A simplified measure of streetscape enclosure for examining built environment influences on walking

Abstract: Urban design is broadly recognized as an important influence on walking, but measuring design variables that impact walkers from a street-level perspective, and integrating these variables into travel analyses, remains a substantial challenge. Design is often characterized by measures of street network accessibility, which can be easily calculated from centerline datasets. These measures do not, however, account for more finely grained aspects of streetscape morphology that may influence walkers' perceptions of safety, comfort, or interest. Urban design literature discusses numerous variables that may contribute to pedestrian-friendly places, but they are often difficult to define and inefficient to measure, posing challenges for incorporation into travel analyses. In order to facilitate more widespread investigation of streetscape-scale variables, I propose a simplified approach for measuring enclosure, a morphological property influenced by proximity to buildings, which is widely discussed by urban designers. This methods paper discusses the rationale for a simplified measure of enclosure, defines a measure of enclosure based on *building distance*, and reports on exploratory analyses that relates building distance to existing built environment measures and mode shares across 94 U.S. urban areas. Results suggest that building distance is moderately independent of common built environment variables, but relationships with walking mode share vary substantially between urban areas and have unexpected signs in some areas. This encourages further research investigating how enclosure influences walking in conjunction with other built environment variables, and how these patterns vary regionally or according to other patterns.

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1 Introduction

Walking as a mode of travel is widely understood to be influenced by built environment design. Transportation and land use researchers commonly use urban design variables such as intersection density, proportion of four-way intersections, and block length—the design component of Cervero & Kockelman's (1997)'s D variables—as core inputs to walking and related travel analyses (Ewing & Cervero, 2010). Urban design literature, however, suggests that more finely grained variables related to streetscape morphology influence how pedestrians perceive safe, interesting, or otherwise satisfactory spaces (Ewing & Handy, 2009). Enclosure, the degree to which streetscapes are surrounded by vertical objects such as buildings—is widely discussed by urban designers as a key ingredient for pedestrian-oriented streetscapes (Ewing & Handy, 2009). Nonetheless, enclosure and other streetscape-scale variables are not typically incorporated into travel analyses, likely owing to the difficulty of defining them precisely and measuring them efficiently.

This methods paper examines the potential to operationalize streetscape enclosure through a simple measure; collect these measurements efficiently across large samples of streetscapes; and incorporate them into an analysis of walking behavior. In doing so, it lays the groundwork for more extensive investigations of how enclosure and other streetscape-scale variables affect walking and related modes such as transit, bicycling, and micromobility. My proposed enclosure measure leverages the substantial influence of building proximity on streetscape enclosure. Buildings with minimal setbacks and spacing between them contribute to greater enclosure, while larger setbacks, greater spacing, or fewer buildings contribute to less enclosure. By calculating the distance to the nearest building from regularly spaced points along street centerlines, and averaging these distances within areal units, it may be possible to approximate streetscape enclosure with widely available data, computational efficiency, and in terms that are straightforward to define and explain. Moreover, this measure is simultaneously sensitive to several morphological factors that impact enclosure—building size, quantity, spacing, setback distance, and orientation—reducing a multidimensional concept into a single ratio variable. While this measure is far too coarse for detailed analyses or planning, I hope that it may offer a foothold for streetscape-scale design to be incorporated into travel analyses alongside existing D variables, which similarly offer simplified characterizations of complex built environmental qualities

In the remainder of this paper, I briefly review how enclosure is defined and operationalized in existing research, describe my simplified measurement approach, and conduct an exploratory analysis with a large sample of U.S. urban areas. Results show that enclosure is moderately independent of D variables and explains additional variability in walking commute mode share aggregated at the block group level, though these effects vary substantially between urban areas and are largely inconsistent with prevailing theory about the relationship between enclosure and walking. This suggests substantial opportunities for investigating these effects with more sophisticated analyses and differences in effects between urban areas.

2 What is Enclosure?

Many urban design theorists describe the importance of enclosed streetscapes for providing pedestrian-friendly urban environments (Alexander, Ishikawa, & Silverstein, 1977; Arnold, 1993; Blumenfeld, 1971; Cullen, 1961; Jacobs, 1993; Lynch, 1981). A common approach to explaining enclosure is that it produces the sensation of an "outdoor room," in which buildings or other large vertical objects, such as trees, may form walls, and the horizontal area of a street provides a floor. Ceiling height may be indicated by consistently aligned cornices, or more concretely, but overhanding awnings or tree branches. Cullen (1961) suggests that "enclosure, or the outdoor room, is, perhaps, the most powerful, the most obvious, of all the devices to install a sense of position, of identity with the surroundings … it embodies the idea of hereness." In part, this is because enclosure provides definition to outdoor spaces that make them legible as spatial entities: "I am outside IT, I am entering IT, am in the middle of IT" (p. 29). Enclosure provides the spatial foundation for referring to streets as coherent spaces. Jacobs (1993) also notes that pedestrians appear to be attracted to enclosure and the vertical edges that delineate it. This observation is consistent with by Appleton's (1975) prospect-refuge theory, which suggests that some degree of enclosure is essential for providing a sense of protective cover. As Cullen dryly notes, "I am enclosed or I am exposed" (p. 29).

