service with information on the urban environment. Having estimated the relationship between walkability and walking, this study provides planners with knowledge of walking behavior wherever a walk score has been calculated. Expected walking mode shares can be combined with other local mode split information to develop more nuanced access plans leading to better impact analyses and better decisions with respect to facility provisions. Also investigated is what thresholds of walk scores should be crossed for cities to have the greatest success in increasing (or decreasing) walk trips.

A test of walkability measures conducted in Montreal, Quebec, Canada, revealed that the metric produced by Walk Score, the most widely available measure, outperformed the other measures in predicting actual walking (*7*). Following the finding of Manaugh and El-Geneidy, the current study uses data from www.walkscore.com to assess walking behavior in four U.S. cities (*7*). Results are consistent with other research that identifies a relationship between walking and the built environment. It is concluded that walk scores represent a reasonable heuristic to assist in assessing trip impacts for individual projects. With the universal availability of such data, planners can establish a consistent, cost-effective tool for assessing walking behavior with robust and transferable results.

PREVIOUS RESEARCH

Past studies have broadly agreed that particular attributes of the built environment are highly correlated with the propensity and intensity of walking. Differences between the studies revolve around three key issues: (*a*) the theoretical link between built form and walking, (*b*) which attributes are most important, and (*c*) how to integrate the sometimes conflicting research evidence into practice. Although the literature is reviewed broadly, it is this last point to which the present research contributes: how to integrate these research findings into practice.

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Theoretical Link Between Built Form and Travel Behavior

Travel behavior theory has informed walkability research most significantly through utility theory, which posits that individuals make rational travel choices to maximize their benefit on the basis of full knowledge of alternatives for any given travel behavior decision (*8, 9*). By using utility theory, some research has emphasized the built environment as a policy lever that makes walking more pleasurable, a “carrot” approach that increases utility for walking (*10*). Other research suggests that to increase walking, the built environment’s strongest effects may be through increasing auto travel costs by reducing speeds (*11*), the complementary “stick” that decreases utility for auto use. Indeed, reducing auto speeds is essential to creating a pleasant walking environment; therefore, the carrot and stick may be one and the same policy. Research on the built environment as a walking amenity emphasizes a highly localized effect by which increased amenities in walkable neighborhoods could spur individuals to walk more (*12*). Goetzke and Andrade find that increases in walking are self-reinforcing, that is, people are more likely to walk where others are walking simply because human behavior can encourage or discourage others from an activity. They identify this social spillover as a factor that is in addition to the common factors of the built environment that would lead to walking (*13*). Other research suggests that to broaden the scope of walking and other non-auto travel beyond the local level, the surrounding areas must be walkable as well (*14–16*), although that finding remains contested (*12*). In addition, some argue [consistent with Chatman (*11*)] that to increase walking, policy must create more costly auto travel (*17–21*) and parking (*22–24*). As noted, these research results are more consistent than they may first appear.

Key Attributes

Although utility theory dominates as an analysis framework for practitioners, modeling success depends on metrics that are not always available. Walking behavior research has been framed around the extent to which the five Ds—density, diversity, design (*25*), destination accessibility, and distance to transit (*26*)—are correlated with particular types of travel outcomes, including higher (or lower) rates of walking.

In practice, much travel behavior research measures density as a proxy for many types of characteristics that affect walking. However, density may not be the most important factor that influences walking behavior (*6*). Instead, many built environment attributes, listed below, are cited as working in concert as predictors of active transportation participation (walking and cycling):

- Density of built environment (*2, 4, 27*),
- Diversity of land use (*2, 4, 27*),
- Distance to transit (*28, 29*),
- Design of street connectivity and built environment (*27*), and
- Destination accessibility (*12, 16, 28*).

Other researchers emphasize the importance of the less frequently discussed sixth and seventh Ds of the built environment: demand management (pricing and parking supply) and demographics (individual preferences). In particular, research focusing on demographics identifies the extent to which individual preferences and socioeconomic characteristics influence demand for active transportation mode participation (*30–32*). Thus, walking is a function of the physical built environment attributes and of the individuals who choose to live in those built environments, each potentially influencing the other (*33*). Finally, crime is often cited as a deterrent to walking—although walking is sometimes cited as a deterrent to crime.

Four potentially important factors that are not characteristics of the built environment are

- Crime (*2*),
- Travel demand management (*24, 34*),
- Demographics (*30–32*), and
- Individual preference (*33, 35*).

Because of the high degree of correlation between these factors, it is less clear which trait is most important and why. Accordingly, substantial research focuses on the difficulty of separating the causal influence of the built environment on travel from the influence of individual self-selection into particular built environments on travel behavior (*35*). Guo argues that the difficulty of separating these effects is the result of difficult issues concerning research design (*36*).

However, for the purpose of practice, separating these discrete causal links may be less important if walkable urban forms are undersupplied and if their provision could substantially change travel behavior and increase health and quality of life (*37*). Thus, from a practitioner’s perspective, if the current development market undersupplies walkable urban environments, parsing the influence of self-selection in location decisions from the more basic influence of the built environment on walking is less important. Instead, practitioners are often more interested in spurring walking (*36*) for its health benefits (*38–42*), quality of life benefits (*27*), relative efficiency (*43*), and environmental benefits of reduced greenhouse gas emissions (*43*). Also from a practitioner’s perspective, an adequate heuristic predictor of walking may be more valuable than a robust explanatory model.

Integration into Practice

Although academic research on the built environment–walkability link has generated some mixed results, there are two clear takeaways. Studies overwhelmingly suggest that (*a*) the link is important from a policy perspective (even when accounting for self-selection) and (*b*) although density of opportunity locations is a very common built form metric, it remains an incomplete indicator. Integrating these findings into practice has been difficult because built form metrics vary substantially, they are not routinely collected, and with insufficient data collection they can be difficult to calculate. Moreover, as walking is an explicitly local action that is subject to local conditions, it is difficult to justify adopting study results from different locations.

In light of the difficulty in identifying a single most important built environment predictor of walking, assuming such a single best measure exists, researchers have developed indices that capture several components of built environment metrics. Leslie et al. developed a built environment index in which residential density, connectivity, land use accessibility, and retail were taken into account (*44*). New sources of data are becoming available as companies provide walkability indices online for the purpose of transport advocacy and information for businesses and residents. For example, walkshed.com developed an algorithm that identifies the relative walkability of

Philadelphia, Pennsylvania, and New York City neighborhoods according to the relative priority given by Web users to amenity access, including grocery stores, farmers markets, restaurants, transit, parks, and retail (*45*). Similarly, www.walkscore.com established estimates of walkability based on access to various amenities such as parks, retail, and other services. Both walkscore.com and walkshed.com standardize their indices on a 100-point scale to enable easy understanding and use by other service providers (such as real estate agents, businesses, and homeowners).

