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Travel and the Built Environment

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Travel and the Built Environment

A Meta-Analysis

Reid Ewing and Robert Cervero

Problem: Localities and states are turning to land planning and urban design for help in reducing automobile use and related social and environmental costs. The effects of such strategies on travel demand have not been generalized in recent years from the multitude of available studies.

Purpose: We conducted a meta-analysis of the built environment-travel literature existing at the end of 2009 in order to draw generalizable conclusions for practice. We aimed to quantify effect sizes, update earlier work, include additional outcome measures, and address the methodological issue of self-selection.

Methods: We computed elasticities for individual studies and pooled them to produce weighted averages.

Results and conclusions: Travel variables are generally inelastic with respect to change in measures of the built environment. Of the environmental variables considered here, none has a weighted average travel elasticity of absolute magnitude greater than 0.39, and most are much less. Still, the combined effect of several such variables on travel could be quite large. Consistent with prior work, we find that vehicle miles traveled (VMT) is most strongly related to measures of accessibility to destinations and secondarily to street network design variables. Walking is most strongly related to measures of land use diversity, intersection density, and the number of destinations within walking distance. Bus and train use are equally related to proximity to transit and street network design variables, with land use diversity a secondary factor. Surprisingly, we find population and job densities to be only weakly associated with travel behavior once these other variables are controlled.

Takeaway for practice: The elasticities we derived in this meta-analysis may be used to adjust outputs of travel or activity models that are otherwise insensitive to variation in the built environment, or be used in sketch planning applications ranging from climate action plans to health impact assessments. However, because sample sizes are small, and very few studies control for residential preferences and attitudes, we cannot say that planners should generalize broadly from our results. While these elasticities are as accurate as currently possible, they should be understood to contain unknown error and have unknown confidence intervals. They provide a base, and as more built-environment/travel studies appear in the planning literature, these elasticities should be updated and refined.

Keywords: vehicle miles traveled (VMT), walking, transit, built environment, effect sizes

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Some of today's most vexing problems, including sprawl, congestion, oil dependence, and climate change, are prompting states and localities to turn to land planning and urban design to rein in automobile use. Many have concluded that roads cannot be built fast enough to keep up with rising travel demand induced by the road building itself and the sprawl it spawns.

The purpose of this meta-analysis is to summarize empirical results on associations between the built environment and travel, especially nonwork travel. A number of studies, including Boarnet and Crane (2001), Cao, Mokhtarian, and Handy (2009b), Cervero (2002a), Cervero and Kockelman (1997), Crane (1996), Kockelman (1997), and Zhang (2004), provide economic and behavioral explanations of why built environments might be expected to influence travel choices. We do not repeat them here, focusing instead on measuring the magnitude of such relationships. We aim to quantify effect sizes while also updating earlier work, including walking and transit use as outcome measures, and addressing the methodological issue of self-selection.

Little work on this topic to date has generalized across studies or helped make sense of differing results. Without this, readers have glimpses of many trees rather than a panoramic view of this complex and rich forest of research. We authored one previous attempt, a literature review (Ewing & Cervero, 2001), in which we derived composite elasticities by informal inspection, an inherently imprecise process. The current meta-analysis, by contrast, is a more systematic way to combine information from many studies, arriving at weighted averages as bottom lines.

There are now more than 200 built-environment/travel studies, of which most were completed since our 2001 review.[1] Compared to earlier studies, the newer ones have estimated effects of more environmental variables simultaneously (expanding beyond density, diversity, design, and destinations, to include distance to transit), controlled for more confounding influences (including traveler attitudes and residential self-selection), and used more sophisticated statistical methods. In response to the U.S. obesity epidemic, the public health literature has begun to link walking to dimensions of the built environment. The first international studies have appeared using research designs similar to those of U.S. studies. This collective and enlarged body of research provides a substantial database for a meta-analysis.

The transportation outcomes we studied in 2001, vehicle miles traveled (VMT) and vehicle trips (VT), are critically linked to traffic safety, air quality, energy consumption, climate change, and other social costs of automobile use. However, they are not the only outcomes of interest. Walking and transit use have implications for mobility, livability, social justice, and public health. The health benefits of walking, in particular, are widely recognized (Badland & Schofield, 2005; Cunningham & Michael, 2004; Frank, 2000; Frank & Engelke, 2001; Humpel, Owen, & Leslie, 2002; Kahn, Ramsey, Brownson, Heath, & Howze, 2002; Krahnstoever-Davison & Lawson, 2006; Lee & Moudon, 2004; McCormack, Giles-Corti, Lange, Smith, Martin, & Pikora, 2004; Owen, Humpel, Leslie, Bauman, & Sallis, 2004; Saelens & Handy, 2008; Transportation Research Board & Institute of Medicine Committee on Physical Activity, Health, Transportation, and Land Use, 2005; Trost, Owen, Bauman, Sallis, & Brown, 2002). Transit use is less obviously related to public health, but is still classified as active travel since it almost always requires a walk at one or both ends of the trip (Besser & Dannenberg, 2005; Edwards, 2008; Zheng, 2008). So, to VMT we add walking and transit use as outcomes of interest.[2]

More than anything else, the possibility of self-selection bias has engendered doubt about the magnitude of travel benefits associated with compact urban development patterns. According to a National Research Council report (Transportation Research Board & Institute of Medicine Committee on Physical Activity, Health, Transportation, and Land Use, 2005), "If researchers do not properly account for the choice of neighborhood, their empirical results will be biased in the sense that features of the built environment may appear to influence activity more than they in fact do. (Indeed, this single potential source of statistical bias casts doubt on the majority of studies on the topic to date…)" (pp. 134–135).

At least 38 studies using nine different research approaches have attempted to control for residential self-selection (Cao, Mokhtarian, & Handy, 2009a; Mokhtarian & Cao, 2008). Nearly all of them found "resounding" evidence of statistically significant associations between the built environment and travel behavior, independent of self-selection influences (Cao, Mokhtarian, et al. 2009a, p. 389). However, nearly all of them also found that residential self-selection attenuates the effects of the built environment on travel.

Using travel diary data from the New York/New Jersey/Connecticut regional travel survey, Salon (2006) concluded that the built environment accounted for one half to two thirds of the difference in walking levels associated with changes in population density in most areas of New York City. Using travel diary data from the Austin travel survey, Zhou and Kockelman (2008) found that the built environment accounted for 58% to 90% of the total influence of residential location on VMT, depending on model specifications. Using travel diary data from northern California, Cao (2010) reported that, on average, neighborhood type accounted for 61% of the observed effect of the built environment on utilitarian walking frequency and 86% of the total effect on recreational walking frequency. Using data from a regional travel diary survey in Raleigh, NC, Cao, Xu, and Fan (2009) estimated that anywhere from 48% to 98%[3] of the difference in vehicle miles driven was due to direct environmental influences, the balance being due to self-selection. Using data from the 2000 San

Francisco Bay Area travel survey, Bhat and Eluru (2009) found that 87% of the VMT difference between households residing in conventional suburban and traditional urban neighborhoods is due to "true" built environment effects, while the remainder is due to residential self-selection. So, while the environment seems to play a more important role in travel behavior than do attitudes and residential preferences, both effects are present.

The D Variables as Measures of the Built Environment

The potential to moderate travel demand by changing the built environment is the most heavily researched subject in urban planning. In travel research, such influences have often been named with words beginning with D. The original "three Ds," coined by Cervero and Kockelman (1997), are density, diversity, and design, followed later by destination accessibility and distance to transit (Ewing & Cervero, 2001; Ewing et al., 2009). Demand management, including parking supply and cost, is a sixth D, included in a few studies. While not part of the environment, demographics are the seventh D, controlled as confounding influences in travel studies.

Density is always measured as the variable of interest per unit of area. The area can be gross or net, and the variable of interest can be population, dwelling units, employment, building floor area, or something else. Population and employment are sometimes summed to compute an overall *activity density* per areal unit.

Diversity measures pertain to the number of different land uses in a given area and the degree to which they are represented in land area, floor area, or employment. Entropy measures of diversity, wherein low values indicate single-use environments and higher values more varied land uses, are widely used in travel studies. Jobs-to-housing or jobs-to-population ratios are less frequently used.

Design includes street network characteristics within an area. Street networks vary from dense urban grids of highly interconnected, straight streets to sparse suburban networks of curving streets forming loops and lollipops. Measures include average block size, proportion of four-way intersections, and number of intersections per square mile. Design is also occasionally measured as sidewalk coverage (share of block faces with sidewalks); 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.

Destination accessibility measures ease of access to trip attractions. It may be regional or local (Handy, 1993). In some studies, regional accessibility is simply distance to the central business district. In others, it is the number of jobs or other attractions reachable within a given travel time, which tends to be highest at central locations and lowest at peripheral ones. The gravity model of trip attraction measures destination accessibility. Local accessibility is different, defined by Handy (1993) as distance from home to the closest store.

Distance to transit is usually measured as an average of the shortest street routes from the residences or workplaces in an area to the nearest rail station or bus stop. Alternatively, it may be measured as transit route density,[4] distance between transit stops, or the number of stations per unit area.

Note that these are rough categories, divided by ambiguous and unsettled boundaries that may change in the future. Some dimensions overlap (e.g., diversity and destination accessibility). We still find it useful to use the D variables to organize the empirical literature and provide order-of-magnitude insights.

Literature

Qualitative Reviews

There are at least 12 surveys of the literature on the built environment and travel (Badoe & Miller, 2000; Cao, Mokhtarian, et al., 2009a; Cervero, 2003; Crane, 2000; Ewing & Cervero, 2001; Handy, 2004; Heath, Brownson, Kruger, Miles, Powell, Ramsey, & the Task Force on Community Preventive Services, 2006; McMillan, 2005, 2007; Pont, Ziviani, Wadley, Bennet, & Bennet, 2009; Saelens, Sallis, & Frank, 2003; Stead & Marshall, 2001). There are 13 other surveys of the literature on the built environment and physical activity, including walking and bicycling (Badland & Schofield, 2005; Cunningham & Michael, 2004; Frank, 2000; Frank & Engelke, 2001; Humpel et al., 2002; Kahn et al., 2002; Krahnstoever-Davison & Lawson, 2006; Lee & Moudon, 2004; McCormack et al., 2004; Owen et al., 2004; Saelens & Handy, 2008; Transportation Research Board & Institute of Medicine Committee on Physical Activity, Health, Transportation, and Land Use, 2005; Trost et al., 2002). There is considerable overlap among these reviews, particularly where they share authorship. The literature is now so vast it has produced two reviews of the many reviews (Bauman & Bull, 2007; Gebel, Bauman, & Petticrew, 2007).