Despite these powerful characterizations, enclosure remains imprecisely defined and there is no single, commonly agreed-upon measure. Some urban designers have offered quantified guidelines for the streetscape proportions and dimensions that may provide enclosure, the most popular of which may be the cross-sectional ratio of building height to cross-street width. Ratios ranging from 1:1 and 1:3 are offered as guidelines for pedestrian-friendly streetscapes, but there is little empirical evidence substantiating an optimum (Alexander, Ishikawa, & Silverstein, 1977; Jacobs, 1993). In earlier work, I developed a computational approach for measuring cross-sectional ratio, but it relied on detailed building height data and a complex appraoch for approximating cross-street width along streetscapes without consistent building frontages (Harvey, Aultman-Hall, Troy, & Hurley, 2016). Moreover, because streetscape width is defined a the distance between opposing façades, it has no clear definition in the common circumstance where there are no buildings along one side.

A survey of urban design literature by Ewing and Handy (2009) identifies potential measures for enclosure based on the proportion of a block face with a façade along it, the proportion of visible sky, and the number of long sight lines. Purciel et al. (2009) operationalize some of these measures computationally, but they rely heavily on detailed datasets specific to their New York City study area. Similar to my earlier method described above (Harvey et al., 2016), they also confront challenges related to operational definitions of geometric entities and relations, such as whether a façade aligns with a block face, that would be fairly easy for a human analyst to gauge qualitatively, but present a substantial challenge for formal definition in a computational environment. These definitional challenges suggest that simplified measures that do not directly emulate qualitative measurements may be the most effective approach for measuring streetscapes computationally.

3 *Building Distance* as a Simplified Measure of Enclosure

To address the need for an enclosure measure that is easily explained, precisely defined, and efficiently computed from widely available datasets, I propose an approach based on the distance between sampling points along street centerlines and the nearest building. The approach relies on just two data inputs—street centerlines and building footprints—that are increasingly ubiquitous. Operationalizing the method involves three steps:

1. **Construct sampling points along street centerlines.** For the exploratory analysis described in the next section, I spaced sampling points evenly at 10-meter intervals. To increase analytical precision, they could be spaced more closely, or spaced farther apart to increase computational efficiency. Points might also be spaced randomly. Further research could investigate the sensitivity of results to different spacing.
2. **Measure the *building distance* between each sampling point and the closest point along a building footprint.** For the exploratory analysis, I limited computational burden by limiting the search to buildings within 200 meters, an arbitrary value intended to reflect an extreme lack of enclosure. Sampling points with no building within 200 meters were assigned this maximum distance. Sampling points were also limited to finding closest buildings that did not require crossing a street centerline, preserving an assumption that a streetscape enclosure is only affected by buildings within blocks to either side.
3. **Aggregate building distances.** In the exploratory analysis, I average building distances among all sampling points within U.S. Census block groups in order to coordinate with other built environment variables and travel statistics reported at that level. Future work might aggregate within block length street segments for more finely grained analysis of travel patterns, such as route choices. Examining sensitivity to different aggregation approaches and units is another potential area for future research.

Figure 1 shows sampling points spaced at ten-meter intervals along street centerlines with lines drawn to the nearest building. The lengths of these lines represent the *building distance* measure.

