Does Compact Development Make People Walk and Use Transit?

Mark R. Stevens
School of Community & Regional Planning
University of British Columbia
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The urban planning discipline has made a significant commitment to the idea that people should drive less and walk or use public transit instead. Planners generally believe that driving is bad (because of pollution, congestion, reliance on fossil fuels, traffic accidents, etc.), and that walking and transit are better (because they reduce most of the problems associated with driving and because they involve more exercise that supports physical health). This belief is so strong that "alternative transportation" has become one of the fundamental features promoted by the dominant contemporary models for land use and transportation planning, such as Smart Growth, New Urbanism, and sustainable development.

The relationship between travel and the built environment is probably the most heavily-researched topic in urban planning (Ewing et al. 2015, p. 1). Planning researchers have spent a lot of time studying whether designing communities according to the principles of compact development will get people to use alternative transportation more often. These researchers commonly report their findings in the form of statistics that estimate the average increase in walking/transit that results when the population density of a community increases, street networks are designed to make walking convenient and safe, and so on. One recent study reported, for example, that the likelihood of people choosing to walk (e.g. rather than drive) from home to non-work based destinations increases by 0.44% when the density of street intersections in their neighborhood increases by 1.00% (Ewing et al. 2013).

In theory, statistics like these can provide planners with useful guidance as they are involved in making decisions about how to design communities to encourage alternative transportation. In practice, the ability of this line of research to guide planners in their work is potentially limited because different studies send different messages: some studies tell planners that compact development features are effective at getting people to walk and use transit while other studies do not. Planners who consult the literature for guidance are thus likely to become confused about whether (for example) a plan to zone land in their community for higher densities will get more people to ride the bus. What planners need is for researchers to synthesize disparate (and sometimes, conflicting) findings from multiple studies into a smaller and more coherent set of findings that provide reliable guidance regarding compact development's influence on alternative transportation.

Researchers to date have reviewed and synthesized the literature on compact development and alternative transportation both qualitatively and quantitatively. Qualitative literature reviews provide a narrative and descriptive summary of findings across studies and sometimes try to extract an "overall message" from the literature regarding compact development's influence on alternative transportation. These reviews are popular with researchers and practitioners alike in part because they do not require expertise in sophisticated statistical methods on the part of the researcher or the reader.

Despite their popularity qualitative literature reviews display several weaknesses that render them incapable of providing a reliable synthesis of a given literature. Among other things, qualitative literature reviews typically (1) lack objective standards for deciding which studies to include in the review, such that the researchers conducting the reviews "often dismiss studies or findings because they do not fit into their preconceived notions or theories" (Stanley and Doucouliagos 2012, p. 2); (2) cover only a small fraction of all relevant studies (p. 13); and (3) only "re-review the studies that are most commonly known" (p. 13). Qualitative literature reviews are also generally incapable of providing a convincing synthesis of conflicting findings, such as when some studies report a positive relationship between two variables and other studies report a negative relationship or no relationship at all.

A quantitative literature review is more commonly referred to as a "meta-analysis", which is an arguably superior method to a qualitative review in the sense that a meta-analysis will generally include all (or at least a representative sample) of the relevant studies on a given topic and can resolve conflicting findings by placing more weight on those that were derived from higher quality studies.[1] The findings from a meta-analysis are typically reported in the form of statistics that (for example) indicate the direction (positive or negative) and strength of the relationship between two variables, such as walking and density. As I explain in more detail below, however, the traditional approach to meta-analysis that has been used to synthesize findings on compact development and alternative transportation has its own shortcomings that can result in a distorted understanding of whether and how changes to the built environment will influence alternative transportation. As a result, neither qualitative nor quantitative reviews of the literature conducted to date can effectively provide planners with reliable guidance regarding whether and how to promote compact development to encourage alternative transportation.

I aim in this paper to provide planners with a clearer understanding of compact development's influence on alternative transportation by synthesizing findings from the literature in a way that addresses the limitations of the traditional qualitative and quantitative approaches to literature review. I use an extension of traditional meta-analysis known as "meta-regression analysis" that is specifically-designed to (1) explain why different studies on the same topic yield different results, and (2) combine different findings from many studies into reliable statistics that can better inform planning practice. I answer these questions: Does compact development make people walk and use transit more, and if so, how much more? Planners need answers to these questions to help them determine whether it is worth promoting compact development as a way to get people to use alternative transportation.

I answer the questions by first describing past research efforts to measure compact development's influence on alternative transportation and how meta-regression analysis can address the limitations of traditional meta-analysis. I then summarize how I used meta-regression analysis to synthesize findings from the literature regarding the influence of compact development features on walking and transit. Next I present and discuss my findings, and then conclude with some thoughts about what they mean for whether planners should promote compact development in order to encourage alternative transportation.

How Have Researchers Measured Alternative Transportation and Compact Development?

Researchers who study compact development's influence on alternative transportation do so in large part to help inform planners in their efforts to get people to walk and use transit instead of driving cars. There are at least two reasons why planners commonly promote walking and transit. First, planners view walking and transit as desirable alternatives to driving. Walking and transit help to reduce (if not eliminate) many of the problems that planners have long attributed to driving, such as traffic congestion and air pollution. In recent decades planners have also looked at alternative transportation as a means to support global climate change mitigation goals, such as those communicated in reports from the *Intergovernmental Panel on Climate Change* (IPCC) that call for "substantial cuts in anthropogenic (greenhouse gas) emissions…through large-scale changes in energy systems and potentially land use" (IPCC

2014, p. 10). Second, planners generally believe that walking and transit are beneficial activities independent of their role as a substitute for driving. Walking and transit are two examples of so-called "active transportation", which is any form of transportation that is powered by humans.[2] Studies have found that participation in active transportation can help to reduce the risk of obesity, cardio vascular disease, and (premature) mortality (Frank et al. 2004; Lopez-Zetina et al. 2006; Flint et al. 2014).

Researchers have measured walking and transit in different ways. Some have measured walking/transit as a choice among a larger set of transportation options, some have measured the number of walking/transit trips made over a given period of time, and some have measured the number of pedestrians that pass a particular location or the number of persons that board a particular bus or train. Regardless of which measure is used, researchers typically examine whether the frequency of walking and transit depend on different characteristics of the built environment in general, and on characteristics of compact development in particular.

Researchers commonly measure five features of compact development that they refer to as "D-variables", because the name of each feature starts with "D". The five D-variables are density, diversity, design, destination accessibility, and distance to transit (Ewing and Cervero 2010). Planning researchers and practitioners like to believe that making strategic changes to one or more D-variables can help to increase alternative transportation by (directly or indirectly) increasing the (monetary and non-monetary) costs of driving and/or decreasing the costs associated with alternative transportation, thus increasing the appeal of alternative transportation options relative to driving. I now describe the D-variables that I focus on in this paper.

1. *Density* measures population, households, businesses, or jobs per unit of area. Higher densities might increase walking/transit by placing destinations closer together, thus reducing trip lengths and making alternative transportation options more feasible.

2. *Diversity* measures the mixture of different land uses in a given area. The land use mix variable and the land use dissimilarity index are measures of diversity that distinguish areas with less mix (i.e. single-use areas) from areas with more mix (i.e. multiple-use areas. The land use mix takes into account the relative percentage of two or more land use types within an area, whereas the dissimilarity index measures the degree to which the distribution of different land uses within a district is similar to the distribution that occurs in the area as a whole (Song et al. 2013, pp. 4-5). Jobs-housing balance is often measured as a ratio of jobs to households in a given area. Higher diversity might increase walking/transit by placing stores, restaurants, jobs, etc. closer to people's homes, thus increasing the likelihood that people will walk or take transit instead of driving and possibly stimulating demand for new walking/transit trips altogether.

3. *Design* measures street network characteristics within an area, helping to differentiate pedestrian-oriented from auto-oriented areas. Different measures of design include block size, the density of intersections/streets, and the proportion of intersections with 4-way stops. These types of design features help to determine how safe, convenient, and enjoyable it is to walk or use transit.

4. *Destination accessibility* measures how easy it is to access trip destinations. It is sometimes measured as the distance from a household to downtown or to stores, or as the number of jobs reachable within a given travel time by walking. Increased access to important destinations nearer to home can make alternative transportation options more feasible by shortening trip lengths and by giving people more reason to leave their homes in the first place.

5. *Distance to transit* is measured as the density of transit stops in an area or the distance from a household to the nearest transit stop while following the shortest street route. Locating transit stops nearer to homes helps to make transit more convenient for potential users.

Researchers commonly use statistical models to evaluate the actual influence that these D-variables have on alternative transportation, and they sometimes convert their model results into "elasticities" that indicate the percent change in walking or transit that can be expected from a 1% increase in a D-variable. Elasticities equal to zero indicate that the D-variable has no influence on walking/transit use; elasticities larger than + or – 1 indicate that walking/transit use changes a lot when D-variables changes; elasticities smaller than + or -1 indicate that walking/transit use does not change much when D-variables change. Elasticities of this type might be useful for planning purposes because they might help planners predict how walking/transit use would change if a choice were to be made in specific communities to pursue compact development.

The practical value of reported elasticities for planners is possibly limited, however, because different studies on the same topic commonly report elasticities of different sizes, which provides planners with mixed messages regarding compact development's influence on alternative transportation. Findings from Boarnet et al. (2011) and Forsyth and Oakes (2014) provide one illustrative example of this problem. Both of these studies examined how sensitive walking trips are to residential density. Boarnet et al.'s elasticity of -0.49 suggests that the number of walking trips goes down as residential density increases, whereas Forsyth and Oakes's elasticity of 0.34 suggests the opposite. A planner that followed the guidance from one study would clearly pursue different policies than a planner that followed the other. Meta-analysis in general (and meta-regression analysis in particular) can help to resolve this type of confusion by synthesizing conflicting findings from multiple studies into "a defensible, consistent, coherent body of knowledge" (Dewald et al. 1986, p. 600).

Using Meta-Regression Analysis to Address the Limitations of Traditional Meta-Analysis

A meta-analysis is a quantitative synthesis of findings from a body of literature. The traditional approach to meta-analysis that researchers have employed has been to calculate an average of the different elasticity estimates that have been reported across multiple studies for a given pair of variables. In some cases the researchers weight each estimate by a measure of its precision (such as sample size or standard error), and then calculate a weighted average that places more weight on estimates that were measured with greater precision. This traditional approach is appealing in large part because it is intuitive, it does not require the use of complex statistical methods, and it produces results that are easy to interpret.

There has been only one meta-analysis to date on compact development and alternative transportation that converted findings for D-variables from multiple studies into elasticities and then averaged the elasticities. Ewing and Cervero (2010) examined the influence of D-variables on walking and transit, and calculated average elasticities weighted by sample size. Their findings suggest that walking and transit are inelastic (i.e. not very sensitive) to changes in D-variables. They found that walking was most sensitive to design (intersection/street density, elasticity of 0.39) and diversity (land use mix, jobs-housing balance, and distance to the nearest store, elasticities ranging from 0.15 to 0.25), and that transit was most sensitive to the distance to the nearest transit stop (elasticity of 0.29) and design (percent 4-way intersections, elasticity of 0.29, and intersection/street density, elasticity of 0.23).

