Appendix A: What the Travel Literature Tells Us[1]

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

The purpose of this meta-analysis is to summarize empirical results on associations between built environments and travel, especially non-work travel. A number of studies, including Crane (1996), Cervero and Kockelman (1997), Kockelman (1997), Boarnet and Crane (2001), Cervero (2002), Zhang (2004), and Cao et al. (2009b), provide economic and behavioral explanations on why built environments might be expected to influence travel choices. We accept these explanations and instead focus on measuring the magnitude of relationships.

Why another review of this literature on built environments and travel, one might ask? There are four reasons for this meta-analysis: the need to quantify effect sizes, the need to update earlier work, the need to expand to other outcome measures, and the need to address the methodological issue of self-selection.

Quantifying Effect Sizes

Existing surveys seldom generalize across studies or make sense of differing results. Readers are left with glimpses of many trees rather than a panoramic view of this complex and rich forest of research. A meta-analysis, by its nature, reduces many studies to a single bottom line.

A literature review by Ewing and Cervero (2001) derived composite elasticities by "eye balling" rather than weighted averaging. It was an inherently imprecise process.

Updating Earlier Work

The number of built environment-travel studies now exceeds 200, most having been completed since our 2001 review. Compared to earlier studies, these newer ones have estimated effects of more environmental variables simultaneously (including a 5th D, distance to transit), controlled for more confounding influences (including traveler attitudes and residential self-selection), and used more sophisticated statistical methods.

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1 This appendix is taken from Ewing, R., & Cervero, R. (2010). Travel and the built environment—A meta-analysis. *Journal of the American Planning Association*, 76(3), 265-294.

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.

Extending to Other Travel Outcomes

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 and Schofield 2005; Cunningham and Michael 2004; Frank 2000; Frank and Engelke 2001; Humpel et al. 2002; Kahn et al. 2002; Krahnstoever-Davison et al. 2006; Lee and Moudon 2004; McCormack et al. 2004; Transportation Research Board 2005; Owen et al. 2004; Saelens and Handy 2008; Trost et al. 2002). Transit use is less obviously related to public health, but it 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.

Addressing Self-Selection

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 (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.)"

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

Using travel diary data from the New York-New Jersey-Connecticut regional travel survey, Salon (2006) concluded that the effect of the built environment itself accounted for 1/2 to 2/3 of the total effect of a change in population density on walking level 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 itself accounted for 58% to 90% of the "total" influence of residential location on VMT, depending on model specifications. Using travel diary data for four traditional and four suburban neighborhoods in Northern California, Cao (2009) reported that that, on average, the causal influences of neighborhood type account for 61% of the total 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 et al. (2009c) estimated that anywhere from 48% to 98% of the difference in vehicle miles driven was due to direct environmental influences, the balance being due to self-selection; the percentage varied between pairs of locations (urban vs. suburban, urban vs. exurban).

So while the environment may play a more important role in travel behavior than do attitudes and residential preferences, both effects are present.

Five Ds of the Built Environment

The potential to moderate travel demand through changes in the built environment is the most heavily researched subject in urban planning. In travel research, urban development patterns have come to be characterized by “D” variables. The original “three Ds,” coined by Cervero and Kockelman (1997), are density, diversity, and design. The Ds have multiplied since Cervero and Kockelman’s original article, with the addition of destination accessibility and distance to transit (Ewing and 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 in travel studies, controlled as confounding influences.

Density is measured in terms of activity level per unit area. It can be measured on gross or net area basis, on a population or dwelling unit basis, and on an employment or building area basis. Population and employment density are two distinct dimensions. The two are sometimes summed to compute an overall “activity density.”

Diversity is related to the number of different land uses in an 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 larger ones denote a variety of land uses, are widely used in travel studies. Job-to-housing or job-to-population ratios are less frequently used. What Handy (1993) refers to as local accessibility is part of diversity. It is measured by distance from home to the closest store or other local trip attraction.

