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Multi-city exploration of built environment and transit mode use: Comparison of Melbourne, Amsterdam and Boston

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ABSTRACT

The built environment is an important determinant of travel demand and mode choice. Establishing the relationship between the built environment and transit use using direct models can help planners predict the impact of neighborhood-level changes, that are otherwise overlooked. However, limited research has compared the impacts of the built environment for different networks and for individual transit modes.

This paper addresses this gap by developing built environment and transit use models for three multimodal networks, Amsterdam, Boston and Melbourne, using a consistent methodology. A sample of train, tram and bus sites with similar station-area built environments are selected and tested to establish if impacts differ by mode. It is the first study that develops neighborhood-level indicators for multiple locations using a consistent approach.

This study compares results for ordinary least squares regression and two-stage least squares (2SLS) regression to examine the impact of transit supply endogeneity on results. Instrumented values are derived for bus and tram frequency in Melbourne and bus frequency in Boston. For other mode and city combinations, the 2SLS approach is less effective at removing endogeneity.

Results confirm that different associations exist between the built environment and transit modes, after accounting for mode location bias, and that this is true in multiple networks. Local access and pedestrian connectivity are more important for bus use than other modes. Tram is related to commercial density. This finding is consistent for all samples. Land use mix and bicycle connectivity also tend to be associated with higher tram use. Train use is highest where opportunities exist to transfer with bus. Population density is commonly linked to ridership, but its significance varies by mode and network.

More research is needed to understand the behavioral factors driving modal differences to help planners target interventions that result in optimal integration of land use with transit modes.

1. Introduction

Knowledge of how the built environment impacts travel helps planners integrate transport and land use efficiently (Moeckel et al., 2019; Saujot et al., 2016). The density of population and activities underpins the latent demand for travel (Rodrigue et al., 2009), while mode choices are impacted by urban design, land use diversity and the accessibility conferred by different modes (Boarnet and Crane, 2001; Ewing and Cervero, 2010).

Aggregate station-level (direct demand) models can help planners predict the impact of neighborhood-level changes, that are otherwise overlooked in large-scale strategic models (Cervero, 2006). It is also of strategic interest to city development to know whether the predictors of transit use differ by mode, as this would allow planners to tailor transport and land use integration approaches according to mode.

Despite important differences in the way transit modes interact with the built environment, there is limited evidence as to whether demand for different modes shows different associations to urban form and land

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use. While the sketch modelling literature includes examples of mode-specific prediction models (Cervero, 2006; De Gruyter et al., 2020; Lane et al., 2006), these studies do not account for the location bias of individual modes. This 'mode location bias', which is the tendency of rail modes to be concentrated in areas of more intense land use relative to bus, makes comparison between modes difficult. A recent study by the authors in Melbourne developed a technique to mitigate this mode location bias and compare the predictors of transit ridership for an unbiased sample of train, tram and bus. The study found the majority of important determinants were not shared between transit modes (Aston et al., 2020b). However, the study was undertaken in only one city; there is a need to apply this approach in multiple cities using a consistent methodology to achieve a wider validity for these conclusions.

This paper addresses this gap by developing built environment indicators for three multimodal networks, Amsterdam, Boston and Melbourne using a consistent methodology including an approach that accounts for mode location bias. By examining multiple locations, this study tests the reproducibility of findings under different cultural, network and policy contexts. Accordingly, this study aims to *determine whether the built environment factors affecting transit ridership differ by mode in three urban networks.*

The next section of this paper provides a brief review of transit and built environment research evidence and applications. The following section outlines the methodology, including study areas, overcoming issues of endogeneity and mode location bias; and linear model estimation. Results are then presented and discussed in the context of the study's aims, before concluding with implications of the research findings.

2. Literature review

2.1. Evidence for built environment impacts on transit use

Most prior studies examining built environment associations with travel behavior focus on one city; a suitable unit of analysis considering most transit networks operate at the city level. Research conducted in Brisbane (Australia) found transit-oriented 'urban' neighborhoods were positively linked to transit use, while activity-center neighborhoods showed no significant impact (Kamruzzaman et al., 2015). In Sydney, activity density has been positively linked to transit use, while the density of dead-ends (a pedestrian barrier) had a negative impact (Tsai et al., 2012). In Melbourne, housing mix and local accessibility have been found to be positively associated with the probability of using transit, while land use diversity and pedestrian connectivity were not significant (Boulange et al., 2017). Research in the Netherlands also found expected associations, with Rubin et al. (2014) finding a positive association between accessibility and transit use. These studies all consider transit use across all available modes in multimodal networks.

Some studies examine multiple networks. Ingvardson and Nielsen (2018) found a positive link between urban-level population and job density and transit use using a sample of 48 European cities. However, once the regional location was accounted for, the built environment was no longer an important predictor of transit use.

Other studies develop direct demand models for transit modes to demonstrate the need for fine-grained built environment modelling tools (Cervero, 2006). Transit-mode specific tools have been developed in operations research, to facilitate the ability of agencies to test different route and service level scenarios in terms of demand impacts (van Oort et al., 2015). Some studies also develop direct demand models for individual modes. A study focusing on bus use in Arnhem-Nijmegen (Netherlands) found positive links with pedestrian and cycling facilities, as well as activity density (Kerkman et al., 2015). A study of rapid transit (light rail and metro) use in Boston found different associations of employment density and pedestrian connectivity with transit use depending on whether the AM or PM peak, or daily average use was considered (Chen and Zegras, 2016). Similar disparities were observed for an earlier study in Boston, with results varying depending on whether the trip was for work or non-work purposes, and whether the trip origin or destination was considered (Zhang, 2004). A meta-regression analysis of such studies found that study design, including whether one or more transit modes is examined, as well as the built environment variables included in the analysis, affects results (Aston et al., 2020a). Yet limited attention has been given to comparing associations of the built environment with demand for train, tram, bus and variants of these public transport modes.

2.2. Differentiating impacts by transit mode

A barrier to examining built environment impacts by mode is the bias associated with the types of locations in which trains, trams and buses are typically supplied. This 'mode location bias' occurs for two reasons. First, the higher capital cost and capacity of rail modes means railway stations tend to be situated in high density areas where ridership returns are more likely to justify the investment. Second, fixed right-of-way modes are perceived as a safer development prospect (Currie, 2006). As a result, policies have tended to favor development intensification around rail, commonly referred to as transit-joint or transit-oriented development (Cervero et al., 2002; Murakami, 2010).

Most prior direct demand studies of transit ridership focus on either one mode, or transit modes in combination. Prior analysis by the authors sought to disentangle the impact of location bias from the predictors of transit use by mode in Melbourne. The study found significant differences in the make-up and magnitude of built environment determinants of bus, train and tram use (Aston et al., 2020b). Population density and level of service were the only predictors common to all three modes. On a modal level, it found train was associated with intermodal transfer opportunities and bike and car parking. Tram use was associated with commercial density, land use diversity, local living score and bicycle connectivity. Bus use showed the weakest association to built-environment factors and was predicted by commercial density and jobs-housing balance.

Repeating the analysis in other research settings, using different data, provides the opportunity to test these results. If the result holds, this increases the confidences of the finding: the possibility that the original finding is related to some aspects of the research setting may be considered weak (Bonnel et al., 2014). Thus, the focus of this study is to validate the finding in Aston et al. (2020b) that the built-environment predictors of transit use differ by mode.