Even though the elasticities reported by Ewing and Cervero are already relatively small to begin with some of them might nevertheless overstate the influence that compact development has on alternative transportation because they are not corrected for possible “selective reporting bias”. Selective reporting is a widespread practice in which researchers select to report only those results that are “statistically-significant” and/or consistent with conventional wisdom (Stanley 2005; Stanley and Doucouliagos 2012). Stevens (Forthcoming) provides a detailed description of how selective reporting can lead to bias in the reported elasticities that estimate the influence of D-variables on travel behavior. In short, the practice of selective reporting can lead to the dissemination of elasticities that are shown to be “more positive” or “more negative” than they really are. Stanley (2008) showed that when selective reporting bias is present, all average elasticities (whether weighted or not) will provide a distorted impression of one variable’s influence on another, such that users of the averages should “refrain from drawing any inferences…unless (selective reporting bias) is formally tested and found to be absent” (Stanley and Doucouliagos 2012, p. 47).

Meta-regression analysis can address this problem through the use of statistical tests and models specifically-designed to (1) determine whether selective reporting bias exists in a dataset, and (2) adjust elasticities to remove the effects of that bias if it is found to exist. (See Appendix for details). Until recently there had been little (if any) effort to detect and correct for selective reporting bias in the planning literature in general or in the subarea of the literature that focuses on travel and the built environment.[3] Stevens (Forthcoming) used meta-regression analysis in a recent study to synthesize findings from the literature on the influence that compact development has on driving. He found evidence of selective reporting bias in the literature that resulted in the weighted average elasticities reported for several D-variables being larger than the corrected elasticities produced through the meta-regression analysis procedure that he employed. In general, he concluded that the literature has given planners and other readers the impression that D-variables have a larger influence on driving than they really do.

Using Meta-Regression Analysis to Determine Whether Compact Development Makes People Walk and Use Transit More

My goal in this paper is to provide planners with a clearer understanding of compact development's influence on alternative transportation by addressing the two questions I previously identified: Does compact development make people walk and use transportation more, and if so, how much more? Answers to these questions are necessary (though not sufficient, for reasons that I explain below) for enabling planners to determine whether it is worth promoting compact development as a means of getting people to use alternative transportation.

I use meta-regression analysis to help answer these questions. Rather than computing an average elasticity, meta-regression analysis uses elasticities reported by multiple studies as the dependent variable in a new regression model aimed at explaining why different studies of the same phenomenon yield different (and sometimes conflicting) results. The model's independent variables are typically features of the elasticities and the studies from which they were drawn, including (for example) measures of how precise the elasticities are[4] and whether the studies followed best practices (such as controlling for residential self-selection). Analysts can use the equation produced by this regression model to calculate a "representative" elasticity that is at a minimum corrected for selective reporting bias and possibly also adjusted to account for other factors that are responsible for differences in findings across studies (such as whether studies controlled for residential self-selection). (See Appendix for details).

Economist Tom Stanley and colleagues developed the meta-regression analysis methodology and introduced it to the literature in 1989 (Stanley and Jarrell 1989). Stanley and colleagues have made several enhancements to the methodology since that time, and it is now the standard approach to synthesizing research in the field of economics.[5] Stanley et al. (2013) estimate, for example, that 200 meta-regression analyses are conducted on economics topics each year. Stanley and colleagues published a "how-to" book on conducting meta-regression analysis (Stanley and Doucouliagos 2012) and an article that provides researchers with guidelines for how to report their own meta-regression analysis methods (Stanley et al. 2013). I followed the guidance provided in these two publications as closely as possible.

I used meta-regression analysis to synthesize findings from multiple studies that reported quantitative estimates of compact development's influence on alternative transportation. The estimates were coefficients from regression models that used walking or transit as the dependent variable and measures of compact development (i.e. a D-variable) as the independent variable. The models controlled for other factors such as household socioeconomic characteristics. I chose to focus only on walking and transit (rather than other forms of alternative transportation, such as bicycling) because they have been the most frequently-studied forms in the literature to date. I focus on the same measures of walking and transit that Ewing and Cervero (2010) focused on in their meta-analysis, which includes the number/proportion of trips made by walking/transit and the choice of walking/transit as the transportation mode relative to other modes (e.g. driving).

I began my search for studies on compact development and alternative transportation by first collecting all of the relevant papers included in the Ewing and Cervero (2010) meta-analysis. I then conducted an internet database search in summer 2015 to locate additional papers on the topic. I searched multiple thousands of online records for English-language studies conducted between 1996 and the present that studied compact development and walking/transit. I went back to 1996 because that is the earliest date for the studies in the Ewing and Cervero (2010) meta-analysis, and because the range of 1996 to 2015 captures a convenient 20-year time period. I searched 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 the keyword "travel", "transit", and "walking". These are the same databases and keywords that Ewing and Cervero used. I reviewed the reference lists in the relevant papers to look for additional papers that might be relevant, and I also reviewed the webpages for leading researchers in this subject area to find relevant papers I had not previously identified.

I found 80 papers that met my criteria for inclusion in this study, which were the same criteria for inclusion that Ewing and Cervero (2010) used in their meta-analysis. A paper had to do the following things in order to be included in my study: (1) use multiple regression with at least one dependent variable being a measure of walking or transit, and at least one independent variable being a D-variable; (2) use disaggregated (e.g. household) data rather than aggregated (e.g. city) data. Ewing and Cervero (2010, p. 269) explain that aggregated data typically yield limited variance in both dependent and independent variables, and can also lead to ecological fallacies when making causal inferences about individuals; (3) examine general population and travel behavior rather than limited populations (e.g. youth) and/or trip purposes (e.g. walking to school). Ewing and Cervero (2010, p. 272) explain that findings based on limited populations and/or trip purposes cannot be generalized and are thus not suitable for inclusion in a meta-analysis aimed at providing a synthesis of findings compact development and alternative transportation; and (4) utilize a regression modeling technique that enables the coefficients to be converted to elasticities. Ewing and Cervero (2010, p. 272) explain that coefficients from certain types of models (e.g. structural equation models, that represent both direct and indirect effects of variables) cannot be aggregated into a single elasticity.[6]

I converted each relevant regression model coefficient from the papers in my study into an elasticity in order to make coefficients from one study comparable to those from every other study. I was unable to obtain information necessary for calculating elasticities for 13 of the 80 papers that I identified in my search, so my sample includes the 67 papers shown in Table 1. The table indicates which alternative transportation and D-variables were examined in each study.

TABLE 1 ABOUT HERE

I entered information necessary for calculating elasticities from the 67 papers into a database. I transcribed elasticities directly into the database when papers reported them; I entered the relevant data and calculated elasticities myself (using the formulae shown in Appendix Table A-1) when papers did not report elasticities. I contacted authors of the studies to ask for missing data when necessary. I was forced to exclude some estimates from my analysis because I could not obtain all of the necessary information from authors. I included in my analysis only those D-variables for which I had at least three estimates[7] that were derived from at least three studies.[8]

I used the statistical methods described by Stanley and Doucouliagos (2012) to generate synthesized elasticity estimates from my database that are corrected for selective reporting bias. (See Appendix for details). I initially intended to adjust my elasticity estimates to account for whether or not the studies controlled for residential self-selection, following the same procedures used by Stevens (Forthcoming). It turned out, however, that too few studies controlled for residential self-selection to enable me to make this adjustment. I replicated Ewing and Cervero (2010) by reversing the sign of the block size, distance to downtown, and distance to nearest transit stop variables so that increases in these variables represent a favorable change from the standpoint of compact development principles for increasing alternative transportation. I expected to find that each of my elasticity estimates would have a positive sign, suggesting that an increase in the D-variable will result in an increase in walking/transit.

My analysis has some limitations. First, my sample sizes are small, which decreases our confidence in the accuracy of elasticity estimates and precluded me from adjusting my estimates to account for whether a study controlled for residential self-selection. This is a limitation that can possibly be addressed in future research as more data become available. Second, as explained by Stevens (Forthcoming), elasticities that report the sensitivity of travel behavior to changes in D-variables only provide planners with information regarding the potential benefits of compact development while saying nothing about the costs. As a result, elasticities by themselves cannot tell planners whether or not it is worth promoting compact development as a means of encouraging alternative transportation. Lastly, my analyses and the research findings I synthesize generally assume that changes in D-variables cause changes in walking/transit. Correlation does not necessarily imply causality, however. Even if my analyses detect statistically-significant relationships between D-variables and walking/transit, it is possible that at least some D-variables do not actually cause changes in walking/transit.

Synthesizing Findings for Compact Development's Influence on Walking and Transit

My synthesis of research findings shown in Tables 2 and 3 suggests that people do tend to walk and use transit more when D-variables change in the direction of compact development. However, they don't tend to walk and use transit very much more.

The variable with the largest influence on walking is business density. The elasticity of 0.36 indicates that walking increases by 0.36% on average when business density increases by 1%. Put another way, we would expect a person to walk 36% more if the local densities of businesses in his/her neighborhood were to double (i.e. increase by 100%). Dense clusters of businesses provide potential walkers with a reason to leave their houses and increase the convenience of walking by enabling patrons to visit several businesses on the same trip.

The convenience of walking also appears to be influenced in part by the size of street blocks. The block size variable has the second largest elasticity at 0.30, suggesting that people walk more as the size of blocks decreases. Smaller blocks help to provide "pedestrian scale" neighborhoods that make walking more feasible and appealing. Shorter blocks can also help to locate destinations more closely together, which also increases the appeal of walking (instead of driving).

Findings for household/population density present both good and bad news for advocates of compact development. On one hand the elasticity of 0.19 is the third largest of all the variables and suggests that people do in fact tend to walk more in areas with higher densities. On the other hand 0.19 is very small from a policy standpoint, especially when considering how difficult it is to increase densities in existing communities. Downs (2004) showed that increasing the density of an existing metropolitan area by even as little as 40% requires extreme investments in new and infill development. A database on the evolution of city population density in the United States showed that only 30 out of 456 cities increased population density more than 40% between 1950 and 1990 (Bryan et al. 2007; Brownstone and Golob 2009). My elasticity estimate suggests that even in cities that are successful at increasing density by 40%, we would only expect walking to increase by roughly 8%.

Two measures of land use diversity yield quite different results. The elasticity for land use dissimilarity (0.17) is nearly six times larger than that for land use mix (0.03), though both are small in absolute terms. This finding seems to suggest that walking is more sensitive to land use diversity in a given neighborhood when that neighborhood is relatively diverse compared to other neighborhoods in the region than when it is found to have a balance of different land uses but without taking into account its relative diversity within its region. Future research should look into this further.