Design includes street network characteristics within a neighborhood. Street networks vary from dense urban grids of highly interconnected, straight streets to sparse suburban networks of curving streets forming “loops and lollipops.” Street accessibility usually is measured in terms of average block size, proportion of four-way intersections, or number of intersections per square mile. In the occasional study, design also is measured in terms of sidewalk coverage, building setbacks, streets widths, pedestrian crossings, presence of street trees, or other physical variables that differentiate pedestrian-oriented environments from auto-oriented ones.

Destination accessibility is synonymous with access to trip attractions. In some studies, destination accessibility is simply represented by distance to the central business district. In other studies, it is represented by 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.

Distance to transit usually is measured from home or work to the nearest rail station or bus stop by the shortest street route. Distance to transit also may be represented by transit route density, stop spacing, or by the presence of stations within the zone or buffer area.

Note that the Ds are rough categories, divided by ambiguous and unsettled boundaries that may change in the future. Some dimensions overlap (e.g., density and destination accessibility). Regardless, it is useful to aggregate empirical results on the influences of each of the D variables on travel, if only to help organize the 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 and Miller 2000; Cao et al. 2009a; Cervero 2003; Crane 2000; Ewing and Cervero 2001; Handy 2006; Heath et al. 2006; McMillan 2005; McMillan 2007; Pont et al. 2009; Saelens et al. 2003; Stead and Marshall 2001). There are another 13 surveys of the literature on the built environment and physical activity, including walking and bicycling (Badland and Schofield 2005; Cunningham and Michael 2004; Frank 2000; Frank and Engelke 2001; Humpel et al. 2002; Kahn et al. 2002; Krahnstoever-Davison et al. 2006; Lee and Moudon 2004; McCormack et al. 2004; National Research Council 2005; Owen et al. 2004; Saelens and Handy 2008; Trost et al. 2002). There is considerable overlap among these reviews, particularly where they share authorship as with the two reviews by McMillan and the National Research Council and Saelens and Handy reviews. The literature is now so vast it has produced two reviews of the many reviews (Bauman and Bull 2007; Gebel et al. 2007).

Weighing the evidence, what can be said , about measured associations between D variables of the built environment and key travel "outcome" variables: *trip frequency*, *trip length*, *mode choice*, and composite measure of travel demand, *vehicle miles traveled (VMT)*? These are the most common outcomes modeled, and hence their relationships can be described with more confidence than can, for example, the relationship of the built environment to trip chaining in multipurpose tours or internal capture of trips within mixed use developments.

We draw on the survey by Ewing and Cervero (2001) for this qualitative description. Trip frequencies are primarily a function of socioeconomic characteristics of travelers and secondarily a function of the built environment; trip lengths are primarily a function of the built environment and secondarily of socioeconomic characteristics; and mode choices depend on both (though probably more on socioeconomics). VMT and 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 for both the home end (that is, residential neighborhoods) and destination end (activity centers) of trips. The dominant environmental effect on trip lengths is destination accessibility.

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 do 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." The urban design factor is a function of intersection density, residential density, and employment density.

Readers are referred to the other reviews cited above for a more complete picture of built environmental relationships. The physical activity literature, in particular, is quite distinct from the travel literature summarized by Ewing and Cervero (2010). There is little doubt that utilitarian travel and leisure-time physical activity are subject to different influences.

Earlier Quantitative Synthesis

Using 14 travel studies that included sociodemographic controls, Ewing and Cervero (2001) synthesized the literature by extracting elasticities of VMT and vehicle trips (VT) with respect to the first four Ds—density, diversity, design, and destination accessibility. These summary measures were incorporated into the EPA's Smart Growth Index (SGI) model, a widely used sketch planning tool for travel and air quality analysis. In the SGI model, density is measured in terms of residents plus jobs per square mile; diversity in terms of the ratio of jobs to residents relative to the regional average; and design in terms of street network density, sidewalk coverage, and route directness (two of three measures relating to street network design).

Table A-1 presents the average elasticities computed in our 2001 study. These elasticities, for example, suggest a doubling of neighborhood density results in approximately a 5 percent reduction in both VT and VMT per capita, all else being equal. Note that the elasticity of VMT with respect to destination accessibility is much larger than the other three, suggesting that areas of high accessibility—such as center cities—may produce substantially lower VMT than dense mixed-use developments in the exurbs.

