STREETSCAPE FEATURES RELATED TO PEDESTRIAN ACTIVITY

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ABSTRACT

Focusing on the street level experience, Ewing et al. (2005, 2006) developed measurement protocols for nine urban design qualities cited in the literature—imageability, enclosure, human scale, transparency, complexity, coherence, linkage, legibility, and tidiness. The first five were successfully operationalized and then related to pedestrian counts on 588 street segments in New York City. Ewing et al. (2013) showed that the one urban design quality--transparency-- is more significant in explaining pedestrian counts than development density, land use diversity, street network design, destination accessibility, distance to transit, or demographics, the so-called D variables. This paper builds on the research of Ewing et al. (2005, 2013) to distinguish which specific streetscape features influence levels of pedestrian activity after controlling for the other D variables: A composite variable comprised of windows overlooking the street, continuous building facades forming a street wall, active street frontage, proportion of historic buildings, number of buildings with identifiers, and number of pieces of street furniture, prove to be highly significant.
INTRODUCTION

Some of today’s most vexing problems, including sprawl, congestion, air pollution, oil dependence, and climate change, are prompting states and localities to turn to land planning and urban design to rein in automobile use. As a consequence, the role of the built environment in influencing travel behavior may be the most widely researched topic in urban planning. In more than 200 studies, the built environment has been measured, or operationalized, in terms of D variables (Badoe & Miller, 2000; Cao, Mokhtarian, et al., 2009; Cervero, 2003; Crane, 2000; Ewing & Cervero, 2001; Ewing and Cervero 2010; Handy, 2005; Heath et al., 2006; McMillan, 2005; McMillan, 2007; Pont, Ziviani, Wadley, Bennet, & Bennet, 2009; Saelens, Sallis, & Frank, 2003; Stead & Marshall, 2001). These, in turn, have been used to explain trip frequencies, mode choices, trip distances, and overall vehicle miles traveled. A large subset of studies have explained pedestrian mode choice or walking frequency in terms of the D variables.

The original three Ds, coined by Cervero and Kockleman (1997) were density, diversity, and design. The Ds were later expanded to include destination accessibility and distance to transit (Ewing & Cervero, 2001). An additional set of D variables, related to demographics, have been controlled in travel studies to determine the independent effect of the built environment on travel behavior.

For four of the D variables, measurement is fairly straightforward (see “D Variables”). While there are choices to be made, and some D variables overlap (e.g., diversity and destination accessibility), academics who conduct research in this area seem comfortable with these four dimensions of the built environment and the metrics used to operationalize them.

The remaining D, design, is more nuanced. Design is widely thought to include street network characteristics of a neighborhood or district. Street networks vary from dense urban grids of highly interconnected, straight streets to sparse suburban networks of curving streets forming loops and lollipops. Design is also occasionally measured in terms of sidewalk coverage; average building setbacks; average street widths; or numbers of pedestrian crossings, street trees, or other physical variables that differentiate pedestrian-oriented environments from auto-oriented ones.

However, urban design also incorporates subtler qualities of the street environment that affect the pedestrian experience. The experience of walking down a given street may have less to do with gross qualities such as average block size than with the micro environment of the street itself. Sometimes referred to as perceptual qualities of the street environment or, alternately, just urban design qualities, these micro qualities are frequently cited in classic readings on urban design (for example, Lynch, 1960; Hedman, 1984; Gehl, 1987). Urban designers presume that these qualities are important for active street life, but have little empirical evidence to back the claim.

Focusing on the street level experience, Ewing et al. (2005, 2006) developed measurement protocols for nine urban design qualities cited in the literature—imageability, enclosure, human scale, transparency, complexity, coherence, linkage, legibility, and tidiness. The first five were successfully operationalized. Their research was conducted under the Active Living Research Program of the Robert Wood Johnson Foundation. The purpose was to arm researchers with measures that could be used to explain and predict levels of physical activity in urban settings. The measures, while assessed for reliability and face validity, were not assessed at the time for internal validity. That is to say, the measures were not shown to actually predict pedestrian behavior or street life.
In the new book *Measuring Urban Design*, Ewing et al (2013) seek to validate the urban design qualities against pedestrian counts on 588 street segments in New York City. They show that the urban design quality of transparency has more explanatory power than any of the standard D variables such as development density, land use diversity, street network design, destination accessibility, distance to transit, and demographics. This paper builds on their research to distinguish which specific streetscape features influence levels of pedestrian activity after controlling for the standard “D” variables.