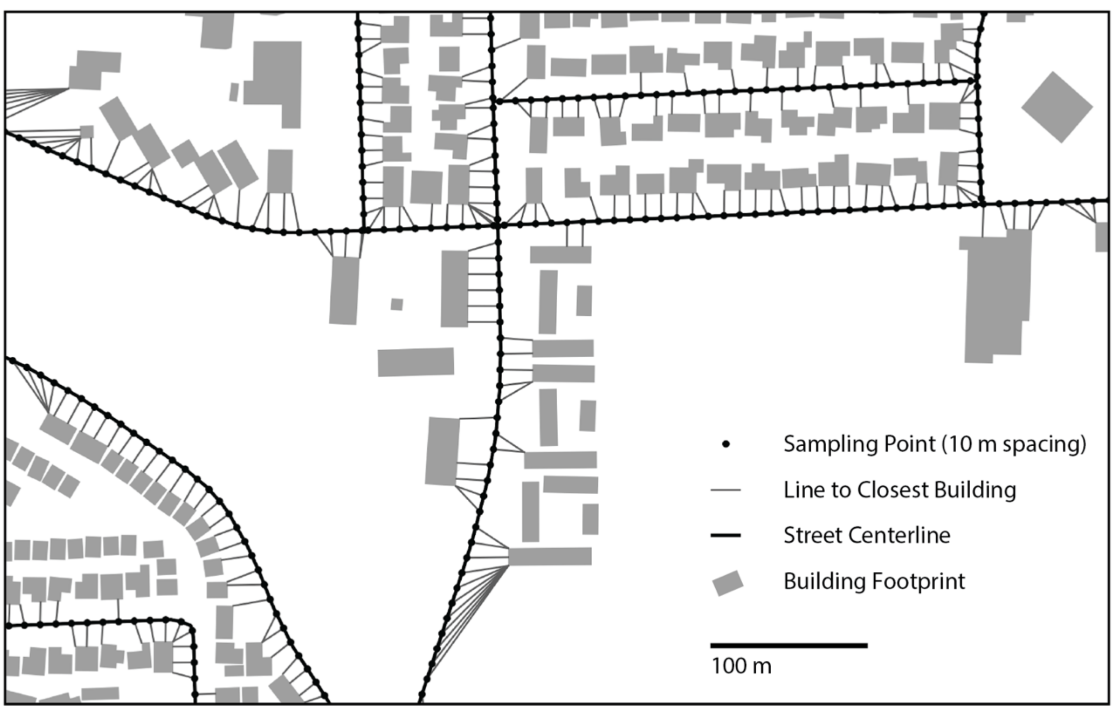

Figure 1. Example of sampling points along street centerlines with lines drawn to closest building footprints.

There is substantial potential to refine this measurement, including potential to discriminate between closest buildings along either side of a street in order to investigate how enclosure along only one side or both sides might influence user experience. The angles of lines connecting sampling points to closest buildings might be analyzed as a measure of façade continuity. If the line to the closest building is non-perpendicular to the centerline, it would indicate a façade gap. Sampling points might also be constructed in a way that distributes them more randomly, since street centerlines may not run precisely down the center of a street, and may, therefore, bias measurements to one side or the other. Such an approach might introduce substantial geoprocessing complexity, so I chose to assume that error in centerline position was randomly distributed across study areas such biases were random.

4 Exploratory Analysis

Data

In order to demonstrate this method and explore its potential for explaining walking behavior alongside more conventional built environment variables, I calculated building distances across 94[1] U.S. Census urban areas that represented diverse sizes, geographies, and built environments. Sampling points were spaced at 10-meter intervals along every street centerline, excluding freeways and off-street trails, available from OpenStreetMap within each of these urban areas. OpenStreetMap data were accessed using OSMnx (Boeing, 2017).

The U.S.-wide building footprint dataset now freely available from Microsoft (2019) allowed for consistent measurements of building distances across every urban area. The Microsoft footprints, derived from machine interpretation of areal imagery, are imprecise compared with building footprint datasets from many local agencies, but offer the benefit of consistent measurements across the diverse study areas.

Building distances at individual sampling points were averaged across 2010 U.S. Census block groups. Block groups with less than 90% of their area within an urban area were excluded in order to minimize analysis of undeveloped areas at urban area edges. Block group-level data from the EPA Smart Location Database were joined to the building distance averages in order to compare them with more conventional built environment measures. Commute mode share statistics from the American Community Survey 2017 5-year averages were also joined to the block group records, summarized as percent of commutes by walking and percent of commutes by walking & transit, based on the assumption that a large proportion of transit users walk to stations. All U.S. Census data were obtained from NHGIS (Manson, 2019).

[1] These 94 urban areas represent the largest 100 U.S. urban areas with the exception of Dallas—Forth Worth—Arlington, Houston, Miami, New York—Newark, Philadelphia, and Washington, D.C., which I was unable to process prior to the submission deadline due to a technical malfunction. I plan to update this manuscript to include these additional urban areas if I am invited to present or revise and resubmit.

Analysis Methods

Within each urban area, Pearson correlations were calculated between building distance and a suit of likely correlates: walking and walking & transit mode share, and built environment variables representing each of the 5Ds that are more commonly associated with travel behavior: population density (*density*), land use entropy (*diversity*), intersection density (*design*), distance to the nearest transit stop (*distance to transit*), and 45-minute job accessibility (*destination accessibility*).

Ordinary least square (OLS) regression models were also used to regress walking mode share on building distance while controlling for the aforementioned built environment variables. For each urban area, one model was estimated with a building distance term, while another excluded this term to serve as a null comparison. Coefficients of determination (R^2) were compared between the models to examine the additional explanatory power of building distance.

Because many of the built environment and mode share variables had non-normal distributions, and this analysis was primarily intended to examine relationship directions, not precise effect sizes, confidence intervals on parameter estimates were not calculated or used as evaluation criteria. Further research should investigate data transformations and model structures that are more suitable for precise estimates of effect sizes and errors.

All data processing and calculations were coded in Python with open-source packages. Geoprocessing, statistical analyses were enabled by the Geopandas, Shapely, OSMnx, and StatsModels packages, as well as customized tools from my StreetSpace package.