With the advent of websites such as www.walkscore.com and www.walkshed.com there is suddenly a preponderance of data on whether a neighborhood is walkable. These metrics include attributes of many of the five primary Ds: density (of opportunity locations), diversity (availability of different opportunities), destination accessibility (the spatial distribution of opportunities), and the design of street connectivity and the built environment. Thus, composite indices are relatively more comprehensive but, like all measurements, are not absolutely complete metrics of the built environment. For example, distance to transit is not directly captured in Walk Score indices and is instead provided as a separate indicator by the makers of Walk Score.

Research suggests that walk score metrics correlate well with objective and subjective understandings of walkability (*46*) and are broadly reliable (*47*). It has also been learned that high walk scores from these websites are correlated with high real estate values (*48*) and that planning departments may already be using walk scores as a metric by which to monitor neighborhood redevelopment (*49*). However, there has yet to be an investigation into the relationship between walkability, which more or less measures "opportunity to walk," and whether people are, in fact, walking in these neighborhoods. If a statistical relationship between walking and walk scores as reported by these sites can be established, every city in the United States and beyond will have new and important information about walking mode shares.

DATA AND METHODOLOGY

By using logistic regression for proportions, walk mode share is modeled at the traffic analysis zone (TAZ) level as a function of walk score and other variables. Because a broad application is of interest, the explanatory variables are limited to readily available data. To estimate the model parameters, trip productions and attractions from four metropolitan planning organizations (MPOs) are used. The source of these productions and attractions is the MPOs' respective household travel surveys. Walkability for TAZs is estimated by weighting census block group walk scores by block group population and aggregating to the TAZ.

Along with other online services, www.walkscore.com collects highly detailed data about neighborhood amenities. Walk Score uses an algorithm based on the findings of several researchers, including Lee and Moudon and Moudon et al., who identify access to retail and parks as important predictors of walking (*50–52*). On www.walkscore.com, the algorithm scores discrete point estimates based on a location's proximity to nine types of amenities (see Table 1) and based on network connectivity and average block length. Each amenity is weighted according to a distance decay function for which closer amenities are more valuable (*50*). After 1 mi the amenity value has decayed completely. Nine amenity categories contribute to Walk Score's 100-point scoring system, as listed in Table 1, and each category is weighted according to previous research. Finally, up to a 10% penalty can be allocated depending on intersection density and average block length—both indicators of pedestrian friendliness.

TABLE 1 Walk Score Amenity Categories and Values

Amenity Type	Maximum Walk Score
Banks	6.67
Books	6.67
Coffee	13.33
Entertainment	6.67
Grocery	20.00
Parks	6.67
Restaurants	20.00
School	6.67
Shopping	13.33
Total	100

In their technical documentation, the Walk Score creators point out that the walk score is not comprehensive and still lacks information (*50*). In particular they indicate that inclusion of design and safety elements, including street characteristics (such as sidewalk conditions and speeding traffic), safety from crime, and natural elements such as topography, could improve the walk score. Moreover, walk scores are currently calculated by using Euclidian distance, thereby ignoring network connectivity. Despite these shortcomings, as is demonstrated in this paper, walk score captures important determinants of walking choice and intensity. The walk score metric includes easily measured attributes of the built environment, thereby enabling planners to monitor and identify changes in walk score for either general planning or site development processes (*50*).

A request for walking data was distributed to MPOs via the Travel Model Improvement Program listserv. The four cities that responded—Boise, Idaho; Denver, Colorado; Portland, Oregon; and San Francisco, California—provided zone-to-zone trip tables for all modes and trip purposes. Although these cities were chosen because of the availability of quality information on walking behavior, they each capture substantial variation in built form. Portland and Denver exhibit substantial variation in built form, ranging from highly developed downtowns to relatively compact suburbs and traditional suburban neighborhood and activity centers. By contrast, San Francisco has, on average, the highest walk score in the nation, and Boise is a smaller city that has relatively smaller pockets of high-walk-score neighborhoods.

TAZs are defined by the MPOs for each of the four cities, and trip productions and attractions are available at the TAZ level. Therefore data from Walk Score are aggregated to the TAZ estimating an average walk score for each TAZ as an indicator of local walking conditions. The focus is on urban and suburban built environments and not on rural or exurban areas (see Figure 1). Because TAZs are of variable size and population, geographic information system files for census block groups are used to weight the relative walkability in various parts of each TAZ. Walk Score staff provided walk scores for census block groups based on longitude and latitude coordinates for the block group centroids (the geometric center of the area). Because block groups are relatively small, the walk score for the centroid is a reasonable