3. Methodology

In this study we use station-level data to identify the built environment predictors of transit use by mode in three urban networks. The first step involves the identification of multimodal transit networks with appropriate access to data, and similar network-level built environment and demographic characteristics. The subsequent steps relate to analysis, and include: data aggregation, testing for threats to empirical validity including endogeneity of transit supply and demand and mode location bias, and finally conducting a cross-sectional multivariate analysis. Each step is elaborated below.

3.1. Study area

Differences in policy, culture and investment may influence travel norms and supply, which in turn affects travel choices (Nijkamp and Pepping, 1998; Ortúzar and Willumsen, 2011). We focus our research on cities that display certain macro similarities. To narrow the search for eligible networks, we conducted a scan of cities based on three criteria and extracting data from the sources listed:

1. Highly urbanized population: % 'urbanized' (World Bank and FAO, 2017)

2. National economic status: national gross domestic product (World Bank and OECD, 2017)
3. Multimodal: a minimum of three public transport modes operational in the city

Melbourne, a city with an extensive train, tram and bus network, was the reference case for this search. A robust data set was already compiled as part of preliminary work to explore and account for mode location bias when comparing built environment impacts by mode (Aston et al., 2020b). Countries whose level of urbanization and GDP fell was within +/− 20% of Australia's were considered eligible. A list of multimodal networks was generated for cities in the shortlisted countries (meeting criteria 1 and 2) by consulting three sources:

- UITP mobility in cities database (UITP, 2015)
- Comparison of transit-oriented development strategies in world cities (Thomas and Bertolini, 2017)
- US National Transit Database (FTA, 2018)

The ability to collect data was also crucial. This led to the narrowing of the search to cities for which contact could be made with local data custodians or researchers. The final cities meeting all criteria were Boston, Rotterdam/The Hague and greater Amsterdam (Stadsregio Amsterdam). Stadsregio Amsterdam was preferred over Rotterdam/The Hague, as it is characterized by a single agglomeration like Boston and Melbourne (although Boston is characterized by two major trip attractors). However, Dutch smartcard data is owned and reported separately by individual operators (van Oort et al., 2015), a number of which are responsible for transport in Stadsregio Amsterdam. The consistency of data gathered for different operators cannot be guaranteed. The study area was narrowed to focus on the Municipality of Amsterdam (henceforth referred to as 'Amsterdam'), where all three transit modes were run by a single operator (GVB). Fig. 1 summarizes the study areas and their similarities (nation-level selection criteria) and high-level urban characteristics.

The population density of Amsterdam was 4662 persons/km^2 (GA 2016b). In contrast greater Melbourne's population density at last census was 450 persons/km^2 (ABS, 2017b), while that of the region served by the Metropolitan Boston Transit Authority catchment (MBTA), was 702 persons/km^2 (U.S. Census Bureau, 2017a). This disparity in population density, driven by the low density urban sprawl in Melbourne and Boston, may affect the comparability of the three samples. As such, the study areas for Melbourne and Boston were confined to areas within approximately 10 km of their respective 'downtown' areas, as depicted in Fig. 1.

Like Melbourne, Amsterdam's transit network comprises bus and tram operating with shared right-of-way. Amsterdam is also served by a metro system which integrates with an intercity railway. Stations associated with both networks are included in the analysis. Melbourne's heavy rail network incorporates some underground stations serving the CBD, but is predominantly a radial system serving suburban stations. Boston's rapid transit network comprises a mix of metro and light rail service. Prior to conducting analysis, the impact of classifying Boston's rapid transit network as an integrated 'metro', or distinct light rail (Green lines and Mattapan Trolley) and metro networks (other lines) was tested. The explanatory power of multivariate models for ridership were compared. Separate models for light rail had much stronger explanatory power than the combined model. Therefore, we generate separate models for light rail and metro lines in this study. Boston also has a bus network of similar scale to Melbourne, as well as a commuter rail which is operated privately, yet serves the inner core in a radial fashion similar to Melbourne's heavy rail network.

3.2. Data aggregation

3.2.1. Aggregating indicators

Table 1 summarizes the definition and source of data for indicators collected across the three study areas. Indicators are grouped according to the unit of analysis that is relevant for their interaction with transit use. The 'facility' refers to properties of the transit service, and includes ridership and service level. The 'transfer zone' encapsulates a small ring around the facility where intermodal transfers take place. We use a 160-m Euclidian buffer from the transit point to demarcate the transfer zone. The 'neighborhood' encompasses land uses from which it is convenient to access transit by foot or bicycle (Monzón et al., 2016). The land uses within the neighborhood are the most important drivers of the underlying demand for transit (Litman and Steele, 2017; Mitchell and Rapkin, 1954). Finally, regional variables measure the relative accessibility to opportunities across the network (Mahmoudi and Zhang, 2018).

3.2.1.1. Facility and transfer-zone variables. Data for tram and bus were collected for transit 'facilities', made up of bus stops within 50 m of each other, or tram or light rail points within 25 m of each other. This clustering of transit stops removed some of the catchment overlap effects that would otherwise be encountered if each stop was treated as an observation.

Data for the outcome variable, transit ridership, was linked to transit stops, however the approach varied by city. In Melbourne, patronage was supplied by the Department of Transport and linked to transit points using the common 'Stop ID' identifiers. Transit points for Boston could also be linked to ridership data published by the Massachusetts Bay Transportation Authority (MBTA) using common stop IDs. Transit point data for Amsterdam was primarily sourced from Open Street Map (GeoFabrik downloads, 2019b). Stop names were used to link this data to ridership supplied by the predominant transit operator in Amsterdam, GVB.

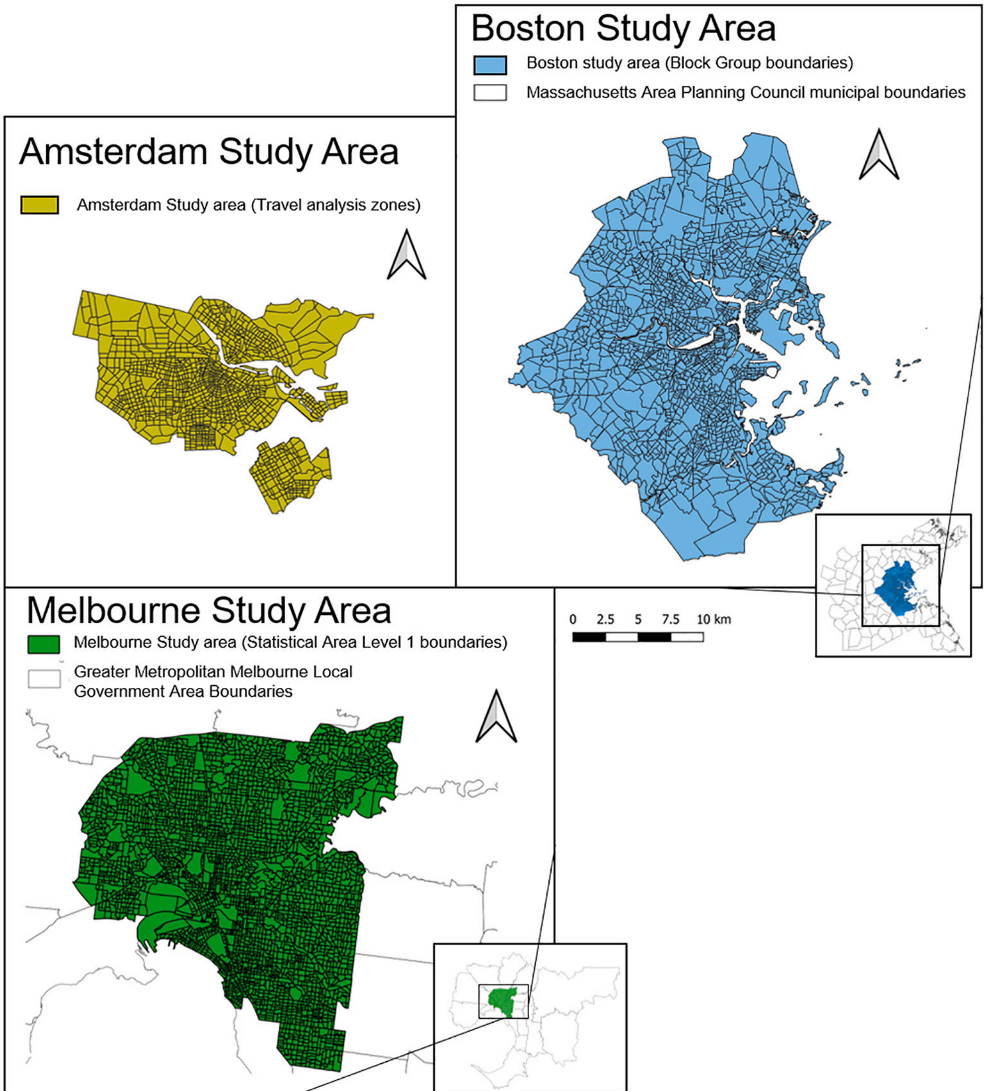
The level of service (LOS) is represented by the daily weekday services corresponding to a stop between 6 am and 7 pm. Schedules were extracted from general transit feed specifications (GTFS) for each operating agency for a single date falling within the data collection period. Where sample locations comprised more than one stop (bidirectional stop pairs and stops at interchanges), ridership and LOS for individual stop IDs were summed to give the total.