Results

Distributions of building distance varied substantially between the 96 urban areas (Figure 1). Predominant building distances within most urban areas were between 20 and 40 meters, with cases above 70 meters quite rare in most areas. Clusters of similar distributions appeared to be organized regionally. Western urban areas, including Los Angeles; Salt Lake City; Portland, OR; Seattle; Layton, UT; and Stockton, CA, formed the cluster of distributions with large peaks around 20 meters, suggesting that streetscape enclosure was fairly high (indicated by low building distances), and also fairly consistent, within each of these urban areas. By contrast, southeastern urban areas, including Raleigh; Winston-Salem; Greenville; Augusta—Richmond, GA; and Chattanooga, tended to have shallower distributions peaking around 35 meters. This suggested that southeast streetscapes had more varied degrees of enclosure and also lower enclosure (larger building distances) overall. Honolulu represented the extreme end of variability in building distance, suggesting that it offered substantial heterogeneity in streetscape enclosure across the urban area. Identifying and understanding regional patterns in these distributions offers a substantial opportunity for further research.

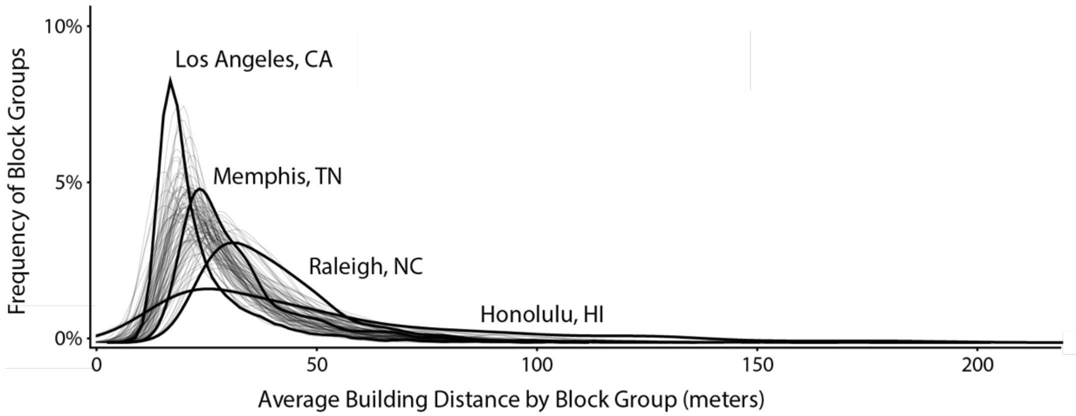

Figure 2. Overlaid frequency distributions of average building distance by block group. One distribution, representing frequency of block groups as a percentage of block groups within a given urban area, is drawn for each urban area. Urban areas that demonstrate contrasting distributions are highlighted.

Results from correlation analyses suggested that building distance were moderately associated with walking mode share and other built environment variables, though not entirely as expected. Figure 3 shows frequency distributions of Pearson correlations between building distance and comparison variables. Each distribution is for a single comparison variable, and each accounts for correlation coefficients across all 96 urban areas.

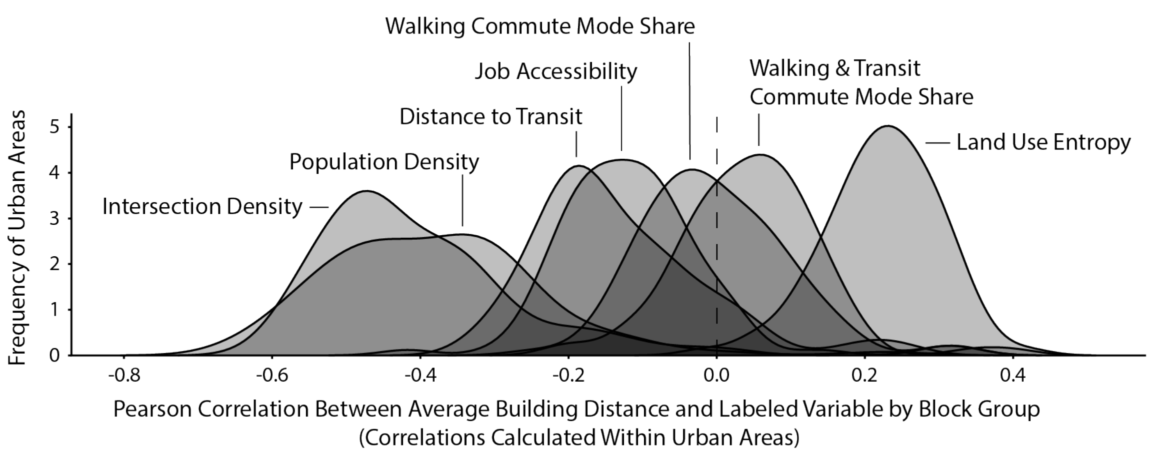

Figure 3. Frequency distributions of Pearson correlations between average building distance and mode share or built environment variables within each urban area. One distribution, representing frequency of urban areas as a count, is draw for each pairwise correlation. Distributions are independently calculated but are presented on the same axis for space economy.