**ORIGINAL STUDY**

The original study by Ewing et al. (2005, 2006) involved 1) recruiting an expert panel of 10 urban designers and planners; 2) creating a library of 200-plus video clips of streetscapes around the U.S.; 3) selecting 48 representative clips to show to the expert panel; 3) having the expert panel rate urban design qualities of videotaped streetscapes with respect to nine urban design qualities; 4) measuring physical features of streetscapes from the videoclips; 5) statistically analyzing relationships between physical features and urban design quality ratings by the expert panel; 7) selecting five urban design qualities for subsequent operationalization based on inter-rater reliability and other criteria; and 8) developing, testing, and refining a field manual that laid out procedures for measuring these qualities.

The five urban design qualities that survived this process were:

**Imageability** - the quality of a place that makes it distinct, recognizable, and memorable. A place has high imageability when specific physical elements and their arrangement capture attention, evoke feelings, and create a lasting impression. From the earlier study, features contributing significantly to imageability are (in order of significance):

- number of people—same side of street
- proportion of historic buildings—both sides of street
- number of courtyards, plazas, and parks—both sides of street
- presence of outdoor dining—same side of street
- number of buildings with non-rectangular silhouettes—both sides of street
- noise level—same side of street
- number of major landscape features—both sides of street
- number of buildings with identifiers—both sides of street

**Enclosure** - the degree to which streets and other public spaces are visually defined by buildings, walls, trees, and other vertical elements. Spaces where the height of vertical elements is proportionally related to the width of the space between them have a room-like quality. From the earlier study, features contributing significantly to the perception of enclosure are (in order of significance):

- proportion street wall—same side of street
- proportion street wall—opposite side of street
- proportion sky—across street
- number of long sight lines—ahead and to either side
- proportion sky—straight ahead

**Human scale** - size, texture, and articulation of physical elements that match the size and proportions of humans and, equally important, correspond to the speed at which humans walk. Building details, pavement texture, street trees, and street furniture all contribute to human scale.
From the earlier study, features contributing significantly to the perception of human scale are (in order of significance):

- number of long sight lines
- number of pieces of street furniture and other miscellaneous items—same side of street
- proportion first floor with windows—same side of street
- building height—same side of street
- number of small planters—same side of street

Transparency - the degree to which people can see or perceive what lies beyond the edge of a street and, more specifically, the degree to which people can see or perceive human activity beyond the edge. Physical elements that influence transparency include walls, windows, doors, fences, landscaping, and openings into midblock spaces. From the earlier study, features contributing significantly to the perception of enclosure are (in order of significance):

- the proportion first floor with windows—same side of street
- the proportion active uses—same side of street
- the proportion street wall—same side of street

Complexity - the visual richness of a place. The complexity of a place depends on the variety of the physical environment, specifically the numbers and kinds of buildings, architectural diversity and ornamentation, landscape elements, street furniture, signage, and human activity. From the earlier study, features contributing significantly to the perception of complexity are (in order of significance):

- Number of people—same side of street
- Number of dominant building colors—both sides of street
- Number of buildings—both sides of street
- Presence of outdoor dining—same side of street
- Number of accent colors—both sides of street
- Number of pieces of public art—both sides of street

**FOLLOW-UP STUDIES**

Soon after the original study, another study was funded by the Robert Wood Johnson Foundation to implement the observational protocol. The researchers, from Columbia University, developed observational data for the five urban design measures for a large sample of streets in New York City (Purciel et al., 2009). These data are used in the current study to validate urban design measures against pedestrian counts.

The Columbia University team began by developing a field manual (Purciel and Marrone, 2006) based on the original field manual by the University of Maryland team (Clemente et al., 2005). All photographic images were specific to New York City. Both field manuals contain detailed measurement protocols for coding the physical features of streets that contribute to the five urban design qualities. However, if anything, the NYC manual provides more detailed guidance to observers than does the original manual.

Using video clips from the original project and the refined field manual, six field observers were trained in the classroom to make observational measurements. Once trained, the observers were sent into field (with the NYC manual) to make measurements for a stratified
sample of 600 block faces in all five boroughs that comprise New York City. The five boroughs cover roughly 225 square miles, 160,000 block faces, and 860,000 parcels.

The field observers completed ratings of 588 of the 600 sampled blocks during the summer of 2006 (for 12 blocks, no block face met their observable criteria). To assess inter-rater reliability, 13 block faces were scored independently by all observers, and inter-class correlation coefficients were calculated for each urban design quality and each rater. Results indicated a high degree of consistency among field observers (Purciel et al., 2009).

Ewing et al. (2013) used Purciel et al. data to validate micro urban design measures against pedestrian counts. It was the first planning research study to use web based street imagery from Google Street View, Bing StreetSide, and EveryScape to establish the equivalency reliability with manual pedestrian counts conducted in the field. It also was the first to use Walk Scores to measure a key D measure, destination accessibility.