Job accessibility by walking is the only remaining variable with an elasticity greater than 0.10. On one hand it makes sense to think that people will walk more as the number of jobs within walking distances of their home increases; on the other hand the elasticity of 0.15 suggests that this effect is not very large. Given that this variable typically measures the number of jobs within walking distance rather than whether or not a given commuter's job is within walking distance, it is possible that people with lots of jobs within walking distance nevertheless choose to not to walk much because *their* job is not within walking distance.

The two remaining variables that have an influence on walking each have very small elasticities ranging from 0.03 to 0.08 in magnitude. These variables include distance to the nearest transit stop and the percent of intersections with 4-way stops. The influence of these variables on walking is statistically significant, but the influence has little substantive significance in the sense that very large changes in these variables (such as doubling their values) would still only yield very small increases in walking. These variables appear to have very little potential for making people walk more, though planners might need to pay attention to them for achieving other objectives (such as increasing the convenience of walking for persons who already choose that travel mode).

The same can be said about job density, activity density, jobs-housing balance, intersection/street density, distance to stores, and distance to downtown, which appear to have no influence on walking whatsoever. These are generally surprising findings because planners tend to expect that each of these measures of compact development will have some effect on people's walking behavior. In addition, Ewing and Cervero (2010) found in their meta-analysis that intersection/street density and distance to stores had the largest influence on walking of any of the D-variables. I revisit this issue in the next section. In the case of job density, activity density, and jobs-housing balance, one possible reason for why locating jobs near houses does not stimulate additional walking might be that people who live near the jobs do not necessarily live near their *own* jobs, such that they might still choose to drive to work.

TABLE 2 ABOUT HERE

Household/population density is the variable with the largest influence on transit. The elasticity of 0.45 is the largest elasticity in my synthesis of findings. This finding likely highlights the fact that transit service is relatively sensitive to density in that transit service is typically not financially viable until certain (relatively high) density levels exist. Transit service differs from walking in this respect, in the sense that people can generally choose whether or not to walk in any given area, whereas they can only choose transit if transit is available. From a policy standpoint, a choice to promote increased densities might actually have no effect on transit use until and unless a density threshold is crossed at which point it becomes viable to provide transit service in the area.

Whereas jobs-housing balance had no effect on walking, it has the second-largest effect on transit. Mixing jobs into residential areas (or vice versa) can theoretically encourage transit use by reducing commute distances to the point that transit becomes a more appealing option. However, the elasticity of 0.15 is still quite small. Activity density is a related concept, in that it measures the density of population and employment in a given area. It has a comparable elasticity of 0.14.

Six remaining variables have a statistically-significant influence on transit, but the magnitude of their influence is so small as to have little substantive meaning. These variables include the percent of intersections with 4-way stops, distance to the nearest transit stop, intersection/street density, land use mix, job density, and transit stop density. Their elasticities range from 0.01 to 0.06. Again, these findings differ from those of Ewing and Cervero (2010), who found that each of these variables (except for transit stop density, which they did not include in their study, and job density, which they found had an elasticity of 0.01) had the largest influence on transit. The findings for the transit stop variables are particularly surprising, given that it would seem intuitive to expect that transit use would be very sensitive to the availability of transit stops. Overall, the decision to use transit appears to be shaped by factors other than the ease by which travelers can access nearby stops. Lastly, the distance to downtown variable does not have a statistically-significant influence on transit.

TABLE 3 ABOUT HERE

Why Are My Findings Different from Those of a Previous Meta-analysis On Compact Development and Alternative Transportation?

One of the primary advantages of using meta-regression analysis to calculate representative elasticities rather than following the traditional meta-analysis procedure of calculating weighted average elasticities is that meta-regression analysis can test and correct for the potential distorting effects of selective reporting bias. To help explore whether using meta-regression analysis to synthesize findings from the literature on compact development and alternative transportation made any difference in this respect, I compare my findings with those from the meta-analysis conducted by Ewing and Cervero (2010), who calculated average elasticities that were weighted by sample size. I focus first on the subset of variables that they found to have the largest effect on walking and transit. Table 4 shows the weighted average elasticities that Ewing and Cervero reported and the representative elasticities that I calculated for eight D-variables.

The differences between the two sets of findings are quite dramatic. All of my representative elasticities are much smaller in magnitude and are all close to or equal to zero. In other words, all of the variables that Ewing and Cervero found to have the largest influence on walking and transit are found in my analysis to have almost no influence at all. What factors might explain such dramatically different results? The answer to that question appears to be "selective reporting bias", and the fact that the weighted elasticities produced by Ewing and Cervero did not account for it.

Stanley and Doucouliagos (2012) describe in detail both informal and formal methods that researchers can use to test for the presence of selective reporting bias in a body of literature. The most useful informal method involves constructing and reviewing a "funnel graph", which is a plot of the reported elasticities for (in this case) a given D-variable in which the horizontal axis measures the size of the elasticity and the vertical axis measures the elasticity's precision (usually measured by the inverse of the elasticity's standard error). In the absence of selective reporting bias the plot of elasticity points will typically form the shape of an upside down funnel that is symmetrical and centered on the elasticity values that were measured with the highest precision, which should be the values that are closest to the "true" value; an asymmetrical plot with many more points on one side of the center than the other indicates that elasticity values on the latter side have been under-reported by researchers, which provides preliminary evidence that selective reporting bias is present in the body of literature used to construct the graph. In particular, an asymmetrical plot is preliminary evidence that researchers have been more likely to report values in one direction (e.g. the positive direction) than the other. (See Appendix for details).

I constructed funnel graphs for each of the eight D-variables shown in Table 4. Figure 1 shows the graphs for walking, and Figure 2 shows the graphs for transit. The graphs reveal a consistent pattern that helps to explain why the weighted average elasticities reported by Ewing and Cervero are so much higher than the representative elasticities that I calculated. In each graph, we can see that the largest elasticities (i.e. those farthest to the right side of the graphs) were also those that were measured with the lowest precision (i.e. toward the bottom of the graphs), and that those that were measured with the highest precision (i.e. toward the top of the graphs) had the smallest elasticities (i.e. toward the left side of the graphs, close to zero in elasticity size). We can also see that the shape of the distribution of points in each graph is asymmetrical, and is more heavily-weighted on the right side of the graphs, where elasticities are greater than zero in size.

These patterns in the graphs provide several important insights. First, they are consistent with the common finding from other meta-regression analyses that studies with small sample sizes (that generally produce low precision) typically report larger elasticities, presumably because the researchers continually changed their models until they produced elasticities that were large enough to be statistically-significant (Stanley and Doucouliagos 2012).[9] Second, the graphs show that elasticities less than zero in size have generally not been reported in the literature, and that researchers have essentially chosen only to report elasticities with values greater than zero. This is likely a result of an underlying *a priori* belief on the part of researchers (and possibly journal personnel as well) that these particular D-variables have a positive influence on walking and transit, such that any negative elasticity that is produced is considered to be "incorrect" and unworthy of being reported or published.

Third, and most importantly, the graphs show us that in each case, the elasticities that were measured with the highest precision are all very close to zero in size. Given that elasticities measured with the highest precision are likely to be closer to the "true" elasticity value than are those measured with the lowest precision (Stanley and Doucouliagos 2012), this means that the true values of the elasticities for these eight D-variables are all likely to be close to zero. The reason why my representative elasticities are all close to zero in size is that the meta-regression analysis model places more weight on the elasticities that were measured with the greatest precision, which in the case of D-variables means that the elasticities with values close to zero were given the most weight. In the case of the weighted average elasticities reported by Ewing and Cervero, we can see by looking at the graphs that the averages (1) would (and could) not have taken into account the fact that elasticities less than zero in magnitude have generally not been reported, and (2) were calculated based on a large number of elasticities that were measured with low precision.

The formal method to test for selective reporting bias involves using a statistical model to test whether or not the distribution of points shown in a funnel graph is symmetrical. The test is thus referred to as the "funnel asymmetry test" (or "FAT") (Stanley and Doucouliagos, 2012). I conducted a FAT for each of the eight D-variables shown in Table 4, and in each case the test detected the presence of positive bias, thus confirming the visual impression that the funnel graphs provide. The results of the FAT suggest that negative elasticity values have generally been under-reported in the literature on compact development and alternative transportation and that this literature has given the impression that compact development has a larger positive influence on alternative transportation than it really does. In other words, the literature has overstated the degree to which planners can get people to walk and use transit by making changes to this set of eight D-variables.

TABLE 4 ABOUT HERE

It is also worth noting that a small number of my representative elasticities are larger than the corresponding average elasticities reported by Ewing and Cervero. In particular, my elasticities for household/population density are much larger than the average elasticities for both walking (0.19 vs. 0.07) and transit (0.45 vs. 0.07). A review of my dataset reveals that the primary reason for these differences is that my dataset includes elasticity estimates that (1) are from recent studies that were published after the Ewing and Cervero study, and (2) are relatively large and positive in size, with relatively high precision. This means that my representative elasticities were influenced by these new additions to the literature that were not available when the weighted averages were computed.

Which D-Variables Matter Most for Getting People to Use Alternative Transportation?

I now summarize my findings in relation to which D-variables seem to matter the most for getting people to use alternative transportation. Table 5 provides a summary of the elasticities for walking and transit, arranged according to the five D-variable categories. Overall, it appears that density and diversity have the most influence on walking and transit, and that design, destination accessibility, and distance to transit have very little influence at all. Density presents an interesting case because it is commonly-viewed as a "proxy" for other D-variables (Handy 2005), in the sense that increasing the density of an area is likely to also result in increased diversity and destination accessibility, increased provision of transit service, and changes to the design of street networks that generally make them more walkable. I cannot say for sure based on my findings, but it is possible that the changes that occur in walking and transit that appear to stem from changes in density actually occur at least in part from changes in the other D-variables that often accompany changes in density. To the extent that this is true, it is also possible that the elasticities for density represent the combined effects on walking and transit associated with not only the changes in density but also the subsequent changes in other D-variables.

Measures of diversity present somewhat of a mixed bag. The land use dissimilarity index had a relatively large influence on walking, and jobs-housing balance had a similarly-sized influence on transit. But the land use mix variable had almost no influence on walking or transit, which appears to suggest that changing a neighborhood to include a balance of multiple land uses is not an effective strategy for promoting alternative transportation. It also appears that designing streets to make them more walkable is not effective, and neither is increasing the availability of transit stops.

In general, all of the elasticities suggest that walking and transit are not very sensitive to changes in D-variables. All of the elasticities are less than 1.00 in magnitude, which means that walking and transit are inelastic to changes in the five features of compact development that planners have paid the most attention to (i.e. density, diversity, design, destination accessibility, and distance to transit). In the next section of the paper I conclude with some thoughts about what these findings mean for whether planners should promote compact development to encourage alternative transportation.

TABLE 5 ABOUT HERE

Should Planners Promote Compact Development to Encourage Alternative Transportation?

