Australasian Transport Research Forum 2019 Proceedings
30 September – 2 October, Canberra, Australia
Publication website: http://www.atrf.info

Meta-analysis of the built environment and transit use relationship in different countries

Laura Aston[1], Cassandra K. Min[1], Graham Currie[1], Md. Kamruzzaman[2], Alexa Delbosc[1], David Teller[3]

[1]Public Transport Research Group, Department of Civil Engineering, Monash University, 23 College Walk, Clayton VIC 3800

[2]Monash Art Design and Architecture, Monash University, Melbourne, Australia

[3]Department of Transport, State of Victoria, Australia

Email for correspondence: ckmin1@student.monash.edu

The data that support the findings of this study are openly available in “figshare” at https://doi.org/10.26180/5c3fe01b7fd7e.

Abstract

Many travel behaviour studies have demonstrated a relationship between public transport ridership and built environment variables such as density, diversity, urban design and accessibility. However, results from past studies show large variability, which limits the transferability of findings outside the research setting. Context is important in travel behaviour research, encompassing many potential sources of this variability. Yet little is known about the link between the social and geographic context of the research setting and different impacts of the built environment on transit use.

In this paper, meta-analysis is used to synthesise evidence relating indicators of the built environment to transit use. Results are compared before and after grouping by the country in which research is conducted, to determine whether this explains variability.

As expected from previous research, results show indicators of transit-friendly urban design, density and accessibility are weakly correlated with increasing transit ridership. The average effect size for density showed significant variance between different countries. However, the majority of variance cannot be accounted for by differences associated with the country of the sample.

This study is limited by small sample sizes once data is grouped by country. This reflects the lack of geographically diverse evidence in the field of land use and travel behaviour research. Furthermore, differences in study design were found to impact results. Future research that seeks to identify contextual sources of variability in the built environment and transit use relationship need to adopt a consistent study design across the locations being tested.

1 Introduction

Population growth and economic development are putting increasing pressure on transport networks. Externalities of car dependence, including urban sprawl, congestion and climate change are intensifying. Research has shown the built environment can be leveraged to encourage sustainable travel behaviour, by promoting the use of modes such as public transport. Urban planning and design theory suggests that mixed land uses in close proximity to transit facilities make it more convenient to travel by transit (Litman and Steele, 2017). Recently, research has focused on understanding the impact of urban design and land use on attitudes to different travel modes. Particular emphasis has been given to walking, which is the predominant means by which transit is accessed, finding that “walkable” and diverse urban environments can change attitudes toward walking (Cao et al., 2009a). However, despite extensive research in this field, mixed results from studies have made this line of research less useful as a source for guiding planning practice (Maat et al., 2005).

Meta-analysis and meta-regression are statistical techniques that have been used to combine data from multiple studies to gain a generalisable understanding of how the built environment influences transit (Ewing and Cervero, 2010, Stevens, 2017). These methods have the potential to identify factors causing mixed results, improving the value of research for planning practice.

Factors associated with national or regional transit quality, policy or culture have not been explored as potential sources of variability in the built environment and transit ridership (BE-TR) relationship. This is despite evidence and frameworks suggesting such contextual factors do impact travel behaviour (Haustein and Nielsen, 2016, Ajzen, 1991). To address this gap, this study has two aims, to:

1. Summarise the relationship between transit use and four built environment variables (density, diversity, design and accessibility).

2. Understand whether differences in the BE-TR relationship are associated with the country in which the research was undertaken.

This paper tests two hypotheses to examine differences in built environment impacts on transit ridership between countries. The first hypothesis is that there is a meaningful difference in average correlations for the BE-TR relationship in different countries. The second hypothesis is that segmenting the average correlations by country enables a large proportion of variance to be explained. Exploring the relationship on a country level will give a clearer understanding of the transferability of built environment and transit use research from one location to another.

The first section of this paper provides an overview of how the BE-TR relationship is measured, sources of variability and findings from past studies. Meta-analytic methods for exploring differences in empirical results are explained. Average correlations and heterogeneity results are presented for all built environment variables, grouped by country. The impact of study design is compared to the impact of different sample locations on results. Further research is suggested to explore the influence of geography and continue to unpack this relationship.

2 Literature review

2.1 Measuring public transport and the built environment

Travel behaviour is a decision-making process which can be influenced by an individual's needs, resources and lifestyle (Næss, 2005, Litman and Steele, 2017), as well as their attitudes, social norms and perceptions (Ajzen, 1991). Transit use is a subset of travel behaviour. The desire to increase the use of sustainable alternatives to private vehicles has engendered much research into the factors that influence transit ridership. The built environment is one factor that has been found to impact transit ridership (Ewing and Cervero, 2010).

The built environment can be embodied by infrastructure and roads, mixes in land use and urban design. For this paper, density, diversity, design and accessibility are used as the built environment indicators to assess BE-TR:

- **Density** measures employment, population or activity per unit area. Higher density may allow destinations to be in closer proximity, reducing trip lengths and thereby increasing transit use as it's more feasible for the commuter (Ewing and Cervero, 2010).
- **Diversity** measures the mixtures of land uses within an area. Increasing the mix of land use and housing balance may have a positive correlation with transit use as destinations such as jobs, supermarkets and schools are in closer reach (Litman and Steele, 2017).
- **Design** refers to street characteristics within an area. Design measures such as pedestrian, cycling and safety amenities may encourage transit use as it allows patrons safer and more convenient access to transit stations and stops (De Gruyter et al., 2019).
- **Accessibility** refers to the ease with which activities can be reached within the public transport network. Improved accessibility to key locations may increase transit use by reducing commute distances and thus allow transit use to become a more competitive travel option (Boulange et al., 2017).

Table 1: Built environment - independent variable indicators (adapted from Aston et al. (2019b)[1])

Variable	Scale	Measure Examples
Density	Continuous	Gross or net jobs/employment per area, gross or net households, dwelling or persons per total area, active floorspace ratio, sum of population and jobs, commercial or retail opportunities per area, commercial or retail density, number of establishments, commercial or retail land use proportion
Diversity	Continuous	Mix of land use (floor area), vertical mix of land use, mix of housing type, mix of housing affordability, mix of tenure type, ethnic diversity of neighbourhood, jobs-housing balance, ratio of trip origins to trip destinations
Design	Continuous	Canopy, street furniture, facilities, four-way intersections, lighting, perception of safety, curbs, shoulder width, total path length, number of pedestrian crossings
	Categorical	Building setback, building orientation, neighbourhood type, presence of side walk
Accessibility	Continuous	WalkScore, local living score, count of services/mixed use opportunities
	Categorical	Located in CBD, TOD or close to transit, high density, discrete categorisation of urbanisation level

Examples of indicators used are shown in Table 1. The variables included in Table 1 are hypothesised to have a positive influence on transit use (Ewing and Cervero, 2010).