Ewing et al. (2013) found that not only is transparency significant after controlling for other D variables, but it has greater significance than any of the standard D variables. The fact the transparency was significant after controlled retail frontage (though it attenuates the effect of retail frontage in the simple model) indicates that transparency is not a simple proxy for retail uses, whose storefronts often have high transparency with display windows. Transparency, as measured, incorporates much more.

Among the other urban design variables, only human scale was significantly related to pedestrian counts, and then only marginally. Imageability and complexity, as measured, had no relationship to pedestrian activity. Enclosure approaches significance at the 0.10 level with an unexpected, negative sign. Perhaps the canyon-like streetscapes of the some New York streets detract from the walking experience.

**METHODS**

Previous research by Ewing et al. broke new ground in two respects: by relating physical features of streetscapes to urban design qualities, and by relating urban design qualities to pedestrian counts. This research takes the next logical step, relating specific streetscape features directly to pedestrian counts.

**Data**

Primary data for this study was compiled by the Columbia University team. For each block face in the sample, field observers measured all variables that comprise the five urban design measures. They also counted pedestrians.

In an effort to make the process replicable, secondary data are limited to those that are publicly available in other parts of the country. GIS data for the study area were acquired directly from the New York City Department of City Planning, including DCPLION street segment centerlines and MapPluto™ parcel layers. Census 2010 SF1 100% and Tiger 2010 Census Block shapefiles were used to calculate roadway network, land use, and demographic variables.
Measures

Pedestrian Activity

The outcome variable explained in this study is the average number of people encountered on four passes up and down a given block face. Columbia University observers visited each of the 588 street segments and conducted four field counts of the number of pedestrians along the block face at a particular time. The students walked the length of the segment one time for each count and included every pedestrian they encountered during that exercise, noting the time of day and weather conditions observed for that period.

Because the sample size is small for these counts (n=4) and the counts aren’t independent but rather made in succession at different times and different days of the week for different street segments, we needed to establish the reliability of our outcome variable. This was done by counting pedestrians on three websites that provide street-level imagery and comparing these counts to the manual counts. The three are Google Street View, Bing StreetSide, and EveryScape. The same street was filmed at different times by the different suppliers of imagery. We, thus, with the field counts, have four independent measures of pedestrian activity.

We performed two tests of reliability with respect to pedestrian counts. The first was a test of inter-rater reliability for the counts from the different websites. It would seem a simple matter to count pedestrians using static images, but because pedestrians are partially hidden by other pedestrians, cars, and other objects, images (particularly EveryScape) are sometimes blurry, and observers suffer from fatigue, there is some error associated with counts for the same streets from the same websites. One student observer counted pedestrians on all streets for which imagery was available. Three others independently counted pedestrians for a random subsample of 30 block faces from the larger sample. The sample of segments included high pedestrian counts and low pedestrian counts.

Various statistical techniques may be used to assess inter-rater reliability in studies like this, where multiple individuals independently rate the same set of cases. We used intra-class correlation coefficients (ICCs), representing the ratio of between-group variance to total variance of counts (Fleiss, 1981).

For assessing inter-rater agreement, ICCs are more appropriate than simple correlation coefficients. Simple correlation coefficients are sensitive only to random errors (chance factors), while ICCs are sensitive to both random errors and systematic errors (statistical bias). For example, if two raters count pedestrians and one of them consistently finds more pedestrians than the other (systematic error), a simple correlation coefficient might indicate complete agreement between them. By contrast, the ICC would accurately portray the extent of disagreement between them. The ICC is the preferred measure of inter-rater reliability when cases are rated in terms of some interval variable or interval-like variable, such as the pedestrian counts in this study.

Our sample size of 30 was comparable to similar studies conducted by Pikora et al. (2002) and Clifton et al. (2007). Inter-rater reliability was high, particularly for Google and Bing. As a general guide, we followed the adjectival ratings suggested by Landis and Koch (1977), who considered Kappa scores between 0.8 and 1.0 as indicating almost perfect agreement and those between 0.6 and 0.8 as indicating substantial agreement. Inter-rater agreement was almost perfect for Google and Bing, and was substantial for EveryScape.

The other test of reliability was to compare field counts conducted by observers from Columbia University to counts from web-based street imagery. Ideally, the Columbia team
would have conducted field counts for extended and standard periods at each block face. Vehicle traffic counts are done in this manner. However, vehicle counts are usually automated rather than manual, and when they are manual (as at individual intersections), sample sizes are small. The number of block faces in this study precluded such a labor intensive approach. Instead, we were forced to rely on four consecutive counts, in a random period, for each block face. This raises issues of reliability.