There are many studies that examine compact development's influence on alternative transportation, which should mean that planners have access to a large body of knowledge to guide them in their efforts to get people to walk and use transit. While researchers have used both qualitative and quantitative approaches to help synthesize this literature in order to make it more useful for planners, the approaches they have employed to date are subject to important limitations that serve to constrain the extent to which the literature can provide planners with reliable guidance. In particular, researchers have yet to synthesize reported findings in a way that adjusts them for the potential distorting effects of selective reporting bias. This is cause for concern in part because of findings from the recent study by Stevens (Forthcoming), who found that selective reporting bias has likely resulted in the literature giving the impression that compact development has a greater influence on driving than it really does.

I designed my quantitative literature review and synthesis to examine whether selective reporting bias has had a similar effect on reported findings regarding compact development's influence on alternative transportation, and to correct the findings for that bias as necessary. I sought to answer these questions: Does compact development make people walk and use transit more, and if so, how much more? I found evidence that researchers have likely under-reported elasticity values showing that compact development has a negative influence (or no influence at all) on alternative transportation, which means that this literature has probably overstated the degree to which compact development can be effective at getting people to walk and use transit. After correcting reported findings for the effects of selective reporting bias I found that compact development does appear to increase walking and transit, but that the magnitude of that increase is generally small. It appears that the choice that people make to use alternative transportation is not very sensitive to changes in D-variables, which suggests that compact development might have limited potential for making people walk and use transit more.

Does this mean that planners should not promote compact development to encourage alternative transportation? The answer to that question is complicated and requires a rigorous assessment of the benefits and costs of compact development that is beyond the scope of this paper. On one hand it is true that communities might reasonably choose to pursue compact development for other legitimate reasons beyond those related to travel behavior, such that the benefits of compact development might not be limited to its ability to promote alternative transportation. On the other hand, there are reasons to believe that the problems associated with driving are urgent enough that society cannot afford to prioritize planning policies that are not very effective at getting people to walk and use transit instead of driving. Urgent calls from the IPCC and other organizations for widespread efforts to reduce greenhouse gas emissions and rising concerns about obesity and other health problems highlight the apparent need for strategies that can actually get people out of their cars and into cleaner and more active transportation options.

My findings cannot resolve for certain whether it is worth promoting compact development in a general sense. What does seem clear, however, is that if communities have ambitious goals for getting people to walk and use transit (especially, as an alternative to driving) then it seems unlikely that such goals will be achieved if compact development is the only tool communities use to influence travel behavior. My findings suggest that communities that pursue compact development in order to make lots of people choose alternative transportation modes are likely to be disappointed with the results.

If there is a silver lining for advocates of compact development it is that my findings are not adjusted for the possible effects of residential self-selection. When Stevens (Forthcoming) adjusted his findings for whether or not studies controlled for residential self-selection, he found that more often than not the magnitude of the elasticities representing the effects of compact development on driving actually increased in size, meaning that compact development was revealed to have a larger effect on driving once the effects of residential self-selection were accounted for. Data constraints prevented me from making similar adjustments, which means that I was unable to examine whether controlling for the effects of residential self-selection makes any difference in the size of the elasticities for alternative transportation. It is therefore possible that my findings for at least some D-variables understate their actual influence on walking and transit. This is an important topic for future research to explore if and when sufficient data are made available.

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Tables

Table 1. 67 Studies Included in the Sample

Study	Alternative transportation	D-variables examined in study[a]
Ameli et al. 2015	Walk	Density
Asad 2013	Walk	Distance
Bento et al. 2005	Walk, Transit	Destination, Diversity, Distance
Bhatia 2004	Walk, Transit	Density
Boarnet et al. 2008	Walk	Density, Design, Destination, Distance
Boarnet et al. 2011	Walk	Density, Design
Boer et al. 2007	Walk	Diversity, Design
Brown et al. 2006	Transit	Diversity, Design
Cao 2006	Walk	Destination
Cao and Mokhtarian 2012	Walk	Diversity
Cao et al. 2006	Walk	Diversity
Cao et al. 2009	Walk	Diversity
Cervero 2002	Transit	Diversity, Design
Cervero 2006	Transit	Density, Destination
Cervero 2007	Transit	Design
Cervero and Duncan 2003	Walk	Destination
Cervero and Guerra 2011	Transit	Density, Destination, Distance
Cervero and Kockelman 1997	Walk, Transit	Density, Diversity, Design, Destination;
Chatman 2009	Walk	Density, Design, Destination
Comendador et al. 2014	Walk, Transit	Density, Diversity, Design, Destination
Concas and DeSalvo 2014	Transit	Density, Destination, Transit
Ding et al. 2014	Transit	Density, Diversity, Design, Destination
Ewing et al. 2009	Walk, Transit	Density, Diversity, Design, Destination, Distance
Ewing et al. 2011	Walk, Transit	Density, Destination
Ewing et al. 2013	Walk, Transit	Density, Diversity, Design, Destination
Ewing et al. 2014	Walk, Transit	Density, Diversity, Design, Destination, Distance
Ewing et al. 2015	Walk	Density
Fan 2007	Walk, Transit	Density, Diversity, Design
Forsyth and Oakes 2014	Walk	Density
Frank et al. 2008	Walk, Transit	Density, Diversity, Design
Frank et al. 2009	Walk, Transit	Density, Diversity, Design, Destination, Distance
Greenwald 2009	Walk, Transit	Density, Diversity, Design, Destination
Greenwald and Boarnet 2001	Walk	Density, Design
Grunfelder and Nielsen 2012	Transit	Density, Destination, Distance
Handy and Clifton 2001	Walk	Diversity
Handy et al. 2006	Walk	Diversity
Hess et al. 1999	Walk	Density, Design
Hubers et al. 2014	Transit	Distance

Joh et al. 2009	Walk	Density, Design
Khan 2012	Walk	Density, Diversity, Design, Distance
Kim et al. 2007	Transit	Distance
Kockelman, 1997	Walk, Transit	Diversity, Distance
Koohsari et al. 2014	Walk	Design
Kuby et al. 2004	Transit	Density, Destination
Lamiquez and Lopez-Dominguez 2015	Walk	Density, Destination
Lee et al. 2014	Walk, Transit	Density, Diversity, Design
Lin and Shin 2008	Transit	Density, Diversity, Design
Lund et al. 2004	Transit	Design, Destination
Marshall and Garrick 2010	Walk, Transit	Design, Destination
McCormack et al. 2012	Walk	Design
Miranda-Moreno et al. 2011	Walk	Density
Naess 2005	Walk	Density, Destination, Distance
Parady et al. 2015	Walk, Transit	Density
Peterson 2011	Transit	Density, Diversity
Rajamani et al. 2003	Walk, Transit	Density, Diversity, Design, Distance
Reilly and Landis 2002	Walk, Transit	Density, Diversity
Renne et al. 2015	Transit	Density, Diversity, Design
Rodriguez and Joo 2004	Walk, Transit	Density, Design
Sadek et al. 2011	Walk, Transit	Density, Diversity, Design, Distance
Saelens et al. 2012	Walk	Design
Saghapour et al. 2015	Walk, Transit	Density, Diversity, Design
Schoner and Cao 2014	Walk	Density, Design
Shay et al. 2006	Walk	Diversity
Sung et al. 2014	Walk	Density, Diversity, Distance
Targa and Clifton 2005	Walk	Density, Diversity, Design, Distance
Thompson et al. 2012	Transit	Density, Diversity, Distance
Zhang 2004	Walk, Transit	Density, Diversity, Design

a. “Destination” is short for “Destination accessibility”; “Distance” is short for “Distance to transit”

Table 2. Elasticities for Walking

D-variable measure	Elasticity	Sample size
Business density	0.36	3
Block size[a]	0.30	3
Household/population density	0.19	13
Land use dissimilarity	0.17	3
Job accessibility by walking	0.15	5
Distance to nearest transit stop[a]	0.08	3
% 4-way intersections	0.03	4
Land use mix (entropy index)	0.03	15
Intersection/street density	-0.00	13
Activity density[b]	0.00[c]	5
Distance to a store	0.00[c]	3
Distance to downtown[a]	0.00[c]	4
Job density	0.00[c]	8
Jobs-housing balance	0.00[c]	7

a. I replicated Ewing and Cervero (2010) by reversing the sign of this variable, so that increases in the variable represent a favorable change from the standpoint of built environment design principles for increasing walk/transit.
b. Activity density measures both population and employment density.
c. The relationship between walking and this D-variable is not statistically-significant. I used a relatively low standard for determining statistical significance (i.e. a t-statistic greater than or equal to + or – 1.00) to account for small sample sizes, which produce low statistical power for testing statistical significance.

Table 3. Elasticities for Transit

D-variable measure	Elasticity	Sample size
Household/population density	0.45	12
Jobs-housing balance	0.16	5
Activity density[a]	0.14	3
% 4-way intersections[b]	0.06	3
Distance to nearest transit stop[c]	0.03	4
Intersection/street density	0.01	10
Land use mix (entropy index)	0.01	12
Job density	0.01	6
Transit stop density	0.01	4
Distance to downtown[c]	0.00[d]	4

a. Activity density measures both population and employment density.
b. The software program (Stata 14.1) did not produce t-statistics for the FAT-PET tests involving transit and % 4-way intersections, and it was thus not possible to determine whether there is a genuine relationship between these two variables.
c. I replicated Ewing and Cervero (2010) by reversing the sign of this variable, so that increases in the variable represent a favorable change from the standpoint of built environment design principles for increasing walk/transit.
d. The relationship between transit and this D-variable is not statistically-significant. I used a relatively low standard for determining statistical significance (i.e. a t-statistic greater than or equal to + or – 1.00) to account for small sample sizes, which produce low statistical power for testing statistical significance.