From our earlier review (Ewing & Cervero, 2001), the most common travel outcomes modeled are trip frequency, trip length, mode choice, and VMT (as a composite measure of travel demand). Hence, we can describe measured associations between D variables and these outcomes with more confidence than we could for outcomes studied less often, like trip chaining in multipurpose tours or internal capture of trips within mixed use developments.

Our earlier review (Ewing & Cervero, 2001) held that trip frequency is primarily a function of socioeconomic characteristics of travelers and secondarily a function of the built environment; trip length is primarily a function of the built environment and secondarily of socioeconomic characteristics; and mode choice depends on both, although probably more on socioeconomics. VMT and vehicle hours of travel (VHT) also depend on both. Trip lengths are generally shorter at locations that are more accessible, have higher densities, or feature mixed uses. This holds true both when comparing home-based trips from different residential neighborhoods and trips to non-home destinations in different activity centers. Destination accessibility is the dominant environmental influence on trip length. Transit use varies primarily with local densities and secondarily with the degree of land use mixing. Some of the density effect is, no doubt, due to better walking conditions, shorter distances to transit service, and less free parking. Walking varies as much with the degree of land use mixing as with local densities.

The third D, design, has a more ambiguous relationship to travel behavior than the first two. Any effect is likely to be a collective one involving multiple design features. It also may be an interactive effect with other D variables. This is the idea behind composite measures such as Portland, Oregon's urban design factor, which is a function of intersection density, residential density, and employment density.

Our Earlier Quantitative Synthesis

Using 14 travel studies that included sociodemographic controls, we previously synthesized the literature on the elasticities of VMT and VT with respect to density, diversity, design, and destination accessibility (Ewing & Cervero, 2001). The U.S. Environmental Protection Agency (EPA) incorporated these summary measures into its Smart Growth Index (SGI) model, a widely used sketch-planning tool for travel and air quality analysis. The SGI model measures density as residents plus jobs per square mile; diversity as the ratio of jobs to residents divided by the regional average of that ratio; and design as street network density, sidewalk coverage, and route directness (road distance divided by direct distance). Two of these three measures relate to street network design.

Our 2001 study (Ewing & Cervero, 2001) suggested, for example, that a doubling of neighborhood density would reduce both per capita VT and VMT by approximately 5%, all else being equal. We also concluded that VMT was more elastic with respect to destination accessibility than the other three built environmental measures, meaning that highly accessible areas such as center cities produce substantially lower VMT than dense mixed-use developments in the exurbs. However, as noted earlier, our 2001 study relied on only 14 studies, and the elasticities were imprecise, some obtained by aggregating results for dissimilar environmental variables (e.g., local diversity measured as both entropy and jobs-housing balance). In this update, we compute weighted averages of results from a larger number of studies, and use more uniformly defined built-environmental variables.

Meta-Analyses in Planning

Unlike traditional research methods, meta-analysis uses summary statistics from individual primary studies as the data points in a new analysis. This approach has both advantages and disadvantages for validity and reliability, as every standard textbook on meta-analysis explains (Borenstein, Hedges, Higgins, & Rothstein, 2009; Hunter & Schmidt, 2004; Lipsey & Wilson, 2001; Littell, Corcoran, & Pillai, 2008; Lyons, 2003 Schulze, 2004).

The main advantage of meta-analysis is that it aggregates all available research on a topic, allowing common threads to emerge. The pooling of samples in a carefully constructed meta-analysis also makes its results more generalizable than those of the smaller primary studies on which it is based. But meta-analysis has drawbacks too. Combining stronger studies with weaker ones may contaminate the results of the former. Further, meta-analysis inevitably mixes apples and oranges due to the variation among studies in modeling techniques, independent and dependent variables, and sampling units. If we compare only very similar studies, sample sizes can become small, threatening statistical reliability, a problem that we admit characterizes some of the subcategories for which we present results in this article. Last, the studies for a meta-analysis are usually chosen from the published literature. This can result in *publication bias*, since studies that show statistical significance are more likely to be published (Rothstein, Sutton, & Borenstein, 2005). Publication bias may inflate the absolute size of the effects estimated with a meta-analysis.

Addressing these potential weaknesses involves tradeoffs. We sought to minimize publication bias in this meta-analysis by searching for unpublished reports, preprints, and white papers, as well as published articles. Online searches using Google Scholar and the Transportation

Research Information Service (TRIS) were particularly helpful in this regard. We sought to minimize the apples-and-oranges problem by focusing on a subset of studies that employed disaggregate data and comparably defined variables. Yet, our efforts to avoid publication bias may have exacerbated the strong-weak study problem, and our efforts to achieve greater construct validity by segmenting the analysis into subgroups sharing comparably defined dependent and independent variables produced small sample sizes.

More than a dozen studies have applied meta-analytical methods to the urban planning field (Babisch, 2008; Bartholomew & Ewing, 2008; Bunn, Collier, Frost, Ker, Roberts, & Wentz, 2003; Button & Kerr, 1996; Button & Nijkamp, 1997; Cervero, 2002b; Debrezion, Pels, & Rietveld, 2003; Duncan, Spence, & Mummery, 2005; Graham & Glaister, 2002; Hamer & Chida, 2008; Lauria & Wagner, 2006; Leck, 2006; Nijkamp & Pepping, 1998; Smith & Huang, 1995; Stamps, 1990, 1999; Zhang, 2009). Bartholomew and Ewing (2008) combined results from 23 recent scenario planning studies to calculate the impacts of land-use changes on transportation greenhouse gas emissions. Button and Kerr (1996) explored the implications of urban traffic restraint schemes on congestion levels. Cervero (2002b) synthesized the results of induced travel demand studies. Debrezion et al. (2003) measured the impact of railway stations on residential and commercial property values. Nijkamp and Pepping (1998) analyzed factors critical to the success of sustainable city initiatives. Smith and Huang (1995) calculated the public's willingness to pay for cleaner air. Stamps (1990, 1999) applied meta-analysis to the visual preference literature.

Most relevant to the present study, Leck (2006) identified 40 published studies of the built environment and travel, and selected 17 that met minimum methodological and statistical criteria. While Leck's meta-analysis stopped short of estimating average effect sizes, it did evaluate the statistical significance of relationships between the built environment and travel, finding residential density, employment density, and land use mix to be inversely related to VMT at the $p < .001$ significance level.

Approach

Sample of Studies

We identified studies linking the built environment to travel using the Academic Search Premier, Google, Google Scholar, MEDLINE, PAIS International, PUBMED, Scopus, TRIS Online, TRANweb, Web of Science, and ISI Web of Knowledge databases using the keywords "built environment," "urban form," and "development," coupled with keywords "travel," "transit," and "walking." We also reviewed the compact discs of the Transportation Research Board's annual programs for relevant papers, contacted all leading researchers in this subject area for copies of their latest research, and put out a call for built-environment/travel studies on the academic planners' listserv, PLANET. Finally, we examined the bibliographies of the previous literature reviews in this topic area to identify other pertinent studies.

We inspected more than 200 studies that relate, quantitatively, characteristics of the built environment to measures of travel. From the universe of built-environment/travel studies, we computed effect sizes for the more than 50 studies shown in Table 1. These studies have several things in common. As they analyze effects of the built environment on travel choices, all these studies control statistically for confounding influences on travel behavior, sociodemographic influences in particular. They use different statistical methods because the outcome variables differ from study to study.[5] All apply statistical tests to determine the significance of the various effects. Almost all are based on sizeable samples, as shown in the appendix tables. Most capture the effects of more than one D variable simultaneously. Most importantly, we selected only studies for which data were available for computing effect sizes.

We left out many quantitative studies for various reasons. Many studies did not publish average values of dependent and independent variables from which point elasticities could be calculated. Although we followed up with authors to try to obtain these descriptive statistics, in many cases the research was several years old and the authors had moved on to other subjects. In a few cases, we could not track the authors down or get them to respond to repeated data requests.

Many studies used highly aggregated city, county, or metropolitan level data (e.g., Newman & Kenworthy, 2006; van de Coevering & Schwanen, 2006). Such studies have limited variance in both dependent and independent variables with which to explain relationships. More importantly, it is inappropriate to make causal and associative inferences about individuals based on results obtained from aggregate data, an error called the *ecological fallacy*. As we would like our elasticities to be suitable for use in models predicting individual behavior, we did not use studies relying on aggregate data.

Several studies used statistical methods from which simple summary effect size measures could not be calculated, including some using structural equation models (SEM) to capture complex interactions among built environment and travel variables (e.g., Bagley & Mokhtarian,

Table 1. Studies included in the sample.