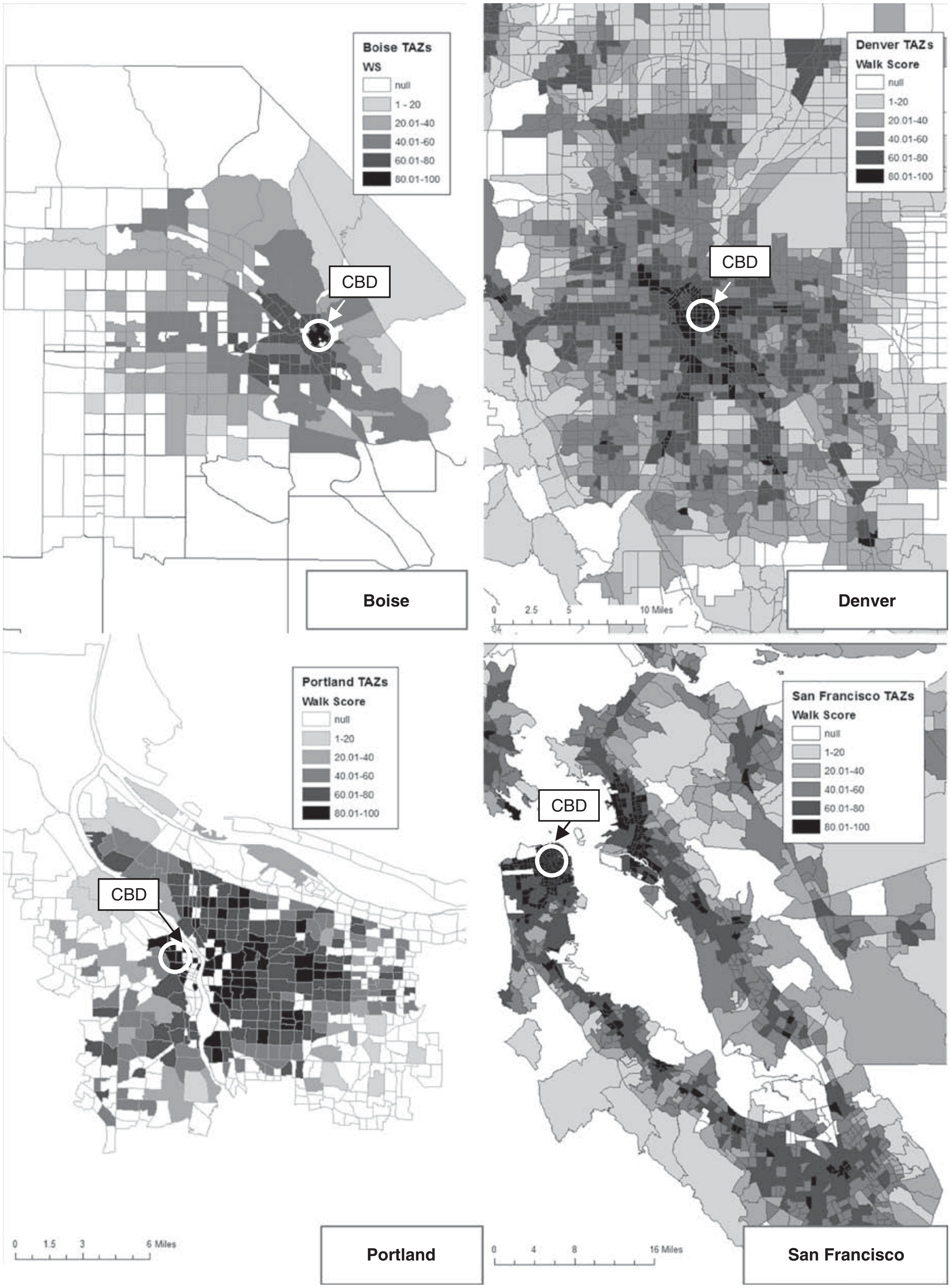

FIGURE 1 Study cities and spatial walk score patterns (CBD = central business district; WS = walk score).

estimate for overall walkability. The population-weighted TAZ walkability was estimated according to Equation 1:

$$WS_k = \frac{\sum_{ik=1}^{nk} WS_{ik} * Pop_{ik}}{\sum_{ik=1}^{nk} Pop_{ik}} \quad (1)$$

where

WS = walk score,
Pop_{ik} = block group population,
i = indexes of block groups, and
k = indexes of TAZs.

To estimate whether Walk Score's metric performs as a predictor of walking, a zone-based logistic regression was estimated. Trip production and attraction tables were obtained from each of the four respective MPOs and were used to estimate the proportion of walking trips to or from each zone for the various trip types. Each MPO defines trip types somewhat differently, so some trip categories were collapsed into a catchall "other" category. Effective 2010, the data are derived from the most recent modeling efforts for each MPO.

As a preliminary assessment, correlations between walk mode share and walk score are calculated for each city and for each trip purpose. Correlation coefficients, shown in Table 2, suggest substantial variation across both cities and trip purposes. The differences between origin and destination zone correlations are negligible because many walking trips in the data set begin and end in the same or adjacent TAZs. Walk score is more highly correlated with walking share in San Francisco and Portland than in Boise or Denver, suggesting the importance of context or a citywide walking culture effect. To capture the walking culture effect, the citywide walk share for all trips was included as an independent variable in the models (measured on a scale of 0 to 100). The use of a city-specific variable was avoided; the citywide walk share was preferred as a stand-in because "Portland-ness" or "Boise-ness" cannot be captured and translated for broad application.

Parameters for three sets of models are estimated. The baseline establishes the relationship between walk score and walking. The next looks at the interaction of walk score and trip purpose. The third looks at walk score ranges to understand potentially important threshold effects. Three variants of the baseline were developed: first walking is examined as a function of trip purpose, population density, and the citywide walking mode share; then the TAZ local walk score is added; and finally an ambient walk score is averaged over the TAZs within a 4-km radius. The ambient score captures network walkability effects, that is, it will pick up the effect of walkability in nearby zones on walking in a particular zone. In the second model the interaction of walk score with trip purposes is included; thus, one has a tool by which to more robustly estimate the modal trip generation effects of new development. The third model set includes threshold effects of different walk score ranges; this last model provides insight into the question: For what kind of amenity density improvements, or at what place along the spectrum, would planners expect to see effects of policy interventions designed to increase walking?

TABLE 2 Walk Score–Walk Mode Share Correlations and 95% Confidence Intervals Across Cities, Trip Types, and Origins or Destinations

	City			
Trip Purpose	Boise[a]	Denver[a]	Portland[a]	San Francisco[a]
Origin				
Work	0.055 (±0.129)	0.176 (±0.038)	0.429 (±0.071)	0.546 (±0.056)
School	0.028 (±0.149)	0.242 (±0.040)	0.554 (±0.061)[b]	0.281 (±0.072)
Shopping	0.184 (±0.138)	0.168 (±0.040)	0.520 (±0.064)	0.520 (±0.058)
Meal	NA	0.163 (±0.040)	NA	0.583 (±0.053)
Social	0.027 (±0.136)	0.201 (±0.038)	NA	0.497 (±0.061)
Other	0.086 (±0.092)	0.150 (±0.027)	0.495 (±0.046)	0.373 (±0.048)
Not home-based trips	0.341 (±0.120)	NA	0.508 (±0.063)	0.451 (±0.064)
Destination				
Work	0.070 (±0.129)	0.178 (±0.036)	0.488 (±0.064)	0.527 (±0.057)
School	0.044 (±0.153)	0.256 (±0.040)	0.300 (±0.755)[b]	0.301 (±0.072)
Shopping	0.209 (±0.137)	0.176 (±0.040)	0.395 (±0.071)	0.513 (±0.059)
Meal	NA	0.158 (±0.041)	NA	0.580 (±0.053)
Social	0.038 (±0.135)	0.198 (±0.038)	NA	0.489 (±0.061)
Other	0.084 (±0.092)	0.154 (±0.028)	0.389 (±0.049)	0.375 (±0.048)
Not home-based trips	0.321 (±0.122)	NA	0.459 (±0.066)	0.454 (±0.063)

NOTE: NA = not available.
[a]First number = walk share correlation; second number (in parentheses) = 95% confidence interval.
[b]University trips, not including secondary or primary school. As a result, many destination trips are to very few TAZs and confidence intervals are very wide.

In the base model, the proportion of walking trips (relative to all trips) to and from each zone is estimated as

$$\text{walk share} = \frac{1}{1+e^{-(\boldsymbol{\beta}\cdot \boldsymbol{x}+\boldsymbol{\gamma}\cdot \boldsymbol{w})}} \tag{2}$$

where

walk share = proportion of walking trips to and from a zone;
$\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ = estimated parameters;
$\boldsymbol{x}$ = city-level walk shares, population density, and trip type indicators; and
$\boldsymbol{w}$ = walk score vector comprising TAZ walk score and ambient walk score calculated over surrounding TAZs within 4-km buffer of subject TAZ.

Three versions of Model 1 are presented in Table 3. In the base model, no effect of walk score (i.e., $w = 0$) is assumed, and walking trips are modeled as a function of trip purpose, population density, and citywide walk share. The second version maintains the initial variables and incorporates the study variable at the TAZ level. The final version in this set maintains all variables from Model Versions 1 and 2 and includes an ambient walk score that comprises the average walk scores of the surrounding TAZs up to a 4-km radius. This additional variable captures a district or network effect.