To test whether the field counts, in fact, are reliable indicators of pedestrian activity, we conducted a test of equivalency reliability. Equivalency reliability is the extent to which different variables measure the same underlying construct, in this case pedestrian activity. Equivalency reliability is determined by relating values of the different variables to one another to highlight the degree of relationship or association.

We have already established that web-based pedestrian counts by different raters are reliable. We next compared counts by one rater for each website to field counts. Sample sizes are different because only Google Street View has imagery for all 588 block faces. Equivalency reliability is judged with Cronbach’s alpha. Cronbach's alpha is widely used in the social sciences to see if items — questions, raters, indicators — measure the same thing. If independent counts—four based on field work and three based on street imagery—agree, we can assume that the field counts are reliable measures of pedestrian activity. Some professionals require a reliability of 0.70 or higher before they will use an instrument. In the case of psychometric tests, most fall within the range of 0.75 to 0.83. Our alpha values are consistent with these guidelines for two out of three websites.

"D" Variables

The explanatory variables of primary interest are streetscape design features. These were measured in the field on each of 588 block faces by the Columbia University team. For control variables, we drew on characterizations of the D variables from Ewing and Cervero (2010) and Ewing et al. (2011). Density is always measured as a variable of interest per unit of area. Two density measures were computed for the 0.25 mile buffer around each street segment. One is the average floor area ratio, computed as the total building floor area for all parcels within the buffer, divided by the total area of tax lots (far). The other is the average population density, computed as the population of all census blocks whose centroids fell within the buffer divided by the total area of residential tax lots whose centroids fell within the buffer, measured in 1000 residents per square mile (population density).

Diversity is related to the number of different land uses in a given area and the degree to which they are balanced in land area, floor area, or employment. An entropy measure of diversity was computed with the formula:

\[
\text{Entropy} = -[\text{residential share} \times \ln(\text{residential share}) + \text{retail share} \times \ln(\text{retail share}) + \text{office share} \times \ln(\text{office share})]/\ln(3)
\]

where the shares were computed based on floor area of each use for tax lots within the buffer.

While much of this paper focuses on streetscape design features, gross metrics of design were computed with GIS. One was intersection density, computed as the number of intersections within 0.25 mile buffer divided by the gross area of the buffer in square miles (intersection density). The other was the proportion of four-way intersections within the buffer (proportion 4-way).

The D variable destination accessibility was represented by Walk Scores (walk score). Walk Score is an Internet-based platform which rates the walkability of a specific address on a
numeric scale (from 0 to 100), by compiling the number of nearby stores and amenities within a one-mile radius of a location (Rauterkus et al., 2010). The platform specifically measures walkability relative to 13 amenity categories including grocery stores, coffee shops, restaurants, bars, movie theaters, schools, parks, libraries, book stores, fitness centers, drug stores, hardware stores and clothing/music stores (Carr et al., 2011). Amenities within 0.25 miles receive maximum points and no points are awarded for amenities farther than one mile. For this study, an address at the approximate midpoint of each block face was retrieved using Google Street View, and then entered into the Walk Score web site to obtain a score for each segment.

The authors identified two studies which tested the reliability of Walk Scores in measuring neighborhood walkability and access to amenities (Carr et al., 2011; Duncan et al., 2011). Both studies used GIS measures to validate Walk Score data; Carr et al. (2011) for 379 addresses in Providence, R.I., and Duncan et al. (2011) for 754 addresses in four U.S. metropolitan areas in distinct geographical regions. Both studies concluded that Walk Score represented a valid and reliable measure of estimating access to walkable amenities. Duncan et al. (2011) added that the platform’s reliability held up “in multiple geographic locations and at multiple spatial scales” (pg. 4161).

Using ArcInfo Network Analyst (ESRI, 2009), and the New York City road centerline shapefile, a network analysis was performed to find the shortest distance from each study segment center point to the closest rail station. The result was a mile distance to transit variable related to each study segment (distance to rail).

The only demographic variable computed was average household size for blocks whose centroids fell with the 0.25 mile buffer around each block face (household size). We would have estimated median household income or per capita from the 2005-2009 American Community Survey, but complete data were only available at the census tract level.

Reasoning that pedestrian counts on a given block face depend as much on land uses along the block face as on development patterns within easy walking distance, we estimated three additional D variables: average floor area ratio for the block face, computed as the total building floor area for parcels abutting the street, divided by the total area of tax lots (block far); an entropy measure based on floor area for parcels abutting the street, computed with the formula above (block entropy); and proportion of retail frontage along the block face, on the assumption that retail frontage generates more pedestrian activity than other frontage (proportion retail).

One final control variable used in this study is the length of each block face (block length). The simple theory is that after controlling for other influences, the longer the block, the more pedestrians will occupy it at any given time.