In addition to simply eyeballing elasticities, and relying on only 14 studies, the 2001 review aggregated results for often dissimilar environmental variables (e.g., entropy and jobs-housing balance as measures of local diversity). This update involves the weighted averaging of results from more studies for more uniformly defined built environmental variables.

Table A-1. Typical Elasticities of Travel with Respect to Four D Variables (Ewing and Cervero 2001)

	Vehicle Trips (VT)	Vehicle Miles Traveled (VMT)
Local density	– .05	– .05
Local diversity (mix)	– .03	– .05
Local design	– .05	– .03
Regional accessibility	.00	– .20

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. From the standpoints of validity and reliability, this practice has both strengths and weaknesses. Every standard textbook on meta-analysis lists both (Lipsey and Wilson 2001; Hunter and Schmidt 2004; Schulze 2004; Littell et al. 2008; Borenstein et al. 2009).

The appeal of meta-analysis is that it aggregates all available research on a topic, allowing common threads to emerge. Pooling of samples provides the basis for greater generalizability. Meta-analysis is particularly appropriate where research outcomes are to be compared.

Meta-analysis has its drawbacks too. The combining of ”strong” and “weak” studies has the potential to contaminate results. Further, meta-analysis inevitably mixes “apples and oranges” due to the variation among studies in modeling techniques, independent and dependent variables, and sampling units. As studies are increasingly segmented in an effort to achieve consistency within categories, sample sizes can become small. With small sample sizes, statistical reliability becomes questionable, which we admit characterizes some of the breakdowns presented in this paper. In this sense, we hope that stratifying the results provide a baseline from which future studies can augment the small-sample results presented in this article. Lastly, the studies for a meta-analysis are usually chosen through a literature review. An inherent selection bias (called publication bias) may arise, since studies may tend to be published more readily if they show statistical significance (Rothstein et al. 2005). Publication bias may inflate effect size estimates in absolute terms.

Publication bias is minimized in this meta-analysis by searching the “gray literature” for unpublished reports, pre-prints, and white papers. Google Scholar and TRIS were particularly helpful in this search. The apples-oranges problem is minimized by focusing on a subset of studies that employed disaggregate data and comparably defined variables. This meta-analysis reflects tradeoffs. In an effort to avoid publication bias, we may have exacerbated the strong-weak study problem. In an effort to achieve greater construct validity by segmenting studies by variable type, this meta-analysis ends up with small sample sizes for dependent-independent variable pairs.

More than a dozen studies have applied meta-analytical methods to the urban planning field (Babisch, 2008; Bartholomew & Ewing, 2008; Bunn et al. 2003; Button & Kerr, 1996; Button & Nijkamp, 1997; Cervero, 2002; Debrezion et al., 2003; Duncan et al., 2005; Graham & Glaister, 2002; Hamer and Chida, 2008; Leck, 2006; Lauria & Wagner, 2006; Nijkamp & Pepping, 1998; Smith & Kaoru, 1995; Stamps, 1990; Stamps, 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 (2002) 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 critical success factors in sustainable city initiatives. Smith and Kaoru (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 this meta-analysis stopped short of estimating average effect sizes, it did evaluate the statistical significance of relationships between the built environment and travel. Residential density, employment density, and land-use mix were found to be inversely related to VMT at the $p < 0.001$ significance level.

Approach

Sample of Studies

Studies linking the built environment to travel were identified as follows. Academic Search Premier, Google, Google Scholar, MEDLINE, PAIS International, PUBMED, Scopus, TRIS Online (National Transportation Library), TRANweb, Web of Science, and ISI Web of Knowledge databases were searched using the key words "built environment," "urban form," and "development," coupled with keywords "travel," "transit," and "walking." CDs of the Transportation Research Board's annual programs were reviewed for relevant papers. All leading researchers in this subject area were contacted for copies of their latest research. A call was put out for built environment-travel studies on the academic planners' listserve, PLANET. The bibliographies of the previous literature reviews were examined to identify other pertinent studies.