Whereas ridership data for Melbourne and Boston were collected for sites identified using stops IDs that are consistent with GTFS (scheduling) standards, this was not the case for Amsterdam. This made it difficult to extract service level information for each facility, since the GTFS identifiers could not be precisely linked to ridership data. Instead, the service level metric for Amsterdam was defined as the centroid-weighted average service level of transit within the transfer zone.

A dummy variable was used to represent the presence of overlapping transit by mode. A '1' was assigned if stops from a different facility were located in the transfer zone, and '0' otherwise.

3.2.1.2. Neighborhood-level variables. Neighborhood catchments were formed by tracing walkable road corridors from the centroid of each transit facility. The extremities of these corridors were joined to form hulls, or polygons. The shapefile containing road centerlines for Melbourne was cleaned of roads of *Class Code* '1' and '2', corresponding to highways and freeways (DELWP, 2018b). Streets of *fclass* 'motorway' and 'motorway_link' were excluded from the roads shapefile for Amsterdam (GeoFabrik downloads, 2019b). Roads and cycle trails for Boston were stored in separate files (DCR, 2019; MassGIS, 2019a). These were combined, and roads of type (*RDTYPE*) '1' and '2', corresponding to limited access highways and major highways, were excluded before generating the walkable catchments.

The distance individuals are prepared to walk or cycle to transit varies by mode, due to differing speed and reliability characteristics (Wu



National level selection criteria		Netherlands	USA	Australia
	% urbanised	91.0	81.8	89.6
	2016 GDP per capita (US$)	45,700	57,600	49,900
Urban area characteristics		**Amsterdam**	**Boston**	**Melbourne**
	Map projection (EPSG)	28992	26986	28355
Total metropolitan area	**Area (km²)**	6,504	4,849	9,992
	Pop (persons)	2,400,000	3,404,000	4,485,000
	Pop. Density	369	702.1	449.9
Study area (pictured)	**Area (km²)**	208.5	487. 0	449.4
	Pop (persons)	971,900	1,519,000	1,368,000
	Pop. Density	4,662	3,118	3,044
	Transit coverage (grouped 'facilities')			
	Bus	671 (377)	5,629 (2,526)	4,515 (2,251)
	Light rail/tram	319 (168)	73 (73)	1,607 (880)
	Metro/train	37 (35)	58 (52)	109 (108)
	Commuter rail		40	

Fig. 1. - Study area boundary and characteristics. Sources: Amsterdam -Metropolitan Area (metropol regioamsterdam, 2020)/Study area (GA 2016b), Boston - (U.S. Census Bureau, 2017a), Melbourne - (ABS, 2017b).

Table 1
Indicator descriptions and data sources.

Indicator	Description	Source: Amsterdam	Source: Boston	Source: Melbourne
Facility-level variables				
Ridership	Daily average normal weekday boardings	(GVB, 2020)	(MBTA, 2020a, 2020b, 2020c)	(DOT, 2019a, 2019b)[1]
Level of Service	Number of daily services by mode (6 am – 7 pm)[2]	(OV, 2019)	(MBTA, 2018, 2019)	(PTV, 2018a, 2018b)
Transfer-zone variables				
Overlapping transit	Count of overlapping transit stops (by mode)	(OV, 2019)	(MBTA, 2019)	(PTV, 2018a)
Neighborhood (access/egress catchment) level				
Population density	Residents/km^2	(GA, 2016b) [3]	(U.S. Census Bureau, 2017a)	(ABS, 2017b)
Jobs density	Jobs (or workers)/km^2	(GA, 2016b) [3]	(Center for Economic Studies, 2019)	(ABS, 2017f)
Commercial density[4]	Fraction of land use zoned 'commercial'	GA GA (Gemeente Amsterdam) (2017)	(MassGIS, 2019b	(DELWP, 2018a)
Land use diversity	$-\frac{\sum_k [(p_i)(ln_{p_i})]}{ln_k}$ (p = prop. Area occupied by land use i; k = 6 land use types)[5] Formula: Shannon (1948)			
Jobs-housing balance	$1-\frac{\lvert(workers_C - population_C)\rvert}{workers_C + population_C}$ Balance of residents to jobs Formula: Cervero (2002)	(GA, 2016b)	(Center for Economic Studies, 2019; U.S. Census Bureau, 2017a)[1]	(ABS, 2017b; ABS, 2017f)
Pedestrian connectivity	3-or-more-way street intersections/km^2	(GeoFabrik downloads, 2019b)	(DCR, 2019; MassGIS, 2019a)	(DELWP, 2017)
Cycle connectivity	Length of cyclable paths (km) within the catchment	(GeoFabrik downloads, 2019b)	(DCR, 2019; MAPC, 2019)	(VicRoads, 2017)
Destination score	Score out of 7 types of destination present[6] Adapted from (Badland et al., 2017; Boulange et al., 2017)	(GA, 2019)	(MassGIS, 2019b)	(GeoFabrik downloads, 2019a; PSMA Australia Limited, 2018)
Proportion employed[7]		(GA, 2016a)	(U.S. Census Bureau, 2017a, 2018)	(ABS, 2017b; ABS, 2017d)
Mean household size		(GA, 2016b)	(U.S. Census Bureau, 2010)	(ABS, 2017b; ABS, 2017c)
Proportion overseas born		(GA, 2016a)	(U.S. Census Bureau, 2017a)	(ABS, 2017a; ABS, 2017b)
Proportion tertiary educated		(GA, 2016a)	(U.S. Census Bureau, 2017b)	(ABS, 2017e)
Regional level variables				
Distance to CBD	km, Euclidian	*Amsterdam Centraal*	*Park Station*	Center of CBD Grid (Elizabeth x Swanston)