Table 4. Weighted Averages vs. Representative Elasticities

D-variable measure	Weighted Average from Ewing and Cervero (2010	Representative Elasticity from This Study
Walking		
Intersection/street density	0.39	-0.00
Distance to nearest store	0.25	0.00
Jobs-housing balance	0.19	0.00
Distance to nearest transit stop	0.15	0.08
Land use mix (entropy index)	0.15	0.03
Transit		
Distance to nearest transit stop	0.29	0.03
% 4-way intersections	0.29	0.06
Intersection/street density	0.23	0.01

Table 5. Summary of Elasticities by D-Variable

D-variable	Measure	Walking	Transit
Density	Business density	0.36	--
	Household/population density	0.19	0.45
	Activity density	0.00	0.14
	Job density	0.00	0.00
Diversity	Land use dissimilarity	0.17	--
	Land use mix (entropy index)	0.03	0.01
	Jobs-housing balance	0.00	0.16
Design	Block size	0.30	--
	Street connectivity	0.05	--
	% 4-way intersections	0.03	0.06
	Intersection/street density	-0.00	0.01
Destination accessibility	Job accessibility by walking	0.15	--
	Distance to a store	0.00	--
	Distance to downtown	0.00	0.00
Distance to transit	Distance to nearest transit stop	0.08	0.03
	Transit stop density	--	0.01

Figures

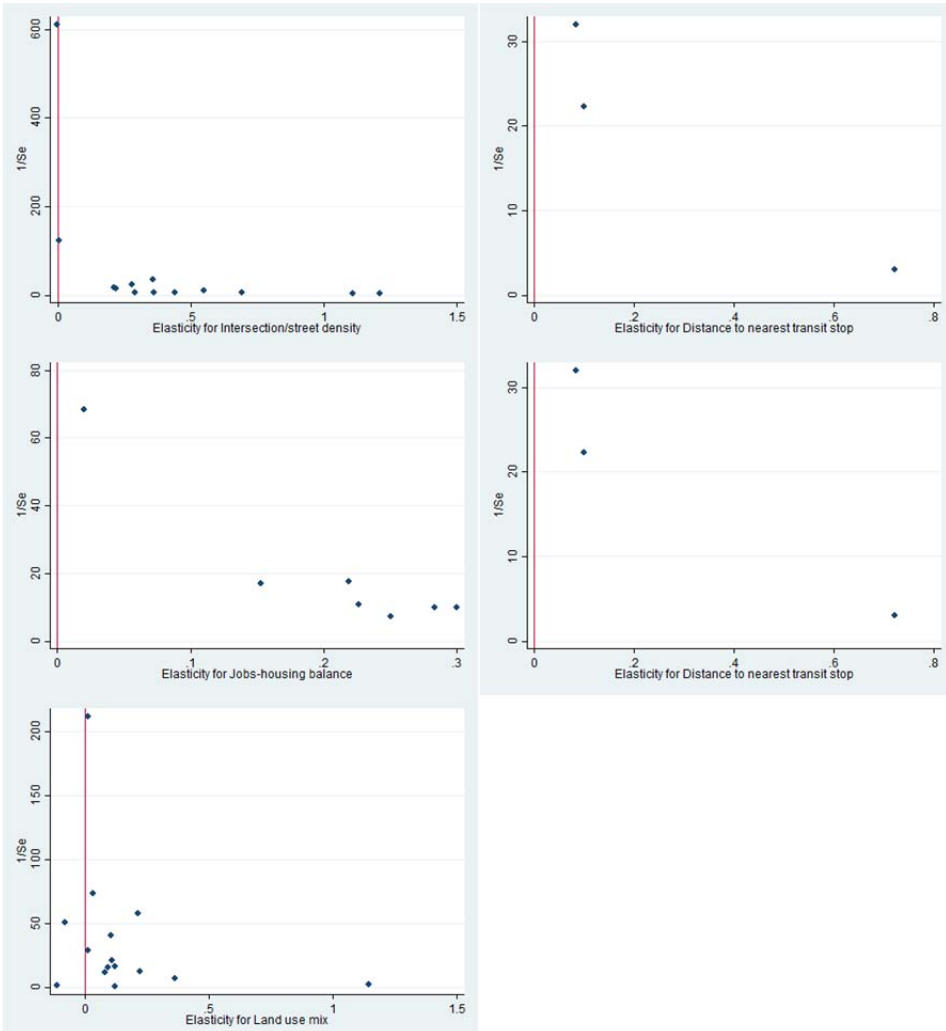

Figure 1. Funnel graphs for Walking

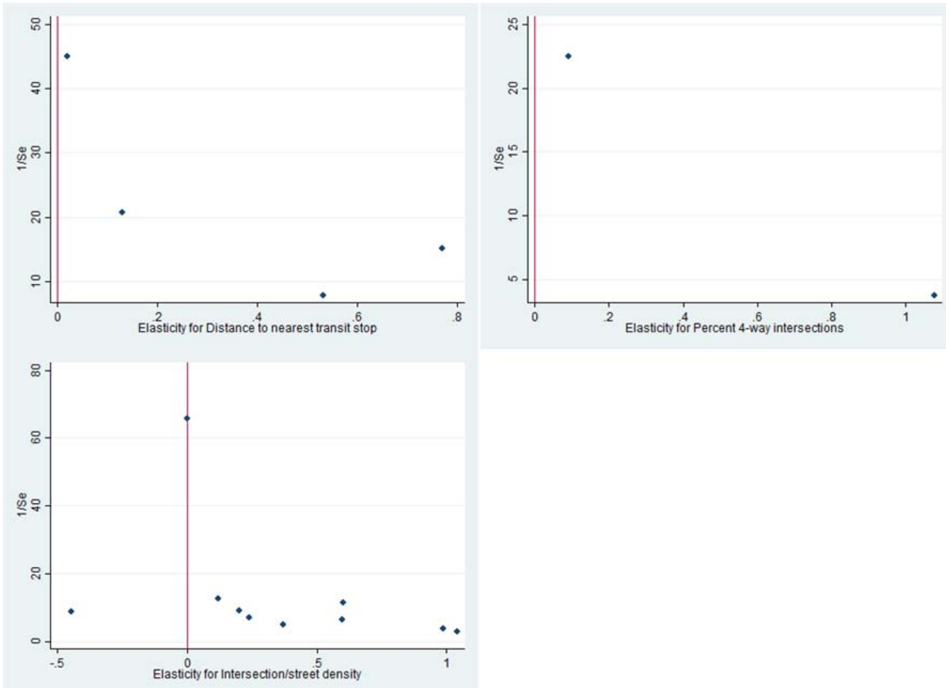

Figure 2. Funnel graphs for Transit

Appendix

Converting Regression Coefficients into Elasticities

I used the formulae in Table A-1 to convert regression model coefficients from the 67 studies I collected into elasticities. These are the same formulae that Ewing and Cervero (2010) used in their meta-analysis. To aid interpretation of the table's contents, β is the unstandardized regression coefficient, $\overline{y}$ is the sample mean of the dependent variable, and $\overline{x}$ is sample mean of the independent variable. I followed the conventional practice of calculating elasticities at the values of the sample means of the dependent and independent variables (Ewing and Cervero 2010).

Table A-1. Elasticity estimation formulae

Regression specification	Elasticity
Linear	$\beta * \frac{\overline{x}}{\overline{y}}$
Log-log	β
Log-linear	$\beta * \overline{x}$
Linear-log	$\frac{\beta}{\overline{y}}$
Logistic	$\beta * \overline{x} * (1 - \overline{y})$
Poisson	$\beta * \overline{x}$
Negative binomial	$\beta * \overline{x}$
Tobit	$\beta * \frac{\overline{x}}{\overline{y}}$

I used the formula described and recommended by Stanley and Doucouliagos (2012) to calculate standard errors for the elasticities. The formula involves dividing the elasticity by the *t*-statistic associated with the regression coefficient that was converted into the elasticity. While other methods (such as the delta method) can be used to produce a standard error for the elasticity, Stanley and Doucouliagos (p. 27) provide the following argument to justify their method: "Given that we wish to model the research process and correct any distortions that might arise from it, we see it as more important to use the *t*-statistics of the regression coefficients, rather than the *t*-statistics of the elasticity. If publication selection is taking place, it is the *t*-values of the reported regression coefficients that are being selected."

Detecting Selective Reporting Bias in the Literature on Compact Development and Alternative Transportation

Selective reporting refers to researchers selecting to report only those models with results that are (1) statistically-significant (particularly for the variables that the researchers really care about), and/or (2) consistent with conventional wisdom, and/or (3) consistent with the story the researchers want to tell. Selective reporting is a widespread practice that can lead to selective reporting bias, which refers to a situation in which the findings that are reported in a body of literature represent a biased subset of all findings that have been produced. This results in the reported elasticities in a body of literature being larger in size than they "really are".

Researchers have developed both informal and formal methods to detect whether selective reporting bias exists in a body of literature. While the informal method does not provide a conclusive result it is nevertheless useful for developing an intuitive understanding of selective reporting bias and how we can detect its presence. I provide a hypothetical example.

Imagine that (1) planning researchers generally believe that increasing density will get people to walk more; (2) the "true" elasticity representing the influence of density on walking is 0.20; (3) there are "many" studies conducted on density and walking with each study reporting an elasticity estimate. Under these conditions we would expect that some elasticity estimates might be (approximately) equal to the true value of 0.20, but that many would not. There might be some reported elasticities of 0.18, 0.25, 0.10, 0.40, 0.05, -0.01, and so on. If researchers were to report all of their elasticities (rather than choosing to report only those that were statistically-significant or that were consistent with the researcher's expectations), statistical theory tells us that the reported elasticities should vary randomly around the true value of 0.20. If we were to construct a histogram of the observed frequencies for each possible elasticity value we would expect the shape of the distribution to be generally symmetrical and in the shape of a bell. There would be roughly equal numbers of reported elasticities with values greater than 0.20 and values less than 0.20, and we would expect the frequency of elasticity estimates for each possible value to decline as they move away from 0.20. (In other words, we would expect to see more estimates close to 0.15 than to 0.10, more estimate close to 0.10 than to 0.05, and so on as we move farther away from 0.20).

We can use a "funnel graph" to perform an informal check for selective reporting bias. The funnel graph is a plot of points with a horizontal axis that measures the size of the elasticity and a vertical axis that measures the elasticity's precision. In the absence of selective reporting bias the plot of points will typically form the shape of an upside down funnel that is symmetrical and centered on the elasticity values that were measured with the highest precision, which should be the values that re closest to the "true" value; an asymmetrical plot with many more points on one side of the center than the other indicates that elasticity values on the latter side have been under-reported by researchers, which provides preliminary evidence that selective reporting bias is present in the body of literature used to construct the graph. (See Stanley and Doucouliagos, 2012, for more details on funnel graphs).

Returning to the hypothetical example, imagine that the funnel graph for the elasticities shows an asymmetrical distribution where there are more reported elasticities to the right of (i.e. greater than) 0.20 than there are to the left. This is likely to be evidence that researchers intentionally chose not to report the elasticities that were less than 0.20. A likely explanation for this behavior is that researchers expected to find the relationship between density and walking to be positive, and wanted to believe that the relationship was strong rather than weak. As a result, they were less likely to report elasticities found to be negative or only slightly greater than 0.

The formal (and rigorous) way to check for selective reporting bias involves using the "funnel-asymmetry test" (known as the "FAT"). The FAT is a statistical test of whether the distribution in the funnel graph is symmetrical (Stanley and Doucouliagos 2012, p. 62), and employs a meta-regression model to test the statistical significance of the constant (or "intercept") term from an ordinary least squares regression model that uses the t-statistic associated with the elasticity as the dependent variable and the inverse of the elasticity's standard error as the independent variable. The FAT involves testing the hypothesis that the constant term = 0, with a rejection of that hypothesis being taken as evidence of selective reporting bias. A constant term with a positive value suggests that the bias is in the positive direction, and vice versa. (See Stanley and Doucouliagos, 2012 for more details,).

Meta-Regression Models

I used the precision-effect estimate with standard error (PEESE) that is described by Stanley and Doucouliagos (2014) to produce the representative elasticities shown in Tables 2 and 3. The PEESE provides an estimate of the "true" elasticity value, corrected for the effects of selective reporting bias. When multiple elasticity estimates from a given study were included in the model used to produce the PEESE estimate for each D-variable, I followed the conventional practice of using cluster-robust standard errors that account for potential interdependence among data points (Stanley and Doucouliagos 2012, p. 33).