As a resource for readers, the bibliography of this article lists more than 200 studies that relate, quantitatively, characteristics of the built environment to measures of travel. From the universe of built environment-travel studies, effect sizes were computed for more than 50 studies (see Table A-2). These studies have several things in common. As they analyze effects of the built environment on travel choices, all selected studies control statistically for confounding influences on travel behavior, in particular, sociodemographic influences. They use different statistical methods because the outcome variables differ from study to study.[1] All apply statistical tests to determine the significance of the various effects. Almost all are based on good size samples (see Appendix). Most capture the effects of more than one D variable simultaneously. And most importantly, what distinguishes these studies from the others is the *availability of data* with which to compute effect sizes.

Many quantitative studies were not selected for one reason or another:

- Many studies failed to publish average values of dependent and independent variables from which point elasticities could be calculated. Follow-up contacts were made with authors in an effort to obtain these descriptive statistics. In many cases, the research was several years old, and authors had moved on to other subjects. In a few cases, it proved impossible to even track down authors, or get them to respond to repeated data requests.
- Many studies have used highly aggregated data, at the city, county, or metropolitan level (e.g., Newman and Kenworthy 2006; van de Coevering and Schwanen 2006). Such studies have limited variance of both dependent and independent variables to explain relationships. Their causal and associative inferences are threatened by the so-called ecological fallacy.
- Several studies used statistical methods from which summary effect size measures could not be calculated. Included are studies using structural equation models to capture complex interactions among built environment and travel variables (e.g., Bagley and Mokhtarian 2002; Cao et al. 2007; Cervero and Murakami, 2010). In SEM, there are multiple influences of the same independent variable via different equations, which have to be aggregated into a single elasticity. Doing that with coefficients and mean values is not sufficient because of the nonlinearity of the interactions between the equations. [2]

- Many studies were excluded because they deal with limited populations or trip purposes (e.g., Chen and McKnight 2007; Li et al. 2005; Waygood et al. 2009). Notably, several recent studies of student travel to school cannot be generalized to other populations and trip purposes. The literature suggests that students' (or their parents') choice of mode for the journey to school is based on very different considerations than other trip making (Ewing et al. 2004; Yarlagadda & Srinivasan 2008).
- Some studies were excluded because they characterize the built environment subjectively rather than objectively, that is, in terms of qualities perceived and reported by travelers rather than measured by researchers (e.g., Craig et al. 2002; Handy et al. 2005). This is common among public health studies. While perceptions are important, they differ from objective measures of the built environment and arguably are less readily influenced by planners or public policy makers (McCormack et al. 2004; McGinn et al. 2007; Livi-Smith 2009). For studies that include both types of measures, relationships were analyzed only for objective measures.
- Finally, several otherwise worthy studies were excluded because they created and then applied built environmental indices without true zero values (for example, 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 and Rodriguez 2008; Frank et al. 2007; Levi-Smith 2009). For the same reason, several excellent studies were excluded because their independent variables, though initially continuous, were reduced to categorical variables to simplify the interpretation of results (Lee and Moudon 2006b; Oakes et al. 2007; McGinn et al. 2007).

Studies using nominal variables to characterize the built environment were analyzed separately from those using continuous variables. Such studies distinguish between traditional urban and conventional suburban development, or between transit-oriented and auto-oriented development. To be included, studies had to analyze disaggregate data and control for individual socioeconomic differences across their samples, thereby capturing the marginal effects of neighborhood type.[3]

Table A-2. Sample of Studies

	study sites	Data	methods	controls	self-selection*
Bento et al. 2003	Nationwide Personal Transportation Survey (114 MSAs)	D	LNR/LGR	SE/LS/OT	no