The Model 1 set results provide insight on average trends, but they do not highlight different effects of walk score on different trip types; that is the purpose of Model 2. The expected advantage of Model 2 is to assist with creating robust development impact assessments. With the use of the second model, the traffic impact of a project in a low, versus high, walk score zone can be assessed with greater analytic rigor than in the past. In the next model, therefore, trip types for which walk mode share is most responsive to walk score are identified. The model functional form is the same as that in Equation 2, but each explanatory variable is interacted with trip type indicators to assess the relative importance of each explanatory variable for each trip type:

$$\text{walk share}_t = \frac{1}{1+e^{-(\beta\cdot x+\gamma\cdot \boldsymbol{t}+\delta\cdot \boldsymbol{v}+\boldsymbol{\lambda}\cdot \boldsymbol{u}+\eta\cdot \boldsymbol{z})}} \tag{3}$$

where

walk share$_t$ = proportion of walking trips to and from a zone by trip type,
β, $\boldsymbol{\gamma}$, $\boldsymbol{\delta}$, $\boldsymbol{\lambda}$, and $\boldsymbol{\eta}$ = estimated parameters,
x = citywide walk shares,
$\boldsymbol{t}$ = vector of trip types,
$\boldsymbol{v}$ = vector of trip types interacted with TAZ walk score,
$\boldsymbol{u}$ = vector of trip types interacted with ambient walk score, and
$\boldsymbol{z}$ = vector of trip types interacted with natural log of population density.

Finally, to identify conditions under which walk score may be a strong walking mode share predictor warranting policy intervention, the focus is on the question of walk score thresholds. Strong evidence is found for a positive relationship between walk scores and walking, so attention turns to the question of whether the relationship is constant throughout the walk score spectrum. For example, a 10-point change from a walk score of 75 to 85 may have a larger effect than a 10-point change in score from 10 to 20 or from 40 to 50. Walk score is separated into bands to test for the strongest returns to walk share from changes in the walk score. This approach provides a way to assess potential targets for higher-impact policy. Data are divided into 10 equal categories, with the first comprising walk scores between 1 and 10, the next with walk scores greater than 10 up to 20, and so forth to the last group comprising areas with walk scores greater than 90 and up to 100.

Comparing the relative importance of walkability for each of the 10 categories can guide planners to enact policies with the highest

TABLE 3 Model 1 Results: Equation 2

	Base Model			Base + Walk Score			Base + Walk Score + Ambient Walk Score		
Variable Name	Estimated Parameter	Odds Ratio	Sig.	Estimated Parameter	Odds Ratio	Sig.	Estimated Parameter	Odds Ratio	Sig.
Intercept (reference = work trips)	–4.425	0.012	***	–6.004	0.002	***	–6.368	0.002	***
City walk mode share: 0–100 (MPO source)	0.067	1.070	***	0.107	1.113	***	0.103	1.108	***
Walk score	na	na	na	0.026	1.027	***	0.015	1.015	***
Ambient walk score (4-km buffer)	na	na	na	na	na	na	0.018	1.018	***
Population density (ln/mi^2)	0.048	1.049	***	–0.018	0.982	***	–0.014	0.986	**
Trip indicator									
School	1.849	6.355	***	1.871	6.494	***	1.867	6.470	***
Shopping	0.940	2.561	***	0.947	2.578	***	0.944	2.571	***
Meals	1.404	4.071	***	1.370	3.935	***	1.362	3.904	***
Social recreation	1.316	3.729	***	1.289	3.631	***	1.284	3.610	***
Other	1.097	2.995	***	1.105	3.019	***	1.104	3.017	***
Not home-based trips	1.152	3.165	***	1.335	3.802	***	1.353	3.870	***
McFadden adjusted pseudo R^2	.0966			.2523			.2722		

NOTE: Sig. = significance; na = not applicable. Both point (and 95% confidence interval) parameter estimates are shown.
*Significant at .10 level or better; **significant at .05 level or better; ***significant at .01 level or better.

potential returns to walking. To test whether the walk score can help prioritize the most important potential walk share returns, the model is modified as follows:

$$\text{walk share}_t = \frac{1}{1+e^{-(\beta\cdot x+\gamma\cdot \boldsymbol{t}+\delta\cdot \boldsymbol{v}_i+\lambda\cdot \boldsymbol{u}+\eta\cdot z)}} \tag{4}$$

where

walk share_t = proportion of walking trips to and from a zone by trip type,
β, $\boldsymbol{\gamma}$, $\boldsymbol{\delta}$, $\boldsymbol{\lambda}$, and η = estimated parameters,
x = citywide walk shares,
$\boldsymbol{t}$ = vector of trip types,
$\boldsymbol{v}_i$ = two vectors of walk score bands (one is continuous and the other discrete),
$\boldsymbol{u}$ = vector of trip types interacted with ambient walk score, and
z = vector of trip types interacted with natural log of population density.

As shown above, the equation is designed to focus on which improvements in walk score are associated with the greatest increase in walking mode share.

Sparsely inhabited, rarely visited places with potentially distorting characteristics were eliminated by restricting the data to include only TAZs for which at least 30 daily trips were estimated, for which the walk score was at least one, for which the average trip distance was positive but less than 60 km, and for which there were some (nonzero) residents.

RESULTS

Model 1 Results

Model 1 results are shown in Table 3. The first set of results shows the zone level walking prediction with neither ambient nor local walk score. Each of the variables exhibits the expected signs. Population density is positively associated with walk mode share, trip type indicators suggest substantial differences across types, and city-level walk mode share is a strong predictor of TAZ-level walk mode share.

Second, when the local walk score is introduced into the base model, the McFadden's adjusted pseudo-R^2 more than doubles, indicating that the walk score is a very strong predictor of walking mode share. However, the influence of population density becomes negative, suggesting that when one controls for other contributors of walking, population density's expected positive association with walk mode share is unclear, which is consistent with other findings that density is relatively less important than many of the other Ds of the built environment (*6*). The correlation of population density and walk score is only 0.35, and variance inflation factors are both below the critical threshold of 10 (2.46 for walk score and 7.42 for population density in the model including ambient walk score), suggesting no issues of multicollinearity.

Table 3 displays model coefficients (positive values indicate that higher independent variable values are associated with walking) and odds ratios (values above one indicate a positive association with walk share, and values below one indicate a negative association with walk share). Thus, results indicate that a one-unit increase in local walk score is associated with a 1.027 increased odds ratio of walking mode choice across each of the four cities. To illustrate this effect at the mean values of walk score (55.7) and walk share (8.5%), with a 10-unit increase in walk score to 65.7, the odds of walking would increase by 1.027^{10}, resulting in an expected increase in walk mode share from 8.5% to 11%.