2.2 Sources of variability in built environment and transit research

Studies report highly variable impacts of built environment variables on transit use, which limits the transferability of research into practice. In addition to sampling error, regional accessibility and residential self-selection are two sources of variability that are increasingly well understood in the field. Contextual sources of variability, linked to different sample locations, are less well understood.

Firstly, some variability from studies may be due to sampling error, which is inevitable when observing a sample as opposed to a population. Since each study relies on different samples, their results will differ even when investigating the same topic. Weighting samples, according to their sample size or standard error, reduces the influence of sampling error on meta-averages.

The accessibility of a given location affects the relative ease of transit use within the area. This variable can be considered controlled if a model includes distance to CBD or share of jobs within the catchment region (Renne et al., 2016). Another source of difference is residential self-selection. Residential self-selection is the idea that people choose to live in certain neighbourhoods based on their travel preferences or needs. Methodological approaches to control residential self-selection include direct questioning, statistical controls, or employing joint discrete choice models (Mokhtarian and Cao, 2008). If a study has no controls for self-selection bias, it may spuriously attribute increased transit ridership to the built environment.

Contextual differences present a source of complexity and variability in the BE-TR relationship (Hu and Iseki, 2018, Ortúzar and Willumsen, 2011). Case studies on different locations have shown examples of geography influencing the BE-TR relationship. Loo et al. (2010) compared metro railway systems in New York and Hong Kong. Different factors predicted rail patronage in each city, as shown in Table 2.

Table 2: Factors affecting railway patronage in cities (adapted from Loo et al. (2010))

New York	Hong Kong
Commercial density (+)	Population density (+) Employment over population (-) Mixed land use (+) Commercial to residential ratio (+)

More research is needed to understand why such differences in travel occur, even when the same study design is used, as in the case of the New York and Hong Kong study.

A study of light rail ridership in Australia, North America and Europe, found a significant role for many country-level variables in predicting transit ridership (Currie et al., 2011). The study identifies many differences in the operating characteristics of the networks in these countries. It finds that in addition to the built environment characteristic of employment density, factors such as integrated ticketing, average vehicle speeds and the fact of being a network in Europe, account for different rates of ridership.

Little is known about which contextual features are associated with differences in BE-TR. Many country- or network-level differences fit within behavioural frameworks that explain travel patterns, such as the theory of planned behaviour (TPB) (Ajzen, 1991). TPB posits that behaviours, such as travelling by a particular transport mode, is determined by attitudes towards social norms and perceived ability to accomplish the behaviour. This theory has been examined predominantly in the context of walking behaviour (Dill et al., 2014). Exposure to pedestrian-friendly environments can influence people's attitude toward walking and therefore increase the share of trips they make in this way. Differences in regional transit accessibility and population density occur at a national level, as summarised in Table 3. The table compares countries that feature prominently in this study's sample.

Table 3: Country-level differences associated with travel patterns

Country	% Urban	Population (millions)	Motor vehicles/ 1000 people
	(World Bank, 2017)		(NationMaster, 2014)
Australia	86	24.9	717
Canada	81	37.1	607
China	59	1,390	83
Hong Kong	100	7.45	77
Netherlands	91	17.2	528
South Korea	81	51.6	376
United Kingdom	83	66.5	519
USA	82	327	797

Differences in the proportion of city-dwelling people (urbanised), the overall population, or population density in occupied land areas, and rates of vehicle ownership might mediate the influence of the built environment on attitudes toward transit use. Car ownership rates are highly variable between countries, which may reflect or contribute to social norms about driving. Highly automobile dependent countries like Australia and USA have the highest per capita vehicle ownership rate (717 and 797 respectively). Finally, different institutional arrangements for the planning and implementation of transit and land use can influence the effectiveness of integrating transport and land use (Thomas and Bertolini, 2017). There are valuable policy implications of understanding whether if social norms, and the quality- or connectivity of transit networks at a regional level impacts the effectiveness of transport and land use integration, aimed at reducing unsustainable travel.

2.3 Meta-analysis in travel behaviour research

Unlike traditional literature reviews, meta-analysis is a quantitative method of synthesis that can increase generalisability of empirical relationships (Borenstein et al., 2009). Two recent meta-analyses have been conducted to generalise the BE-TR relationship, determining average effects. Characteristics from both studies are summarised in Table 4. In 2010, meta-analysis was used to synthesise data points representing the relationship of design, diversity and density with transit use (Ewing and Cervero, 2010). This study reported positive associations for all independent variables, with design as the strongest variable. Similar findings were reported in a study that considered a wider geographic sample (Aston et al., 2019b).

Table 4: Characteristics of prior meta-analyses

	(Ewing and Cervero, 2010)	(Aston et al., 2019b) [1]
Density	0.01-0.07	0.1-0.14
Diversity	0.12	0.07
Design	0.23-0.29	0.06
Accessibility		0.19
Location of Samples	Canada, Hong Kong, USA	Australia, Canada, China, Korea, Latin America, Netherlands, South Korea, United Kingdom, USA

Stevens (2017) also estimated average elasticities between the built environment and automobile use, using meta-regression to identify and correct for any significant impacts resulting from specification errors in studies. Meta-regression is simple linear regression with study-level differences coded to form the independent variables. The dependent or outcome variables are the effect sizes from these studies, such as the relationship between a built environment variable and vehicle miles travelled. Study-level factors that are consistently associated with trends in the effect sizes will be detected as significant predictors, in the same way that linear regression identified predictors. Meta-regression used in this way enabled Stevens (2017) to identify that studies in which individuals' pre-existing preference for living in areas where they could drive less (self-selection) was producing different results to those that did not

3 Methodology

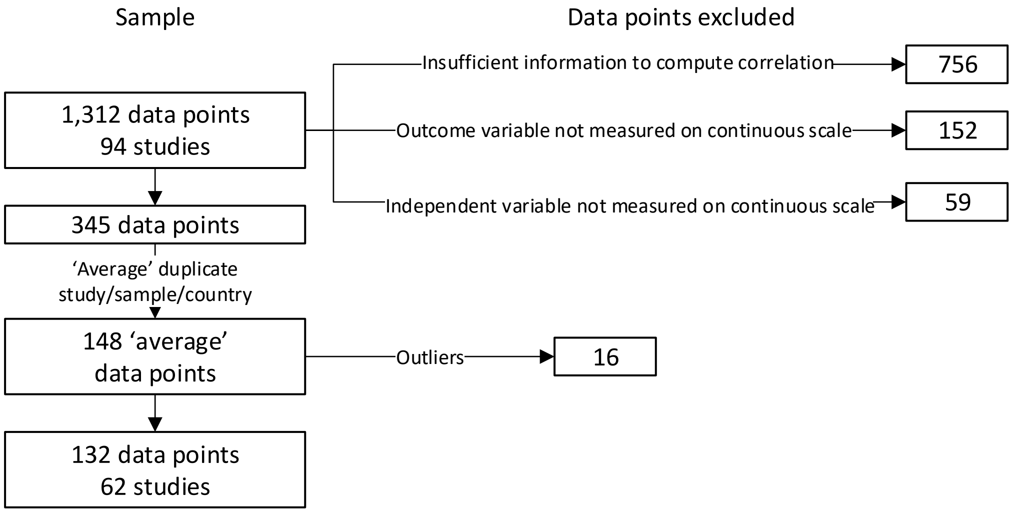
To generalise the BE-TR relationship for different countries, this project synthesised a database of studies relating to the built environment and transit use through employing an established meta-analysis methodology (Borenstein et al., 2009).