Bahtia 2004	20 communities in Washington DC	A	LNR	SE	no
Boarnet et al. 2004	Portland	D	LNR/PRR	SE/OT	no
Boarnet et al. 2008	Portland	D	TOR	SE	yes
Boarnet et al. 2009	8 neighborhoods in Southern California	D	NBR	SE	no
Cao et al. 2006	6 neighborhoods in Austin	D	NBR	SE/AT	yes
Cao et al. 2009b	8 neighborhoods in Northern California	D	SUR	SE/AT	yes
Cao et al. 2009c	Raleigh, NC	D	PSM	SE/AT	yes
Cervero 2002	Montgomery County, MD	D	LGR	SE/LS	no
Cervero 2006	225 LRT stations in 11 metropolitan areas	A	LNR	ST/LS	no
Cervero 2007	26 TODs in five California regions	D	LGR	SE/ LS/WP/AT	yes
Cervero and Duncan 2003	San Francisco Bay	D	LGR	SE/OT	no
Cervero and Duncan 2006	San Francisco Bay	D	LNR	SE/WP	no
Cervero and Kockelman 1997	50 neighborhood in San Francisco Bay	D	LNR/LGR	SE/LS	no
Chapman and Frank 2004	Atlanta	D	LNR	SE	no
Chatman 2003	Nationwide Personal Transportation Survey	D	TOR	SE/WP	no
Chatman 2008	San Francisco/San Diego	D	LNR/NBR	SE/LS/OT	no

Chatman 2009	San Francisco/San Diego	D	NBR	SE/LS/OT/AT	yes
Ewing et al. 1996	Palm Beach County/Dade County	D	LNR	SE	no
Ewing et al. 2009	52 MXDs in Portland	D	HLM	SE	no
Fan 2007	Raleigh-Durham	D	LNR	SE/LS/OT/AT	yes
Frank et al. 2005	Seattle	D	LNR	SE/LS	no
Frank et al. 2007	Seattle	D	LGR	SE/LS	no
Frank et al. 2009	Seattle	D	LNR	SE	no
Greenwald 2009	Sacramento	D	LNR/TOR/NBR	SE	no
Greenwald and Boarnet 2001	Portland	D	OPR	SE/LS	no
Handy and Clifton 2001	6 neighborhoods in Austin	D	LNR	SE	no
Handy et al. 2006	8 neighborhoods in Northern California	D	NBR	SE/AT	yes
Hedel and Vance 2007	German Mobility Panel Survey	D	LNR/PRR	SE/OT	no
Hess et al. 1999	12 neighborhood commercial centers in Seattle	A	LNR	SE	no
Holtzclaw et al. 2002	Chicago/Los Angeles/San Francisco	A	NLR	SE	no
Joh et al. 2009a	8 neighborhoods in Southern California	D	LNR	SE/CR/AT	yes
Khattak and Rodriguez 2005	2 neighborhoods in Chapel Hill	D	NBR	SE/AT	yes
Kitamura et al.	5 communities in San	D	LNR	SE/AT	yes

1997	Francisco region				
Kockelman 1997	San Francisco Bay	D	LNR/LGR	SE	no
Kuby et al. 2004	268 LRT stations in nine metropolitan areas	A	LNR	ST/OT	no
Kuzmyak et al. 2006	Baltimore	D	LNR	SE	no
Kuzmyak 2009a	Los Angeles	D	LNR	SE	no
Kuzmyak 2009b	Phoenix	D	LNR	SE	no
Lee and Moudon 2006a	Seattle	D	LGR	SE/LS	yes
Lund 2003	8 neighborhoods in Portland	D	LNR	SE/AT	yes
Lund et al. 2004	40 TODs in four California regions	D	LGR	SE/LS/WP/AT	yes
Naess 2005	29 neighborhoods in Copenhagen	D	LNR	SE/WP/AT	yes
Pickrell and 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	A	SLE	SE/LS	no
Rajamani et al. 2003	Portland	D	LGR	SE/LS	no
Reilly 2002	San Francisco	D	LGR	SE/OT	no
Rodriguez and 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	one neighborhood in Chapel Hill	D	NBR	SE/AT	yes
Shay and Khattak 2005	2 neighborhoods in Chapel Hill	D	LNR/NBR	SE	no
Shen 2000	Boston	A	LNR	SE	no
Sun et al. 1998	Portland	D	LNR	SE	no
Targa and Clifton 2005	Baltimore	D	POR	SE/AT	yes
Zegras 2006	Santiago	D	LNR/LGR	SE	no
Zhang 2004	Boston/Hong Kong	D	LGR	SE/LS/OT	no
Zhou and Kockelman 2008	Austin	D	LNR/PRR	SE	yes

Abbreviations:

A=aggregate

D=disaggregate

GEE=generalized estimating equations

HLM=hierarchical linear modeling

LGR=logistic regression

LNR=linear regression

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

AT=attitudinal variables

CR=crime variables

LS=level of service variables

OT=other variables

SE=socioeconomic variables

ST=station variables

WP=workplace variables

* Per Cao et al. (2009a), nine different approaches have been used to control for residential self-selection. From least to most rigorous, they range from direct incorporation of attitudinal measures in multivariate regression models to jointly estimated models of residential choice and travel behavior, where residential choice is treated as an endogenous variable.