1 – Melbourne train and tram patronage has correction factor applied for non-touch-on rate. Tram touch-ons are assigned to a 'polygon' of tram stops and divided evenly among composite stops.
2 – LOS for Amsterdam is centroid-weighted average of all stops within transfer zone.
3 – Data obtained from the Amsterdam transport model were linearly interpolated for 2018, from 2015 and 2020 data.
4 – Pooled model uses commercial density standardized at city-level.
5 – Land use zones: Civic, commercial, industrial, other, recreation, residential.
6 – Destination types: Community, culture and leisure; Convenience; Early years; Education; Food; Health and social services; Transport.
7 – Pooled model uses proportion employed standardized at city-level.

and Levinson, 2018), as well as by individual and contextual factors across a network (Tao et al., 2020). Therefore, we tested the sensitivity of ridership models to different buffer sizes for each mode. The mix of variables and model fit differed little from the standard catchment buffers specified in Melbourne's planning provisions (DELWP, 2006). Therefore, walking catchments of 400 m for bus, 600 m for tram and light rail, and 800 m for heavy rail, including trains, metro and commuter rail, are used across all three locations. This testing procedure highlighted the unique associations of Boston's commuter rail network. For example, it was the only mode that did not show significant associations with service level. This is consistent with the findings from other studies (Chen and Zegras, 2016). Therefore, commuter rail was not examined in the pooled models.

Neighborhood-level variables, including density and measures of land use diversity, were estimated by calculating the proportional overlap of census geographic units or land use zones/parcels, with the catchment. The geographic unit for which data was collected for each varied in size; with implications for the precision of variables in each city. Most variables were able to be operationalized using consistent input data. However, commercial density and level of employment could not be measured using comparable data. This is addressed under 'Location errors', below.

Sensitivity tests were used to determine the appropriate transformation of population and employment density, which can vary logarithmically with ridership (Voulgaris et al., 2017). The logarithmic transformation of employment density, and linear form of population density were found to provide the best fit with the ridership data.

3.2.1.3. *Regional variable.* The study locations were chosen due to the radial nature of their transit networks which service a dominant central trip generator (or 'Central Business District'). The proximity of any given stop in the network to the CBD is likely to be an indicator of accessibility to jobs and activity. Therefore, distance to the urban downtown was estimated as a measure of regional or network-level accessibility for all study areas.

3.2.2. *Location errors*

Differences exist in the way data is collected in each city. This can affect the comparability of the data. Some studies adopt location constants to account for these impacts (Currie and Delbosc, 2013). A recent study of obesity developed a multi-city built environment dataset which was examined for a pooled sample without location constants. Although some indicators varied among cities by orders of magnitude, these tended to reflect real variation in the built environment patterns in the study sites (Kerr et al., 2013). In this study, we examined the network-level averages and standard deviation of the indicators to gauge the comparability of scores between the study areas.

Three indicators had large discrepancies: commercial density, proportion employed and pedestrian connectivity. The classification of land use types in the Netherlands yielded a substantially smaller fraction of commercial land overall. The definition of 'employed' reported in national statistics also varied, with Australia reporting 'full time equivalent' employment, and USA reporting workforce participation as 'employment'. Therefore, these two indicators were scaled at the city level before being incorporated into the clusters (commercial density) and the pooled regression model (both).

The third variable with large discrepancies was pedestrian connectivity. The average intersection density (the measure of pedestrian connectivity) in Amsterdam was almost six times larger than in Melbourne. On closer examination, this was traced to differences in the street typology in Amsterdam, which was characterized by multi-part crossing with numerous refuges and sidewalks available to pedestrians to stem vehicular traffic and provide safer crossings for pedestrians. As such, this measure was kept in its unstandardized form. As more 'off-the-shelf' tools for extracting network data become available, they could be harnessed in future studies to streamline the network data extraction process (Boeing, 2017; Lovelace, 2021).

3.3. Accounting for endogeneity between transit supply and demand

Ordinary least square regression is a suitable analysis method for relationships that are unidirectional (Wooldridge, 2013). If this assumption is violated, such that the outcome variable also influences one or more of the independent variables, the model suffers 'endogeneity'. Endogeneity is a specification issue in travel behavior modelling because transit service level both impacts, and is impacted by, ridership (Holmgren, 2007; Louviere et al., 2005). Transit demand studies have increasingly adopted two stage least squares regression (2SLS) to address this bias (Diab et al., 2020; Estupiñán and Rodríguez, 2008; Mattson, 2020; Taylor et al., 2009). 2SLS involves (1) defining an equation to estimate a proxy value for the expected level of the endogenous variable; and (2) estimating the outcome using the expected value of the endogenous variable, instead of the original value (Stock, 2001; Tyvimaa and Kamruzzaman, 2019).

Instrument must be relevant and exogenous, and ideally should not already be included in the explanatory equation (Spearing et al., 2012; Stock, 2001). Some transit demand studies use the presence of nearby transit as an instrument (Estupiñán and Rodríguez, 2008). Some use novel measures such as agency operating budget and voting patterns which are hypothesized to affect the quality of transit provision (Diab et al., 2020; Taylor et al., 2009). Most use a measure of catchment density (Diab et al., 2020; Estupiñán and Rodríguez, 2008; Mattson, 2020; Taylor et al., 2009). However, if the population density of a catchment is used as the instrument then it should be excluded from the main model. To avoid dropping important explanatory variables from the main model, we developed spatially 'lagged' measures of transit stops, built environment density and walkability, to predict transit service level. Spatially lagged variables are those which are spatially offset from the observation. They are used in 2SLS models developed in similar fields examining spatial correlations with demand, such as demand for housing (Tyvimaa and Kamruzzaman, 2019). In this case, we tested average measures derived from catchments neighboring (intersecting) each observation, as well as measures estimated for the 200 m 'ring' just beyond the neighborhood catchment boundary for each mode.

We develop models for each mode in each city using the 2SLS approach. The selection of an instrument was guided by the 'relevance' test based on the F-statistic when regressed exclusively on transit supply. Instrument exogeneity was tested using the Hausman test; carried out after the second stage model was developed. The Hausman test checks whether the regressors are correlated with the errors. The null hypothesis is that the errors are uncorrelated. The most appropriate test for endogeneity is a comparison of fixed and random models; however, this is not possible for cross-sectional data. Instead, we use the Wu-Durbin-Hausman test to retrospectively determine whether the instrument was efficient at removing endogeneity (Durbin, 1954; Nakamura and Nakamura, 1981).

For the purpose of testing for endogeneity on a sample-by-sample basis, we jointly instrument for transit service level and run the second stage of the regression using the *ivreg* package in RStudio (Fox et al., 2020). This approach ensures that the errors estimated in the second stage model are correct (Colonescu, 2016). For the samples exhibiting endogeneity, the instrumented values of service level are used in the subsequent, pooled sample. The original values are used for samples that are unaffected by endogeneity.

3.4. Testing and mitigating mode location bias

Bias between groups that are the subject of comparison can threaten the validity of observations made between the groups (Stuart, 2010). We checked whether the location characteristics of transit stops by mode was characterized by such bias. To do this, we computed the standardized mean difference of built environment and sociodemographic variables between modes, using a pooled sample the three networks, segmented by mode. We used a constant catchment size of 800-m for all modes just for the purpose of comparing the neighborhood of transit stops. If the mean difference of a variable exceeds 0.25 standard deviations when compared between two modes, we consider their locations to suffer from imbalance, or mode location bias (Cochran, 1968). Thirteen neighborhood variables were compared; most were imbalanced suggesting systematic bias in the locations of different modes. Ten variables were imbalanced between bus and train and bus and tram. Four variables were imbalanced for train and tram.