3.1 Sample

An existing database[2] containing statistical and contextual information (effect size, sample size, geography) on studies relating to the relationship between built environment indicators (independent variable) and transit use (dependent variable) was used for this paper. Data were screened for inclusion in the sample through a process illustrated in Figure 1.

Comparison between studies requires that the variables measure the same underlying phenomenon (Borenstein et al., 2009). Two fundamentally different measures of transit use are prevalent in the literature. These include studies that analyse aggregate demand ("ridership"), and those that analyse mode choice using discrete choice methods (Ortúzar and Willumsen, 2011). While ridership is measured on a continuous scale, mode choice measures discrete outcomes. Their different measurement scales make them inappropriate for comparison. Similarly, the independent variables of urban design and accessibility are often measured using categorical or binary scales. The impact of moving from one category to the next is not comparable to moving along a numeric (continuous) scale with infinitely small increments. Categorical accessibility and design indicators were thus excluded.

Figure 1: Process for the selection of primary studies for meta-analysis



In this study, the unit of analysis is a data point rather than a study. Some studies contained more than five individual data points for a single variable, while many contained just one. Researchers can choose to analyse all datapoints ('all in'), take only the most representative data point ('best of') or average the data points for an individual study to minimise bias (Stanley and Jarrell, 2005). For the purpose of this analysis, an 'average' approach was taken. Data points from the same study that were identical in the country, sample size, and built environment variable were treated as duplicates of a study and therefore averaged. This resulted in the amalgamation of 345 data points into 148.

3.1.1 Conversion to common effect sizes

From the studies included for the meta-analysis, there were four types of formats used to report statistical results. These are summarised in Table 5 along with the computation strategy for converting them into correlations. In this meta-analysis, the effect size is used to describe the strength of the relationship between two variables.

Table 5: Computation strategy for conversion (adapted from Sharmin and Kamruzzaman (2018))

Type	n	Reported estimate	Data	Conversion
1	6	**Pearson's correlation coefficient:** Describes the magnitude of correlation between the built environment measures and transit use	- Pearson's or Spearman's correlation coefficient - Sample size	No conversion
2	3	**Fisher's Z value:** statistical measure of strength of relationship	- Z – value - Sample size	$r = \sqrt{\frac{z^2}{n}}$ [Eq.1]
3	284	**t- statistics:** used in linear regression models to describe calculated difference.	- T – statistic - Sample size - Degrees of freedom of the test	$r = \sqrt{\frac{t^2}{t^2 + df}}$ [Eq.2]
4	52	**p-values:** expresses the significance of a relationship	- p-value - tails in t-test (assumed: two) - sample size ➔z-value from conversion table	[Eq.1]

To combine results from different study designs, conversions to a common effect size measure were needed. The chosen metric for this paper is the correlation coefficient, r, which can measure the strength and direction of a linear correlation between two variables. The results are between -1 and 1, with ±1 indicating total positive or negative linear correlation and 0 indicating no linear correlation. The correlations, now of comparable form, were checked for outlying values. Extreme outliers were removed by inspection. The final sample contained 132 data points from 62 studies (See Appendix: Table 8).

3.2 Meta-analysis: average effects

Comprehensive Meta-Analysis (CMA) is a software which was used in this study to convert, analyse and report the statistical data (Borenstein et al., 2013). Since primary studies were performed independently, it was assumed that the studies would not have one true effect size. As such, the “random effect” model was used to estimate averages, as this model assumes that the true effect size varies from one study to another. In contrast, fixed effect analysis would assume the true effect size is the same in all studies, and that variation would only be caused by sampling error (Borenstein et al., 2009). The random effect model assigns particular weights to individual studies to calculate the average correlation. The weights assigned to each study are estimated from the standard error of the studies, which itself is calculated from the sample size and magnitude of the correlation, as shown in Equation 3 to 5 below (Borenstein et al., 2013).

$$Fisher's\ Z = 0.5 * (\frac{\log(1+corr)}{1} - corr) \quad \text{[Eq. 3]}$$

$$SE_{Fisher'sZ} = \frac{1}{S\sqrt{N-3}} \quad \text{[Eq. 4]}$$

$$SE_{corr} = 1 - corr^2 * \ SE_{Fisher'sZ} \quad \text{[Eq. 5]}$$

Generally, an effect size of +/- 0.10, +/- 0.30 and +/- 0.50 shows a small, medium and large effect size, respectively (Card, 2012). A p-value of less than 0.1 has been used throughout this paper as the cut off for reporting statistically significant variables. To identify and quantify variance, Q-statistics and I^2 statistic were used. Excess variance is estimated as the difference between Q and the degree of freedom (Borenstein et al., 2009). The I^2 statistic was used to describe the percentage of variation across studies that is due to heterogeneity rather than chance.

Subgroup analysis was used to determine whether estimates grouped by geography were distinct, and whether this explains some of the variation in the overall mean for a variable. A Q-test based on analysis of variance was then used to partition the total variance from the built environment variables into variance within subgroups and variance between subgroups (Borenstein et al., 2009). Variance explained by differences in the country subgroups (total ‘between’ variance) and the unexplained variance remaining (total ‘within’ variance) were calculated and compared.

3.3 Meta-regression: identifying significant sources of variability

Meta-regression analysis was used to check the impact of country variables on the BE-TR relationship while simultaneously accounting for differences in study design. Artificial categories were created to represent characteristics suspected of contributing to significant differences in the results from study to study. In this particular study, the country in which the study was undertaken; and appropriate controls for self-selection and regional accessibility, were the study-level differences of interest. The country of a study was treated as a categorical variable, with 'Australia' as the references case. Studies that included appropriate sociodemographic or attitudinal controls for self-selection were assigned (1) as controlling for self-selection, compared to the references case (0) of studies that did not. Studies that considered the accessibility of their sample relative to jobs or employment districts were considered as controlling regional accessibility (1) and compared to those that did not (0). Ordinary least squares regression was then used to identify significant predictors of the BE-TR relationships. This procedure was also conducted using CMA (Borenstein et al., 2013). The impact of any significant predictors on the relationship can be observed by 'solving' the regression equation, that is, substituting the coefficients for any significant study design factors and re-calculating an effect size (Stanley and Doucouliagos, 2012).