Third, when the ambient and local walk scores are added to the base model, the influence of walk score on walk mode share appears to function at two scales: the local scale (within the given TAZ) and at a scale containing the ambient average walk scores for surrounding zones within 4 km of a given TAZ, but excluding the local TAZ. The estimated influence of population density is significant and negative. Although other parameter estimates are stable, the reduced parameter estimate for ambient walk score indicates a jointly functioning process at a highly localized scale and at an ambient 4-km radius scale.

Model 2 Results

Although Model 1 and its alternatives indicate a strong relationship between walk score and walking, results do not indicate which types of trips are most influenced by walk score. Model 2 results are shown in Table 4 and demonstrate variations in the walk score–walk mode share link between different trip purposes. With the exception of trip-type indicators (for which each coefficient is compared with the intercept reference, work trips), model results in Table 4 have been transformed so that each coefficient estimate and significance level can be compared with a null hypothesis of a zero relationship. Point estimates, odds ratios, and 95th percentile confidence interval (CI) point estimates are shown.

All explanatory variables consistently predict the expected variation in walking mode share, with the exception of population density. Trip-variant estimates of the population density parameter vary substantially and some are negative, a theoretically unexpected outcome. By contrast, model estimates indicate that all trip types are sensitive to local or ambient walk score, but that the degree of sensitivity varies somewhat by trip type. Not all differences in parameter point estimates are statistically significant according to Wald tests using a test statistic with a chi-square distribution. High and low parameter estimates according to the 95th-percentile CIs can be used to directly compare differences while accounting for uncertainty in the point parameter estimates.

Moreover, results indicate significant differences in the expected sensitivity to local or ambient (within a 4-km radius) walk score. These results imply potentially important differences in the relative importance of regional versus local built environment characteristics between different trip types. Results suggest that school trips are relatively more sensitive to unit changes in ambient walk score than to local walk score (odds ratio of 1.028 versus 1.005). In contrast, results provide weak evidence that non-home-based trips are more sensitive to unit changes in local walk score (odds ratio of 1.021) than to ambient walk score (odds ratio of 1.008). Nevertheless, although these latter two differences may be substantively important, the parameter estimate differences are not significant according to Wald tests.

These results suggest that walk score is a more important predictor of walking for some trips than for others and could be implemented in practical applications, including site impact assessments and planning studies. Planners and engineers can use similar techniques to estimate mode share for regional planning or for local traffic impact statements. However, for the purposes of comprehensive planning designed to facilitate walking, these results do not indicate what built environment shifts may be most instrumental in increasing walking.

TABLE 4 Model 2 Results with Trip-Type Variation: Equation 3

Variable Name	Estimate–Low (95% CI)	Estimate–High (95% CI)	Point Estimate	Odds Ratio for Point Estimate	Sig.
Intercept (reference = work trips)	–7.970	–7.168	–7.562	0.001	***
City walk share: 0–100 (MPO source)	0.093	0.115	0.104	1.110	***
Trip indicator					
School	2.426	3.313	2.864	17.535	***
Shopping	2.038	2.973	2.501	12.200	***
Meals	2.240	3.176	2.704	14.938	***
Social recreation	2.190	3.117	2.649	14.138	***
Other	1.827	2.688	2.252	9.504	***
Not home-based trips	0.776	3.021	1.933	6.907	***
Walk score for work trips (interacted)	0.016	0.030	0.023	1.023	***
School trips (interacted)	0.001	0.008	0.005	1.005	***
Shopping trips (interacted)	0.015	0.024	0.019	1.019	***
Meal trips (interacted)	0.014	0.023	0.019	1.019	***
Social or recreation trips (interacted)	0.009	0.018	0.014	1.014	***
Other trips (interacted)	0.013	0.020	0.016	1.017	***
Not home-based trips (interacted)	0.011	0.031	0.021	1.021	***
Ambient average walk score within 4 km for work trips (interacted)	0.016	0.033	0.024	1.025	***
School trips (interacted)	0.024	0.032	0.028	1.028	***
Shopping trips (interacted)	0.009	0.020	0.014	1.014	***
Meal trips (interacted)	0.010	0.021	0.015	1.015	***
Social or recreation trips (interacted)	0.011	0.022	0.017	1.017	***
Other trips (interacted)	0.011	0.018	0.014	1.014	***
Not home-based trips (interacted)	–0.002	0.017	0.008	1.008	—
Population density (ln/km^2) for work trips (interacted)	–0.012	0.030	0.009	1.009	—
School trips (interacted)	–0.001	0.030	0.015	1.015	*
Shopping trips (interacted)	–0.101	–0.068	–0.084	0.919	***
Meal trips (interacted)	–0.071	–0.039	–0.055	0.946	***
Social or recreation trips (interacted)	–0.035	–0.002	–0.019	0.982	**
Other trips (interacted)	–0.003	0.025	0.011	1.011	—
Not home-based trips (interacted)	–0.056	0.256	0.095	1.100	—

NOTE: — = not statistically significant; CI = confidence interval. McFadden's adjusted pseudo R^2 = .2747.
*Significant at .1 level or better; **significant at .05 level or better; ***significant at .01 level or better.

Model 3 Results

To identify those incremental changes in walk score that are most associated with walk mode share improvements, Model 3 explores threshold effects by focusing on ten 10-unit walk score bands (0.1 to 10, 10.1 to 20 . . . , and 90.1 to 100). As described in Equation 4, Model 3 applies two techniques to estimate variations in the strength of the walk score–walking mode choice relationship between different walk score thresholds by using walk score band indicators and identifying differences in walk mode share returns across for incremental changes in each band.

First, band indicators are used to identify estimated changes in walk mode share when shifting from one walk score band to the next, while controlling for the same covariates as those in previous models (see Table 5). Unmodified odds ratios (see Table 5) correspond to expected walk mode share changes compared with the reference band, ranging from 0.1 to 10. Results suggest that the initial walk score changes (e.g., across thresholds of 10 or 30) yield highest expected changes in walk mode share. Moreover, results suggest increasing marginal returns to walk share from walk score for each threshold increase between 50 and 90.

Second, band-membership indicators are interacted with walk score to identify important threshold effects and the conditions under which the walk score–walking relationship is strongest. Control variables are highly stable; parameter estimates are virtually identical to the band indicator model. Band-variant parameter estimates of walk score exhibit a trend similar to those in the band indicator model. To identify the effect of marginal changes in walk score band width—for example, by moving from the band ranging from 60.1 to 70 up to 70.1 to 80—the effect of walk score shifts is estimated by using the median walk score (55.7) and walk share (8.5%) as a reference point of comparison for work trips. Figure 2 illustrates predicted walk mode shares by using the band-variant parameter results. Similar to the band indicator model, parameter estimates indicate an initially strong relationship (between walk score 10 and 20) and a stronger relationship as bands increase from walk score 50 to walk score 100.