Two methods were developed in past research to address this mode location bias. These include (1) sampling stops that are co-located, and (2) stratified sampling based on built environment typologies (clusters) *[citation redacted to facilitate blind review]*. The former approach reduces the sample size to a small number of co-located sites. Competition between the co-located modes also affects results. The stratified sampling approach is more flexible and lends itself to larger sample sizes. By considering all transit facilities, not just co-located facilities, it produces a sample that may be expected to be more representative of the entire set of stops in a network *[citation redacted to facilitate blind review]*.

The aim of sampling using subclassifications is to remove bias by sampling from clusters of "like" observations (with respect to the covariates) (Stuart, 2010). Stratified sampling achieves this by grouping observations into similar built environment clusters and then sampling in equal proportion across modes.

Seven variables, representing distinctive aspects of the built environment were used to form built environment clusters across the three networks. These were: population density, land use diversity, jobs-housing balance, pedestrian connectivity, cycle connectivity, destination score and distance to CBD. Cluster solutions ranging from three to ten centroids were examined. The optimal clustering solution was chosen based on the percentage reduction in within-cluster sum of squared errors (WSS), as well as the distinctiveness and reproducibility of the clusters when examined visually. R's inbuilt k-means clustering function was used to generate clusters, and ggplot2 was used to visualize the clusters against two principal dimensions (RCore team, 2019; Wickham, 2016). A six-cluster solution with good interpretability and distinctive clusters was chosen. The WSS was reduced by 54.6%, compared to 50.3% for the five-cluster solution or 57.7% for a seven-cluster solution. The modes were first interpreted based on the cluster variables. The clusters were validated by checking the theoretical plausibility of the average ridership for each cluster, based on their physical characteristics (Kamruzzaman et al., 2014).

The unbiased sample was formed by selecting an equal number of observations for each mode from each cluster. The sampling rate for each cluster is set by the mode with the least members in that cluster. Metro or train sites were the constraining case for all six clusters. The inbuilt R function for random sampling was used to select observations from the non-constraining cases (RCore team, 2019). The distribution of transit in each of the study areas, and the reduced distribution of transit modes in the sample, is illustrated in Fig. 2.

3.5. Pooled direct demand model estimation

Multivariate linear models were developed for the pooled and stratified samples for all modes. All theoretically relevant variables were checked for multicollinearity using the variance inflation factor (VIF). Those with VIF exceeding five were excluded from the maximally adjusted model. Linear regression proceeded with the remaining variables. Insignificant variables were removed in a stepwise fashion,

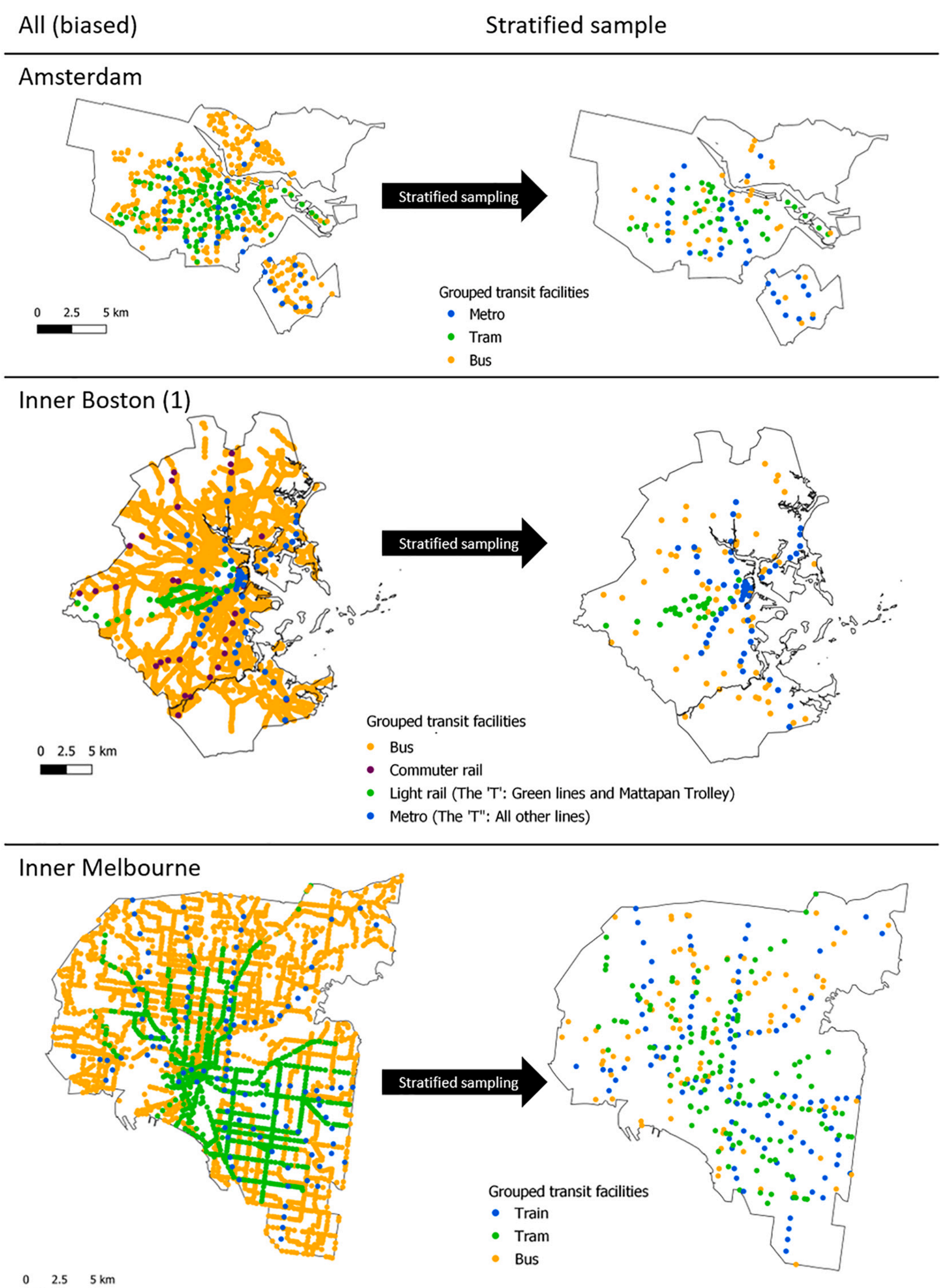


Fig. 2. Biased and stratified samples for study areas.

commencing with the variable showing the least significant effect. The parsimonious model was accepted when the subsequent iteration after a variable was removed showed reduced explanatory power (signified by the R^2 value). In the latter case, the variable was returned to the model. The residual plots of parsimonious models were checked for concordance with the assumptions of linear regression. If the assumptions were not met due to one or two clear outliers, or an individual value exceeded Cook's distance, the outlier(s) were removed, and the estimation process was repeated.

4. Results

4.1. Tests for endogeneity

Table 2 summarizes the endogeneity tests performed for all modes and networks. The optimal instrument for each sample differed, as shown in the table. The biased model results for each city, with and without instrumenting for service level, are included as supplementary Tables 6–8.