Individual Elasticity Estimates

Tables A-2 through A-11 present the individual elasticity estimates that were reported directly in the studies, or that I calculated using the formulae shown in Table A-1. Each row in each table lists the author and year of the study, the sample size (*N)*, the dependent variable in the regression model (*y*) that was a measure of walking or transit, the independent variable (*x*) that was a D-variable measure, the elasticity estimate (*e*), and whether or not the estimate was included in the meta-regression models that produced the findings shown in Tables 2 and 3.

Table A-2. Elasticity of walk trips with respect to density

Study	N	y	x	e	In meta-regression model?
Ameli et al. 2015	179	Pedestrian per 30 minutes	Population density	0.15	
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. 2011	1,370	Number of walk trips	Residential density	-0.49	y
Boarnet et al. 2011	1,365	Walk mode choice	Residential density	-1.58	y
Boarnet et al. 2011	1,370	Number of walk trips	Business density	0.40	y
Boarnet et al. 2011	1,365	Walk mode choice	Business density	0.52	y
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	
Commendador et al. 2014	8,526	Walk mode choice	Employment density	0.03	y
Commendador et al. 2014	8,526	Walk mode choice	Population density	0.11	y
Ewing et al. 2009	239	Walk mode choice for work trips	Population + job density	0.00	
Ewing et al. 2009	239	Walk mode choice for other trips	Population + job density	0.37	y
Ewing et al. 2011	239	Walk mode choice	Population + employment	0.37	y
Ewing et al. 2014	62,011	Number of household walk trips	Population + employment	0.01	y
Ewing et al. 2015	588	Pedestrian counts	Population density	0.00	
Fan 2007	988	Daily walking time per person	Parcel density	0.08	
Forsyth and Oakes 2014	316	Number of walk trips	Household density	0.34	y
Frank et al. 2008	8,707	Walk mode choice for work trips	Retail floor area ratio	0.07	
Frank et al. 2008	8,707	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 and Boarnet 2001	1,370	Walktrips per person for nonwork purposes	Population density	0.34	y
Greenwald and Boarnet 2001	1,370	Walktrips per person for nonwork purposes	Retail job density	0.11	y
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	
Khan 2012	1,115	# Nonmotorized trips	Population + employment	0.00	
Khan 2012	1,013	Walk mode choice	Population + employment	-0.02	y
Kockelman 1997	8,050	Walk/bike mode choice	Population density	0.00	
Lamiquez and Lopez-Dominguez 2015	150	Walk mode share	Residents + jobs + students	0.21	y
Lee et al. 2014	6,246	Walk mode choice for work trips	Population density (destination)	0.31	y
Lee et al. 2014	10,413	Walk mode choice for other trips	Population density (origin)	0.29	y
Lee et al. 2014	10,413	Walk mode choice for other trips	Population density (destination)	0.48	y

Lee et al. 2014	6,246	Walk mode choice for work trips	Employment density (destination)	0.13	*y*
Lee et al. 2014	6,246	Walk mode choice for work trips	Employment density (origin)	0.35	*y*
Miranda-Moreno et al. 2011	519	Pedestrian counts	Population density	0.34	
Miranda-Moreno et al. 2011	519	Pedestrian counts	Job density	0.28	
Naess 2005	1,406	Weekday travel distance by walk/bike per person	Population and employment	0.00	
Parady et al. 2015	7,408	Number of walk/bike trips	Commercial density	0.34	*y*
Parady et al. 2015	7,408	Number of walk/bike trips	Population density	0.00	
Rajamani et al. 2003	2,500	Walk mode choice for nonwork trips	Population density	0.01	
Reilly and Landis 2002	7,604	Walk mode choice for nonwork trips	Population density	0.16	
Sadek et al. 2011	23,518	Proportion non-motorized mode choice	Population density	0.48	*y*
Sadek et al. 2011	23,518	Proportion non-motorized mode choice	Employment density	-0.18	*y*
Saghapour et al. 2015	93,838	Walk mode choice	Population density	0.00	
Schoner and Cao 2014	1,191	Number of days walked to store	Population density	0.33	
Sung et al. 2014	1,808	Average daily walking time	Residential floor area ratio	-0.08	
Sung et al. 2014	1,808	Average daily walking time	Commercial floor area ratio	-0.03	
Sung et al. 2014	1,808	Number of walking days	Residential floor area ratio	-0.03	
Sung et al. 2014	1,808	Number of walking days	Commercial floor area ratio	0.05	
Targa and 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)	1,036	Walk/bike mode choice for nonwork trips	Population density	0.06	*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	Job density	0.00	*y*

Table A-3. Elasticity of walk trips with respect to diversity

Study	N	y	x	e	In meta-regression model?
Ameli et al. 2015	179	Pedestrian per 30 minutes	Entropy	1.65	
Bento et al. 2005	4,456	Walk/bike mode choice	Job-housing imbalance [a]	0.30	y
Boer et al. 2007	29,724	Miles walked per person	Business types in neighborhood	0.20	
Cao and Mokhtarian 2012	1,393	# walk trips to store	Distance to closest grocery store [a]	0.14	
Cao and Mokhtarian 2012	1,393	# walk trips to store	# business types w/in 400 metres	0.07	
Cao and Mokhtarian 2012	1,393	# walk trips to store	# business types w/in 800 metres	0.18	
Cao et al. 2006	837	Walk trips to store to person	Distance to store [a]	0.56	
Cao et al. 2009	1,436	Nonwork walk trips per person	# business types within 400m	0.44	
Cao 2006	1,480	Walking to the store frequency	Number of businesses within 800m	0.29	
Cervero and Kockelman 1997	2,850	Non-person vehicle choice for nonwork trips	Land use dissimilarity	0.00	
Cervero and Kockelman 1997	2,850	Non-person vehicle choice for nonwork trips	Proportion vertical mix	0.00	
Cervero and Kockelman 1997	2,850	Non-person vehicle choice for nonwork trips	Proportion of population within 1/4 mile of store	0.00	
Comendador et al. 2014	8,526	Walk mode choice	Land use mix	0.01	y
Ewing et al. 2009	239	Walk mode choice for work trips	Job-population balance	0.23	y
Ewing et al. 2009	239	Walk mode choice for other trips	Job-population balance	0.22	y
Ewing et al. 2013	239	Walk mode choice for work trips	Job-population balance	0.28	y
Ewing et al. 2013	239	Walk mode choice for other trips	Job-population balance	0.15	y
Ewing et al. 2014	62,011	Number of household walk trips	Entropy	0.10	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	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	y
Handy and Clifton 2001	1,368	Walk trips to store to person	Distance to nearest store [a]	0.48	
Handy et al. 2006	1,480	Walk trips to store to person	Distance to nearest grocery [a]	0.17	
Handy et al. 2006	1,480	Walk trips to store to person	# business types within 800m	0.29	
Khan 2012	1,013	Walk mode choice	Land use mix	-0.11	y
Kitamura et al. 1997	14,639	Fraction walk/bike trips	Distance to nearest park [a]	0.11	
Kockelman 1997	8,050	Walk/bike mode choice	Land use mix (entropy mix at origin)	0.11	y
Kockelman 1997	8,050	Walk/bike mode choice	Land use mix (entropy mix at destination)	0.01	y
Lee et al. 2014	6,246	Walk mode choice	Dissimilarity index (at origin)	0.16	y
Lee et al. 2014	6,246	Walk mode choice	Dissimilarity index (at destination)	0.91	y
Lee et al. 2014	6,246	Walk mode choice	Entropy	1.15	y
Rajamani et al. 2003	2,500	Walk mode choice for nonwork trips	Land use mix (diversity index)	0.36	y
Reilly and Landis 2002	7,604	Walk mode choice for nonwork trips	Distance to closest commercial use [a]	0.16	
Sadek et al. 2011	23,518	Proportion non-motorized mode choice	Dissimilarity index	-0.50	y

Saghapour et al. 2015	93,838	Walk mode choice	Land use mix (entropy)	0.21	*y*
Shay et al. 2006	348	Walk trips per household	Distance to commercial center [a]	0.98	
Sung et al. 2014	1,808	Average daily walking time	Land use mix	0.11	
Sung et al. 2014	1,808	Number of walking days	Land use mix	0.11	
Targa and Clifton 2005	2,934	Walk trips per person	Land use mix (entropy in)	-0.08	*y*
Zhang 2004	1,619	Walk/bike mode choice for work trips	Land use mix (entropy mix at origin)	0.00	*y*
Zhang 2004	1,619	Walk/bike mode choice for work trips	Land use mix (entropy mix at destination)	0.00	
Zhang 2004	1,036	Walk/bike mode choice for nonwork trips	Land use mix (entropy mix at origin)	0.12	*y*
Zhang 2004	1,036	Walk/bike mode choice for nonwork trips	Land use mix (entropy mix at destination)	0.12	

a. These signs were reversed, following the procedure established by Ewing and Cervero (2010, p. 274) that involves reporting elasticity values in such a way that higher values of the D-variable indicate better accessibility.

Table A-4. Elasticity of walk trips with respect to design

Study	N	y	x	e	In meta-regression model?
Ameli et al. 2015	179	Pedestrian per 30 minutes	% 4-way intersections	0.00	
Ameli et al. 2015	179	Pedestrian per 30 minutes	Intersection density	0.28	
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. 2011	1,338	Number of walk trips	% 4-way intersections	0.00	y
Boarnet et al. 2011	1333	Walk mode choice	% 4-way intersections	0.47	y
Boarnet et al. 2011	1,338	Number of walk trips	Block size	0.36[a]	
Boarnet et al. 2011	1,333	Walk mode choice	Block size	-0.39[a]	
Boer et al. 2007	29,724	Miles walked per person	Proportion 4-way intersections	0.39	
Boer et al. 2007	29,724	Miles walked per person	Block length (long side)	-0.31[a]	
Cervero and Kockelman 1997	2,850	Non-private vehicle choice for nonwork trips	Proportion 4-way intersections	0.00	
Cervero and Kockelman 1997	2,850	Non-private vehicle choice for nonwork trips	Proportion quadrilateral blocks	0.00	
Cervero and Kockelman 1997	2,850	Non-private vehicle choice for nonwork trips	Sidewalk width	0.09	
Cervero and 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	y
Comendador et al. 2014	8,526	Walk mode choice	Street density	0.00	y
Ewing et al. 2009	3,823	Walk mode choice	Intersection density	0.43	
Ewing et al. 2009	3,823	Walk mode choice	Sidewalk coverage	0.27	
Ewing et al. 2013	239	Walk mode choice for work trips	Intersection density	0.00	
Ewing et al. 2013	239	Walk mode choice for other trips	Intersection density	0.44	y
Ewing et al. 2014	62,011	Number of household walk trips	%4-way intersections	0.03	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 and Boarnet 2001	1,084	Walktrips per person for nonwork purposes	Pedestrian environment factor	0.25	
Greenwald 2009	3,938	Walk/bike trips per household	Intersection density	1.11	y
Hess et al. 1999	12	Pedestrians per hour	Block size	0.35[a]	
Joh et al. 2009	2,125	Walk trips per person	% 4-way intersections	-0.27	
Joh et al. 2009	2,125	Walk trips per person	Block size	0.01[a]	
Khan 2012	1,115	# Nonmotorized trips	Intersection density (3-way)	0.01[a]	
Khan 2012	1,115	# Nonmotorized trips	Intersection density (4-way)	0.36	y
Khan 2012	1,013	Walk mode choice	Intersection density (3-way)	0.26[a]	
Khan 2012	1,013	Walk mode choice	Intersection density (4-way)	0.36	y
Koohsari et al. 2014	2,544	Walk frequency	Intersection density	1.21	y
Lee et al. 2014	6,246	Walk mode choice	Street density	0.69	y