Urban design literature proposes that greater enclosure, indicated by lower building distance, is more conducive to walking, so we would expect a negative correlation between building distance and walking mode share. This expectation is upheld within many urban areas, as indicated by the distribution marked "Walking Commute Mode Share" in Figure 3. Nonetheless, a large proportion of urban areas feature a positive correlation with walking mode share, suggesting either that building distance does not adequately represent the influence of enclosure, or that enclosure is not, on its own, clearly associated with commuting by walking. The distribution for "Walking & Transit

Commute Mode Share" is even less consistent with the expectation of a negative correlation. Examining what differentiates urban areas with positive and negative correlations is a possible area for future research.

Correlations between building distances and other built environment variables were low to moderate in magnitude, suggesting that building distance, and the underlying property of enclosure, offers a fairly independent measure of urban form. Correlations with intersection density, commonly used as an indicator of "design," were somewhat higher than those with other built environment variables, but still generally less than -0.5. The signs of correlations with built environment variables were generally consistent with expectations. Lower building distance reflects greater built environment density, so negative correlations with intersection density, population density, and distance to transit and employment metrics were expected. It was interesting that correlations with land use entropy were generally positive, but this may reflect greater enclosure in predominantly residential areas and lower enclosure in non-downtown commercial areas. A more detailed analysis of associations between building distance and land uses would be useful for interpreting this result.

Regression models that examined relationships between building distance and walking mode share while controlling for other built environment variables also yielded somewhat unexpected results. In models that included a building distance term, parameter estimates for this variable were predominantly positive (see table in Appendix 1). This indicates that, all else equal, less enclosed streetscapes were associated with greater walking mode share. While counterintuitive, this suggests that enclosure may have poorly understood influences on walking in places where enclosure and other built environment variables are combined in unusual ways. These results may also have been impacted by the narrow focus of census statistics on walking for commuting while excluding walking for other purposes, including recreation. Further research ought to refine this analysis with more sophisticated models, interactions between built environment variables, and more robust representations of walking behavior.

Comparisons model fit between OLS models with and without building distance terms suggested that marginal effects of enclosure on walking behavior varied substantially between different urban areas (see table in Appendix 1). At the extreme end of distribution, R^2 in the Columbia, SC urban area increased by 0.22 with the addition of the building distance term. In many other urban areas, building distance added no explanatory power. Given the simplicity of these models, effect sizes and fit statistics should be interpreted cautiously, but investigating variation in effect sizes and model fit could be fruitful area for further research.

5 Conclusions

Urban design theory suggests that accounting for streetscape-scape design variables in travel analyses offers substantial potential to better account of walking and other modes where user experiences are directly influenced by design contexts. Once such variable, enclosure, may efficiently approximated by sampling distances to building footprints, and increasingly common urban dataset. This paper describes how such a simplified measure, *building distance*, can be calculated, and explores whether it accounts for additional variability in urban form and walking mode share. Results suggest that building distance is fairly independent from more traditional built environment variables and may have substantially different relationships with walking behavior depending on context, including relationships that are counterintuitive to prevailing theory. There are myriad avenues for further research to refine the building distance measure, more precisely identify its relationship with travel behavior, and examine how these relationships are organized by geographic region or other contextual factors.

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Appendix 1 – Statistics by Urban Area

Column Definitions

Analysis Units

Points: Count of analysis points along street centerlines at which the distance to closest building was measured

Block Groups: Count of block groups within distances to closest building were averaged

Pearson Correlation with Distance to Closest Building (block group unit of analysis)

Walk + Transit Mode Share: Proportion of commutes made by walking and transit (2015-2017 American Community Survey)

Walk Mode Share: Proportion of commutes made by walking (2015-2017 American Community Survey)

Pop. Dens.: Gross population density (people/acre) (EPA Smart Location Database)

L.U. Entr.: Emplyment and household entropy (EPA Smart Location Database)

Int. Dens.: Street intersection density without auto-oriented intersections (EPA Smart Location Database)

Transit Dist.: Distance from population weighted block group centroid to nearest transit stop (EPA Smart Location Database)

Job Accs.: Jobs within 45 minutes auto travel time, decay weighted (EPA Smart Location Database)

OLS Regression (block group unit of analysis)

$\beta_{Dist.}$: Parameter estimate for building distance while regressing walking mode share on building distance, population density, land use entropy, intersection density, distance to transit, job accessibility, and a constant intercept.

ΔR^2: Difference in R^2 between models that include a building distance term and a comparison model without it. Both models include terms for population density, land use entropy, intersection density, distance to transit, job accessibility, and a constant intercept.