	Study sites	Data	Methods	Controls	Self-selection controlled for[a]
Bento et al., 2003	Nationwide Personal Transportation Survey (114 metropolitan statistical areas)	D	LNR/LGR	SE/LS/OT	no
Bhat & Eluru, 2009	San Francisco Bay Area, CA	D	COP	SE/OT	yes
Bhat, Sen, et al., 2009	San Francisco Bay Area, CA	D	MDC/LGR	SE/OT	no
Bhatia, 2004	20 communities in Washington, DC	A	LNR	SE	no
Boarnet et al., 2004	Portland, OR	D	LNR/PRR	SE/OT	no
Boarnet et al., 2008	Portland, OR	D	TOR	SE	yes
Boarnet et al., in press	8 neighborhoods in southern CA	D	NBR	SE	no
Boer et al., 2007	10 U.S. metropolitan areas	D	PSM	SE/WE	no
Cao et al., 2006	6 neighborhoods in Austin, TX	D	NBR	SE/AT	yes
Cao, Mokhtarian, et al., 2009b	8 neighborhoods in northern CA	D	SUR	SE/AT	yes
Cao, Xu, et al., 2009	Raleigh, NC	D	PSM	SE/AT	yes
Cervero, 2002a	Montgomery County, MD	D	LGR	SE/LS	no
Cervero, 2006	225 light rail transit stations in 11 metropolitan areas	A	LNR	ST/LS	no
Cervero, 2007	26 TODs in five CA regions	D	LGR	SE/ LS/WP/AT	yes
Cervero & Duncan, 2003	San Francisco Bay Area, CA	D	LGR	SE/OT	no
Cervero & Duncan, 2006	San Francisco Bay Area, CA	D	LNR	SE/WP	no
Cervero & Kockelman, 1997	50 neighborhoods in the San Francisco Bay Area, CA	D	LNR/LGR	SE/LS	no
Chapman & Frank, 2004	Atlanta, GA	D	LNR	SE	no
Chatman, 2003	Nationwide Personal Transportation Survey	D	TOR	SE/WP	no
Chatman, 2008	San Francisco, CA/San Diego, CA	D	LNR/NBR	SE/LS/OT	no
Chatman, 2009	San Francisco, CA/San Diego, CA	D	NBR	SE/LS/OT/AT	yes
Ewing et al., 1996	Palm Beach County/Dade County, FL	D	LNR	SE	no
Ewing et al., 2009	52 mixed use developments in Portland	D	HLM	SE	no
Fan, 2007	Raleigh-Durham, NC	D	LNR	SE/LS/OT/AT	yes
Frank & Engelke, 2005	Seattle, WA	D	LNR	SE/LS	no
Frank et al., 2008	Seattle, WA	D	LGR	SE/LS	no
Frank et al., 2009	Seattle, WA	D	LNR	SE	no
Greenwald, 2009	Sacramento, CA	D	LNR/TOR/NBR	SE	no
Greenwald & Boarnet, 2001	Portland, OR	D	OPR	SE/LS	no
Handy & Clifton, 2001	6 neighborhoods in Austin, TX	D	LNR	SE	no
Handy et al., 2006	8 neighborhoods in northern CA	D	NBR	SE/AT	yes
Hedel & Vance, 2007	German Mobility Panel Survey	D	LNR/PRR	SE/OT	no
Hess et al., 1999	12 neighborhood commercial centers in Seattle, WA	A	LNR	SE	no
Holtzclaw et al., 2002	Chicago, IL/Los Angeles, CA/San Francisco, CA	A	NLR	SE	no
Joh et al., 2009	8 neighborhoods in southern CA	D	LNR	SE/CR/AT	yes
Khattak & Rodriguez, 2005	2 neighborhoods in Chapel Hill, NC	D	NBR	SE/AT	yes
Kitamura et al., 1997	5 communities in San Francisco, CA region	D	LNR	SE/AT	yes
Kockelman, 1997	San Francisco Bay Area, CA	D	LNR/LGR	SE	no
Kuby et al., 2004	268 light rail transit stations in nine metropolitan areas	A	LNR	ST/OT	no
Kuzmyak et al., 2006	Baltimore, MD	D	LNR	SE	no
Kuzmyak, 2009a	Los Angeles, CA	D	LNR	SE	no
Kuzmyak, 2009b	Phoenix, AZ	D	LNR	SE	no
Lee & Moudon, 2006a	Seattle, WA	D	LGR	SE/LS	yes
Lund, 2003	8 neighborhoods in Portland, OR	D	LNR	SE/AT	yes
Lund et al., 2004	40 TODs in four CA regions	D	LGR	SE/LS/WP/AT	yes
Naess, 2005	29 neighborhoods in Copenhagen, Denmark	D	LNR	SE/WP/AT	yes

Table 1. (continued).

	Study sites	Data	Methods	Controls	Self-selection controlled for[a]
Pickrell & Schimek, 1999	Nationwide Personal Transportation Survey	D	LNR	SE	no
Plaut, 2005	American Housing Survey	D	LGR	SE/OT	no
Pushkar et al., 2000	795 zones in Toronto, Ontario, Canada	A	SLE	SE/LS	no
Rajamani et al., 2003	Portland, OR	D	LGR	SE/LS	no
Reilly, 2002	San Francisco, CA	D	LGR	SE/OT	no
Rodriguez & Joo, 2004	Chapel Hill, NC	D	LGR	SE/LS/OT	no
Rose, 2004	3 neighborhoods in Portland	D	LNR/POR	SE	no
Schimek, 1996	Nationwide Personal Transportation Survey	D	SLE	SE	no
Shay et al., 2006	1 neighborhood in Chapel Hill, NC	D	NBR	SE/AT	yes
Shay & Khattak, 2005	2 neighborhoods in Chapel Hill, NC	D	LNR/NBR	SE	no
Shen, 2000	Boston, MA	A	LNR	SE	no
Sun et al., 1998	Portland, OR	D	LNR	SE	no
Targa & Clifton, 2005	Baltimore, MD	D	POR	SE/AT	yes
Zegras, 2007	Santiago, Chile	D	LNR/LGR	SE	no
Zhang, 2004	Boston, MA/Hong Kong	D	LGR	SE/LS/OT	no
Zhou & Kockelman, 2008	Austin, TX	D	LNR/PRR	SE	yes

Notes:
We use the following abbreviations:

Data: A = aggregate
D = disaggregate

Methods: COP = Copula-based switching model
GEE = generalized estimating equations
HLM = hierarchical linear modeling
LGR = logistic regression
LNR = linear regression
MDC = multiple discrete continuous extreme value model
NBR = negative binomial regression
NLR = nonlinear regression
OPR = ordered probit regression
POR = Poisson regression
PRR = probit regression
PSM = propensity score matching
PSS = propensity score stratification
SLR = simultaneous linear equations
SUR = seemingly unrelated regression
TOR = Tobit regression

Controls: AT = attitudinal variables
CR = crime variables
LS = level of service variables
OT = other variables
SE = socioeconomic variables
ST = station variables
WE = weather variables
WP = workplace variables

a. Cao, Mokhtarian, et al. (2009a) notes nine different approaches used to control for residential self-selection. The least rigorous incorporates attitudinal measures in multivariate regression models, while the most rigorous jointly estimates models of residential choice and travel behavior, treating residential choice as an endogenous variable.

2002; Cao, Mokhtarian, & Handy, 2007; Cervero & Murakami, 2010). In SEM, different equations represent different effects of variables on one another, both direct and indirect through intermediate variables. These cannot be aggregated into a single elasticity.[6]

We excluded many studies because they dealt with limited populations or trip purposes (e.g., Chen & McKnight, 2007; Li, Fisher, Brownson, & Bosworth, 2005; Waygood, Sun, Kitamura, 2009). Notably, several recent studies of student travel to school cannot be generalized to other populations and trip purposes. The literature suggests that the choice of mode for the journey to school is based on very different considerations than those for other trip making (Ewing, Schroeer, & Greene, 2004; Yarlagadda & Srinivasan, 2008).

We excluded some studies because they characterized the built environment subjectively rather than objectively, that is, in terms of qualities perceived and reported by travelers rather than variables measured in a standardized way by researchers (e.g., Craig, Brownson, Cragg, & Dunn, 2002; Handy, Cao, & Mokhtarian, 2005). Subjective measures are common in public health studies. While perceptions are important, they differ from objective measures of the built environment and are arguably more difficult for planners and public policymakers to influence (e.g., Livi-Smith, 2009; McCormack et al., 2004; McGinn, Evenson, Herring, Huston, & Rodriguez, 2007). For studies that include both types of measures, we analyzed relationships only for the objective measures.

Finally, we excluded several studies because they created and then applied built environmental indices without true zero values (e.g., indices derived through factor analysis). There is no defensible way to compute elasticities, the common currency of this article, for such studies (e.g., Estupinan & Rodriguez, 2008; Frank, Saelens, Powell, & Chapman, 2007; Livi-Smith, 2009). For the same reason, we excluded several excellent studies whose independent variables, although initially continuous, had been converted to categorical variables to simplify the interpretation of results (e.g., Lee & Moudon, 2006b; McGinn et al., 2007; Oakes, Forsyth, & Schmitz, 2007).

We analyzed studies using nominal variables to characterize the built environment separately from those using continuous variables. Examples of the former include studies distinguishing between traditional urban and conventional suburban development or between transit-oriented and auto-oriented development. We only included such studies if they analyzed disaggregate data and controlled for individual socioeconomic differences across their samples, thereby capturing the marginal effects of neighborhood type.[7]

Common Metrics

To combine results from different studies, a meta-analysis requires a common measure of effect size. Our common metric is the elasticity of some travel outcome with respect to one of the D variables. An *elasticity* is the ratio of the percentage change in one variable associated with the percentage change in another variable (a *point elasticity* is the ratio when these changes are infinitely small). Elasticities are dimensionless (unit-free) measures of the associations between pairs of variables and are the most widely used measures of effect size in economic and planning research.

For outcomes measured as continuous variables, such as numbers of walk trips, an elasticity can be interpreted as the percent change in the outcome variable when a specified independent variable increases by 1%. For outcomes measured as categorical variables, such as the choice of walking over other modes, an elasticity can be interpreted as the percent change in the probability of choosing that alternative (or the percent change in that alternative's market share) when the specified independent variable increases by 1%.

Elasticities in Individual Studies in the Sample

We obtained elasticities from the individual studies in our sample in one of four ways, just as in Ewing and Cervero (2001). We either: (1) copied them from published studies where they were reported explicitly; (2) calculated them ourselves from regression coefficients and the mean values of dependent and independent variables; (3) derived them from data sets already available to us or made available by other researchers; or (4) obtained them directly from the original researchers. Most commonly, we used one of the formulas shown in Table 2 to compute elasticities, depending on which statistical method was used to estimate coefficient values.

When regression coefficients were not significant, we could have chosen to drop the observations or substitute zero values for the elasticities, since the coefficients were not statistically different from zero, but we chose instead to use the reported coefficients to compute elasticities, again using the formulas in Table 2. Dropping the observations would have biased the average elasticities away from the null hypothesis of zero elasticity, and thus we rejected this option. Substituting zero values for computed elasticities would have had the opposite effect, biasing average values toward the null hypothesis, thus we rejected it as well. Instead, we used the best available estimates of central tendency in all cases, the regression coefficients themselves, to compute elasticities. This is the standard approach in meta-analysis (see, e.g., Melo, Graham, & Noland, 2009).

Table 2. Elasticity estimation formulas.