**Streetscape Features**

Previous research (Ewing et al. 2005, 2013) suggests that physical features of streetscapes can help explain pedestrian activity. In this research, we go a step further to quantify relationships between streetscape features and pedestrian counts on those same New York City streets. Ewing et al.’s panel of experts listed more than eighty physical features of streetscapes that they deemed important. After conducting statistical analyses of their reliability and explanatory power, we narrowed the list of physical features to 19 items (see Table 1).

**TABLE 1 – Measured Physical Features of Streetscape**

<table>
<thead>
<tr>
<th>Variable Long Name</th>
<th>Counting Criteria</th>
<th>Measurement Protocol</th>
</tr>
</thead>
</table>

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<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion of historic buildings</td>
<td>Counted buildings, and fronting along street and passed or 500 feet ahead, both sides</td>
</tr>
<tr>
<td></td>
<td>Estimating the proportion of the street that is fronted by buildings that are historic. Architecture that can be determined to have originated from the world war II era or before will be considered historic.</td>
</tr>
<tr>
<td>Courtyards/plazas/parks-both sides</td>
<td>Counting individual courtyards, plazas, and parks that are on either side of the street or that are within 50 feet the observer. Large parks that occupy a whole block count as one park.</td>
</tr>
<tr>
<td>Outdoor dining</td>
<td>Counting the number of district places that provide outdoor dining. Counting outdoor dining areas even if there are no diners. However, not counting outdoor dining if the dining area appears closed.</td>
</tr>
<tr>
<td>Buildings with nonrectangular silhouettes</td>
<td>Counting the buildings that have been counted whose shape is not a simple rectangular box. Pitched roofs on buildings that are viewed at an angle and make the building look nonrectangular do count as nonrectangular.</td>
</tr>
<tr>
<td>Major Landscape features</td>
<td>Counting each type of tree, bush, and visible ground cover.</td>
</tr>
<tr>
<td>Buildings with identifiers</td>
<td>Counting buildings, and fronting along street and passed or 500 feet ahead, both sides</td>
</tr>
<tr>
<td></td>
<td>Counting the buildings whose use can be determined by building features. For example, a church can be identified by a steeple. Stores can be identified by signs that can be easily recognized. If a building has been subdivided by several occupants, only count the building as identifiable if a majority of the occupants’ uses can be determined by building features.</td>
</tr>
<tr>
<td>Proportion of street wall—same side</td>
<td>Counted buildings fronting along street and passed or 500 feet ahead, same side</td>
</tr>
<tr>
<td></td>
<td>Determining the proportion of street that is occupied by a continuous wall or façade adjacent to the sidewalk. Facades set back by parking or lawn and driveways do not count as street wall. Intersecting streets and ends of blocks, however, should not count against street wall.</td>
</tr>
<tr>
<td>Proportion of street wall—opposite side</td>
<td>Same as above for the opposite side</td>
</tr>
<tr>
<td>Long sight lines</td>
<td>1,000 feet ahead</td>
</tr>
<tr>
<td></td>
<td>Indicate the number of directions in which the camera can see far into the distance. Maximum number is 3 (right, left, front). “Far into the distance” will be defined as seeing at least 1,000 feet into the distance.</td>
</tr>
<tr>
<td>Topic</td>
<td>Details</td>
</tr>
<tr>
<td>------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Proportion of sky ahead</td>
<td>None</td>
</tr>
<tr>
<td>All street furniture and other street items</td>
<td>Within 50 feet, same side</td>
</tr>
<tr>
<td>Proportion of first floor with windows</td>
<td>Fronting along street, and passed or feet ahead, and set back no more than 50 feet same side</td>
</tr>
<tr>
<td>Building height-same side</td>
<td>Passed or 500 feet ahead, same side</td>
</tr>
<tr>
<td>Small planters</td>
<td>Less than 10 square feet and within 50 feet, same side</td>
</tr>
<tr>
<td>Proportion of active uses</td>
<td>Counted buildings fronting along street and passed or 50 feet ahead, same side</td>
</tr>
<tr>
<td>Number of buildings</td>
<td>20% screen height, both sides</td>
</tr>
<tr>
<td>Dominant building colors</td>
<td>Counted buildings</td>
</tr>
<tr>
<td>Accent colors</td>
<td>Counted buildings, objects that occupy 20% of screen height or within 50 feet, both sides</td>
</tr>
<tr>
<td>Public art</td>
<td>20% screen</td>
</tr>
</tbody>
</table>

Estimating the proportion of sky, at the initial view ahead the street. Estimating proportions in increments of 0.05.

Counting all pieces of street furniture. Counting all kinds of signs, benches, parking meters, trash cans, newspaper boxes, bike racks, bollards, street lights, and so forth.