	Analysis Units		Pearson Correlations with Building Distance							OLS Regression	
Urban Area (sorted by correlation between Walk + Transit Mode Share and Building Distance)	**Points**	**Block Groups**	**Walk + Transit Mode Share**	**Walk Mode Share**	**Pop. Dens.**	**L.U. Entr.**	**Int. Dens.**	**Transit Dist.**	**Job Accs.**	$\beta_{Dist.}$	ΔR^2
Lancaster, PA	200291	187	-0.24	-0.20	-0.53	0.15	-0.57	-0.11	-0.14	-0.04	0.00
Allentown, PA--NJ	422462	390	-0.17	-0.12	-0.44	0.26	-0.51	-0.20	-0.06	0.01	0.00
Port St. Lucie, FL	374409	186	-0.15	-0.11	-0.46	0.36	-0.51		-0.08	-0.02	0.00
Harrisburg, PA	306185	254	-0.15	-0.03	-0.55	0.11	-0.55	-0.02	-0.22	0.18	0.04
Madison, WI	205686	202	-0.13	-0.20	-0.26	0.16	-0.48	-0.21	-0.11	0.08	0.00
Milwaukee, WI	931459	1106	-0.13	-0.03	-0.46	0.32	-0.37	-0.23	-0.18	0.06	0.01
Seattle, WA	1950821	2119	-0.12	-0.01	-0.28	0.21	-0.36	-0.17	-0.17	0.08	0.00
New Haven, CT	370784	417	-0.12	-0.12	-0.39	0.20	-0.45	0.01	-0.20	0.12	0.01
San Francisco--Oakland, CA	1284921	2247	-0.11	-0.04	-0.26	0.19	-0.18	-0.07	-0.12	0.03	0.00
Louisville/Jefferson County, KY--IN	674946	660	-0.11	-0.01	-0.51	0.24	-0.29	-0.23	-0.18	0.08	0.01

Urban Area (sorted by correlation between Walk + Transit Mode Share and Building Distance)	Analysis Units		Pearson Correlations with Building Distance							OLS Regression	
	Points	Block Groups	Walk + Transit Mode Share	Walk Mode Share	Pop. Dens.	L.U. Entr.	Int. Dens.	Transit Dist.	Job Accs.	$\beta_{Dist.}$	ΔR^2
Charleston--North Charleston, SC	408188	275	-0.11	-0.12	-0.44	0.21	-0.46		-0.09	0.07	0.01
Murrieta--Temecula--Menifee, CA	224386	148	-0.11	-0.09	-0.49	0.22	-0.59	-0.18	-0.19	-0.01	0.00
Reno, NV--CA	250567	244	-0.11	-0.05	-0.45	0.15	-0.52	-0.29	-0.19	0.01	0.00
Baltimore, MD	1210111	1554	-0.10	-0.05	-0.28	0.22	-0.24	-0.14	-0.01	0.02	0.00
Tucson, AZ	596676	518	-0.10	0.00	-0.45	0.12	-0.36		-0.23	0.09	0.01
Grand Rapids, MI	374309	335	-0.09	0.08	-0.58	0.26	-0.58		-0.42	0.16	0.05
Hartford, CT	588290	621	-0.09	-0.03	-0.36	0.25	-0.42		-0.10	0.06	0.00
Nashville-Davidson, TN	678009	543	-0.09	-0.07	-0.37	0.24	-0.20	0.02	-0.17	0.06	0.01
Rochester, NY	418758	539	-0.08	0.09	-0.57	0.26	-0.48	-0.27	-0.18	0.21	0.03
St. Louis, MO--IL	1621605	1431	-0.08	0.01	-0.46	0.22	-0.32	-0.20	-0.13	0.07	0.01
Poughkeepsie--Newburgh, NY--NJ	289011	260	-0.07	-0.02	-0.50	0.05	-0.56	-0.06	-0.21	0.22	0.04
Chicago, IL--IN	4436333	5904	-0.07	0.06	-0.14	0.20	-0.03	-0.18	-0.08	0.03	0.00
Columbus, OH	860908	920	-0.07	-0.06	-0.36	0.32	-0.35	-0.24	-0.17	0.06	0.01
Richmond, VA	775364	526	-0.07	-0.01	-0.33	0.30	-0.48		-0.15	0.09	0.01
Atlanta, GA	3514229	2013	-0.07	-0.01	-0.28	0.29	-0.31	-0.19	-0.20	0.08	0.01
Augusta-Richmond County, GA--SC	296264	192	-0.07	-0.05	-0.46	0.31	-0.43		-0.20	0.13	0.02
Fresno, CA	394915	387	-0.06	0.02	-0.43	0.16	-0.43		-0.17	0.02	0.00
Ogden--Layton, UT	315390	270	-0.06	0.01	-0.62	0.21	-0.56	-0.16	-0.07	-0.03	0.00
Mission Viejo--Lake Forest--San Clemente, CA	307304	357	-0.06	-0.05	-0.33	0.22	-0.37	-0.04	0.02	-0.01	0.00
Worcester, MA--CT	289262	296	-0.06	-0.05	-0.46	0.25	-0.49	0.04	-0.01	0.19	0.04
Denton--Lewisville, TX	258318	208	-0.05	-0.04	-0.34	0.28	-0.54	0.24	0.33	0.03	0.02
Minneapolis--St. Paul, MN--WI	1910009	1857	-0.04	0.05	0.00	0.33	-0.30	-0.23	-0.15	0.03	0.00
Bakersfield, CA	277940	267	-0.04	0.01	-0.55	0.25	-0.48	-0.18	-0.14	0.08	0.04
Denver--Aurora, CO	1531321	1602	-0.04	-0.01	-0.30	0.25	-0.32	-0.16	-0.15	0.02	0.00
Boston, MA--NH--RI	2574067	2989	-0.03	0.07	-0.18	0.19	-0.18	-0.20	-0.04	0.07	0.00
Baton Rouge, LA	430727	302	-0.03	0.01	-0.34	0.31	-0.37		-0.06	0.04	0.01
Memphis, TN--MS--AR	745953	635	-0.03	0.01	-0.33	0.23	-0.39	0.03	-0.18	0.04	0.01
Buffalo, NY	550316	778	-0.03	0.07	-0.44	0.16	-0.25	-0.24	-0.29	0.16	0.04
Akron, OH	409508	431	-0.03	0.05	-0.40	0.23	-0.57		-0.24	0.11	0.01
Birmingham, AL	680630	482	-0.03	-0.01	-0.37	0.29	-0.43	-0.16	-0.10	0.06	0.01
Albany--Schenectady, NY	391822	426	-0.02	0.04	-0.48	0.27	-0.42	-0.30	-0.06	0.35	0.06
Los Angeles--Long Beach--Anaheim, CA	4472682	7780	-0.02	0.04	-0.26	0.17	-0.18	-0.11	-0.09	0.07	0.01
San Antonio, TX	1061806	1065	-0.02	0.10	-0.50	0.23	-0.47		-0.24	0.04	0.01
Austin, TX	803476	665	-0.02	-0.05	-0.31	0.22	-0.40	-0.15	-0.15	0.07	0.02
Cape Coral, FL	764865	392	-0.02	0.07	-0.44	0.18	-0.43	-0.25	-0.04	0.01	0.00