Common Metrics

To combine results from different studies, a meta-analysis requires a common measure of effect size, a "common denominator" if you will. Our common metric is the elasticity of some travel outcome with respect to one of the D variables. An elasticity is a percentage change in one variable with respect to a one percent change in another variable (actually, the ratio of infinitely small changes). It is a dimensionless (unit-free) metric that measures the strength of association between two variables. Elasticities are the most widely used measures of effect size in economic and planning research.

For continuous outcomes such as number of walk trips, elasticities are the percent change in the outcome variable with respect to a one percent increase in the independent variables. For discrete outcomes such as the choice of walking over other modes, elasticities are the percent change in the probability of choosing a particular alternative when an independent variable is increased by one percent. Although they are not identical, these elasticities can be compared to demand elasticities because they also can be interpreted as the percent change in the market share (similar to demand) of the particular alternative when an independent variable is increased by one percent.

Individual Elasticities

For individual studies, elasticity estimates were derived in one of four ways (as in Ewing and Cervero, 2001): (1) from published studies, taken at face value; (2) from regression coefficients and mean values of dependent and independent variables (called "midpoint elasticities"), either as reported in original studies or obtained directly from researchers; (3) from data sets already available to the authors, or made available by other researchers; or (4) by the original researchers at the authors' behest.

Different formulas were used to compute elasticities for the different studies, in keeping with the different statistical methods used to estimate coefficient values (see Table 1 for statistical methods). The formulas employed are presented in Table A-3 (where β represents the regression coefficient value, y_o the mean value of the travel variable of interest, and x_o the mean value of the built environmental variable of interest).

Table A-3. Elasticity Estimation Formulas

Regression Specification	Elasticity
Linear	$\beta\, x_o / y_o$

log-log	B
log-linear	β x_o
linear-log	β / y_o
Logistic	β x_o (1 - y_o/n)*
Poisson	β x_o
negative binomial	β x_o
Tobit	β x_o/ y_o (for y_o > 0)**

* y_o/n is the mean estimated probability of occurrence.

** Applied only to positive values of the Tobit distribution.

When regression coefficients were statistically significant, elasticities were computed from reported coefficients using the formulas above. When regression coefficients were not significant, we had a choice: drop the observations, substitute zero values for the elasticities since the coefficients were not statistically different from zero, or use the reported coefficients to compute elasticities using the formulas above. Dropping the observations would have biased average elasticity values away from the null hypothesis of zero elasticity, and thus was rejected. Substituting zero values for computed elasticities would have had the opposite effect, biasing average values toward the null hypothesis, and was therefore also rejected. Instead we used the best available estimates of central tendency in all cases, the regression coefficients themselves, to compute elasticities. This is the common approach in meta-analysis (see, for example, Melo et al. 2009). Borenstein et al. (2009) argue against the use of significance levels as proxies for effect size since they depend not only on effect size but 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)" (Borenstein et al. 2009, p. 300).

Ideally, elasticities would have been computed for each observation (trip/traveler/household) individually, and then averaged over the sample. Indeed, a few of the researchers who reported elasticities have done exactly that (e.g., Bento et al. 2003 and Rodriguez and Joo 2004). To do so consistently would have required all other researchers to go back and compute elasticities for each observation, assuming a 1% change in each independent variable, estimate the % change in the dependent variable, and then average over the sample. Obviously, this would have been too much to ask of busy people, and we have instead estimated elasticities at the overall sample means of the dependent and/or independent variables.

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 (logistic functions, for example). "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: 42). Talvitie (1976, as cited by Train) 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 concern, we note, with discrete-choice models versus linear regression-based analyses that, as revealed in Table A-2, are more common in the study of built environments and travel.