4 Results

4.1 Descriptive analysis

A total of 132 data points from 62 studies were used for this meta-analysis. In terms of country distribution, most data points were conducted in USA (89), followed by South Korea (7), China (5), Canada (4), Australia (3), Spain (3), Hong Kong (2), Netherlands (2), Taiwan (2), United Kingdom (2), Brazil (1), Denmark (1) and Japan (1). Nine studies collected data in multiple countries. This geographic distribution of data points shows that the influence of built environment measures on transit use have not been widely investigated on a global scale.

4.2 Meta-analysis of built environment variables

4.2.1 Overall average effects

Individual correlations from primary studies were used to compute an average correlation (ρ) for BE-TR, for four built environment indicators. The average estimates for the four variables are shown in Table 6.

Table 6 - Estimates of average correlations and variance for BE-TR (*p<0.1, **p<0.05, ***p<0.01)

Country	Density			Diversity			Design			Accessibility		
	N	ρ	I^2	N	ρ	I^2	N	ρ	I^2	N	ρ	I^2
Average	**64**	**0.154*** **	**0.979**	**Not significant**			**24**	**0.035** **	**0.899**	**16**	**0.145*** **	**0.902**
Australia	3	0.220**	0.815									
Canada	2	0.360***	0.497									
China										1	0.312*	n/a
Hong Kong	1	0.407**	n/a									
South Korea							2	0.088*	0.0			
Taiwan							1	0.360**	n/a			
USA	40	0.156***	0.983	19	-0.032*	0.882	18	0.030*	0.916	12	0.140***	0.924
Within-group variance	2,345***			151***			153***			203***		
Between-group variance	21.9*			Not significant			Not significant			Not significant		
I^2 denotes the proportion of variance that can be explained by covariates and not by sampling error. N denotes the number of error-weighted data points (deriving from unique statistical models)												

As expected from previous literature, findings from this meta-analysis suggest that density, design and accessibility all have a significant, positive correlation to transit use. The correlation between indicators of design, accessibility and density show a significant, positive association to transit use, aligning with findings from past meta-analysis.

The variable with the largest influence on transit use is density, with a correlation of 0.154. Density is the most commonly analysed built environment variable. 64 unique estimates for density and transit ridership were available from the dataset, compared to 28 for diversity, 24 for design and 16 for accessibility. Given the reduced sensitivity of larger samples to outliers, it is not surprising that the most significant estimates were found for density at the country-level. Accessibility showed the second strongest average correlation with ridership, with an average estimate of 0.145. A significant relationship was also found for design (ρ= 0.035). Diversity, measured in terms of land use mix (or entropy), housing diversity and the balance of trip attractors and generators, shows inconsistent impacts on ridership, with many studies finding a negative association. Its average impact was not significant.

4.2.2 Country-level estimates and variance

Correlations between the built environment and transit use, grouped geographically, are also included in Table 6. The I^2 statistic, which represents the proportion of variance that is not attributable to chance, is shown in the third column for each indicator. No obvious patterns in the ranking of the countries across the indicators is visible to suggest substantially different patterns of association between the built environment and transit use.

Four country-level estimates for density were significant. Hong Kong yielded the largest estimate with a correlation between density and transit use of 0.407, followed by Canada (ρ = 0.360), Australia (ρ = 0.220) and USA (ρ = 0.156). The estimate for diversity in USA was significant (ρ=-0.032), even though the population average was not. This is an unexpected result, however, since diversity was expected to increase transit use, although this assumption was primarily based on evidence of the impact of diversity on the reduction of automobile travel. This suggests that results emanating from the USA, which formed only a subset of the entire sample, were more consistent than the sample as a whole.

Significant correlations between accessibility and ridership were identified for China (ρ = 0.312) and USA (ρ = 0.140). The association of design with ridership was significant for three countries, the largest being Taiwan, from a single data point (ρ = 0.360). Estimates from a single data point are not 'averages', although they are weighted and converted in the same way as the other estimates.

According to the I^2, the variance explained by sampling error for the four variables is minimal, with real variance accounting for 97.9% (density) to 89.9% (design) and 90.2% (accessibility) of the variance. However, when examined at the level of different countries, some of this real variance disappears. Single-data point groups do not have an associated I^2 statistic, as more than one estimate is needed to estimate within-group variance. The within- and between- group variance provide insight to the degree to which grouping by country improves consistency in the results. The country estimates for one of the variables, density, were distinct from each other. This is signified by the total between-group variance of 21.9.

4.2.3 Meta-regression of study design and country

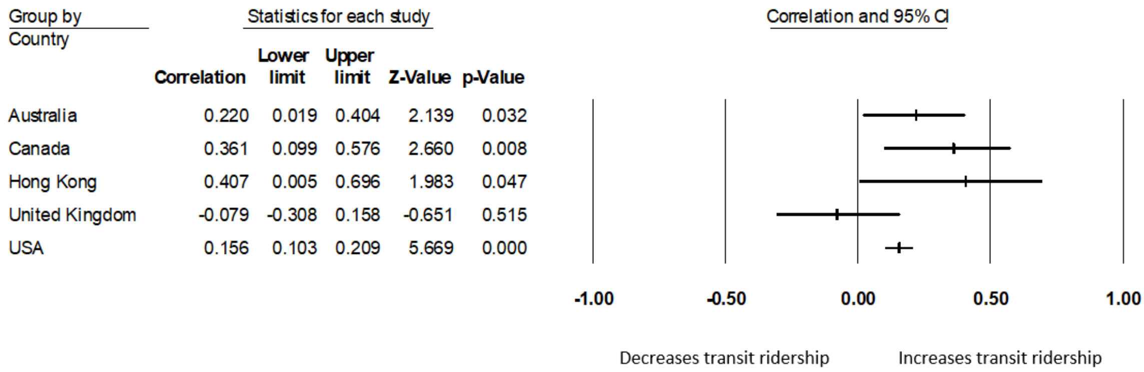
Table 7 summarises the result of meta-regression, which was used to explore the impact of three expected sources of variability. These were: the country in which data was collected; and the specification issues of regional accessibility and self-selection.

Table 7: Results of meta-regression of study design factors and country on BE-TR

	Density	Diversity	Design	Accessibility
Sample size	64	28	24	16
Intercept	0.2239	-0.063	0.088	0.296
Regional accessibility (ref: not controlled)		0.073***		
Self-selection (ref: not controlled)			-0.083***	-0.195***
UK (ref: Australia)	-0.3031*			
R^2		0.79	0.62	0.24
Adjusted correlation	-0.079	0.010	0.005	0.101

In the case of density, meta-regression revealed that significant differences exist between the mean of estimates in UK studies, compared to Australia. Other than this distinction, represented by the error bars for UK not overlapping the mean correlation for Australia in Figure 2, all other estimates had overlapping means.