Estimating the proportion of the first floor of buildings that front the street on the same side that are passed or are within 50 feet from the camera at the end of the clip that is window. Use 0.10 intervals.

Estimating the average building height of buildings on the same side of the street based on the proportion of street fronted by each building.

Counting the number of small planting pots with shrubs or flowers. Small planters should be permanent elements of the streetscape and not pots that are taken in at the end of the day.

Determining the proportion of street frontage that has active uses. Active uses are defined as shops, restaurants, public park, and other uses that generates significant pedestrian traffic. Inactive uses include blank walls, parking lots, vacant lots, abandoned buildings, and offices with no apparent activity. In regard to residential uses, when the density appears to be more than 10 units per acre, assume the land use to be active.

Count buildings along the street and in the distance that occupy at least 20% of screen height. Large structures that are subdivided count as one building.

Counting the different dominant building colors for buildings that have been counted. If the roof color of a building is different from the building color, the roof color will count as an accent color.

Count the number of accent colors. Accent colors contrast with the dominant building colors and can come from street furniture, awning, business signs, and building trim. Accent colors will be counted only from objects that meet one of the counting criteria.

Counting the pieces of public art such as
PRINCIPAL COMPONENT ANALYSIS AND RESULTS

To further reduce the list of highly correlated variables, we first conducted a principal component analysis of all nineteen streetscape features to identify a single component that could best represent physical features of streetscapes. We then used principal component analysis again, this time only with those variables that loaded heavily on the first principal component, to develop a parsimonious model. These two operations allowed us represent the first principal component as a linear sum of just a few highly correlated streetscape features. Factor loadings on this component, which we refer to as streetscape quality, are shown in Table 2. To be included in stage two, streetscape features had to have loadings on the first principal component of 0.5 or greater. Pursuant to this procedure, streetscape quality became a linear function of the proportion of historic buildings on the street, the proportion of street wall on the same side of the street, the proportion of active use on the same side of the street, the number of buildings with identifiers, and the number of pieces of street furniture.

TABLE 2 – Component Matrix – Principal Component Analysis (stage one and stage two)

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Component 1(stage one)</th>
<th>Component 1(stage two)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion of historic buildings</td>
<td>.662</td>
<td>.666</td>
</tr>
<tr>
<td>Courtyards/plazas/parks- both sides</td>
<td>.033</td>
<td>-</td>
</tr>
<tr>
<td>Outdoor dining</td>
<td>.292</td>
<td>-</td>
</tr>
<tr>
<td>Buildings with nonrectangular silhouettes</td>
<td>-.346</td>
<td>-</td>
</tr>
<tr>
<td>Major Landscape features</td>
<td>.010</td>
<td>-</td>
</tr>
<tr>
<td>Buildings with identifiers</td>
<td>.699</td>
<td>.733</td>
</tr>
<tr>
<td>Proportion of street wall –same side</td>
<td>.722</td>
<td>.687</td>
</tr>
<tr>
<td>Proportion of street wall –opposite side</td>
<td>.641</td>
<td>-</td>
</tr>
<tr>
<td>Long sight lines</td>
<td>-.019</td>
<td>-</td>
</tr>
<tr>
<td>Proportion of sky ahead</td>
<td>.101</td>
<td>-</td>
</tr>
<tr>
<td>All street furniture and other street items</td>
<td>.604</td>
<td>.631</td>
</tr>
<tr>
<td>Proportion of first floor with windows</td>
<td>.716</td>
<td>.786</td>
</tr>
<tr>
<td>Building height-same side</td>
<td>.485</td>
<td>-</td>
</tr>
<tr>
<td>Small planters</td>
<td>-.220</td>
<td>-</td>
</tr>
<tr>
<td>Proportion of active uses</td>
<td>.599</td>
<td>.652</td>
</tr>
<tr>
<td>Number of buildings</td>
<td>-.091</td>
<td>-</td>
</tr>
<tr>
<td>Dominant building colors</td>
<td>-.086</td>
<td>-</td>
</tr>
<tr>
<td>Accent colors</td>
<td>.319</td>
<td>-</td>
</tr>
<tr>
<td>Public art</td>
<td>.089</td>
<td>-</td>
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</table>

NEGATIVE BINOMIAL REGRESSION AND RESULTS

With an overall streetscape quality metric in hand, we sought to explain pedestrian counts on the 588 sampled street. The method of analysis was dictated by the distribution of the dependent variable, the average pedestrian count for four passes up and down each block face.
rounded to the nearest integer. Many streets have low pedestrian counts, few streets have high pedestrian counts, and no streets can have negative counts. Counts range from 0 to 176, with a mean value of 5.78 and a standard deviation of 12.97. The assumptions of ordinary least squares (OLS) regression are violated in this case. Specifically, the dependent variable is not normally distributed, and the error term will not be homoscedastic nor normally distributed.