Weighted Average Elasticities

Given individual elasticities from primary studies, we were able to compute weighted average elasticities for many dependent-independent variable pairs. Weighted average elasticities are presented in Tables A-4 through A-6. Averages are presented where three conditions are 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. Study sample sizes are as indicated in Table A-4 through A-6.

These results should be used only as ballpark estimates for two reasons. The first is our choice of minimum sample size required to conduct a meta-analysis. The second is our choice of weighting factor to compute weighted average elasticities.

Regarding the first reason, sample size, we settled on a minimum number of three studies due to data limitations (as in Tompa et al. 2008). While the built environment and travel is the most heavily researched subject in urban planning, when studies are segmented by variable type, we are left with samples that never reach what some would consider a reasonable minimum sample size (Lau et al. 2006). Also, to maximize our sample sizes, we mixed the relatively few studies that control for self-selection with the many that do not. Readers are advised to exercise caution in the use of elasticities when based on small samples of primary studies. Because we have sought to seed the meta-study of "built environments and travel" with the expectation that others will augment and expand our database over time, we opted to present elasticity estimates as long as they were drawn from three or more studies. We quote one study from another field that settled on seven studies as a minimum for a meta-analysis (Rodenburg et al., 2009):

> "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)."

Regarding the second reason, weighting, we used sample size as a weighting factor, again, due to data limitations. The optimal way to estimate average effect size is to weight each effect size value by a term that represents its precision. 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 effect size values, the actual weights are computed as the inverse of the squared standard error values—called *inverse variance weights* in a meta-analysis (Lipsey and Wilson 2001; Hunter and Schmidt 2004; Schulze 2004; Littell et al. 2008; Borenstein et al. 2009). From a statistical standpoint, such weights are optimal since they minimize the variance of the average effect size estimates. Intuitively, such weights also make sense since they give the greatest weight to the most precise estimates from individual studies.

In this meta-analysis, optimal pooling procedures weren't feasible. Lacking consistent standard error estimates from individual studies, we were forced to use sample size as the weighting factor. Weighting by sample size is by far the most common approach in meta-analyses since sample sizes are nearly always known (Shadish and Haddock 1994, p. 264). Inasmuch as variances of estimated effects decrease with increasing sample size, weighting by sample size may produce weighted averages that are not too different from those that would have been obtained using an optimal weighting scheme. However, when any weighting factor other than standard error is used, it is not possible to judge whether the resulting weighted averages are statistically different from zero. Since we combine significant and insignificant individual effect sizes, and because of data limitations, do not test for significance, statistical confidence is not reported for any of the results. It is thus possible that any given meta-elasticity is not significantly different from zero.

Table A-4. Weighted Average Elasticities of VMT with Respect to Built Environment Variables

	n total (n with controls for self selection)	*e*
DENSITY		
household/population density	9 (1)	-0.04
job density	5 (1)	0.0

DIVERSITY		
land use mix (entropy index)	10 (0)	-0.09
job-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

Table A-5. Weighted Average Elasticities of Walking with Respect to Built Environment Variables

	n total (n with controls for self selection)	*e*
DENSITY		
household/population density	10 (0)	0.07
job density	6 (0)	0.04
commercial FAR	3 (0)	0.07

DIVERSITY		
land use mix (entropy index)	8 (1)	0.15
job-housing balance	4 (0)	0.19
distance to store	5 (3)	0.25
DESIGN		
intersection/street density	7 (2)	0.39
% 4-way intersections	5 (1)	-0.06
DESTINATION ACCESSIBILITY		
jobs within one mile	3 (0)	0.15
DISTANCE TO TRANSIT		
distance to nearest transit stop	3 (2)	0.14

Table A-6. Weighted Average Elasticities of Transit Use with Respect to Built Environment Variables

	n total (n with controls for self selection)	*e*
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		
distance to nearest transit stop	3 (1)	0.29

Discussion

As in our 2001 meta study, the D variable that is most strongly associated with VMT is destination accessibility. The elasticity from the earlier meta study, -0.20, is confirmed by this meta-analysis (based on "job accessibility by auto"). In fact, the -0.19 VMT elasticity is nearly as large as the highest elasticities of the first three D variables—density, diversity, and design—combined. This too is consistent with the earlier meta study.