Figure 2: Forest plot of density and transit use relationship (random-effect model)



Study design was an important predictor of the relationship between transit ridership and diversity, design and accessibility. Studies that controlled regional accessibility were predicted to find larger BE-TR relationships for diversity. Studies that controlled self-selection were predicted to have an inverse BE-TR relationship for design and accessibility. Where the average correlation for design was calculated to be 0.035 without controlling study design, once self-selection was accounted for this was predicted to reduce to 0.005. Similarly, the estimate for accessibility corrected for self-selection impacts reduced from 0.145 to 0.101.

5 Discussion

5.1 How well does geography explain variance?

To explore whether the BE-TR relationship varies according to the geography of the sample, results were grouped by the country from which they were sourced. Generally, a subgroup explains variance well if large variation exists between subgroups and little variation exists within subgroups (Borenstein et al., 2009). This was not the case in the present sample.

Between group variance was only observed for density. Significant estimates of the association between density and ridership for Hong Kong (ρ= 0.407), Canada (ρ = 0.360), Australia (ρ = 0.220) and USA (ρ = 0.156) were higher than the average for all geographies in the sample (ρ = 0.154). The universal average is brought down by smaller, and in some cases negative, estimates of the relationships from locations including Denmark, Brazil, South Korea and the Netherlands. The country groupings for diversity, design and accessibility were not distinct from each other, signified by the absence of any between group variance. Therefore, the variance explained by the country subgroups is only a small portion of the overall variance.

Although differences between country groupings were not significant, there were some estimates for which the country averages had much less real variability than the overall sample. Since I^2 measures variability that is not attributable to chance, the fact that the country groupings were smaller does not explain the reduction in the variance. In fact, in the case of estimates for USA, the true variance was higher than that of the overall sample. The results of meta-regression suggest that the reduction in variance when grouped by country might be explained by similar study designs among research undertaken in the same country.

The meta-regression analysis reveals that study design significantly impacts the magnitude of findings for built environment indicators and ridership. Specifically, the meta-regression results in Table 7 suggest that studies that control regional accessibility find higher ridership for increasing diversity. Conversely, studies that control self-selection are predicted to negatively impact ridership associations with design and accessibility. Similarity in the study design of estimates from a single country is more likely to explain the reduction in variance, than country-level differences. Attempts to examine country- or network-level factors that mediate the built environment and transit use relationship identified by different studies are likely to be confounded by the different designs of these studies.

Synthesising estimates at the country level facilitates comparison of built environment and travel behaviour associations. However, it cannot explain why differences occur. Although averages appeared to vary across country, this does not say anything about whether the role of the built environment differs, or if this is instead a symptom of contextual differences between countries. Evidence exists for the ability of cultural norms and regional-level accessibility to mediate the built environment and transit ridership relationship, via their impact on attitudes and perceptions about travel (Dill et al., 2014, Renne et al., 2016). Examining each of the regional attributes that could be expected to impact transit use will improve understanding of how, and under what conditions, the built environment contributes to the formation of attitudes about different travel alternatives. This in turn will make research more transferrable.

5.2 Limitations and further study suggestions

The four “D-variables” used in this study, including density, diversity, design and destination accessibility are commonly used in the literature to represent the built environment (Ewing and Cervero, 2010). However, the relationship for these variables and transit ridership has been shown to vary depending on the indicator used to represent the variable (Aston et al., 2019b). Therefore, this study’s assumption that 'density', 'diversity', 'design' and 'accessibility' are homogeneous characteristics of the built environment is a simplification. Once again, the need to obtain a large enough sample to enable country-level averages to be computed warranted the examination at the 'variable' rather than 'indicator' level. Analysis at the indicator level would reduce variance that is caused by the choice of indicator.

A limitation within this meta-analysis is the lack of studies from diverse locations. This is not a failing of our method; all published studies were included, it's a failing of the field since more studies in diverse geographies are needed. Most studies within this paper are from USA and since other groups do not have as many eligible data points, the summary effects for the smaller geographical groups are less conclusive. This calls for more research in other regions, particularly Asia, Latin America, Africa and Europe.

6 Conclusion

This study used meta-analysis to examine the impact of controlling country-level differences on the consistency of estimates of the relationship between the built environment and transit ridership. Differences in mobility styles, social norms and transit network accessibility were theorised to drive country-level differences in the BE-TR relationship. When results were averaged across all available evidence, irrespective of country, the meta-averages showed large variability, and only weak correlations between three built environment indicators and transit ridership.

Large variance within the countries persisted across the indicators. Meta-analysis with comparison between results grouped by studies, failed to account for the majority of variability. Furthermore, the results of meta-regression analysis suggest that study design is a more important source of variability than regional differences. Studies that control for regional accessibility find significantly smaller diversity impacts on transit use, while studies that control for residential self-selection find a significantly smaller role for design and accessibility in predicting ridership.

Multi-country empirical analysis that adopts a consistent study design might be a more effective way to of examining regional factors that impact the built-environment and transit use relationship. Such findings would also have broad implications for travel behaviour research and policy.

7 Notes

1 – This study references findings from a manuscript that is under review (Aston et al., 2019b)

2 – The database builds on an existing database and metadata available on figshare at: https://doi.org/10.26180/5c3fe01b7fd7e (Aston et al., 2019a)

8 Acknowledgements

This study was conducted in collaboration with the Sustainable and Effective Public Transport Graduate Research Industry Partnership (SEPT-GRIP), jointly sponsored by the Department of Transport (State of Victoria) and Monash University

9 References

ADITJANDRA, P. T., CAO, X. & MULLEY, C. 2016. Exploring changes in public transport use and walking following residential relocation: A British case study. *Journal of Transport and Land Use,* 9**,** pp 77-95.

AJZEN, I. 1991. The theory of planned behavior. *Organizational Behavior and Human Decision Processes,* 50**,** 179-211.

ARMBRUSTER, B. 2010. *Factors affecting transit ridership at the metropolitan level 2002-2007.* 1475071 M.P.P., Georgetown University.

ASAD, F. 2013. City centres: understanding the travel behaviour of residents and the implications for sustainable travel. Manchester, United Kingdom: University of Salford.

ASTON, L., CURRIE, G., DELBOSC, A., KAMRUZZAMAN, M., O'HARE, T. & TELLER, D. 2019a. Built environment and transit use empirical research database. 4 ed.

ASTON, L., CURRIE, G., DELBOSC, A., KAMRUZZAMAN, M. & TELLER, D. 2019b. Which built environment attributes increase transit ridership? Meta-analysis of evidence since 2000. *Article under review*.

BHATTACHARYA, T. 2013. *Impact of transit system design on job accessibility of choice and transit dependent riders: A study of Atlanta metropolitan region's transit systems.* 3596460 Ph.D., The Florida State University.