	Analysis Units		Pearson Correlations with Building Distance							OLS Regression	
Urban Area (sorted by correlation between Walk + Transit Mode Share and Building Distance)	**Points**	**Block Groups**	**Walk + Transit Mode Share**	**Walk Mode Share**	**Pop. Dens.**	**L.U. Entr.**	**Int. Dens.**	**Transit Dist.**	**Job Accs.**	$\beta_{Dist.}$	ΔR^2
Sarasota--Bradenton, FL	685815	419	-0.02	0.00	-0.50	0.11	-0.51	-0.22	-0.13	0.02	0.00
Syracuse, NY	263969	305	-0.02	0.08	-0.49	0.34	-0.47		-0.19	0.31	0.04
Orlando, FL	930748	550	-0.02	-0.01	-0.23	0.25	-0.46		-0.09	0.02	0.00
Palm Bay--Melbourne, FL	412564	231	-0.02	0.06	-0.55	0.34	-0.50	-0.07	0.14	0.02	0.00
Tampa--St. Petersburg, FL	1934371	1687	-0.02	0.06	-0.29	0.24	-0.45	-0.18	-0.08	0.04	0.01
Cleveland, OH	1085732	1393	-0.01	0.04	-0.31	0.26	-0.33	-0.23	-0.11	0.10	0.01
Providence, RI--MA	833532	865	-0.01	0.03	-0.50	0.28	-0.53	-0.22	-0.25	0.18	0.03
Phoenix--Mesa, AZ	2486010	2296	0.00	0.06	-0.31	0.17	-0.38	0.02	-0.16	0.04	0.01
McAllen, TX	413726	252	0.01	0.04	-0.64	-0.02	-0.55		-0.23	0.05	0.02
Chattanooga, TN--GA	370378	228	0.01	0.10	-0.53	0.15	-0.48		-0.17	0.08	0.01
Detroit, MI	2732811	3222	0.02	0.06	-0.45	0.27	-0.29	-0.08	-0.05	0.03	0.00
Des Moines, IA	290614	279	0.02	0.03	-0.61	0.36	-0.48		-0.22	0.09	0.04
Winston-Salem, NC	363309	226	0.02	0.11	-0.36	0.06	-0.41		-0.19	0.15	0.04
Raleigh, NC	669308	369	0.02	0.02	-0.31	0.11	-0.50	-0.19	-0.19	0.08	0.02
Dayton, OH	536095	486	0.02	0.03	-0.55	0.19	-0.49		0.01	0.15	0.03
Jacksonville, FL	797459	526	0.02	0.09	-0.31	0.22	-0.37	0.05	-0.10	0.08	0.03
Pittsburgh, PA	1270960	1300	0.02	0.09	-0.34	0.18	-0.34	-0.15	0.00	0.18	0.03
Indianapolis, IN	1101595	792	0.03	0.13	-0.45	0.26	-0.36	-0.18	-0.10	0.08	0.02
Toledo, OH--MI	351561	404	0.03	0.14	-0.54	0.29	-0.44		-0.15	0.07	0.01
Cincinnati, OH--KY--IN	1039390	1114	0.05	0.07	-0.38	0.20	-0.15	-0.19	-0.08	0.15	0.04
Kansas City, MO--KS	1211079	1073	0.05	0.08	-0.39	0.20	-0.26	-0.10	-0.03	0.06	0.02
Sacramento, CA	995547	1017	0.05	0.09	-0.12	0.29	-0.45	-0.17	-0.12	0.03	0.01
Wichita, KS	348665	318	0.05	0.08	-0.39	0.22	-0.55		-0.09	0.02	0.00
Springfield, MA--CT	379831	380	0.05	0.09	-0.32	0.13	-0.48	-0.20	-0.12	0.18	0.02
Little Rock, AR	336827	244	0.05	0.10	-0.61	0.31	-0.54	-0.29	-0.20	0.07	0.01
Portland, OR--WA	1081712	1112	0.06	0.18	-0.31	0.30	-0.32	-0.17	-0.13	0.19	0.03
Concord, CA	351499	331	0.06	0.02	-0.10	0.14	-0.35	-0.22	0.03	0.03	0.00
El Paso, TX--NM	459013	458	0.07	0.03	-0.54	0.25	-0.47		-0.15	0.11	0.04
San Diego, CA	1330484	1671	0.07	0.18	-0.29	0.29	-0.31	-0.16	-0.06	0.07	0.02
Bridgeport--Stamford, CT--NY	633315	632	0.07	0.10	-0.42	0.14	-0.47	-0.01	-0.14	0.17	0.02
Charlotte, NC--SC	965848	621	0.07	0.15	-0.28	0.11	-0.35	-0.05	-0.11	0.08	0.04
Las Vegas--Henderson, NV	1138494	1222	0.08	0.12	-0.34	0.27	-0.35	-0.19	-0.07	0.08	0.02
Greenville, SC	338638	186	0.08	0.07	-0.27	0.17	-0.49	0.23	-0.24	0.11	0.03
San Jose, CA	715933	1015	0.08	0.07	-0.13	0.20	-0.11	0.18	0.01	0.03	0.00
Omaha, NE--IA	577556	641	0.09	0.11	-0.51	0.24	-0.51		-0.13	0.07	0.02