The variable with the next strongest relationship to VMT is proximity distance to downtown (the inverse of distance to downtown). This variable is a proxy for many of the other Ds: living in the core city typically means higher densities in mixed-use settings with good regional accessibility. Next most strongly associated with VMT are design metrics expressed in terms of intersection density or 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 elasticities of these two street network variables are fairly similar. Both short blocks and many interconnections shorten travel distances, apparently to about the same extent.

Equally surprising is the positive, albeit small, elasticity of VMT with respect to job density. Conventional literature holds that density at the work end of trips is as important as density at the home end as a VMT moderator (Ewing and Cervero, 2001). Since Table A-4 captures travel by residents, not employees, high job densities could reflect imbalanced environments that prompt some residents to travel farther by car.

As walking and transit use were not addressed by Ewing and Cervero (2001), the results in Tables A-5 and A-6 have no benchmarks against which to compare them. The mode share and likelihood of walk trips is most strongly associated with the design and diversity dimensions of built environments. Several variables that often go hand-in-hand with population density have elasticities that are well above that of density. Intersection density and jobs-housing balance appear to be most strongly associated with walking. A doubling of intersection density is accompanied by a 44 percent increase in walking, all else being equal. Interestingly, intersection density is a more significant variable than street connectivity. You can have great connectivity, but if the blocks are long superblocks, walkability may be limited. 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. Table A-5 also suggests that having transit stops nearby may stimulate walking (Cervero, 2001; Ryan and Frank, 2009). On the other hand, high job accessibility by car may discourage walking. Finally, Table 5 shows that as with VMT, job density is less strongly related to walking than is population density.

The mode share and likelihood of transit trips are most strongly associated with transit access. Living near a bus stop appears to be an inducement to transit riding, supporting the transit industry's standard of running buses within a quarter mile of most residents. Next in importance are design (intersection density) and diversity (jobs-housing balance). High intersection density shortens access distances, and provides more routing options for transit users. Jobs-housing balance 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 elasticity of population density in Table 6. In fact, the elasticity of transit riding with respect to retail density is three times greater than that of population density. High retail FAR increases the number of trip attractions near transit and may improve the walking environment.

No clear pattern emerges from scanning across the Tables A-4 to A-6. Perhaps what can be said with the most degree of confidence is that destination accessibility is most strongly related to both motorized (i.e., VMT) and non-motorized (i.e., walking) travel and that among the remaining Ds, density has the weakest association. 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 reflect density's role as an intermediate variable that ultimately gets expressed by the other Ds – i.e., dense settings usually have mixed uses with small blocks and plentiful intersections that shorten trips and encourage walking. Among design variables, intersection density more strongly sways the decision to walk or take transit than street connectivity. This suggests that block size matters more than gridded designs if significant numbers of Americans are to be lured out of their cars. And among diversity variables, jobs-housing balance is a stronger predictor of non-auto mode choice than land-use mix measures. Linking where people live and work allows more to commute by foot and by transit which appears to shape mode choice more than sprinkling a multiplicity of land uses within a neighborhood.

Controls for residential self-selection appear to increase the absolute magnitude of elasticities (if they have any effect at all). There may be good explanations for this unexpected result. In a region with few pedestrian- and transit-friendly neighborhoods, residential self-selection may lead to better matching of individual preferences with place characteristics, actually increasing the effect of the D variables. This possibility is posited by Lund et al. (2006, p. 256).

> ". . . 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."

Similarly, Chatman (2009) hypothesizes that "Residential 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." He carries out regressions that explicitly test for this, and finds that self-selection is more likely to enhance than diminish built environmental influences.

The elasticities derived in this meta-analysis are based on arguably the most complete data available to date. However, sample sizes are small, and the number of studies controlling for residential preferences and attitudes is still miniscule. Also, data limitations prevent us from reporting confidence intervals for meta-analysis results. These shortcomings need to be weighed when applying results to any particular context or local setting. As more built environment-travel studies appear in the planning literature, it will be necessary to update and refine these meta-analytic results.