Jointly, the band indicator model and the model with band-variant walk score parameters both suggest that the initial improvements in walk score (particularly crossing the walk score thresholds of 10 or 30) are most strongly associated with higher walking mode shares. Moreover, both models suggest increasing strength in the relationship as areas have higher walk scores, as shown in Figure 2.

CONCLUSION

Although walking has many benefits, in regard to both transportation and health, it is oddly neglected in most planning exercises. One reason for this neglect is that appropriate data collection and analysis are prohibitively expensive. Given the importance of this mode and the harm caused by its neglect, this paper explores the possibility of capitalizing on a relatively new source of data on

TABLE 5 Model 3 Results with Walk Score Deciles and Trip Purpose Variation: Equation 4

	Band Indicators					Band-Variant Parameters				
	95% CI					95% CI				
Variable Name	Low Estimate	High Estimate	Point Estimate	Odds Ratio	Sig.	Low Estimate	High Estimate	Point Estimate	Odds Ratio	Sig.
Intercept (reference-work trips)	–7.768	–6.878	–7.314	0.001	***	–7.874	–6.879	–7.371	0.001	***
City walk mode share: 0–100 (MPO source)	0.093	0.115	0.104	1.110	***	0.095	0.117	0.106	1.112	***
Trip indicator										
School	2.266	3.112	2.683	14.630	***	2.25	3.097	2.671	14.448	***
Shopping	1.966	2.855	2.406	11.084	***	1.956	2.842	2.395	10.964	***
Meals	2.156	3.048	2.597	13.427	***	2.150	3.038	2.589	13.318	***
Social recreation	2.084	2.968	2.521	12.442	***	2.077	2.957	2.512	12.333	***
Other	1.741	2.560	2.145	8.541	***	1.734	2.549	2.136	8.462	***
Not home-based trips	0.633	2.813	1.756	5.787	***	0.627	2.797	1.745	5.725	***
Walk score band	Band Indicators (dummy variables)					Band-Variant Continuous Metrics				
0.1 to 10	Reference case					–0.046	0.074	0.015	1.015	—
10.1 to 20	0.151	0.702	0.420	1.523	***	0.011	0.054	0.032	1.033	***
20.1 to 30	–0.005	0.544	0.263	1.301	*	0.001	0.028	0.014	1.014	**
30.1 to 40	0.329	0.844	0.579	1.784	***	0.009	0.028	0.019	1.019	***
40.1 to 50	0.366	0.879	0.615	1.850	***	0.009	0.023	0.016	1.016	***
50.1 to 60	0.364	0.876	0.612	1.845	***	0.007	0.019	0.013	1.013	***
60.1 to 70	0.490	1.006	0.741	2.097	***	0.008	0.018	0.013	1.013	***
70.1 to 80	0.687	1.210	0.942	2.564	***	0.010	0.019	0.014	1.014	***
80.1 to 90	0.829	1.373	1.094	2.986	***	0.010	0.019	0.014	1.015	***
90.1 to 100	1.193	1.748	1.464	4.323	***	0.013	0.021	0.017	1.017	***
Ambient average walk score for work trips	0.025	0.036	0.031	1.031	***	0.024	0.035	0.030	1.030	***
School trips	0.016	0.022	0.019	1.019	***	0.015	0.021	0.018	1.018	***
Shopping trips	0.014	0.022	0.018	1.018	***	0.013	0.021	0.017	1.017	***
Meal trips	0.015	0.023	0.019	1.019	***	0.014	0.022	0.018	1.018	***
Social or recreation trips	0.012	0.019	0.015	1.015	***	0.011	0.018	0.014	1.015	***
Other trips	0.013	0.018	0.015	1.016	***	0.012	0.017	0.015	1.015	***
Not home-based trips	0.006	0.019	0.012	1.012	***	0.005	0.018	0.011	1.011	***
Population density (ln) work trips	–0.009	0.033	0.012	1.012	—	–0.010	0.031	0.010	1.010	—
School trips	–0.003	0.027	0.012	1.012	—	–0.005	0.025	0.010	1.010	—
Shopping trips	–0.100	–0.067	–0.083	0.920	***	–0.102	–0.069	–0.085	0.918	***
Meal trips	–0.070	–0.039	–0.055	0.947	***	–0.073	–0.041	–0.057	0.945	***
Social or recreation	–0.034	–0.002	–0.018	0.982	**	–0.036	–0.004	–0.020	0.980	**
Other trips	–0.001	0.026	0.012	1.013	*	–0.003	0.024	0.010	1.010	—
Not home-based trips	–0.023	0.276	0.122	1.130	—	–0.026	0.272	0.119	1.126	—
McFadden's adjusted pseudo R^2	0.4052					0.2758				

NOTE: — = not statistically significant.
*Significant at .10 level or better; **significant at .05 level or better; ***significant at .01 level or better.

walkability (from www.walkscore.com); these data are an important predictor of walking mode choice. Walk Score data are available throughout much of North America, can be universally accessed, and are a strong predictor of walking behavior with potential applications to planning practice.

This research demonstrates how Walk Score data can be used to estimate walk mode share and can be applied in planning practice for the site-development process and for general planning. This method can be a tool for traffic impact assessments in site development, thereby enabling better walk mode share estimates linked to changes in broader neighborhood walkability and walking behavior as a result of particular projects. Moreover, this method can be applied in general planning to identify incremental changes in the built environment associated with the largest expected shifts in walking behavior. In fact, walk score appears to be a strong predictor of walking and shows much potential for integration in estimating the built environment's influence on other types of travel behavior as well.

Results suggest that the walk score is a better predictor of walking mode choice across several trip purposes compared with population density—often applied as the built environment metric of choice. Second, when variation across trip types is considered in the sensitivity of walk mode share to walk score and other predictors, significant differences are identified. For example, walking mode share for work trips is consistently more sensitive to the walk score. Moreover, school trips are most sensitive to ambient walk score (within 4 km) and less sensitive to local walk score, whereas the opposite is true for social trips. Variation across trip purposes is important and can be used by practitioners to estimate walk mode share for new developments through the site review process. Third, threshold effects of walk score are explored to highlight those incremental walk score improvements expected to most influence mode share, finding that the very strongest expected increases in walk mode share are likely to be achieved through the initial increases in the walk score (between 10 and 30) and that the relationship gains