BLUMENBERG, E., SMART, M. & TRANSPORTATION RESEARCH, B. Travel In the 'Hood: Ethnic Neighborhoods and Mode Choice. 2009. 19p.

BORENSTEIN, M., HEDGES, L., HIGGINS, J. & ROTHSTEIN, H. 2013. Comprehensive Meta-Analysis. 3 ed. Englewood, New Jersey: Biostat.

BORENSTEIN, M., HEDGES, L. V., HIGGINS, J. & ROTHSTEIN, H. 2009. *Introduction to meta-analysis,* Chichester, U.K., John Wiley & Sons Ltd.

BOULANGE, C., GUNN, L., GILES-CORTI, B., MAVOA, S., PETTIT, C. & BADLAND, H. 2017. Examining associations between urban design attributes and transport mode choice for walking, cycling, public transport and private motor vehicles. *Journal of Transport & Health*.

BROWN, J. R. & NEOG, D. 2012. Central Business Districts and Transit Ridership: A Reexamination of the Relationship in the United States. *Journal of Public Transportation,* 15**,** 1-22.

BROWN, S., CABLE, F., CHALMERS, K., CLARK, C., JONES, L., KUEBER, G., LANDFRIED, E., LILES, C., LINDQUIST, N., PAN, X., RAY, R. A., SHAHAN, Z., TEAGUE, C., YASUKOCHI, E. & UNIVERSITY OF NORTH CAROLINA, C. H. 2006. Understanding How the Built Environment Around TTA Stops Affects Ridership: A Study for Triangle Transit Authority.

CAO, X., MOKHTARIAN, P. L. & HANDY, S. L. 2009a. Examining the Impacts of Residential Self-Selection on Travel Behaviour: A Focus on Empirical Findings. *Transport reviews.,* Vol. 29**,** 359-395.

CAO, X., MOKHTARIAN, P. L. & HANDY, S. L. 2009b. The relationship between the built environment and nonwork travel: A case study of Northern California. *Transportation Research Part A: Policy and Practice,* 43**,** pp 548-559.

CARD, N. A. 2012. *Applied meta-analysis for social science research,* New York, New York : Guilford Press.

CARDOZO, O. D., GARCIA-PALOMARES, J. C. & GUTIERREZ, J. 2012. Application of geographically weighted regression to the direct forecasting of transit ridership at station-level. *Applied Geography,* 34**,** 548-558.

CERVERO, R. 2006. Alternative approaches to modeling the travel-demand impacts of smart growth. *Journal of the American Planning Association,* 72**,** 285-295.

CERVERO, R. & MURAKAMI, J. 2008. Rail + Property Development: A Model of Sustainable Transit Finance and Urbanism.

CERVERO, R., MURAKAMI, J. & MILLER, M. 2010. Direct ridership model of bus rapid transit in Los Angeles County, California. *Transportation Research Record***,** 1-7.

CHATMAN, D. G. 2008. Deconstructing development density: Quality, quantity and price effects on household non-work travel. *Transportation Research Part A: Policy and Practice,* 42**,** 1008-1030.

CHEN, S. H. & ZEGRAS, C. 2016. Rail transit ridership: Station-area analysis of Boston's Massachusetts Bay Transportation Authority. *Transportation Research Record.*

CHOI, J., LEE, Y. J., KIM, T. & SOHN, K. 2012. An analysis of Metro ridership at the station-to-station level in Seoul. *Transportation,* 39**,** 705-722.

CURRIE, G., AHERN, A. & DELBOSC, A. 2011. Exploring the drivers of light rail ridership: an empirical route level analysis of selected Australian, North American and European systems. *Transportation,* 38**,** 545-560.

CURRIE, G. & DELBOSC, A. 2013. Exploring comparative ridership drivers of bus rapid transit and light rail transit routes. *Journal of Public Transportation,* 16**,** 47-65.

DE GRANGE, L., TRONCOSO, R. & GONZALEZ, F. 2012. An empirical evaluation of the impact of three urban transportation policies on transit use. *Transport Policy,* 22**,** 11-19.

DE GRUYTER, C., CURRIE, G., TRUONG, L. T. & NAZNIN, F. 2019. A meta-analysis and synthesis of public transport customer amenity valuation research. *Transport Reviews,* 39**,** 1-23.

DENG, T. T., MA, M. L. & WANG, J. 2013. Evaluation of Bus Rapid Transit Implementation in China: Current Performance and Progress. *Journal of Urban Planning and Development,* 139**,** 226-234.

DILL, J., MOHR, C. & MA, L. 2014. How can psychological theory help cities increase walking and bicycling? *Journal of the American Planning Association,* 80**,** 36-51.

DILL, J. & WARDELL, E. 2007. Factors Affecting Work Site Mode Choice: Findings from Portland, Oregon. *Transportation Research Record: Journal of the Transportation Research Board***,** pp 51-57.

DUGGAL, M., RADAKOVIC, N., BHOWMICK, A. & DATLA, S. 2016. Sketch Model for Estimating Station Level Ridership for LRT. *TAC 2016: Efficient Transportation - Managing the Demand - 2016 Conference and Exhibition of the Transportation Association of Canada***,** 1.

DURNING, M. & TOWNSEND, C. 2015. Direct ridership model of rail rapid transit systems in Canada. *Transportation Research Record.*

EWING, R. & CERVERO, R. 2010. Travel and the built environment: A meta-analysis. *Journal of the American Planning Association,* 76**,** 265-294.

EWING, R., TIAN, G., GOATES, J. P., ZHANG, M., GREENWALD, M. J., JOYCE, A., KIRCHER, J. & GREENE, W. 2015. Varying influences of the built environment on household travel in 15 diverse regions of the United States. *Urban Studies,* 52**,** 2330-2348.

GORDON, P. 2004. Neighborhood attributes and commuting behavior: Transit choice. California Department of Transportation, Metrans Transportation Center, Department of Transportation,.

GREENWALD, M. J. 2003. The road less traveled - New urbanist inducements to travel mode substitution for nonwork trips. *Journal of Planning Education and Research,* 23**,** 39-57.

GUERRA, E., CERVERO, R. & TISCHLER, D. 2011. The Half-Mile Circle: Does It Best Represent Transit Station Catchments?: . *IDEAS Working Paper Series from RePEc.* St. Louis: University of California Transportation Center, Working.

GUTIÉRREZ, J., CARDOZO, O. D. & GARCÍA-PALOMARES, J. C. 2011. Transit ridership forecasting at station level: An approach based on distance-decay weighted regression. *Journal of Transport Geography,* 19**,** 1081-1092.

HAMIDI, S. & EWING, R. 2014. A longitudinal study of changes in urban sprawl between 2000 and 2010 in the United States. *Landscape and Urban Planning,* 128**,** 72-82.