	Analysis Units		Pearson Correlations with Building Distance							OLS Regression	
Urban Area (sorted by correlation between Walk + Transit Mode Share and Building Distance)	**Points**	**Block Groups**	**Walk + Transit Mode Share**	**Walk Mode Share**	**Pop. Dens.**	**L.U. Entr.**	**Int. Dens.**	**Transit Dist.**	**Job Accs.**	$\beta_{Dist.}$	ΔR^2
Riverside--San Bernardino, CA	939627	948	0.09	0.12	-0.47	0.17	-0.48	-0.03	0.02	0.07	0.02
Tulsa, OK	485032	385	0.09	0.05	-0.38	0.25	-0.54		-0.13	0.07	0.03
Colorado Springs, CO	373123	297	0.11	0.13	-0.44	0.29	-0.52	-0.11	-0.17	0.06	0.03
Albuquerque, NM	557371	446	0.11	0.12	-0.35	0.12	-0.43	-0.08	-0.08	0.08	0.02
Spokane, WA	269714	241	0.11	0.15	-0.51	0.30	-0.48	-0.31	-0.08	0.16	0.03
Oklahoma City, OK	696948	683	0.12	0.11	-0.53	0.20	-0.37		-0.04	0.08	0.04
Virginia Beach, VA	989190	949	0.13	0.15	-0.20	0.29	-0.39	-0.08	-0.06	0.10	0.04
Provo--Orem, UT	266461	274	0.15	0.15	-0.23	0.05	-0.43	-0.09	-0.08	0.18	0.06
New Orleans, LA	631433	860	0.15	0.13	-0.35	0.20	-0.10	-0.10	0.03	0.16	0.04
Stockton, CA	169349	205	0.15	0.13	-0.42	0.32	-0.46	-0.22	-0.01	0.12	0.04
Knoxville, TN	493528	249	0.17	0.18	-0.19	0.42	-0.47		-0.05	0.23	0.10
Salt Lake City--West Valley City, UT	596698	585	0.18	0.18	-0.31	0.19	-0.34	-0.17	-0.11	0.19	0.06
Columbia, SC	448671	290	0.31	0.34	-0.28	0.17	-0.53		-0.19	0.53	0.22
Urban Honolulu, HI	248899	457	0.32	0.40	0.23	0.22	0.01	-0.11	0.30	0.06	0.02