Lee et al. 2014	6,246	Walk mode choice	Street connectivity	0.99	
Marshall and Garrick 2010	205	Walk mode choice	Intersection density	0.22	*y*
McCormack et al. 2012	1,681	Transport walking (any)	Sidewalk length	2.19	
McCormack et al. 2012	611	Transport walking (minutes)	Sidewalk length	1.89	
Rajamani et al. 2003	2,500	Walk mode choice for nonwork trips	%Culs-de-sac	0.00	
Rodriguez and Joo 2004	448	Walk mode choice for commute trips	Sidewalk coverage	1.23	
Rodriguez and Joo 2004	448	Walk mode choice for commute trips	Path directness	0.03	
Sadek et al. 2011	23,518	Proportion non-motorized mode choice	Street network density	0.00	*y*
Sadek et al. 2011	23,518	Proportion non-motorized mode choice	Junction kernel density	0.29	
Saelens et al. 2012	2,121	Walking minutes	Intersection density	19.99	
Saghapour et al. 2015	93,838	Walk mode choice	Street density	0.01	*y*
Schoner and Cao 2014	1,191	Number of days walked to store	Number of cul-de-sacs	0.09[a]	
Targa and Clifton 2005	2,934	Walk trips per person	Block size	0.32[a]	*y*
Zhang 2004	1,619	Walk/bike mode choice for work trips	Street connectivity	0.07	
Zhang 2004	1,036	Walk/bike mode choice for nonwork trips	Street connectivity	0.05	

a. These signs were reversed, following the procedure established by Ewing and Cervero (2010, p. 274) that involves reporting elasticity values in such a way that higher values of the D-variable indicate better accessibility.

Table A-5. Elasticity of walk trips with respect to destination accessibility

Study	***N***	***y***	***x***	***e***	**In meta-regression model?**
Bento et al. 2005	4,456	Walk/bike mode choice	Population centrality	1.00	
Boarnet et al. 2008	6,362	Miles walked per person	Distance to CBD	0.49[a]	
Cao 2006	1,480	Walking to the store frequency	Distance to nearest grocery	0.17[a]	
Cao 2006	1,480	Walking to the store frequency	Stores within walking distance	0.91	
Cao et al. 2006	837	Walk trips to store	Distance to nearest store	0.56	*y*
Cao and Mokhtarian 2012	1,393	Walk trips to store	Distance to nearest grocery	0.14	*y*
Cervero and Duncan 2003	7,836	Walk mode choice	Jobs within one mile	0.04	*y*
Cervero and Kockelman 1997	2,850	Non-private vehicle choice for nonwork trips	Job acccessibility by auto	0.00	
Chatman 2009	999	Walk/bike trips per person	Distance to downtown	0.29[a]	*y*
Comendador et al. 2014	8,526	Walk mode choice	Distance to CBD	0.01[a]	*y*
Ewing et al. 2009	239	Walk mode choice for work trips	Jobs within one mile	0.39	*y*
Ewing et al. 2009	239	Walk mode choice for other trips	Jobs within one mile	0.45	*y*
Ewing et al. 2013	239	Walk mode choice for work trips	Employment within 1 mile	0.00	
Ewing et al. 2013	239	Walk mode choice for other trips	Employment within 1 mile	0.00	
Ewing et al. 2014	62,011	Number of household walk trips	Job accessibility	0.07	
Greenwald 2009	3,938	Walk/bike trips per household	Job acccessibility by auto	-0.32	
Kockelman 1997	8,050	Walk/bike mode choice	Job accessibility by walking (origin)	0.16	*y*
Kockelman 1997	8,050	Walk/bike mode choice	Job accessibility by walking (destination)	0.16	*y*
Lamiquez and Lopez-Dominguez 2015	150	Walk mode share	Distance to CBD	0.07[a]	*y*
Marshall and Garrick 2010	205	Walk mode choice	Distance to CBD	0.50[a]	*y*
Naess 2005	1,406	Proportion of distance traveled by walk/bike	Distance to downtown	0.29[a]	
Shay et al. 2006	438	Walk trips per household	Distance to commercial center	0.98	*y*

a. These signs were reversed, following the procedure established by Ewing and Cervero (2010, p. 274) that involves reporting elasticity values in such a way that higher values of the D-variable indicate better accessibility.

Table A-6. Elasticity of walk trips with respect to transit access

Study	***N***	***y***	***x***	***e***	**In meta-regression model?**
Ameli et al. 2015	179	Pedestrian per 30 minutes	Distance to nearest rail station	0.71[a]	
Asad 2013	140	Walk/bike mode choice for shopping	Distance to train	0.72[a]	*y*
Bento et al. 2005	4,456	Walk/bike mode choice	Distance to nearest transit stop	0.30[a]	
Boarnet et al. 2008	6,362	Miles walked per person	Distance to light rail	-0.17[a]	
Ewing et al. 2014	62,011	Number of household walk trips	Bus stop density	0.04	
Khan 2012	1,115	# Nonmotorized trips	Bus stop density	0.15	
Khan 2012	1,013	Walk mode choice	Bus stop density	0.00	
Kitamura et al. 1997	14,639	Fraction walk/bike trips	Distance to nearest bus stop	0.10[a]	*y*
Naess 2005	1,406	Proportion distance traveled by foot/bike	Distance to rail station	0.00[a]	
Rajamani et al. 2003	2,500	Walk mode choice for nonwork trips	% within walking distance of bus	0.02	
Sadek et al. 2011	23,518	Proportion non-motorized mode choice	Transit kernel density	0.21	
Sung et al. 2014	1,808	Average daily walking time	Bus stop density	0.09	
Sung et al. 2014	1,808	Average daily walking time	Rail density	0.02	
Sung et al. 2014	1,808	Number of walking days	Bus stop density	0.03	
Sung et al. 2014	1,808	Number of walking days	Rail density	0.01	
Targa and Clifton 2005	2,934	Walk trips per person	Distance to nearest bus stop	0.08[a]	*y*

a. These signs were reversed, following the procedure established by Ewing and Cervero (2010, p. 274) that involves reporting elasticity values in such a way that higher values of the D-variable indicate better accessibility.

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

Study	N	y	x	e	In meta-regression model?
Bhatia, 2004	20	Transit trips per household	Household density	0.37	
Cervero and Guerra 2011	1,449	Weekday boardings and alightings	Population density	0.09	
Cervero and Guerra 2011	1,449	Weekday boardings and alightings	Job density	0.20	
Cervero 2002	427	Transit mode choice	Gross population density (origin)	0.51	y
Cervero 2002	427	Transit mode choice	Gross population density (destination)	0.27	y
Cervero 2006	225	Weekday boardings per station	Population density	0.19	
Comendador et al. 2014	8,526	Transit mode choice	Population density	0.27	y
Comendador et al. 2014	8,526	Transit mode choice	Employment density	-0.03	y
Concas and DeSalvo 2014	8,212	Household transit trips	Retail establishments density	0.08	
Ding et al. 2014	980	Transit mode choice	Residential density (origin)	0.02	y
Ding et al. 2014	980	Transit mode choice	Residential density (destination)	0.05	y
Ding et al. 2014	980	Transit mode choice	Employment density (origin)	-0.03	y
Ding et al. 2014	980	Transit mode choice	Employment density (destination)	0.29	y
Ewing et al. 2009	239	Transit mode choice for work trips	Population + job density	0.00	
Ewing et al. 2009	239	Transit mode choice for other trips	Population + job density	0.32	y
Ewing et al. 2013	239	Transit mode choice for other trips	Population + employment density	0.25	y
Ewing et al. 2013	239	Transit mode choice	Proportion of population, employment, activity within 10 miles	1.02	
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	
Frank et al. 2008	8,707	Transit mode choice for other trips	Retail floor area ratio	0.17	
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
Grunfelder and Nielsen 2012	453	Transit mode choice	Employment density	0.00	
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	0.11	
Lee et al. 2014	6,246	Transit mode choice for work trips	Population density (destination)	0.28	y
Lee et al. 2014	10,413	Transit mode choice for other trips	Population density (origin)	0.24	y
Lee et al. 2014	10,413	Transit mode choice for other trips	Population density (destination)	0.44	y
Lee et al. 2014	6,246	Transit mode choice for work trips	Employment density (origin)	0.35	y
Lee et al. 2014	6,246	Transit mode choice for work trips	Employment density (destination)	0.22	y
Lin and Shin 2008	46	Daily passengers entering/leaving metro station	Residential density	0.00	
Lin and Shin 2008	46	Daily passengers entering/leaving metro station	Employment density	0.00	
Lin and Shin 2008	46	Daily passengers entering/leaving metro station	Retail floor area ratio	0.00	
Parady et al. 2015	7,408	Number of transit trips per person	Population density	0.20	y
Parady et al. 2015	7,408	Number of transit trips per person	Commercial density	0.00	
Peterson 2011	5,916	Weekly bus boardings	Housing density	0.04	
Rajamani et al. 2003	2,500	Transit mode choice for nonwork trips	Population density	0.08	y

Reilly and Landis 2002	7,604	Transit mode choice for nonwork trips	Population density	0.20	
Renne et al. 2015	4,400	Transit mode share	Population + job density	0.18	*y*
Rodriguez and Joo 2004	454	Transit mode choice for commute trips	Population density	-0.20	*y*
Sadek et al. 2011	23,518	Transit mode choice proportion	Population density	0.00	
Sadek et al. 2011	23,518	Transit mode choice proportion	Employment density	0.00	
Saghapour et al. 2015	93,838	Transit mode choice	Population density	0.00	
Thompson et al. 2012	40,436	Number of bus work trips	Population density	-1.31	
Thompson et al. 2012	40,436	Number of bus work trips	Employment density	-0.31	
Zhang 2004 (Boston)	1,619	Transit mode choice for work trips	Population density	0.12	
Zhang 2004 (Boston)	1,036	Transit mode choice for nonwork trips	Population density	0.13	
Zhang 2004 (Boston)	1,619	Transit mode choice for work trips	Job density	0.09	
Zhang 2004 (Boston)	1,036	Transit mode choice for nonwork trips	Job density	0.00	
Zhang 2004 (Hong Kong)	20,246	Transit mode choice for work trips	Population density	0.01	
Zhang 2004 (Hong Kong)	15,281	Transit mode choice for nonwork trips	Population density	0.01	
Zhang 2004 (Hong Kong)	20,246	Transit mode choice for work trips	Job density	0.01	
Zhang 2004 (Hong Kong)	15,281	Transit mode choice for nonwork trips	Job density	0.01	