HAUSTEIN, S. & NIELSEN, T. A. S. 2016. European mobility cultures: A survey-based cluster analysis across 28 European countries. *Journal of Transport Geography,* 54**,** 173-180.

HU, L. & ISEKI, H. 2018. Land use and transportation planning in a diverse world. *Transport Policy* [Online].

IMAM, R. & TARAWNEH, B. 2012. Exploring BRT ridership drivers: An empirical study on European systems. *Jordan Journal of Civil Engineering,* 6**,** 234-242.

KERKMAN, K., MARTENS, K. & MEURS, H. 2015. Factors Influencing Stop-Level Transit Ridership in Arnhem-Nijmegen City Region, Netherlands. *Transportation Research Record***,** 23-32.

KIM, D., AHN, Y., CHOI, S. & KIM, K. 2016. Sustainable mobility: Longitudinal analysis of built environment on transit ridership. *Sustainability (Switzerland),* 8.

KUBY, M., BARRANDA, A. & UPCHURCH, C. 2004. Factors influencing light-rail station boardings in the United States. *Transportation Research Part A: Policy and Practice,* 38**,** 223-247.

LANE, B. W. 2011. TAZ-level variation in work trip mode choice between 1990 and 2000 and the presence of rail transit. *Journal of Geographical Systems,* 13**,** 147-171.

LANE, C., DICARLANTONIO, M. & USVYAT, L. 2006. Sketch Models to Forecast Commuter and Light Rail Ridership: Update to TCRP Report 16. *Transportation Research Record: Journal of the Transportation Research Board***,** 198-210.

LAWRENCE FRANK & CO. INC, THE SACRAMENTO AREA COUNCIL OF GOVERNMENTS & BRADLEY, M. 2009. I-PLACE3S health & climate enhancements and their application in King County. *HealthScape Project.* Federal Transit Administration.

LEE, S., AN, Y. & KIM, K. 2017. Relationship between transit modal split and intra-city trip ratio by car for compact city planning of municipalities in the Seoul Metropolitan Area. *Cities,* 70**,** pp 11-21.

LIN, J.-J. & SHIN, T.-S. 2008. Does transit -oriented development affect metro ridership ? Evidence from Taipei, Taiwan. *Transportation Research Record***,** 149-58.

LITMAN, T. & STEELE, R. 2017. Land Use Impacts on Transport: How Land Use Factors Affect Travel Behavior. Victoria Transport Policy Institute.

LIU, C., ERDOGAN, S., MA, T., DUCCA, F. W. & TRANSPORTATION RESEARCH, B. How to Increase Rail Ridership in Maryland? Direct Ridership Models (DRM) for Policy Guidance. 2014. 17p.

LOO, B. P. Y., CHEN, C. & CHAN, E. T. H. 2010. Rail-based transit-oriented development: Lessons from New York City and Hong Kong. *Landscape and Urban Planning,* 97**,** 202-212.

MAAT, K., VAN WEE, B. & STEAD, D. 2005. Land use and travel behaviour: Expected effects from the perspective of utility theory and activity-based theories. *Environment and Planning B: Planning and Design,* 32**,** 33-46.

MANGAN, M. M. 2013. *Integrating first and last mile access measures in the estimation of light rail transit ridership.* 1547390 M.C.P., San Diego State University.

MOKHTARIAN, P. L. & CAO, X. 2008. Examining the impacts of residential self-selection on travel behavior: A focus on methodologies. *Transportation research.,* Vol. 42**,** 204-228.

NÆSS, P. 2005. Residential location affects travel behavior - but how and why? The case of Copenhagen metropolitan area. *Progress in planning,* 63**,** 165-257.

NATIONMASTER. 2014. *All countries compared for Transport > Road > Motor vehicles per 1000 people* [Online]. Available: http://www.nationmaster.com/country-info/stats/Transport/Road/Motor-vehicles-per-1000-people [Accessed].

NAWROCKI, J., NAKAGAWA, D., MATSUNAKA, R. & OBA, T. Measuring walkability and its effect on light rail usage: A comparative study of the USA and Japan. 20th International Conference on Urban Transport and the Environment, UT 2014, May 28, 2014 - May 30, 2014, 2014 Algarve, Portugal. WITPress, 305-318.

ORTÚZAR, J. D. & WILLUMSEN, L. G. 2011. *Modelling Transport,* Chichester, West Sussex, United Kingdom, John Wiley & Sons Ltd.

PETERSON, D. 2011. Transit Ridership and the Built Environment. Upper Great Plains Transportation Institute, Mountain-Plains Research Consortium, Innovative Technology Administration,.

PITOMBO, C., SOUSA, A. J. & FILIPE, L. N. 2009. Classification and Regression Tree, Principal Components Analysis and Multiple Linear Regression to Summarize Data and Understand Travel Behavior. *Transportation Letters: The International Journal of Transportation Research,* 1, pp 295-308.

RENNE, J., HAMIDI, S. & EWING, R. 2016. Transit commuting, the network accessibility effect, and the built environment in station areas across the United States. *Research in Transportation Economics,* 60, 35-43.

RYAN, S. & FRANK, L. F. 2009. Pedestrian Environments and Transit Ridership. *Journal of Public Transportation,* 12, pp 39-57.

SHARMIN, S. & KAMRUZZAMAN, M. 2018. Meta-analysis of the relationships between space syntax measures and pedestrian movement. *Transport Reviews,* 38, 524-550.

SPEARS, S. P. 2013. *The Perception-Intention-Adaptation (PIA) Model: A theoretical framework for examining the effect of behavioral intention and neighborhood perception on travel behavior.* 3597850 Ph.D., University of California, Irvine.

STANLEY, T. D. & DOUCOULIAGOS, H. 2012. Meta-regression analysis in economics and business. London and New York: Routledge.

STANLEY, T. D. & JARRELL, S. B. 2005. Meta-Regression Analysis: A Quantitative Method of Literature Surveys. *Journal of Economic Surveys,* 19, 299-308.

STEVENS, M. 2017. Does Compact Development Make People Drive Less? *Journal of the American Planning Association,* 83, 7-18.

SUN, L. S., WANG, S. W., YAO, L. Y., RONG, J. & MA, J. M. 2016. Estimation of transit ridership based on spatial analysis and precise land use data. *Transportation Letters,* 8, 140-147.

SUNG, H.-G. 2005. *Transit -friendly areas: The role of residential relocation and housing development in rail ridership over time.* 3175226 Ph.D., University of California, Los Angeles.

SUNG, H., CHOI, K., LEE, S. & CHEON, S. 2014. Exploring the impacts of land use by service coverage and station-level accessibility on rail transit ridership. *Journal of Transport Geography,* 36, 134-140.

TALBOTT, M. R. 2011. Bus stop amenities and their relationship with ridership : a transportation equity approach.