Regression specification	Elasticity
Linear	$\beta * \frac{\bar{x}}{\bar{y}}$
Log-log	β
Log-linear	$\beta * \bar{x}$
Linear-log	$\frac{\beta}{\bar{y}}$
Logistic[a]	$\beta * \bar{x}\left(1-\left(\frac{\bar{y}}{n}\right)\right)$
Poisson	$\beta * \bar{x}$
Negative binomial	$\beta * \bar{x}$
Tobit[b]	$\beta * \left(\frac{\bar{x}}{\bar{y}}\right)$

Notes:
β is the regression coefficient on the built-environment variable of interest, $\bar{y}$ the mean value of the travel variable of interest, and $\bar{x}$ the mean value of the built-environment variable of interest.
a. $\left(\frac{\bar{y}}{n}\right)$ is the mean estimated probability of occurrence.
b. Applied only to positive values of the Tobit distribution (i.e., where $y > 0$).

Borenstein et al. (2009) argue against another possibility, using significance levels as proxies for effect size, since they depend not only on effect size but also on sample size: "Because we work with the effect sizes directly we avoid the problem of interpreting nonsignificant *p*-values to indicate the absence of an effect (or of interpreting significant *p*-values to indicate a large effect)" (p. 300).

Ideally, the original studies would have computed elasticities for each observation (trip, traveler, or household) and then averaged them over the sample. Indeed, a few of the researchers who reported elasticities did exactly that (e.g., Bento, Cropper, Mobarak, & Vinha, 2003; Bhat, Sen, & Eluru, 2009; Rodriguez & Joo, 2004). However, since we could not ask all these busy people to go back and compute elasticities, we have instead estimated elasticities at the overall sample means of the dependent and/or independent variables, as indicated in Table 3.

While commonplace, this procedure could introduce a fair amount of error in the elasticity estimates. Elasticities calculated at mean values of dependent and independent variables may differ significantly from the average values of individual elasticities due to the nonlinear nature of many of the functions involved (e.g., logistic functions). "In general, the probability evaluated at the average utility underestimates the average probability when the individuals' choice probabilities are low and overestimates when they are high" (Train, 1986, p. 42). Train (1986) cites work by Talvitie (1976), who found in a mode choice analysis that elasticities at the average representative utility can be as much as two to three times greater or less than the average of individual elasticities. This is a greater concern with discrete choice models than with the linear regression models that Table 1 shows are most commonly used to study the built environment and travel.

Due to the large number studies we summarize here, we show the effect sizes for individual studies in appendix tables for each travel outcome of interest (VMT, walking, and transit use) with respect to each built environment variable of interest (density, diversity, design, destination accessibility, distance to transit, and neighborhood type). All effect sizes are measured as elasticities, except those for neighborhood type, which is a categorical variable. The effect size for neighborhood type is the proportional difference in a travel outcome between conventional suburban neighborhoods and more compact, walkable neighborhoods.

Table 3. Weighted average elasticities of VMT with respect to built-environment variables.

		Total number of studies	Number of studies with controls for self-selection	Weighted average elasticity of VMT(*e*)
Density	Household/population density	9	1	−0.04
	Job density	6	1	0.00
Diversity	Land use mix (entropy index)	10	0	−0.09
	Jobs-housing balance	4	0	−0.02
Design	Intersection/street density	6	0	−0.12
	% 4-way intersections	3	1	−0.12
Destination accessibility	Job accessibility by auto	5	0	−0.20
	Job accessibility by transit	3	0	−0.05
	Distance to downtown	3	1	−0.22
Distance to transit	Distance to nearest transit stop	6	1	−0.05

We consistently report the elasticity values with a positive sign indicating the effects of greater accessibility, which required reversing signs in many cases, as noted in the tables. Thus, for example, a negative elasticity of VMT with respect to measures of destination accessibility in our appendix tables always indicates that VMT drops as destination accessibility improves. Where destination accessibility was measured originally in terms of jobs reachable within a given travel time, our sign is the same as that obtained by the original study. However, where destination accessibility was measured in terms of distance to downtown, for example, we reversed the sign of the elasticity in the original source so that higher values of the independent variable correspond to better, not worse, accessibility.

Where studies reported results for general travel and, in addition, for different trip purposes or different types of travelers, we report effect sizes only for the most general class of travel. Thus, for example, if a study estimated VMT models for all trips and for work trips alone, we present only the former. A few studies analyzed only subcategories of travel, and in these cases, we sometimes present more than one set of results for a given study.

Weighted Average Elasticities

We used individual elasticities from primary studies to compute weighted average elasticities for many dependent/independent variable pairs representing travel outcomes and attributes of the built environment. We show the resulting weighted average elasticities in Tables 3, 4, and 5. We calculated averages where three conditions were met: (1) a sample of at least three studies was available; (2) for these particular studies, dependent and independent variables were comparably defined; and (3) for these particular studies, disaggregate travel data were used to estimate models. The numbers of studies in each sample are as indicated in Tables 3, 4, and 5.

These results should be used only as ballpark estimates, both because of the minimum sample size we chose and because of how we computed weighted average elasticities. We settled on a minimum sample size of three studies[8] due to data limitations (as in Tompa, de Oliveira, Dolinschi, & Irvin, 2008). While the relationship between the built environment and travel is the most heavily researched subject in urban planning, when studies are segmented by variable type, samples never reach what some would consider a reasonable minimum sample size (Lau, Ioannidis, Terrin, Schmid, & Olkin, 2006). Also, to maximize our

Table 4. Weighted average elasticities of walking with respect to built environment variables.

		Total number of studies	Number of studies with controls for self-selection	Weighted average elasticity of walking (*e*)
Density	Household/population density	10	0	0.07
	Job density	6	0	0.04
	Commercial floor area ratio	3	0	0.07
Diversity	Land use mix (entropy index)	8	1	0.15
	Jobs-housing balance	4	0	0.19
	Distance to a store	5	3	0.25
Design	Intersection/street density	7	2	0.39
	% 4-way intersections	5	1	–0.06
Destination accessibility	Job within one mile	3	0	0.15
Distance to transit	Distance to nearest transit stop	3	2	0.15

Table 5. Weighted average elasticities of transit use with respect to built environment variables.

		Total number of studies	Number of studies with controls for self-selection	Weighted average elasticity of transit use
Density	Household/population density	10	0	0.07
	Job density	6	0	0.01
Diversity	Land use mix (entropy index)	6	0	0.12
Design	Intersection/street density	4	0	0.23
	% 4-way intersections	5	2	0.29
Distance to transit	Distance to nearest transit stop	3	1	0.29

sample sizes, we mixed the relatively few studies that control for self-selection with the many that do not. We advise readers to exercise caution when using the elasticities based on small samples of primary studies (see Tables 3, 4, and 5), but rather than omit the categories for which only small samples were available, we aimed in this analysis to seed the meta-study of built environments and travel, expecting that others would augment and expand our database over time.

We computed weighted average elasticities using sample size as a weighting factor because we lacked consistent standard error estimates from individual studies. Weighting by sample size is by far the most common approach in meta-analyses, since sample sizes are nearly always known (Shadish & Haddock, 1994, p. 264). However, it is not the optimal weighting scheme. Hedges and Olkin (1985) demonstrated that optimal weights are related to the standard errors of the effect size estimates, and this has become the gold standard in meta-analysis. Specifically, because larger standard errors correspond to less precise estimates of effect sizes, the preferred method is to calculate a meta-analysis weight as an *inverse variance weight,* or the inverse of the squared standard error (Borenstein et al., 2009; Hunter & Schmidt, 2004; Lipsey & Wilson, 2001; Littell et al., 2008; Schulze, 2004). From a statistical standpoint, such weights are optimal since they minimize the variance of the average effect size estimates. They also make intuitive sense, as they give the greatest weight to the most precise estimates from individual studies.

No weighting factor except standard error allows judging whether the resulting weighted averages are statistically different from zero. Since we combine significant and insignificant individual effect sizes, and do not have the data necessary to test for significance, we do not report statistical confidence for any of the results. It is thus possible that any given meta-elasticity is not significantly different from zero. We particularly advise readers to exercise caution in using weighted average elasticities when the elasticities on which they are based are statistically insignificant, as shown in the appendix tables.

Discussion

For all of the variable pairs we discuss here, the relationships between travel variables and built environmental variables are inelastic. The weighted average elasticity with the greatest absolute magnitude is 0.39, and most elasticities are much smaller. Still, the combined effect of several built environmental variables on travel could be quite large.

As in our 2001 meta-study (Ewing & Cervero, 2001), the D variable most strongly associated with VMT is destination accessibility. Our elasticity of VMT with respect to "job accessibility by auto" in this meta-analysis, –0.20, is identical to the elasticity in the earlier study. In fact, the –0.20 VMT elasticity is nearly as large as the elasticities of the first three D variables (density, diversity, and design) combined; this too is consistent with our earlier meta-study.

Equally strongly, though negatively, related to VMT is the distance to downtown. This variable is a proxy for many Ds, as living in the city core typically means higher densities in mixed-use settings with good regional accessibility. Next most strongly associated with VMT are the design metrics intersection density and street connectivity. This is surprising, given the emphasis in the qualitative literature on density and diversity, and the relatively limited attention paid to design. The weighted average elasticities of these two street network variables are identical. Both short blocks and many interconnections apparently shorten travel distances to about the same extent.

Also surprising are the small elasticities of VMT with respect to population and job densities. Conventional wisdom holds that population density is a primary determinant of vehicular travel, and that density at the work end of trips is as important as density at the home end in moderating VMT. This does not appear to be the case once other variables are controlled.

Our previous study (Ewing & Cervero, 2001) did not address walking and transit use, thus we have no benchmarks against which to compare the results in Tables 4 and 5. The meta-analysis shows that mode share and likelihood of walk trips are most strongly associated with the design and diversity dimensions of built environments. Intersection density, jobs-housing balance, and distance to stores have the greatest elasticities. Interestingly, intersection density is a more significant variable than street connectivity. Intuitively this seems right, as walkability may be limited even if connectivity is excellent when blocks are long. Also of interest is the fact that jobs-housing balance has a stronger relationship to walking than the more commonly used land use mix (entropy) variable. Several variables that often go hand-in-hand with population density have elasticities that are well above that of population density. Also, as with VMT, job density is less strongly related to walking than is population density. Finally, Table 5 suggests that having transit stops nearby may stimulate walking (Cervero, 2001; Ryan & Frank, 2009).