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

Study	N	y	x	e	In meta-regression model?
Bento et al. 2005	4,456	Transit mode choice (bus)	Job-housing imbalance	0.60[a]	y
Bento et al. 2005	4,456	Transit mode choice (rail)	Job-housing imbalance	0.60[a]	y
Brown et al. 2006	148	Total boardings and alightings	Land use mix	-0.02	
Cervero and Kockelman 1997	1,544	Non-personal vehicle choice for work trips	Land use dissimilarity	0.00	
Cervero and Kockelman 1997	1,544	Non-personal vehicle choice for work trips	Proportion vertical mix	0.00	
Cervero and Kockelman 1997	1,544	Non-personal vehicle choice for work trips	Proportion of population within 1/4 mile of store	0.00	
Cervero 2002	427	Transit mode choice	Land use mix (entropy index) at destination	0.45	y
Cervero 2002	427	Transit mode choice	Land use mix (entropy index) at origin	0.62	y
Comendador et al. 2014	8,526	Transit mode choice	Land use mix	0.19	y
Ding et al. 2014	980	Transit mode choice	Land use mix at destination	0.02	y
Ding et al. 2014	980	Transit mode choice	Land use mix at origin	0.14	y
Ewing et al. 2014	62,011	Number of HH transit trips	Job-population balance	0.12	y
Ewing et al. 2014	62,011	Number of HH transit trips	Entropy	0.07	y
Fan 2007	154	Daily transit travel time per person	Retail store count	-0.04	
Frank et al. 2008	10,475	Transit mode choice for other trips	Land use mix (entropy index) at destination	0.19	y
Frank et al. 2008	10,475	Transit mode choice for other trips	Land use mix (entropy index) at origin	0.09	y
Frank et al. 2008	8,707	Transit mode choice for work trips	Land use mix (entropy index)	0.09	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	y
Kitamura et al. 1997	14,639	Fraction transit trips	Distance to nearest park	0.11	
Lee et al. 2014	6,246	Transit mode choice	Entropy	1.19	y
Lee et al. 2014	10,413	Transit mode choice	Dissimilarity index at origin	0.14	
Lee et al. 2014	10,413	Transit mode choice	Dissimilarity index at destination	0.83	
Lin and Shin 2008	46	Daily passengers entering/leaving metro station	Job-housing balance	0.00	
Lin and Shin 2008	46	Daily passengers entering/leaving metro station	Land use mix	0.00	
Peterson 2011	5,916	Weekly bus boardings	Land use mix	0.14	
Rajamani et al. 2003	2,500	Transit mode choice for nonwork trips	Land use mix (diversity index)	-0.04	
Reilly and Landis 2002	7,604	Transit mode choice for nonwork trips	Distance to closest commercial use	-0.19	
Renne et al. 2015	4,400	Transit mode share	Job population balance	0.23	y
Renne et al. 2015	4,400	Transit mode share	Entropy	0.00	
Sadek et al. 2011	23,518	Transit mode choice proportion	Dissimilarity index	1.48	
Saghapour et al. 2015	93,838	Transit mode choice	Land use mix (entropy)	0.01	y
Thompson et al. 2012	40,436	Number of bus work trips	Entropy at origin	0.99	
Thompson et al. 2012	40,436	Number of bus work trips	Entropy at destination	-0.78	
Zhang 2004 (Boston)	1036	Transit mode choice for nonwork trips	Land use mix (entropy index)	0.12	
Zhang 2004 (Boston)	1,619	Transit mode choice for work trips	Land use mix (entropy index)	0.00	

a. Sign reversed

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

Study	N	y	x	e	In meta-regression model?
Brown et al. 2006	148	Total boardings and alightings	Intersection density	-0.32	
Cervero and Kockelman 1997	1,544	Non-personal vehicle choice for work trips	Proportion 4-way intersections	0.00	
Cervero and Kockelman 1997	1,544	Non-personal vehicle choice for work trips	Proportion front and side parking	0.00	
Cervero and Kockelman 1997	1,544	Non-personal vehicle choice for work trips	Sidewalk width	0.00	
Cervero and Kockelman 1997	1,544	Non-personal vehicle choice for work trips	Proportion quadrilateral blocks	0.00	
Cervero 2002	427	Transit mode choice	Sidewalk ratio (at destination)	0.33	
Cervero 2002	427	Transit mode choice	Sidewalk ratio (at origin)	0.00	
Cervero 2007	726	Transit mode choice for work trips	% 4-way intersections	1.08	y
Comendador et al. 2014	8,526	Transit mode choice	Street density	-0.45	y
Ding et al. 2014	980	Transit mode choice	Block size (at origin)	0.01	
Ding et al. 2014	980	Transit mode choice	Block size (at destination)	-0.11	
Ewing et al. 2013	239	Transit mode choice	Intersection density	0.99	y
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 other trips	Intersection density	0.24	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
Lee et al. 2014	10,413	Transit mode choice	Street density	0.60	y
Lee et al. 2014	6,246	Transit mode choice	Connectivity	0.00	
Lee et al. 2014	10,413	Transit mode choice	Street connectivity	0.85	
Lin and Shin 2008	46	Daily passengers entering/leaving metro station	% 4-way intersections	-0.58	
Lin and Shin 2008	46	Daily passengers entering/leaving metro station	Sidewalk length	0.00	
Lund et al. 2004	967	Transit mode choice	% 4-way intersections as destination	1.08	y
Marshall and Garrick 2010	205	Transit mode choice	Intersection density	0.60	y
Rajamani et al. 2003	2,500	Transit mode choice for nonwork trips	%Culs-de-sac	0.00	
Renne et al. 2015	4,400	Transit mode share	% 4-way intersections	0.09	y
Rodriguez and Joo 2004	454	Transit mode choice for commute trips	Path directness	0.01	
Rodriguez and Joo 2004	454	Transit mode choice for commute trips	Sidewalk coverage	0.28	
Sadek et al. 2011	23,518	Transit mode choice proportion	Street network density	1.04	y
Sadek et al. 2011	23,518	Transit mode choice proportion	Junction kernel density	0.00	
Saghapour et al. 2015	93,838	Transit mode choice	Street density	0.00	y
Zhang 2004 (Boston)	1,619	Transit mode choice for work trips	Street connectivity	0.08	
Zhang 2004 (Boston)	1,036	Transit mode choice for nonwork trips	Street connectivity	0.04	

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

Study	***N***	***y***	***x***	***e***	**In meta-regression model?**
Bento et al. 2005	4,456	Transit mode choice	Population centrality	0.00	
Cervero and Guerra 2011	1,449	Weekday boardings and alightings	Distance to CBD	0.02[a]	
Cervero 2006	225	Weekday boardings per station	Distance to CBD	0.21[a]	
Comendador et al. 2014	8,526	Transit mode choice	Distance to CBD	0.07[a]	*y*
Concas and DeSalvo 2014	8,212	HH transit trips	Distance to CBD	0.09	
Ding et al. 2014	980	Transit mode choice	Distance to CBD (origin)	-0.33[a]	*y*
Ding et al. 2014	980	Transit mode choice	Distance to CBD (destination)	-0.19[a]	*y*
Ewing et al. 2009	239	Transit mode choice	Job accessibility by transit	0.29	
Ewing et al. 2011	239	Transit mode choice	Job accessibility	0.21	
Ewing et al. 2014	62,011	Number of HH transit trips	Job accessibility	0.04	
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 acccessibility by auto	0.05	
Grunfelder and Nielsen 2012	453	Transit mode choice	Distance to urban centre	0.33[a]	
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	
Marshall and Garrick 2010	205	Transit mode choice	Distance to CBD	-0.06[a]	*y*

a. Sign reversed

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

Study	*N*	*y*	*x*	*e*	In meta-regression model?
Bento et al. 2005	4,456	Transit mode choice	Supply of transit	1.00	
Cervero and Guerra 2011	1,449	Weekday boardings and alightings	Distance to nearest station	-0.01[a]	
Concas and DeSalvo 2014	8,212	HH transit trips	Walking distance to nearest transit station	0.77[a]	*y*
Ewing et al. 2009	239	Transit mode choice for work trips	Bus stop density	0.36	*y*
Ewing et al. 2009	239	Transit mode choice for other trips	Bus stop density	0.47	*y*
Ewing et al. 2014	62,011	Number of HH transit trips	Bus stop density	0.01	*y*
Frank et al. 2009	2,697	Transit trips per household	Distance to bus stop squared	0.02[b]	*y*
Grunfelder and Nielsen 2012	453	Transit mode choice	Distance to transit stop	0.00	
Hubers et al. 2014	1,280	Transit mode choice	Distance to nearest rail station	0.53[a]	*y*
Kim et al. 2007	407	Bus mode choice to transit	Distance to transit station	0.00	
Kim et al. 2007	407	Walk mode choice to transit	Distance to transit station	0.59[a]	
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	0.02	
Sadek et al. 2011	23,518	Transit mode choice proportion	Transit kernel density	-0.21	*y*
Thompson et al. 2012	40,436	Number of bus work trips	Walk time to transit	0.45[a]	

a. Sign reversed

[1] The quality of a study is best captured by measuring the precision of the study's findings. Precision is best measured by using the standard errors of the statistics that a study reports (Stanley and Doucouliagos 2012).
[2] While transit involves buses and trains that are not human-powered, it is nevertheless considered to be powered by humans in part because transit typically requires more walking to and from transit stops to destinations than is required when the traveler drives a car instead.
[3] I use "planning literature" loosely to refer to the set of academic journals in which planning researchers typically publish their papers, though there is no hard-and-fast way to perfectly distinguish the planning literature from related literatures (e.g. urban studies, economics, transportation engineering, etc.).
[4] Researchers commonly use the inverse of an elasticity's standard error to measure the precision of the elasticity.
[5] Meta-regression analysis is also widely used in other fields including business and medicine.
[6] Along these lines, and following the procedures established by Ewing and Cervero in their 2010 meta-analysis, I did not include results for ordered probit regression models because the breakpoint parameters were not available and I was thus unable to calculate marginal effects.
[7] I do not present findings for D-variables that have been studied in the literature but for which I only had two or fewer estimated elasticities.
[8] Three is the minimum number of studies to permit a meta-analysis (Treadwell, Tregear, Reston, and Turkelson 2006).
[9] While studies with small sample sizes do not automatically produce relatively large elasticities, it has commonly been observed that such studies tend to report larger elasticities than do studies with large sample sizes. The generally-accepted explanation for this observed phenomenon is that researchers who work with small sample sizes commonly respecify and retest their models until the models produce elasticities that are large enough to be declared statistically-significant in spite of the small sample sizes that otherwise make it more difficult to produce statistically-significant results (Stanley and Doucouliagos 2012, p. 60).