TAYLOR, B. D., MILLER, D., ISEKI, H. & FINK, C. 2009. Nature and/or nurture? Analyzing the determinants of transit ridership across US urbanized areas. *Transportation Research Part A: Policy and Practice,* 43, 60-77.

THOMAS, R. & BERTOLINI, L. 2017. Defining critical success factors in TOD implementation using rough set analysis. *Journal of Transport and Land Use,* 10, 139-154.

TRACY, A. J., SU, P., SADEK, A. W. & WANG, Q. 2011. Assessing the impact of the built environment on travel behavior: a case study of Buffalo, New York. *Transportation,* 38, 663-678.

TSAI, C. H., MULLEY, C. & CLIFTON, G. 2012. The spatial interactions between public transport demand and land use characteristics in the Sydney Greater Metropolitan Area. *Road & Transport Research,* 21, 62-73.

TSAI, C. H., MULLEY, C. & CLIFTON, G. 2014. Forecasting public transport demand for the Sydney Greater Metropolitan Area: A comparison of univariate and multivariate methods. *Road & Transport Research,* 23, 51-68.

VAN DE COEVERING, P. & SCHWANEN, T. 2006. Re-evaluating the impact of urban form on travel patterns in Europe and North-America. *Transport Policy,* 13, 229-239.

VERBAS, I., FREI, C., MAHMASSANI, H. & CHAN, R. 2015. Stretching resources: sensitivity of optimal bus frequency allocation to stop-level demand elasticities. *Public Transport,* 7, 1-20.

VERGEL-TOVAR, C. E. 2016. *Examining the reciprocal relationship between bus rapid transit and the built environment in Latin America.* 10145870 Ph.D., The University of North Carolina at Chapel Hill.

WOLDEAMANUEL, M. & KENT, A. 2016. Measuring Walk Access to Transit in Terms of Sidewalk Availability, Quality, and Connectivity. *Journal of Urban Planning and Development,* 142.

WORLD BANK. 2017. *Urban Population (% of total)* [Online]. Available: https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS [Accessed 20/12/17 2017].

ZAMIR, K. R., NASRI, A., BAGHAEI, B., MAHAPATRA, S. & ZHANG, L. 2014. Effects of Transit-Oriented Development on Trip Generation, Distribution, and Mode Share in Washington, DC, and Baltimore, Maryland. *Transportation Research Record***,** 45-53.

ZHAO, J., DENG, W., SONG, Y. & ZHU, Y. 2014. Analysis of Metro ridership at station level and station-to-station level in Nanjing: An approach based on direct demand models. *Transportation,* 41**,** 133-155.

ZHAO, P. J. & LU, B. 2011. Managing urban growth to reduce motorised travel in Beijing: one method of creating a low-carbon city. *Journal of Environmental Planning and Management,* 54**,** 959-977.

Appendix 1

Table 8: List of studies used for this meta-analysis (n = number of data points)

Name	n	Variable	Country
(Aditjandra et al., 2016)	1	Accessibility	UK
(Armbruster, 2010)	1	Density	USA
(Asad, 2013)	1	Density	UK
(Bhattacharya, 2013)	4	Density	USA
(Blumenberg et al., 2009)	2	Density, Diversity	USA
(Brown and Neog, 2012)	3	Accessibility	USA
(Brown et al., 2006)	6	Diversity, Design, Accessibility	USA
(Cao et al., 2009b)	2	Density, Diversity	USA
(Cardozo et al., 2012)	1	Density	Spain
(Cervero, 2006)	3	Density	USA, Canada
(Cervero and Murakami, 2008)	1	Density	Hong Kong
(Cervero et al., 2010)	1	Density	USA
(Chatman, 2008)	1	Density	USA
(Chen and Zegras, 2016)	3	Density, Accessibility, Design	USA
(Choi et al., 2012)	3	Density, Design	South Korea
(Currie and Delbosc, 2013)	1	Density	Varies
(Currie et al., 2011)	1	Density	Australia, North America, Europe
(de Grange et al., 2012)	1	Density	Varies
(Deng et al., 2013)	1	Density	China
(Dill and Wardell, 2007)	1	Design	USA
(Duggal et al., 2016)	1	Density	Canada
(Durning and Townsend, 2015)	3	Density, Diversity, Design	Canada
(Ewing et al., 2015)	3	Diversity, Design	USA
(Gordon, 2004)	10	Density	USA
(Greenwald, 2003)	12	Density, Diversity, Design	USA
(Guerra et al., 2011)	2	Density	USA
(Gutiérrez et al., 2011)	2	Density, Diversity	Spain
(Hamidi and Ewing, 2014)	3	Diversity, Design, Accessibility	USA
(Imam and Tarawneh, 2012)	1	Density	Europe, Canada, USA
(Kerkman et al., 2015)	2	Density	Netherlands
(Kim et al., 2016)	1	Density, Diversity	USA
(Kuby et al., 2004)	2	Density	USA
(Lane, 2011)	1	Density	USA
(Lane et al., 2006)	3	Accessibility	USA
(Lawrence Frank & Co. Inc et al., 2009)	1	Design	USA
(Lee et al., 2017)	2	Density, Diversity	South Korea
(Lin and Shin, 2008)	2	Density, Diversity	Taiwan
(Liu et al., 2014)	2	Density	USA
(Loo et al., 2010)	1	Diversity	Hong Kong

Name	n	Variable	Country
(Mangan, 2013)	2	Design, Diversity	USA
(Næss, 2005)	1	Density	Denmark
(Nawrocki et al., 2014)	2	Accessibility	Japan, USA
(Peterson, 2011)	2	Density, Diversity	USA
(Pitombo et al., 2009)	1	Density	Brazil
(Renne et al., 2016)	4	Density, Diversity, Accessibility, Design	USA
(Ryan and Frank, 2009)	1	Design	USA
(Spears, 2013)	1	Design	USA
(Sun et al., 2016)	1	Diversity	China
(Sung, 2005)	4	Diversity	USA
(Sung et al., 2014)	2	Density, Diversity	South Korea
(Talbott, 2011)	2	Design	USA
(Taylor et al., 2009)	1	Density	USA
(Tracy et al., 2011)	2	Diversity, Design	USA
(Tsai et al., 2012)	3	Density, Diversity, Design	Australia
(Tsai et al., 2014)	2	Density, Diversity	Australia, North America, Europe
(van de Coevering and Schwanen, 2006)	1	Accessibility	Europe, Canada, USA
(Verbas et al., 2015)	2	Accessibility	USA
(Vergel-Tovar, 2016)	3	Density, Diversity, Design	Latin America
(Woldeamanuel and Kent, 2016)	1	Design	USA
(Zamir et al., 2014)	2	Density, Diversity	USA
(Zhao and Lu, 2011)	2	Density, Accessibility	China
(Zhao et al., 2014)	1	Density	China