The mode share and likelihood of transit trips are strongly associated with transit access. Living near a bus stop appears to be an inducement to ride transit, supporting the transit industry's standard of running buses within a quarter mile of most residents. Next in importance are road network variables and, then, measures of land use mix. High intersection density and great street connectivity shorten access distances and provide more routing options for transit users and transit service providers. Land use mix makes it possible to efficiently link transit trips with errands on the way to and from transit stops. It is sometimes said that "mass transit needs 'mass'"; however, this is not supported by the low elasticities of transit use with respect to population and job densities in Table 5.

No clear pattern emerges from scanning across the Tables 3, 4, and 5. Perhaps what can be said with the highest degree of confidence is that destination accessibility is most strongly related to both motorized (i.e., VMT) and nonmotorized (i.e., walking) travel and that among the remaining Ds, density has the weakest association with travel choices. The primacy of destination accessibility may be due to lower levels of auto ownership and auto dependence at central locations. Almost any development in a central location is likely to generate less automobile travel than the best-designed, compact, mixed-use development in a remote location.

The relatively weak relationships between density and travel likely indicate that density is an intermediate variable that is often expressed by the other Ds (i.e., dense settings commonly have mixed uses, short blocks, and central locations, all of which shorten trips and encourage walking). Among design variables, intersection density more strongly sways the decision to walk than does street connectivity. And, among diversity variables, jobs-housing balance is a stronger predictor of walk mode choice than land use mix measures. Linking where people live and work allows more to commute by foot, and this appears to shape mode choice more than sprinkling multiple land uses around a neighborhood.

Controls for residential self-selection appear to increase the absolute magnitude of elasticities if they have any effect at all. This conclusion follows from a simple review of elasticities in the appendix. There may be good explanations for this unexpected result. In a region with few pedestrian- and transit-friendly neighborhoods, residential self-selection likely matches individual preferences with place characteristics, increasing the effect of the D variables, a possibility posited by Lund, Willson, and Cervero (2006).

> …if people are simply moving from one transit-accessible location to another (and they use transit regularly at both locations), then there is theoretically no overall increase in ridership levels. If, however, the resident was unable to take advantage of transit service at their prior residence, then moves to a TOD (transit-oriented development) and begins to use the transit service, the TOD is fulfilling a latent demand for transit accessibility and the net effect on ridership is positive. (p. 256)

Similarly, Chatman (2009) hypothesizes that "[r]esidential self-selection may actually cause underestimates of built environment influences, because households prioritizing travel access—particularly, transit accessibility—may be more set in their ways, and because households may not find accessible neighborhoods even if they prioritize accessibility" (p. 1087). He carries out regressions that explicitly test for this, and finds that self-selection is more likely to enhance than diminish built environmental influences.

Still, we are left with a question. Most of the literature reviewed by Cao, Mokhtarian, et al. (2009a) shows that the effect of the built environment on travel is attenuated by controlling for self-selection, whereas we find no effect (or enhanced effects) after controlling for self-selection. The difference may lie in the different samples included in our study and that of Cao, Mokhtarian, et al. (2009a), or in the crude way we operationalized self-selection, lumping all studies that control for self-selection together regardless of methodology.

Applications

This article provides elasticities in two forms that may be useful to planners: elasticity estimates from primary studies (in the appendix tables) and average elasticities from our pooled samples (in Tables 3, 4, and 5). If a planner happens to have an application in a location near one of those listed in the appendix tables, if not too many years have intervened since that study was completed, and if the study included the right D variables, he or she can simply borrow an elasticity estimate from the appendix, provided that the appendix table indicates it meets conventional statistical significance criteria. Thus, for applications in Boston in the near future, Zhang's (2004) estimate of the elasticity of walk/bike mode choice with respect to population density (0.11) may be used without modification.

More commonly, geographic and functional gaps in the literature may make the elasticities in Tables 3, 4, and 5 useful to planners. These elasticities may be applied in sketch planning to compute estimates of VMT, walking, and transit use relative to a base case, or in post-processing travel and activity forecasts from four-step travel demand models to reflect the influence of the five Ds.

The literature covers post-processing applications well (Cervero, 2006; DKS Associates, 2007; Johnston, 2004; Walters, Ewing, & Allen, 2000). These new elasticity values can be used in exactly the same way as earlier elasticity estimates.

Sketch planning applications are limited only by the creativity of planning analysts. To illustrate, climate action planning of the type currently underway in California and 18 other states will require VMT estimates in order to extrapolate current trends and project an alternative lower-carbon future. These states have set greenhouse gas emission reduction targets and, with their metropolitan planning organizations, will need to pull together verifiable plans that include smart growth elements. If planners are willing to make assumptions about the increases in density and other D variables that can be achieved with policy changes, they can use elasticity values from this article to estimate VMT reductions in urbanized areas and to translate these in turn into effects on CO_2.

Another potential sketch planning application could be to assess health impacts. Rates of physical activity, including walking, are inputs to health assessment models. Again, once planners make assumptions about changes in the D variables under future scenarios, increases in walking can easily be computed using elasticities. Until now there has been no empirically grounded methodology for making such projections.

Elasticities could also be applied to traffic impact analysis. There has been no way to adjust the Institute of Transportation Engineers' (ITE) trip generation rates for walking and transit use, which has left developers of dense developments at urban sites paying impact fees and other exactions at the same rate as their suburban counterparts. The only adjustment previously allowed was for internal capture of trips within mixed-use developments, which did nothing for the typical infill project. Elasticity values can be used to adjust ITE trip rates for suburban developments to reflect how greater densities and other environmental attributes would affect trip making.

The elasticities in this meta-analysis are based on the most complete data available as of late 2009. However, as we acknowledge, sample sizes are small and the number of studies controlling for residential preferences and attitudes is still miniscule. We also do not know the confidence intervals around our meta-analysis results. Users should weigh these shortcomings when applying results to any particular context or local setting. However, they provide a base on which to build. As more built environment-travel studies appear in the planning literature, it will be important to update and refine our results.

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Notes

1. A full list of studies is available from the corresponding author.
2. Vehicle trips (VT) is not studied as widely as these other outcome measures and is not related to as many important outcomes. However, it is a critical determinant of regulated vehicle emissions, which was the focus of our 2001 literature review.
3. The percentage varied depending on which locations were paired and compared, whether urban and suburban locations, urban and exurban, etc.
4. Transit route density is measured by miles of transit routes per square mile of land area.
5. Linear regression is used where the travel variable in continuous, Poisson regression where the travel variable is a count, logistic regression where the dependent variable is a probability, and so forth.
6. Several studies applied ordered probit regression to data on counts of walk and transit trips. We excluded all but one of these studies from the meta-analysis because the breakpoint parameters (μ) for the ordered categories were unavailable, which meant we could not calculate marginal effects. These parameters were available for one ordered probit study (Greenwald & Boarnet, 2001), and Jason Cao computed elasticities for us. We used elasticities for the median ordered category.
7. Due to a dearth of solid research, we could not study certain important travel outcomes with meta-analysis. Most notably, this article is silent regarding the effects of the built environment on trip chaining in multipurpose tours, internal capture of trips within mixed-use developments, and the choice of bicycling as a travel mode.
8. The following quotation from Rodenburg, Benjamin, de Roos, Meijer, and Stams (2009) explains that a meta-analysis in another field settled on seven studies as a minimum sample size:

> Some limitations of this meta-analytic study should be mentioned. Although the minimum number of studies to permit a meta-analysis is only three studies (Treadwell, Tregear, Reston, & Turkelson, 2006) and many published meta-analyses contain nine or fewer studies (Lau, Ioannidis, Terrin, Schmid, & Olkin, 2006), the small number of seven studies included in this meta-analytic review limits the generalizability of our findings and the possibilities of examining and adjusting for publication bias by means of more complex analytic methods (Macaskill, Walter, & Irwig, 2001). (p. 605)

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Appendix: Individual Study Results

Table A-1. Elasticity of VMT with respect to density.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Bhatia, 2004	20	VMT per household	Household	−0.34 *	
Boarnet et al., 2004	6,153	Nonwork VMT per person	Population	−0.04	
Boarnet et al., 2004	6,153	Nonwork VMT per person	Job	0.03	
Boarnet et al., 2004	6,153	Nonwork VMT per person	Retail job	−0.02	
Chatman, 2003	14,478	VMT for commercial trips per person	Household	−0.58	
Chatman, 2003	14,478	VMT for commercial trips per person	Job	−0.34 ψ	
Chatman, 2008	527	Nonwork VMT per person	Population per road mile	−1.05 ψ	
Chatman, 2008	527	Nonwork VMT per person	Retail job	−0.19 **	
Ewing et al., 1996 (Dade County)	1,311	VHT per household	Population and employment	−0.05	
Ewing et al., 1996 (Palm Beach County)	764	VHT per household	Population and employment	0.00	
Ewing et al., 2009	1,466	VMT per household	Population	0.00	y
Ewing et al., 2009	1,466	VMT per household	Job	−0.06	y
Fan, 2007	7,422	Miles traveled per person	Parcel	−0.07 **	
Frank & Engelke, 2005	4,552	VMT per household	Net residential	0.00	y
Greenwald, 2009	3,938	VMT per household	Net residential	−0.07	y
Greenwald, 2009	3,938	VMT per household	Net job	0.01	y
Hedel & Vance, 2007	28,901	VKT per person	Commercial	−0.01	
Holtzclaw et al., 2002 (Chicago)	314	VMT per household	Household	−0.14	
Holtzclaw et al., 2002 (Los Angeles)	1,459	VMT per household	Household	−0.11	
Holtzclaw et al., 2002 (San Francisco)	1,047	VMT per household	Household	−0.14	
Kockelman, 1997	8,050	VMT per household	Population	0.00	y
Kockelman, 1997	8,050	VMT per household	Job	0.00	y
Kuzmyak, 2009a	5,926	VMT per household	Household	−0.04 **	y
Kuzmyak, 2009b	3,615	VMT per household	Household	0.00	y
Naess, 2005	1,414	Weekday travel distance by car per person	Population and employment	0.00	
Pickrell & Schimek, 1999	40,000	Miles driven per vehicle	Population	−0.06 **	
Schimek, 1996	15,916	VMT per household	Population	−0.07	y
Sun et al., 1998	4,000	VMT per household	Job	0.00	y
Zegras, 2007	4,279	Daily automobile use per household	Dwelling unit	−0.04 **	y
Zhou & Kockelman, 2008	1,903	VMT per household	Population	−0.12 **	y
Zhou & Kockelman, 2008	1,903	VMT per household	Job	0.02 ψ	y

ψ$p < .10$ *$p < .05$ **$p < .01$

Table A-2. Elasticity of VMT with respect to diversity.