The chosen instruments explain relatively little of the variation in the outcome variable (transit supply). Many prior studies of built environment and transit use have used explanatory power as a test of the suitability of the instrument in terms of relevance, typically finding stronger associations between the instruments (e.g. population density and voting patterns) with transit supply than those used in this study (Diab et al., 2020). This is indicated by the R^2 of the OLS model, used to derive the predicted values of service level. Nevertheless, the instrument tests suggest they perform adequately, and in some cases very well, as indicated by the F-statistics greater than 10 in all but one case, and a weak probability of the null hypothesis being true (Colonescu, 2016). The F-statistics ranged from 9.59 (applied to bus service level, Melbourne) to 277 (bus service level, Boston).

When the instrumented values for level of service were used to predict ridership for tram and bus in Melbourne, and bus in Boston, endogeneity was detected. The endogeneity tests suggest that the remaining samples were not affected by endogeneity. Nevertheless, there are many differences between the instrumented (2SLS) and non-instrumented (OLS) models. In many cases, this is caused by multicollinearity in the instrumented model, which introduced the need to remove additional covariates. In the subsequent analysis, the instrumented values for level of service were used in those samples for which endogeneity was detected: bus and tram in Melbourne and bus in Boston. For the remaining samples, the original values of LOS were used.

4.2. Mode location bias mitigation

Six distinctive built environment clusters were formed using k-means clustering. The clusters were first interpreted based on the mean ('centroid') for each of the seven input variables: population density, commercial density scaled for each city, balance, land use mix, destination score, pedestrian connectivity and cycle connectivity. Fig. 3 depicts the distribution of the clusters. The clusters are colored on a spectrum ranging from highest anticipated transit use ('downtown core') to lowest ('balanced suburbia'), based on the built environment characteristics of each. The average ridership of observations in each cluster is shown in the first row of the descriptive table, and membership is broken down by mode and city.

The clusters provide a meaningful typology of station-area built environments because of their distinctiveness and logical association with ridership. However, as Fig. 3 reveals, the distribution of clusters by study area is uneven. Amsterdam is dominated by the 'active mode friendly cluster'. Melbourne is not represented in this cluster. This reflects a systematic difference in the supply of bicycle and pedestrian paths in Amsterdam, compared to Melbourne and Boston. Both Melbourne and Boston exhibit 'downtown core' properties, characterized by extremely high job densities. Boston has the highest representation of 'high-density residential'. Both Melbourne and Boston have a high proportion of sites with low scores, reflecting of the higher average auto mode share in these two cities compared to Amsterdam, which had not sites in the 'suburban residential' cluster.

Stratification also reduced the size of the sample significantly. Metro or train services were the constraining variable in all six clusters. As a result, just 194 of the available 5021 bus and 1109 tram facilities are included in this study. Despite over-representation of certain clusters across study areas, the final sample contained a mix of train, tram and bus from different clusters in each city. Amsterdam is more evenly represented after stratification, constituting 19% of sties, compared to just 9% initially. Sites from Melbourne make up 57% of the sample and sites from Boston make up 24%.

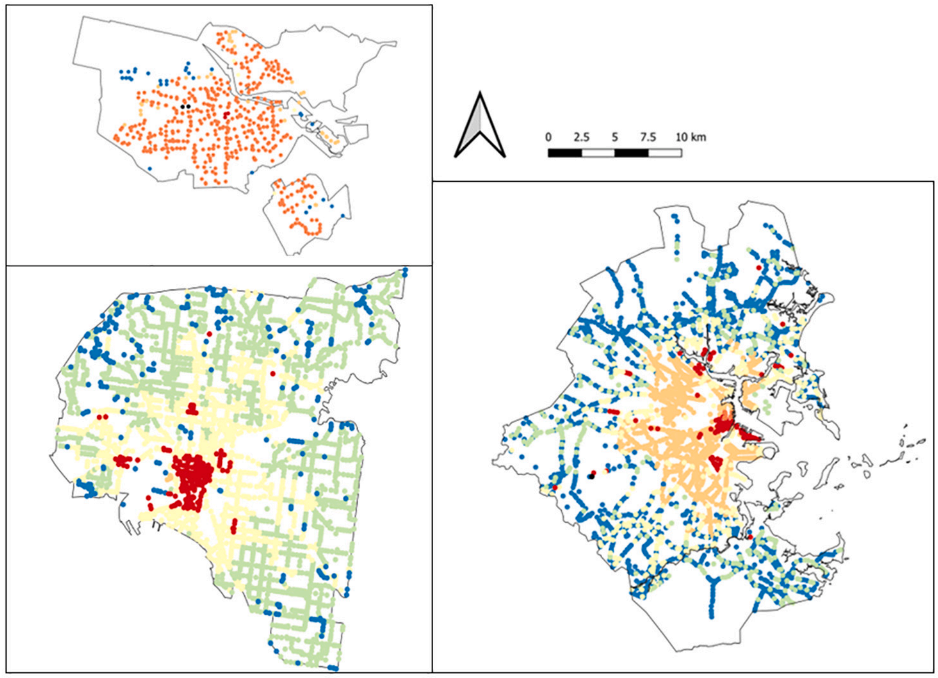
Table 3 summarizes the results of testing for imbalance between each mode pair before ('Biased') and after ('Stratified') mitigating location bias. Stratification succeeded at eliminating bias for most variables, with 85% of pairs improved or balanced after stratification. The low rate of imbalanced between train:tram pairs suggests train and tram are less susceptible to location bias, considering the "inner" urban nature of the study areas. This contrasts to the empirical study for greater metropolitan Melbourne, which found large differences in the distribution of these modes.

4.3. Built environment and transit use models

This study aims to determine whether the predictors of transit use differ by mode. The stratified samples contain observations that are located in similar, or unbiased, built environments, irrespective of the mode. This means the predictors for each mode in the subset of sites in the stratified sample can be robustly compared. However, to account for the possibility that transit supply is adjusted in response to ridership (a bidirectional relationship), service level was instrumented using two stage least squares regressions. Ridership models were developed for each mode in each city, using the expected (instrumented) service level

Table 2
Summary of diagnostic test results for 2SLS for all samples (Significance levels: *: $p < 0.1$, **: $p < 0.05$, *** $p < 0.01$).

Sample		Endog. var.	Instrument	1st step			2nd step			
					Instrument test		Wu-Hausmann endogeneity test			
				R^2	F	Pr > |p|	F	PR > |p|	R^2	VIF
Amsterdam	bus	ln(LOS)	Log of activity density for intersecting catchments	0.065	9.59	0.002***	0.04	0.850	0.406	3.30
	tram	LOS	Commercial density for intersecting catchments	0.200	11.4	<0.001***	1.86	0.174	0.416	4.18
	train	ln(LOS)	Count of buses within transfer zone of stop	0.669	28.1	<0.001***	0.24	0.632	0.774	2.55
Boston	bus	ln(LOS)	Activity density for 200 m ring outside catchment	0.132	277	<0.001***	22.55	<0.001***	0.072	1.37
	LRT	LOS	Ped. connectivity for intersecting catchments	0.499	29.3	<0.001***	<0.001	0.992	0.877	2.79
	metro	LOS	Ped. connectivity for intersecting catchments	0.237	12.9	<0.001***	0.17	0.685	0.518	1.65
Melbourne	bus	ln(LOS)	Log of activity density for 200 m ring outside catchment	0.053	37.5	<0.001***	4.18	0.041**	0.465	3.57
	tram	LOS		0.291	90.5	<0.001***	5.18	0.023**	0.651	3.92
	train	ln(LOS)	Activity density for 200 m ring outside catchment	0.612	42.6	<0.001***	2.69	0.105	0.802	4.18



Cluster	Downtown core	Active mode friendly	High density residential	Localized suburbia	Residential suburbia	Balanced suburbia	
Average patronage	3,236	1,501	521.0	307.3	101.7	76.9	
	Membership (sample)						**Total**
Total	319	505	737	1,518	1,903	1,376	6,361 (582)
Amsterdam (subtotal)	5	497	37	4	0	29	574 (109)
Boston (subtotal)	93	8	696	372	297	1,083	2,559 (141)
Melbourne (subtotal)	221	0	4	1142	1,597	264	3,228 (332)
Bus (subtotal)	168 (15)	318 (33)	653 (20)	997 (68)	1,566 (44)	1,317 (14)	5,021 (194)
Tram (subtotal)	133 (15)	154 (33)	55 (20)	446 (68)	290 (44)	30 (14)	1,109 (194)
Train (subtotal)	**15 (15)**	**33 (33)**	**20 (20)**	**68 (68)**	**44 (44)**	**14 (14)**	**194 (194)**

Fig. 3. Cluster distribution and membership by mode and study area.