Two basic methods of analysis are available when the dependent variable is a count, with nonnegative integer values, many small values and few large ones. The methods are Poisson regression and negative binomial regression, both fairly new to the planning field. They have mostly been used in crash studies because of the high skewed nature of crash counts (Dumbaugh & Rae 2008; Hadi et al., 1995; Marshall & Garrick, 2011; Schepers et al. 2011).

The models differ in their assumptions about the distribution of the dependent variable. Poisson regression is the appropriate model form if the mean and the variance of the dependent variable are equal. Negative binomial regression is appropriate if the dependent variable is overdispersed, meaning that the variance of counts is greater than the mean. Because the negative binomial distribution contains an extra parameter, it is a robust alternative to the Poisson model.

“A central distributional assumption of the Poisson model is the equivalence of the Poisson mean and variance. This assumption is rarely met with real data. Usually the variance exceeds the mean, resulting in what is termed overdispersion… Overdispersion is, in fact, the norm and gives rise to a variety of other models that are extensions of the basic Poisson model. Negative binomial regression is nearly always thought of as the model to be used instead of Poisson when overdispersion is present in the data” (Hilbe, 2011, pg. 140).

Popular indicators of overdispersion are the Pearson and $\chi^2$ statistics divided by the degrees of freedom, so-called dispersion statistics. If these statistics are greater than 1.0, a model is said to be overdispersed (Hilbe, 2011, pp. 88, 142). By these measures, we have overdispersion and the negative binomial model is more appropriate than the Poisson model. The Wald and likelihood ratio tests are also used to check for overdispersion (Greene, 2012, p. 810). For our data, both approaches reject the Poisson hypothesis of equidispersion. The likelihood ratio chi square statistics for the tests against the null Poisson model exceed 1,000 for both models specified below. Wald statistics for the overdispersion parameters both are far in excess of 1.96.

We used the software package SPSS to estimate two negative binomial models of pedestrian counts (see Table 3). Model 1 contains the standard D variables without the streetscape design component, while Model 2 includes the streetscape design. Both models have highly significant likelihood ratio chi-squares, indicating a good fit to the data relative to a null model with only intercept terms. The likelihood ratio chi-square of Model 2 relative to Model 1, 34.1 with 1 degrees of freedom, indicates that the fit is significantly better for Model 2 at the 0.001 probability level.

In both models, the three density measures—buffer FAR, buffer population density, and block FAR are directly and significantly related to pedestrian counts. In both models, our measures of buffer and block land use diversity, entropy, are not significant. None of the two measures of street network design, intersection density or proportion of 4-way intersections, is significant. This is surprising, as intersection density is strongly associated with walking in household-level travel studies (Ewing and Cervero, 2010). Our measure of destination accessibility, walk score, is not significant in either model. This is also surprising, given the
emphasize on destination accessibility in the household travel literature (Ewing and Cervero, 2010). Distance to rail is significant with the expected negative sign, pedestrian counts dropping off with distance. The proportion of retail frontage is positively related to pedestrian counts in both models. Apparently having equal proportions of residential, retail, and office on a block face is less conducive to pedestrian activity than having a disproportionate share of retail frontage. Household size is positively related to pedestrian counts in both model, but only in model one is at significant level. Block length is directly related to pedestrian counts at significant levels at both models.

As for the streetscape design component in Model 2, it is significant after controlling for other D variables, and it has greater significance than any of the standard D variables. This is a novel finding, to our knowledge the first time anything like this has been reported in the literature.

**TABLE 3. Negative Binomial Regression Models of Pedestrian Counts (588 Block Faces)**

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
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<tr>
<td></td>
<td>coeff.</td>
<td>std. error</td>
<td>p-value</td>
<td>coeff.</td>
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<td>intercept</td>
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<td>.5827</td>
<td>.001</td>
<td>-1.098</td>
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<td>far</td>
<td>.148</td>
<td>.0407</td>
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<td>population density</td>
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<td>.000</td>
<td>.008</td>
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<td>.3252</td>
<td>.274</td>
<td>.364</td>
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<td>intersection density</td>
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<td>.0010</td>
<td>.517</td>
<td>-.001</td>
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<td>proportion 4-way</td>
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<td>.313</td>
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<td>walk score</td>
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<td>.123</td>
<td>.003</td>
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<td>block far</td>
<td>.046</td>
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<td>.039</td>
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<td>block entropy</td>
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<td>.2309</td>
<td>.181</td>
<td>.060</td>
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<td>proportion retail</td>
<td>1.136</td>
<td>.1792</td>
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<td>.478</td>
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<td>household size</td>
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<td>.205</td>
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<td>5.834</td>
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<td>Streetscape Design</td>
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<td>.445</td>
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<td>likelihood ratio chi-</td>
<td>622.277</td>
<td>(12)</td>
<td></td>
<td>656.384</td>
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<td>square (df)</td>
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</table>