Study	***N***	***y***	***x***	***e***	**In meta-analysis?**
Bento et al., 2003	6,808	VMT per household	Job-housing imbalance	−0.06 ψa	y
Cervero & Kockelman, 1997	896	VMT per household	Land use dissimilarity	0.00	
Cervero & Kockelman, 1997	896	VMT per household	Proportion vertical mix	0.00	
Cervero & Kockelman, 1997	896	VMT per household	Proportion of population within 1/4 mile of store	0.00	
Chapman & Frank, 2004	8,592	VMT per person	Land use mix (entropy index)	−0.04 **	y
Ewing et al., 1996 (Palm Beach County)	764	VHT per household	Job-population balance	−0.09	
Ewing et al., 2009	1,466	VMT per household	Job-population balance	0.00	y
Fan, 2007	7,422	Miles traveled per person	Retail store count	0.00	
Frank & Engelke, 2005	4,552	VMT per household	Land use mix (entropy index)	−0.02 **	y
Frank et al., 2009	2,697	VMT per household	Land use mix (entropy index)	−0.04	y
Greenwald, 2009	3,938	VMT per household	Non-retail job-housing balance	0.03	y
Greenwald, 2009	3,938	VMT per household	Retail job-housing balance	−0.01	y
Greenwald, 2009	3,938	VMT per household	Job mix (entropy index)	0.01	
Hedel & Vance, 2007	28,901	VKT per person	Land use mix (entropy index)	−0.06	y
Kockelman, 1997	8,050	VKT per household	Land use dissimilarity	−0.10 **	
Kockelman, 1997	8,050	VKT per household	Land use mix (entropy index)	−0.10 *	y
Kuzmyak et al., 2006	2,707	VMT per household	Land use mix (entropy index)	−0.09	y
Kuzmyak et al., 2006	2,707	VMT per household	Walk opportunities within 1/2 mile of home	−0.10 *	y
Kuzmyak, 2009a	5,926	VMT per household	Land use mix (entropy index)	−0.27 **	y
Kuzmyak, 2009b	3,615	VMT per household	Land use mix (entropy index)	−0.09 **	y
Pushkar et al., 2000	795	VKT per household	Land use mix (entropy index)	−0.11 **	
Sun et al., 1998	4,000	VMT per household	Land use mix (entropy index)	−0.10	y
Zegras, 2007	4,279	Automobile use per household	Land use diversity	−0.01 **	y

$^{\psi}p < .10$ $^{*}p < .05$ $^{**}p < .01$

Note:

VKT is vehicle kilometers of travel.

a. Sign reversed.

Table A-3. Elasticity of VMT with respect to design.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Bhat & Eluru, 2009	3,696	VMT per household	Bicycle lane density	−0.08 **	
Bhat, Sen, et al., 2009	8,107	VMT per household	Bicycle lane density	−0.05 *	
Bhat, Sen, et al., 2009	8,107	VMT per household	Street block density	0.01 *	
Boarnet et al., 2004	6,153	Nonwork VMT per person	Intersection density	−0.19 **	
Boarnet et al., 2004	6,153	Nonwork VMT per person	Proportion 4-way intersections	−0.06 *	
Boarnet et al., 2004	6,153	Nonwork VMT per person	Pedestrian environment factor	0.05	
Cervero & Kockelman, 1997	896	VMT per household	Proportion 4-way intersections	0.00	y
Cervero & Kockelman, 1997	896	VMT per household	Proportion quadrilateral blocks	0.19 **	
Cervero & Kockelman, 1997	896	VMT per household	Sidewalk width	0.00	
Cervero & Kockelman, 1997	896	VMT per household	Proportion front and side parking	0.00	
Chapman & Frank, 2004	8,592	VMT per person	Intersection density	−0.08 **	y
Chatman, 2008	527	Nonwork VMT per person	4-way intersection density	−0.06	
Ewing et al., 2009	1,466	VMT per household	Intersection density	−0.31 *	y
Fan, 2007	7,422	Miles traveled per person	Proportion connected intersections	−0.11	y
Fan, 2007	7,422	Miles traveled per person	Sidewalk length	−0.02 ψ	
Frank & Engelke, 2005	4,552	VMT per household	Intersection density	−0.10 **	y
Frank et al., 2009	2,697	VMT per household	Intersection density	−0.11 **	y
Greenwald, 2009	3,938	VMT per household	Intersection density	−0.29 **	y
Hedel & Vance, 2007	28,901	VKT per person	Street density	−0.04 *	y
Pushkar et al., 2000	795	VKT per household	Intersections per road km	−0.04 *	
Zegras, 2007	4,279	Automobile use per household	Proportion 3-way intersections	−0.15 *[a]	y
Zegras, 2007	4,279	Daily automobile use per household	Plaza density	−0.03 *	

ψ$p < .10$ *$p < .05$ **$p < .01$

Note:

a. Sign reversed.

Table A-4. Elasticity of VMT with respect to destination accessibility.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Bento et al., 2003	6,808	VMT per household	Population centrality	−0.15 **	
Bhat & Eluru, 2009	3,696	VMT per household	Accessibility to shopping	−0.01 **	
Bhatia, 2004	20	VMT per household	Job/household accessibility by transit	−0.19 *	
Boarnet et al., 2004	6,153	Nonwork VMT per person	Distance to CBD	−0.18 **	
Cervero & Duncan, 2006	16,503	Work VMT per person	Job accessibility by auto	−0.31 **	
Cervero & Duncan, 2006	16,503	Shopping VMT per person	Retail job accessibility by auto	−0.17 **	
Cervero & Kockelman, 1997	896	VMT per household	Job accessibility by auto	−0.27 **	y
Ewing et al., 1996 (Palm Beach County)	764	VHT per household	Job accessibility by auto	−0.04 **	
Ewing et al., 1996 (Dade County)	1,311	VHT per household	Job accessibility by auto	−0.15 **	
Ewing et al., 2009	1,466	VMT per household	Job accessibility by auto	−0.03	y
Frank et al., 2009	2,697	VMT per household	Job accessibility by transit	−0.10 **	y
Greenwald, 2009	3,938	VMT per household	Job accessibility by auto	−0.06 **	y
Kockelman, 1997	8,050	VMT per household	Job accessibility by auto	−0.31 **	y
Kuzmyak et al., 2006	2,707	VMT per household	Job accessibility by auto and transit	−0.13 *	
Kuzmyak, 2009a	5,926	VMT per household	Job accessibility by transit	−0.04 **	y
Kuzmyak, 2009b	3,615	VMT per household	Job accessibility by transit	−0.03 **	y
Naess, 2005	1,414	Weekday travel distance by car per person	Distance to downtown	−0.27 **[a]	y
Pushkar et al., 2000	795	VKT per household	Distance to CBD	−0.20 **[a]	
Shen, 2000	3,565	Average commute time	Job accessibility by auto and transit	−0.18	
Sun et al., 1998	4,000	VMT per household	Job accessibility by auto	−0.17 **	y
Sun et al., 1998	4,000	VMT per household	Household accessibility by auto	−0.34 **	
Zegras, 2007	4,279	Daily automobile use per household	Distance to CBD	−0.20 **[a]	y

$^{\psi}p < .10$ $^{*}p < .05$ $^{**}p < .01$

Note:

a. Sign reversed.

Table A-5. Elasticity of VMT with respect to transit access.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Bento et al., 2003	6,808	VMT per household	Distance to transit stop	−0.08 **a	
Frank & Engelke, 2005	4,546	VMT per household	Distance to bus stop	−0.01 a	y
Frank et al., 2009	2,697	VMT per household	Distance to bus stop squared	−0.04 **a,b	y
Hedel & Vance, 2007	28,901	VKT per individual	Walk minutes to transit	−0.02 ψa	y
Naess, 2005	1,414	Weekday travel distance by car per person	Distance to rail station	−0.14 *a	y
Pushkar et al., 2000	795	VKT per household	Distance to transit station	−0.03 **a	
Zegras, 2007	4,279	Daily automobile use per Household	Distance to Metro	−0.19 **a	y

$^{\psi}p < .10$ $^{*}p < .05$ $^{**}p < .01$

Notes:

a. Sign reversed.

b. Sign reversed and multiplied by 2 to make *x* variable equivalent to others.

Table A-6. Effect on VMT[a] of neighborhood type.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Bhat & Eluru, 2009	3,696	VMT per household	Urban neighborhood	−0.34 **	
Cao, Xu, et al., 2009	3,376	Vehicle miles driven per person	Urban neighborhood	−0.28 **	
Cervero, 2007	226	Commute VMT per person	Transit-oriented development	−0.29 **	
Khattak & Rodriguez, 2005	302	Daily miles traveled per household	New urbanist neighborhood	−0.20 ψ	
Shay & Khattak, 2005	399	Auto VMT per household	New urbanist neighborhood	−0.22 *	

$^{\psi}p < .10$ $^{*}p < .05$ $^{**}p < .01$

Note:

a. Proportional reduction relative to conventional suburban neighborhood.

Table A-7. Elasticity of walk trips with respect to density.