Table 3
Rate of imbalance between modes before and after Stratification.

		Tram:Bus	Train:Bus	Train:Tram
	# variables tested	13	13	13
Biased	Balanced	3	3	9
	Imbalanced	10	10	4
Stratified	Balanced	8	13	10
	Imbalanced	5	0	3
	% Improved or balanced	92%	100%	85%

(supplementary Tables 6–8). Endogeneity was detected in three of the city-level models: bus and tram in Melbourne and bus in Boston. For these three subsamples, the instrumented value for level of service was used instead of the actual level of service in the pooled model. Table 4 presents the standardized coefficients for the pooled linear regression models for each mode. All variables which add explanatory power to the models are shown.

The most consistent finding for all modes and at all levels of aggregation is the positive association of ridership to service level. In the combined bus model, the coefficient for pedestrian connectivity was larger than service level after instrumentation. The high explanatory power of the train models and the limited number of other significant predictors in the model, suggests that service level explains more variability in train ridership than all aspects of the built environment.

Increasing commercial density is associated with higher tram or light rail use. This finding is consistent for all study areas for tram, including the combined sample. In contrast, commercial density only shows associations with train use in Boston; and with bus use in Melbourne. This is an intuitive finding: tram 'corridor' intensification is a strategy that has been promoted and supported for its bidirectional benefits for real estate values, appropriate growth and ridership gains (Parsons Brinckerhoff Quade and Douglas Inc. et al., 1996; Woodcock et al., 2013). Prior empirical research verified this (Currie et al., 2011). An empirical study of the land use change that occurred at three light rail lines in Houston, Texas, found that vacant commercial land was more likely to be activated than vacant residential land, following the introduction of the light rail corridor (Lee and Sener, 2017). At the inter-network level, commercial density is also detected as a significant predictor of heavy rail use, although its magnitude is not as large as for tram ridership. This study confirms commercial density is strongly linked to tram use; and is more important for tram use than use of other transit modes.

This study finds positive associations of ridership with population density, but only in certain contexts. For train, population density is the strongest built environment predictor of ridership at the inter-network level. However, at the intra-network level, population density is not a

Table 4
Regression results for unbiased, pooled samples (Significance levels: *: $p < 0.1$, **: $p < 0.05$, *** $p < 0.01$).

	Bus	Tram/light rail	Metro/Heavy rail transit
Outliers removed	6	7	4
Sample size	188	187	190
	Standardized regression coefficient (β)		
Population density		0.156**	0.233***
ln(job density)	−0.091		
Jobs density			
Rel. commercial density[1]		0.278***	0.213***
Jobs-housing balance	−0.087		
Land use diversity	0.086	0.129**	0.059
Pedestrian connectivity	0.484***		−0.416***
Bicycle connectivity	−0.204**	0.122*	
Destination score	0.136**		
Dist. to CBD		*−0.233****	0.060
Rel. prop. employed[1]		−0.197***	
Mean household size		−0.106*	
Prop. foreign born	0.092		
Prop. tertiary educated		−0.066	0.052
Ln(LOS)	0.340***		
LOS		0.321***	0.878***
N bus (overlapping)			0.068*
N tram (overlapping)		−0.199***	
N metro (overlapping)			
N commuter rail (overlapping)			0.114***
Intercept (p)	0.003***	<0.001***	<0.001***
Residual standard error	1.331	0.610	0.5156
df	179	176	180
R^2	0.454	0.668	0.778
Adjusted R^2	0.430	0.649	0.767

'Relative' measures (standardized at city-level to account for measurement differences.

significant predictor of ridership. This suggests that variation in population density within cities does not have a meaningful impact on ridership. However, when comparing cities with more variation in population density, its impact on ridership becomes pronounced. Population density is linked to tram use at the inter-network level, and also within Amsterdam and Boston. Population density is not associated with tram use in Melbourne. This may be due to the comparably lower speeds of trams in high density areas, which research has found is negatively associated with ridership (Currie et al., 2011).

Bus use is linked to population density within Melbourne and Amsterdam, but not at the inter-city level. Bus use was highest overall in Amsterdam by an order of magnitude compared to the other two cities. The effect of population density may be obscured by other variables that show a different pattern of association with bus ridership at the inter-city level: namely pedestrian connectivity and destination score.

In all samples except Amsterdam, train use was positively linked to the number of overlapping bus stops within the transfer zone. Bus often serves as a feeder to train stations. Other studies also finding a significant link between rail use and the presence of bus services (Liu et al., 2016). This suggests bus is most commonly acting expand the rail catchment beyond the walkable access and egress corridor, thereby increasing ridership demand. In contrasts, where bus services overlap with other buses, they are found to be in competition (Amsterdam and Melbourne).

Three built environment variables explain bus use in the pooled sample: pedestrian connectivity (+), cycle connectivity (−) and destination score (+). However, none of these variables is significant for individual networks. This gives another indication that variability at within an urban network is not sufficient to produce a marked effect on ridership. Pedestrian connectivity is six times higher, on average, in Amsterdam than in Melbourne and Boston. Bus ridership is ten times higher in Amsterdam. Therefore, much of this difference is attributable to the gradient in crossing opportunities. Bicycle connectivity is also higher in Amsterdam; however, its negative impact suggests that when considering pedestrian connectivity and bicycle connectivity together, those locations where pedestrian access is superior to bicycle access are associated with higher bus use. In contrast, pedestrian connectivity in negatively associated with train use. In Amsterdam, metro ridership is slightly lower than Boston, which accounts for this effect. The high pedestrianisation of Amsterdam means that distances between destinations are small, which negates some of the demand for train use, compared to a city like Boston where the metro provides a more critical link to key destinations across the city.

Destination score is also important for bus use. It is related to pedestrian connectivity as it captures the provision of daily services within walking distance from the train catchment. The better the walkability of a catchment, the larger the area that can be covered in a given amount of time. This in turn increases the catchment of places, or destinations, accessible to bus users.

Land use diversity represents the evenness of different land use types within a catchment, and is positively associated with tram use across cities. Land use mix can be considered a measure of the mixture of trip origins and destinations. Tram ridership is highest, therefore, where there is a consistent spread of different uses, including commercial, residential, institutional (government) and recreational. Bicycle connectivity is also positively associated with tram use. Trip chaining between bicycle and tram is uncommon (Rijsman et al., 2019); therefore, this finding may suggest that the types of locations that are suited to bicycle routes, such as low-traffic streets, are also suited to trams.