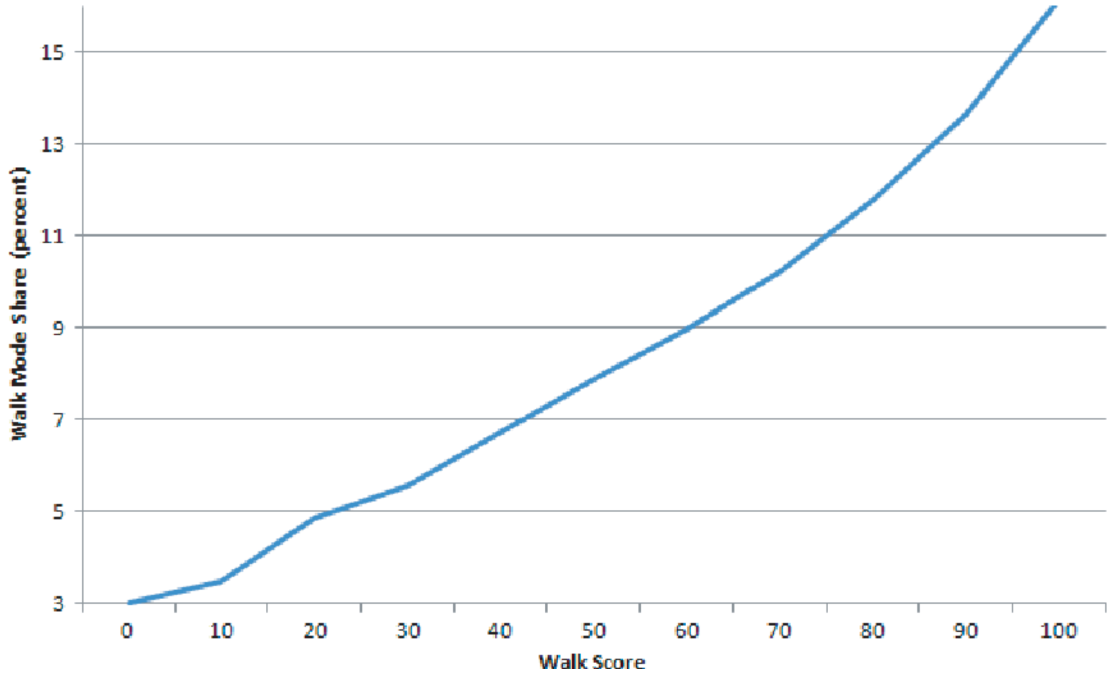

FIGURE 2 Walk score–walking threshold effects and relationship strength.

in strength, particularly between walk score values of 50 and 100. Consequently, the largest potential local changes in walk mode share may be achieved primarily by focusing on improving the walkability of the least walkable neighborhoods and secondarily by making already walkable neighborhoods even more walkable. In concert, these findings highlight the largest potential shifts in walking mode share through the comprehensive planning process and identify the outlook for walking trips at developments subject to the site environmental review process.

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REFERENCES

1. Cao, X. Exploring Causal Effects of Neighborhood Type on Walking Behavior Using Stratification on the Propensity Score. *Environmental Planning A,* Vol. 42, 2010, pp. 487–504.
2. Craig, C., C. L. Brownston, S. E. Cragg, and A. L. Dunn. Exploring the Effect of the Environment on Physical Activity: A Study Examining Walking to Work. *American Journal of Preventive Medicine,* Vol. 23, No. 2, 2002, pp. 36–43.
3. Ewing, R., S. Handy, R. C. Brownson, O. Clemente, and E. Winston. Identifying and Measuring Urban Design Qualities Related to Walkability. *Journal of Physical Activity and Health,* Vol. 3, No. 1, 2006, pp. 223–240.
4. Saelens, B., and S. Handy. Built Environment Correlates of Walking: A Review. *Medicine and Science in Sports and Exercise,* Vol. 40, 2008, pp. 550–566.
5. Shoup, D. Roughly Right or Precisely Wrong. *Access,* Vol. 20, 2002, pp. 20–25.
6. Ewing, R., and R. Cervero. *Travel and the Built Environment,* Vol. 76, No. 3, 2010, pp. 265–294.
7. Manaugh, K., and A. A. El-Geneidy. Validating Walkability Indices: How Do Different Households Respond to the Walkability of Their Neighborhood? *Transportation Research Part D: Transport and Environment,* Vol. 16, No. 4, 2011, pp. 309–315.
8. Keeler, T. E., and K. A. Small. Optimal Peak-Load Pricing, Investment, and Service Levels on Urban Expressways. *Journal of Political Economy,* Vol. 85, 1977, pp. 1–25.
9. Ben-Akiva, M., and S. R. Lerman. *Discrete Choice Analysis: Theory and Application to Travel Demand.* MIT Press, Cambridge, Mass., 1985.
10. Giles-Corty, B., and R. J. Donovan. Relative Influence of Individual, Social Environment, and Physical Environmental Correlates of Walking. *American Journal of Public Health,* Vol. 93, No. 9, 2003, pp. 1583–1589.
11. Chatman, D. G. Deconstructing Development Density: Quality, Quantity, and Price Effects on Household Non-Work Travel. *Transportation Research Part A: Policy and Practice,* Vol. 42, No. 7, 2008, pp. 1008–1030.
12. Greenwald, M. J., and M. G. Boarnet. Built Environment as Determinant of Walking Behavior: Analyzing Nonwork Pedestrian Travel in Portland, Oregon. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1780,* TRB, National Research Council, Washington, D.C., 2001, pp. 33–42.
13. Goetzke, F., and P. M. Andrade. Social Network Effects in Walking: A Spatially Autoregressive Instrumental Variable Linear Probability Mode Choice Model Approach. In *Progress in Spatial Analysis* (A. Paez et al., eds.), Springer, Heidelberg, Germany, 2010, pp. 217–232.