Study	N	y	x	e	In meta-analysis?
Bhatia, 2004	20	Walk trips per household	Household density	0.83 **	
Boarnet et al., 2008	6,362	Miles walked per person	Population density	0.13 *	
Boarnet et al., 2008	6,362	Miles walked per person	Retail job density	0.07 **	
Boarnet et al., 2008	6,362	Miles walked per person	Job density	0.00	
Boarnet et al., 2009	1,370	Walk trips per person	Residential density	–0.50	y
Boarnet et al., 2009	1,370	Walk trips per person	Business density	0.14 *	y
Boer et al., 2007	29,724	Miles walked per person	Housing density	0.21 [b]	
Chatman, 2009	999	Walk/bike trips per person	Population per road mile	0.16	
Chatman, 2009	999	Walk/bike trips per person	Retail job density	0.00	
Ewing et al., 2009	3,823	Walk mode choice	Population density	0.01	y
Ewing et al., 2009	3,823	Walk mode choice	Job density	0.10	y
Fan, 2007	988	Daily walking time per person	Parcel density	0.08 ψ	
Frank et al., 2008	8,707	Walk mode choice for work trips	Retail floor area ratio	0.07 *	
Frank et al., 2008	10,475	Walk mode choice for other trips	Retail floor area ratio	0.04 *	
Frank et al., 2009	2,697	Walk trips per household	Retail floor area ratio	0.20 **	
Frank et al., 2009	2,697	Walk trips per household	Number of retail parcels	0.08 **	
Greenwald & Boarnet, 2001	1,084	Walk trips per person for nonwork purposes	Population density	0.34 **[a]	y
Greenwald & Boarnet, 2001	1,084	Walk trips per person for nonwork purposes	Retail job density	0.11 *[a]	
Greenwald, 2009	3,938	Walk/bike trips per household	Residential density	0.28 **	y
Greenwald, 2009	3,938	Walk/bike trips per household	Job density	0.03	y
Hess et al., 1999	12	Pedestrians per hour	Population density	1.39	
Joh et al., 2009	2,125	Walk trips per person	Neighborhood business density	0.19 **	
Kockelman, 1997	8,050	Walk/bike mode choice	Population density	0.00	y
Kockelman, 1997	8,050	Walk/bike mode choice	Job density	0.00	y
Naess, 2005	1,406	Weekday travel distance by walk/bike per person	Population + employment density	0.00	
Rajamani et al., 2003	2,500	Walk mode choice for nonwork trips	Population density	0.01	y
Reilly, 2002	7,604	Walk mode choice for nonwork trips	Population density	0.16 **	y
Targa & Clifton, 2005	2,934	Walk trips per person	Household density	0.03	y
Zhang, 2004 (Boston)	1,619	Walk/bike mode choice for work trips	Population density	0.11 *	y
Zhang, 2004 (Boston)	1,619	Walk/bike mode choice for work trips	Job density	0.03 *	y
Zhang, 2004 (Boston)	1,036	Walk/bike mode choice for nonwork trips	Population density	0.06 *	y
Zhang, 2004 (Boston)	1,036	Walk/bike mode choice for nonwork trips	Job density	0.00	y

ψ$p < .10$ *$p < .05$ **$p < .01$

Notes:

a. Computed at median cutpoint by Jason Cao.

b. Significance level indeterminate.

Table A-8. Elasticity of walk trips with respect to diversity.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Bento et al., 2003	4,456	Walk/bike mode choice	Job-housing imbalance	0.30 *[a]	y
Boer et al., 2007	29,724	Miles walked per person	Business types in neighborhood	0.20 [b]	
Cao, Mokhtarian, et al., 2009b	1,277	Nonwork walk trips per person	Business types within 400 meters	0.07 **	
Cao et al., 2006	837	Walk trips to store per person	Distance to store	0.56 **[a]	y
Cervero & Kockelman, 1997	2,850	Non-person vehicle choice for nonwork trips	Land use dissimilarity	0.00	
Cervero & Kockelman, 1997	2,850	Non-person vehicle choice for nonwork trips	Proportion vertical mix	0.00	
Cervero & Kockelman, 1997	2,850	Non-person vehicle choice for nonwork trips	Proportion of population within 1/4 mile of store	0.00	
Ewing et al., 2009 (Portland)	3,823	Walk mode choice	Job-population balance	0.18	y
Frank et al., 2008	8,707	Walk mode choice for work trips	Land use mix (entropy index)	0.22 **	y
Frank et al., 2008	10,475	Walk mode choice for other trips	Land use mix (entropy index)	0.03 *	y
Frank et al., 2009	2,697	Walk trips per household	Land use mix (entropy index)	0.08 [y]	
Greenwald, 2009	3,938	Walk/bike trips per household	Non-retail job-housing balance	0.25 [ψ]	y
Greenwald, 2009	3,938	Walk/bike trips per household	Retail job-housing balance	0.02	y
Greenwald, 2009	3,938	Walk/bike trips per household	Job mix (entropy index)	0.09	
Handy & Clifton, 2001	1,368	Walk trips to store per person	Distance to nearest store	0.48 **[a]	y
Handy et al., 2006	1,480	Walk trips to store per person	# Business types within 800m	0.29 **	
Handy et al., 2006	1,480	Walk trips to store per person	Distance to nearest grocery	0.17 **[a]	y
Kitamura et al., 1997	14,639	Fraction walk/bike trips	Distance to nearest park	0.11 *[a]	
Kockelman, 1997	8,050	Walk/bike mode choice	Land use mix (entropy index)	0.23 *	y
Rajamani et al., 2003	2,500	Walk mode choice for nonwork trips	Land use mix (diversity index)	0.36 *	y
Reilly, 2002	7,604	Walk mode choice for nonwork trips	Distance to closest commercial use	0.16 **[a]	y
Shay et al., 2006	348	Walk trips per household	Distance to commercial center	0.98 **[a]	y
Targa & Clifton, 2005	2,934	Walk trips per person	Land use mix (entropy index)	0.08 **	y
Zhang, 2004 (Boston)	1,619	Walk/bike mode choice for work trips	Land use mix (entropy index)	0.00	y
Zhang, 2004 (Boston)	1,036	Walk/bike mode choice for nonwork trips	Land use mix (entropy index)	0.12	y

[ψ]$p < .10$ *$p < .05$ **$p < .01$

Notes:

a. Sign reversed.

b. Significance level indeterminate.

Table A-9. Elasticity of walk trips with respect to design.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Boarnet et al., 2008	6,362	Miles walked per person	Intersection density	0.45 **	
Boarnet et al., 2008	6,362	Miles walked per person	Pedestrian environment factor	0.04	
Boarnet et al., 2009	1,370	Walk trips per person	Block size	0.35 [a]	y
Boarnet et al., 2009	1,370	Walk trips per person	% 4-way intersections	−0.09	y
Boer et al., 2007	29,724	Miles walked per person	Proportion 4-way intersections	0.39 [d]	
Boer et al., 2007	29,724	Miles walked per person	Block length (long side)	−0.31 [a,d]	
Cervero & Kockelman, 1997	2,850	Non-private vehicle choice for nonwork trips	Proportion 4-way intersections	0.00	
Cervero & Kockelman, 1997	2,850	Non-private vehicle choice for nonwork trips	Proportion quadrilateral blocks	0.00	
Cervero & Kockelman, 1997	2,850	Non-private vehicle choice for nonwork trips	Sidewalk width	0.09 *	
Cervero & Kockelman, 1997	2,850	Non-private vehicle choice for nonwork trips	Proportion front and side parking	0.12 **[a]	
Chatman, 2009	999	Walk/bike trips per person	4-way intersection density	0.30 *	
Ewing et al., 2009	3,823	Walk mode choice	Intersection density	0.43 **	y
Ewing et al., 2009	3,823	Walk mode choice	Sidewalk coverage	0.27 **	y
Fan, 2007	988	Daily walking time per person	% connected intersections	0.40 **	
Fan, 2007	988	Daily walking time per person	Sidewalk length	0.12 **	
Frank et al., 2008	8,707	Walk mode choice for work trips	Intersection density	0.21 **	y
Frank et al., 2008	10,475	Walk mode choice for other trips	Intersection density	0.28 **	y
Frank et al., 2009	2,697	Walk trips per household	Intersection density	0.55 **	y
Greenwald, 2009	3,938	Walk/bike trips per household	Intersection density	1.11 **	y
Greenwald & Boarnet, 2001	1,084	Walk trips per person for nonwork purposes	Pedestrian environment factor	0.25 [b]	
Hess et al., 1999	12	Pedestrians per hour	Block size	0.35 **[a]	
Joh et al., 2009	2,125	Walk trips per person	Block size	0.01 [a]	y
Joh et al., 2009	2,125	Walk trips per person	% 4-way intersections	−0.27	y
Rajamani et al., 2003	2,500	Walk mode choice for nonwork trips	% Culs-de-sac	0.00 **[c]	y
Rodriguez & Joo, 2004	448	Walk mode choice for commute trips	Sidewalk coverage	1.23 **	
Rodriguez & Joo, 2004	448	Walk mode choice for commute trips	Path directness	0.03 $^{\psi}$	
Soltani & Allan, 2006	1,842	Walk/bike mode choice	Path directness	0.11	
Targa & Clifton, 2005	2,934	Walk trips per person	Block size	0.32 **[a]	y
Zhang, 2004 (Boston)	1,619	Walk/bike mode choice for work trips	Street connectivity	0.07 $^{\psi}$	y
Zhang, 2004 (Boston)	1,036	Walk/bike mode choice for nonwork trips	Street connectivity	0.05	

$^{\psi}p < 0.10$ $^{*}p < 0.05$ $^{**}p < 0.01$

Notes:

a. Sign reversed.

b. Computed at the median cutpoint by Jason Cao.

c. Because either the elasticity or significance level must be misreported in the published article we dropped this observation from the meta-analysis.

d. Significance level indeterminate.

Table A-10. Elasticity of walk trips with respect to destination accessibility.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Bento et al., 2003	4,456	Walk/bike mode choice	Population centrality	1.00 ψ	
Boarnet et al., 2008	6,362	Miles walked per person	Distance to cbd	0.49 **a	
Cervero & Duncan, 2003	7,836	Walk mode choice	Jobs within one mile	0.04	y
Cervero & Kockelman, 1997	2,850	Non-person vehicle choice for nonwork trips	Job accessibility by auto	0.00	
Chatman, 2009	999	Walk/bike trips per person	Distance to downtown	0.29 ψa	
Ewing et al., 2009	3,823	Walk mode choice	Jobs within one mile	0.23 *	y
Greenwald, 2009	3,938	Walk/bike trips per household	Job accessibility by auto	−0.32 **	
Kockelman, 1997	8,050	Walk/bike mode choice	Job accessibility by walking	0.22 **	y
Naess, 2005	1,406	Weekday travel distance by walk/bike per person	Distance to downtown	0.29 **a	

ψ$p < .10$ *$p < .05$ **$p < .01$
Note:
a. Sign reversed.