**DISCUSSION**

This study has sought to explain pedestrian counts on 588 block faces in New York City in terms of D variables—development density, land use diversity, street network design, destination accessibility, distance to transit, and demographics, plus micro streetscape features such as windows providing “eyes on the street. Not all of the tested D variables have the expected relationships to pedestrian counts at high significant levels. However, the streetscape design features add significantly to the explanatory power to our second model. A principal component—comprised of windows on the street, continuous building facades forming a street wall, active street frontage, proportion of historic buildings, number of buildings with identifiers,
and number of pieces of street furniture—is more significant than any of the standard D variables. Streetscape design features have almost the same explanatory power as proportion of retail frontage, the variable most predictive of pedestrian counts. This is a novel finding that suggests that urban design generally, and streetscapes in particular, have a powerful influence on pedestrian activity.

What are the implications for planning practice? First, context is important, particularly FAR and population density, within a quarter mile of commercial streets. Zoning can be amended to achieve high values of each of these variables. Accessibility to rail transit can have positive impact on street life. In addition, streets themselves should have high FARs and predominantly retail frontage.

From the perspective of urban design practice, it is important to know which streetscape futures have significant relationship to pedestrian activity and how to operationalize these features. In this research, active uses are defined as shops, restaurants, public parks, and other uses that generate significant pedestrian traffic. Inactive uses include blank walls, driveways, parking lots, vacant lots, abandoned buildings, and offices with no apparent activity. In regard to residential uses, when the density is more than 10 units per acre, we assume that the land use is active. Street walls are defined as continuous walls or building facades adjacent to the sidewalk. Facades set back behind parking lots or lawn and driveways do not count as street walls. Street furniture is defined as all kinds of signs, benches, parking meters, trash cans, newspaper boxes, bollards, street lights, and so forth, anything at human scale that increases the complexity of the street. “Buildings with identifiers” are defined as those whose use can be determined by building features. For example, a church can be identified by a steeple. Stores can be identified by signs that are easily recognized.

The six streetscape features that proved to be significantly related to pedestrian activities are most often defined and prescribed in urban design guidelines and land development codes. For example, “windows as a percentage of ground floor façade” is a common operational definition of transparency. Promoting active uses, creating continuous streetwalls, and providing urban furniture are also common strategies in urban design guidelines. “Proportion of historic buildings” is related to the concept of urban preservation and “buildings with identifiers” is related to the concept of imageability.

A first step for any collaboration is finding common language. To achieve a common language, codes will need to be restructured in a more fundamental way. What comes to mind are the requirements and restrictions of form-based codes.

One of the best known and most successful applications of form-based codes is in Arlington County, VA’s Columbia Pike Special Revitalization District. The form-based code requires that buildings be built to a required building line adjacent to the property line and sidewalk. The street is thus a “coherent space, with consistent building forms on both sides of the street.” Generally, retail uses are required on the ground floor of main street sites. “Retail” is broadly defined to include comparison retail stores, convenience retail stores, personal business services, professional offices, restaurants, grocery stores, and hotel, theater, and other uses that “provide visual interest and create active street life.” Main street building facades are required to have 60 to 90 percent fenestration (measured as a percentage of the facade that is between 2 and 10 feet above the fronting sidewalk). Upper story facades are required to have 30 to 70 percent fenestration (measured for each story as a percentage of the façade that is between 3 and 9 feet above the finished floor).
We conclude by acknowledging limitations of this study both in validity and reliability. Obviously, New York City is unique among cities in the U.S., which limits the external validity of our findings. While wide swaths of the city, including much of Staten Island and the North Bronx are suburban in nature, New York City is overwhelmingly urban. Four of five counties that comprise the city rank as the four most compact counties in the nation (Ewing et al., 2003). The metropolitan area has by far the highest walk mode share, 21.4 percent, of any large metropolitan area (National Household Travel Survey, 2009). Our first research recommendation would be to repeat this validation study in more typical cities.

The main threat to the reliability of our results is the limited counts done on each block face. The day and time of the counts were variable. Only four counts were done on each block face, as field observers walked up and down the block face. Our second research recommendation would be to conduct longer standardized counts on each street segment in any future study. If replicated we believe that this study and its progeny will provide urban planners and urban designers with some of the clearest and most compelling guidance yet available for creating vibrant street life.
REFERENCES


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