14. Greenwald, M.J., and M.G. Boarnet. Land Use, Urban Design, and Nonwork Travel: Reproducing Other Urban Areas' Empirical Test Results in Portland, Oregon. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1722,* TRB, National Research Council, Washington, D.C., 2000, pp. 27–37.
15. Boarnet, M., and S. Sarmiento. Can Land-Use Policies Really Affect Travel Behavior? A Study of the Link Between Non-Work Travel and Land-Use Characteristics. *Urban Studies,* Vol. 35, No. 7, pp. 1155–1169.
16. Hoehner, C.M., L.K. Brennan Ramirez, M.B. Elliott, S.L. Handy, and R.C. Brownson. Perceived and Objective Environment Measures and Physical Activity Among Urban Adults. *American Journal of Preventive Medicine,* Vol. 28, No. 2S2, 2005, pp. 105–116.
17. Santos, G., and G. Fraser. Road Pricing: Lessons from London. *Economic Policy,* 2006, pp. 264–310.
18. Odeck, J., and S. Brathen. Travel Demand Elasticities and User Attitudes: A Case Study of Norwegian Toll Projects. *Transportation Research Part A: Policy and Practice,* Vol. 42, 2008, pp. 77–94.
19. Ramjerdi, F., H. Minken, and K. Ostmoe. Norwegian Urban Tolls. *Research in Transportation Economics,* Vol. 9, 2004, pp. 237–249.
20. Jones, P., and A. Hervik. Restraining Car Traffic in European Cities: An Emerging Role for Road Pricing. *Transportation Research Part A: Policy and Practice,* Vol. 26A, No. 2, 1992, pp. 133–145.
21. Olszewski, P., and L. Xie. Modelling the Effects of Road Pricing on Traffic in Singapore. *Transportation Research Part A: Policy and Practice,* Vol. 39, 2005, pp. 755–772.
22. Vaca, E., and J. R. Kuzmyak. *TCRP Report 95: Traveler Response to Transportation System Changes: Chapter 13: Parking Prices and Fees.* Transportation Research Board of the National Academies, Washington, D.C., 2005.
23. Dueker, K. J., J. G. Strathman, and M. J. Bianco. *TCRP Report 40: Strategies to Attract Auto Users to Public Transportation*. TRB, National Research Council, Washington, D.C., 1998.
24. Shoup, D. *The High Cost of Free Parking*. Planners Press, Chicago, Ill., 2004.
25. Cervero, R., and K. Kockelman. Travel Demand and the 3Ds: Density, Diversity, and Design. *Transportation Research Part D: Transport and Environment,* Vol. 2, 1997, pp. 199–219.
26. Ewing, R., and R. Cervero. Travel and the Built Environment: A synthesis. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1780,* TRB, National Research Council, Washington, D.C., 2001, pp. 87–114.
27. Saelens, B.E., J.F. Sallis, and L.D. Frank. Environmental Correlates of Walking and Cycling: Findings from the Transportation, Urban Design, and Planning Literatures. *Environment and Physical Activity,* Vol. 25, No. 2, 2003, pp. 80–91.
28. De Bourdeaudhuij, I., J.F. Sallis, and B.E. Saelens. Environmental Correlates of Physical Activity in a Sample of Belgian Adults. *American Journal of Health Promotion,* Vol. 18, No. 1, 2003, pp. 83–92.
29. Schlossberg, M., A.W. Agrawal, and V. L. Bekkouche. *How Far, By Which Route, and Why? A Spatial Analysis of Pedestrian Preference.* MTI Report 06-06. Mineta Transportation Institute, College of Business, San Jose State University, Calif., June 2007.
30. Frank, L.D., and G. Pivo. Impacts of Mixed Use and Density on Utilization of Three Modes of Travel: Single-Occupant Vehicle, Transit, Walking. In *Transportation Research Record 1466,* TRB, National Research Council, Washington, D.C., 1994, pp. 44–52.
31. Forsyth, A. Does Residential Density Increase Walking and Other Physical Activity? *Urban Studies,* Vol. 44, No. 4, 2007, pp. 679–697.
32. Forsyth, A., M. Hearst, J.M. Oakes, and K.H. Schmitz. Design and Destination: Factors Influencing Walking and Total Physical Activity. *Urban Studies,* Vol. 45, No. 9, 2008, pp. 1973–1996.
33. Bagley, M., and P. Mokhtarian. The Impact of Residential Neighborhood Type on Travel Behavior: A Structural Equations Modeling Approach. *The Annals of Regional Science,* Vol. 36, 2002, pp. 279–297.
34. Gillen, D.W. Estimation and Specification of the Effects of Parking Costs on Urban Transport Mode Choice. *Journal of Urban Economics,* Vol. 4, 1977, pp. 186–199.
35. Mokhtarian, P., and X. Cao. Examining the Impacts of Residential Self-Selection on Travel Behavior: A Focus on Methodologies. *Transportation Research Part B: Methodological,* Vol. 42, 2008, pp. 204–228.
36. Guo, Z. Does the Built Environment Affect the Utility of Walking? A Case of Path Choice in Downtown Boston. *Transportation Research D: Transport and Environment,* Vol. 14, No. 2009, pp. 343–352.
37. Levine, J., A. Inam, and G.-W. Torng. A Choice-Based Rationale for Land Use and Transportation Alternatives: Evidence from Boston and Atlanta. *Journal of Planning Education and Research,* Vol. 24, 2005, pp. 317–330.
38. Rodriguez, D. A., A.J. Khattak, and K.R. Evenson. Can New Urbanism Encourage Physical Activity? Comparing a New Urbanist Neighborhood with Conventional Suburbs. *Journal of the American Planning Association,* Vol. 72, No. 1, 2006, pp. 43–54.
39. Rodriguez, D. A., and J. Joo. The Relationship Between Non-Motorized Mode Choice and the Local Physical Environment. *Transportation Research Part D: Transport and Environment,* Vol. 9, 2004, pp. 151–173.
40. Warburton, D. E. R., C. W. Nicol, and S. S. D. Bredin. Health Benefits of Physical Activity: The Evidence. *Canadian Medical Association Journal,* Vol. 174, No. 6, 2006.
41. Morris, J. N., and A. E. Hardman. Walking to Health. *Sports Medicine,* Vol. 23, No. 5, 1997, pp. 306–332.
42. Takano, T., K. Nakamura, and M. Watanabe. Urban Residential Environments and Senior Citizens Longevity in Megacity Areas: The Importance of Walkable Green Spaces. *Journal of Epidemiology and Community Health,* Vol. 56, 2002, pp. 913–918.
43. New York City Office of the Mayor. *Mobility Needs Assessment 2007–2030*. City of New York, 2007.
44. Leslie, E., N. Coffee, L. Frank, N. Owen, A. Bauman, and G. Hugo. Walkability of Local Communities: Using Geographic Information Systems to Objectively Assess Relevant Environmental Attributes. *Health and Place,* Vol. 13, 2007, pp. 111–122.
45. walkshed. www.walkshed.com. Accessed April 28, 2011.
46. Carr, L.J., S.I. Dunsiger, and B.H. Marcus. Walk Score as a Global Estimate of Neighborhood Walkability. *American Journal of Preventive Medicine,* Vol. 39, 2010, pp. 460–463.
47. Carr, L.J., S.I. Dunsiger, and B.H. Marcus. Validation of Walk Score for Estimating Access to Walkable Amenities. *British Journal of Sports Medicine,* Vol. 45, 2010, pp. 1144–1148.
48. Cortright, J. Walking the Walk: How Walkability Raises Home Values in U.S. Cities. *CEOs for Cities,* 2009.
49. Tregoning, H. *Getting to Walkability—Using Walk Score as a Planning Metric and Goal.* District of Columbia Planning Office. http://www.slideshare.net/mrlerner/getting-to-walkability?from=ss_embed. Accessed Feb. 4, 2010.
50. *Walk Score Neighborhood Ranking Methodology.* 2010. http://www.walkscore.com/rankings/ranking-methodology.shtml. Accessed May 4, 2010.
51. Lee, C., and A. V. Moudon. Correlates of Walking for Transportation or Recreation Purposes. *Journal of Physical Activity and Health,* Vol. 3, 2006, pp. S77–S98.
52. Moudon, A.V., C. Lee, A.D. Cheadle, C. Garvin, D. Johnson, T.L. Schmid, R.D. Weathers, and L. Lin. Operation Definitions of Walkable Neighborhood: Theoretical and Empirical Insight. *Journal of Physical Activity and Health,* Vol. 3, 2006, pp. S9–S117.

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