Table A-11. Elasticity of walk trips with respect to transit access.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Bento et al., 2003	4,456	Walk/bike mode choice	Distance to nearest transit stop	0.30 a	y
Boarnet et al., 2008	6,362	Miles walked per person	Distance to light rail	−0.17 *a	
Kitamura et al., 1997	14,639	Fraction walk/bike trips	Distance to nearest bus stop	0.10 *a	y
Naess, 2005	1,406	Weekday travel distance by walk/bike per person	Distance to closest rail station	0.00 a	
Rajamani et al., 2003	2,500	Walk mode choice for nonwork trips	% within walking distance of bus	0.02 a	
Targa & Clifton, 2005	2,934	Walk trips per person	Distance to nearest bus stop	0.08 **a	y

ψ$p < .10$ *$p < .05$ **$p < .01$
Note:
a. Sign reversed.

Table A-12. Effect on walk trips[a] of neighborhood type.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Cao, Mokhtarian, et al., 2009b	1,277	Nonwork walk trips per person	Traditional neighborhood	0.44 **	
Handy & Clifton, 2001	1,368	Walk trips to store per person	Traditional neighborhood	1.20 **	
Khattak & Rodriguez, 2005	302	Walk trips per household	New urbanist neighborhood	3.06 **	
Lund, 2003	427	Destination walk trips per person	Neighborhood with retail	0.38 **	
Lund, 2003	427	Destination walk trips per person	Neighborhood with retail and park	0.85 **	
Plaut, 2005	26,950	Walk mode choice for commute trips	Neighborhood with retail	0.79 **	
Rose, 2004	244	Walk trips per person	New urbanist neighborhood	0.35 *	

ψ$p < .10$ *$p < .05$ **$p < .01$
Note:
a. Proportional increase relative to conventional neighborhood.

Table A-13. Elasticity of transit trips with respect to density.

Study	N	y	x	e	In meta-analysis?
Bhatia, 2004	20	Transit trips per household	Household density	0.37 *	
Cervero, 2002a	427	Transit mode choice	Gross population density	0.39 *	y
Cervero, 2006	225	Weekday boardings per station	Population density	0.19 **	
Ewing et al., 2009	3,823	Transit mode choice	Population density	−0.01	y
Ewing et al., 2009	3,823	Transit mode choice	Job density	0.08	y
Fan, 2007	154	Daily transit travel time per person	Parcel density	0.00	
Frank et al., 2008	8,707	Transit mode choice for work trips	Retail floor area ratio	0.21 **	y
Frank et al., 2008	10,475	Transit mode choice for nonwork trips	Retail floor area ratio	0.17 **	y
Greenwald, 2009	3,938	Transit trips per household	Net residential density	0.41 **	y
Greenwald, 2009	3,938	Transit trips per household	Net job density	−0.05 *	y
Kuby et al., 2004	268	Weekday boardings per station	Population within walking distance	0.11 *	
Kuby et al., 2004	268	Weekday boardings per station	Employment within walking distance	0.07 *	
Rajamani et al., 2003	2,500	Transit mode choice for nonwork trips	Population density	0.08	y
Reilly, 2002	7,604	Transit mode choice for nonwork trips	Population density	0.20 *	y
Rodriguez & Joo, 2004	454	Transit mode choice for commute trips	Population density	−0.20	y
Zhang, 2004 (Boston)	1,619	Transit mode choice for work trips	Population density	0.12 *	y
Zhang, 2004 (Boston)	1,036	Transit mode choice for nonwork trips	Population density	0.13 *	y
Zhang, 2004 (Boston)	1,619	Transit mode choice for work trips	Job density	0.09 *	y
Zhang, 2004 (Boston)	1,036	Transit mode choice for nonwork trips	Job density	0.00	y
Zhang, 2004 (Hong Kong)	20,246	Transit mode choice for work trips	Population density	0.01	y
Zhang, 2004 (Hong Kong)	15,281	Transit mode choice for nonwork trips	Population density	0.01 *	y
Zhang, 2004 (Hong Kong)	20,246	Transit mode choice for work trips	Job density	0.01 **	y
Zhang, 2004 (Hong Kong)	15,281	Transit mode choice for nonwork trips	Job density	0.01	y

$^{\psi}p < .10$ $^{*}p < .05$ $^{**}p < .01$

Table A-14. Elasticity of transit trips with respect to diversity.

Study	***N***	***y***	***x***	***e***	**In meta-analysis?**
Bento et al., 2003	4,456	Transit mode choice	Job-housing imbalance	0.60 [a]	y
Cervero, 2002a	427	Transit mode choice	Land use mix (entropy index)	0.53 *	y
Cervero & Kockelman, 1997	1,544	Non-personal vehicle choice for work trips	Land use dissimilarity	0.00	
Cervero & Kockelman, 1997	1,544	Non-personal vehicle choice for work trips	Proportion vertical mix	0.00	
Cervero & Kockelman, 1997	1,544	Non-personal vehicle choice for work trips	Proportion of population within 1/4 of store	0.00	
Fan, 2007	154	Daily transit travel time per person	Retail store count	−0.04 $^{\psi}$	
Frank et al., 2008	8,707	Transit mode choice for work trips	Land use mix (entropy index)	0.09 *	y
Frank et al., 2008	10,475	Transit mode choice for nonwork trips	Land use mix (entropy index)	0.19	y
Greenwald, 2009	3,938	Transit trips per household	Job-housing balance	0.23 *	y
Greenwald, 2009	3,938	Transit trips per household	Job mix (entropy index)	0.04	
Kitamura et al., 1997	14,639	Fraction transit trips	Distance to nearest park	0.11 *	
Rajamani et al., 2003	2,500	Transit mode choice for nonwork trips	Land use mix (diversity index)	−0.04	y
Reilly, 2002	7,604	Transit mode choice for nonwork trips	Distance to closest commercial use	−0.19 **	
Zhang, 2004 (Boston)	1,619	Transit mode choice for work trips	Land use mix (entropy index)	0.00	y
Zhang, 2004 (Boston)	1,036	Transit mode choice for nonwork trips	Land use mix (entropy index)	0.12	y

$^{\psi}p < .10$ $^{*}p < .05$ $^{**}p < .01$

Note:

a. Sign reversed.

Table A-15. Elasticity of transit trips with respect to design.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Cervero, 2002a	427	Transit mode choice	Sidewalk ratio	0.16	
Cervero, 2007	726	Transit mode choice for work trips	% 4-way intersections	1.08	y
Cervero & Kockelman, 1997	1,544	Non-personal vehicle choice for work trips	Proportion front and side parking	0.00	
Cervero & Kockelman, 1997	1,544	Non-personal vehicle choice for work trips	Proportion 4-way intersections	0.00	
Cervero & Kockelman, 1997	1,544	Non-personal vehicle choice for work trips	Sidewalk width	0.00	
Cervero & Kockelman, 1997	1,544	Non-personal vehicle choice for work trips	Proportion quadrilateral blocks	0.19	
Fan, 2007	154	Daily transit travel time per person	% connected intersections	0.27	
Fan, 2007	154	Daily transit travel time per person	Sidewalk length	0.00	
Frank et al., 2008	8,707	Transit mode choice for work trips	Intersection density	0.20 *	y
Frank et al., 2008	10,475	Transit mode choice for nonwork trips	Intersection density	0.24 ψ	y
Frank et al., 2009	2,697	Transit trips per household	Intersection density	0.12	y
Greenwald, 2009	3,938	Transit trips per household	Intersection density	0.37 *	y
Lund et al., 2004	967	Transit mode choice	% 4-way intersections at destination	1.08 **	y
Rajamani et al., 2003	2,500	Transit mode choice for nonwork trips	% Culs-de-sac	0.00 [a]	y
Rodriguez & Joo, 2004	454	Transit mode choice for commute trips	Sidewalk coverage	0.28 *	
Rodriguez & Joo, 2004	454	Transit mode choice for commute trips	Path directness	0.01 ψ	
Zhang, 2004 (Boston)	1,619	Transit mode choice for work trips	Street connectivity	0.08 ψ	y
Zhang, 2004 (Boston)	1,036	Transit mode choice for nonwork trips	Street connectivity	0.04	y

$^{\psi}p < .10$ $^{*}p < .05$ $^{**}p < .01$
Note:
a. Sign reversed.

Table A-16. Elasticity of transit trips with respect to destination accessibility.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Bento et al., 2003	4,456	Transit mode choice	Population centrality	0.00	
Cervero, 2006	225	Weekday boardings per station	Distance to CBD	0.21 **[a]	
Ewing et al., 2009	3,823	Transit mode choice	Job accessibility by transit	0.29 **	
Frank et al., 2009	2,697	Transit trips per household	Job accessibility by transit	0.16 *	
Greenwald, 2009	3,938	Transit trips per household	Job accessibility by auto	0.05	
Kuby et al., 2004	268	Weekday boardings per station	Average time to other stations	0.95 **[a]	
Lund et al., 2004	967	Transit mode choice	Job accessibility by auto	−0.70 **	

$^{\psi}p < .10$ $^{*}p < .05$ $^{**}p < .01$
Note:
a. Sign reversed.

Table A-17. Elasticity of transit trips with respect to transit access.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Bento et al., 2003	4,456	Transit mode choice	Distance to transit stop	1.00 [a]	y
Ewing et al., 2009	3,823	Transit mode choice	Bus stop density	0.08	
Frank et al., 2009	2,697	Walk trips per household	Distance to bus stop squared	0.02 [b]	y
Kitamura et al., 1997	14,639	Fraction transit trips	Distance to rail station	0.13 **[a]	y
Rajamani et al., 2003	2,500	Transit mode choice for nonwork trips	% within walking distance of bus	0.42 *	

$^{\psi}p < .10$ $^{*}p < .05$ $^{**}p < .01$

Notes:

a. Sign reversed.

b. Sign reversed and multiplied by 2 to make x variable equivalent to others.

Table A-18. Effect on transit trips[a] of neighborhood type.

Study	*N*	*y*	*x*	*e*	In meta-analysis?
Rose, 2004	244	Transit trips per person	New urbanist neighborhood	0.66	

Note:

a. Proportional increase relative to conventional neighborhood.