Tram ridership was also lower for stops located further from the CBD. For urban areas like Melbourne, Amsterdam and Boston with strong downtown areas, this finding is expected. The mobility networks of each city are also spatially biased; with areas close to the CBD characterized by a higher density of transit stops. This pattern reflects the assumptions of transit friendly design set out in Chapter 2 and 5 (Aston et al., 2021).

4.3.1. Tests for overfitting of data and the impact of residual endogeneity

Given the relatively small sample sizes and concern for endogeneity, we also ran some tests to check for model overfitting. We split the samples in half using random sampling, and estimated models for each sub-sample with and without service level included among the covariates. We observed the following variables to have relatively stable effects across the models; meaning they showed consistent, significant effects across the four models:

- Bus: pedestrian connectivity (+), service level (+), bicycle connectivity (−)
- Tram: service level (+), commercial density (+), Distance to CBD (−), Proportion employed (−), overlapping tram (−), bicycle connectivity (+)
- Train: Service level (+), pedestrian connectivity (−), population density (+)

Some variables were consistent for two or three of the models:

- Bus: destination score (+)
- Tram: land use diversity (+), Population density (+)
- Train: overlapping bus (+)

In the train sub-samples without service level included in the covariates, jobs density was revealed to have a significant association with ridership. This suggests that train service level is endogenous to jobs density, which means its effect on ridership is masked in our main models. Other variables that had some or no significant associations with ridership may also exert an influence that we failed to detect, whether due to endogeneity or other reasons. Nevertheless, the observations that are most pronounced in the full model presented in Table 4 held true in all subsamples. In the ensuing discussion, we focus on these observations, as the most reliable among our findings.

5. Discussion

5.1. Comparing ridership predictors between modes

When comparing the results obtained at the inter-city level (pooled models, Table 4) to those obtained for modes within each city (supplementary Tables 6–8), it is apparent that many variables show different associations with ridership depending on both the mode and the network. It is clear that both urban context and mode are important factors influencing the relationship between the built environment and transit use. Furthermore, due to limitations in this study's design, the absence of associations for particular variables and modes cannot conclusively be interpreted as the absence of an effect. It means that for the samples and specification strategy we adopted, some relationships were detected for certain modes and not others. Table 5 summarizes these patterns. The table distinguishes attributes that are revealed to affect individual modes on multiple levels:

- Within and between urban networks
- Only at the inter-urban level (between networks)
- Only at the intra-urban level (within networks)

Patterns identified for individual modes at different levels include:

- Ridership is strongly linked to transit supply for all modes
- Commercial density is a strong predictor of tram use.
- Population density is important, but effects vary
- Train use is highest where opportunities exist to transfer with bus
- Local access and pedestrian connectivity are important for bus use
- Land use mix and bicycle connectivity are important for tram

Most of the remaining associations between the built environment and transit are specific to each network and mode. One possible explanation is that differences in the study locations, or differences in the data collected from each, are much more important than the built environment for explaining ridership at the inter-urban level. As a result, the results generated from a combined sample of data sets has limited precision for predicting mode use in individual cities. Urban-level comparison of modes would be useful to understand the specific predictors of modes in each location.

5.2. Residual endogeneity in transit supply and demand

The makeup of explanatory variables differed between the instrumented and non-instrumented models for all samples (supplementary Tables 6–8). Yet endogeneity was only detected in three out of the nine samples. This suggests that the instrumental variable models are inefficient (Durbin, 1954; Nakamura and Nakamura, 1981). Why do these results depart from the conventional logic that transit service level has a bidirectional relationship with demand? While most prior studies that adopt 2SLS to address endogeneity of transit supply and demand report on the relevance of the chosen instrument to transit service level, using the coefficient of determination (Diab et al., 2020; Mattson, 2020; Taylor et al., 2009), it is less clear how the instruments performed according to diagnostic tests and whether endogeneity was actually present.

Another question arising from these results is why results differ between the OLS models and the 2SLS models, if no endogeneity was detected. The answer to this is not clear but there are three factors limiting the strength of the 2SLS models in this study that suggest a different approach is needed to address the conceptual issue of bidirectional transit supply and demand. First, no consistent instrument could be found which was regarded as ‘strong’ across the simples. Instruments were tailored to each mode/network because it was essential that they be relevant to ridership. This creates comparability issues, but also demonstrates further that there are differences in the patterns of associations between attributes of transit modes and their predictors. Second, the instruments explained only a small amount of the variation in service level. As a result, the predicted values for service level are likely to show a different relationship with ridership compared to the actual values. Finally, the most pervasive source of difference between the models is likely to be the collinearity introduced due to choosing spatially-derived instruments, which introduced collinearity issues with other variables in the model. In some cases, predictors which were among the strongest explanatory factors in the OLS model had to be removed from the 2SLS model due to collinearity. While finding a stronger instrument is an obvious remedy to these issues, this is very challenging in practice (Spearing et al., 2012; Tyvimaa and Kamruzzaman, 2019). Subject to data availability, it may be worth testing whether demographic or policy indicators such as transit investment, can overcome the pitfalls of spatial indicators. Such indicators have received relatively less attention as instruments, but do feature in some transit use studies (Diab et al., 2020; Taylor et al., 2009). Nevertheless, this lack of stability highlights the need to investigate more robust ways to account for the bidirectionality of transit supply and demand, which was not able to be resolved by 2SLS in this study.

Table 5
Framework for built environment associations with transit use by mode.

Variable	Level of discernible influence	Mode affected: Bus	Tram	Train
Commercial density	within *and* between networks		+	
Population density	within *and* between networks		+	
Bus transfers	within *and* between networks			+
Population density	between networks			+
Commercial density	between networks			+
Land use mix	between networks		+	
Pedestrian connectivity	between networks	+		
Destination score	between networks	+		
Bicycle connectivity	between networks	−	+	
Distance to CBD	between networks		−	

5.3. Distilling complexity for forecasting applications

This is the first study to combine data aggregated to individual stations, for networks in three countries. Doing so reveals that several distinctive patterns by mode are important at the inter-network level. However, as the city-level models in supplementary Tables 6–8 reveal, most of the associations are specific to network and mode.

These findings add complexity to the already difficult process of integrated modelling and planning. It is not clear how useful these findings are in practice, and whether they would translate to meaningful differences in project appraisals. Research finds that this complexity acts as a key barrier to adopting integrated land use and transport models in practice (Saujot et al., 2016; te Brömmelstroet and Bertolini, 2010). This also introduces additional margin for error (Alonso, 1968; Bonnel et al., 2014).

While the results of this study suggest find different impacts by mode, it would be useful to evaluate the value-add of a mode-specific direct modelling approach, compared to generalized transit modelling. Voulgaris (2019) recommends two tests that could be used for this evaluation: usefulness and accuracy. First, it would be useful to explore whether a different decision would be made concerning the location of a particular mode or the mode chosen for a particular location, based on the ridership that is predicted when using direct models by mode (a test of ‘usefulness’). Second, it is important to gauge the relative accuracy of mode-specific models. If mode-specific predictions provide more tolerable errors, then it may be worth incurring the added complexity of segmenting future forecasts by mode.

6. Conclusion

This study aimed to determine whether the built environment factors affecting transit ridership differ by mode in multiple cities. It combined data for three cities - Amsterdam, Boston and Melbourne - to ensure the result was not contingent on the properties of any one city. It adopted a stratified sampling approach to mitigate bias in the types of locations that modes are typically situated, to facilities robust comparison.

The variables used in this study are measured at four levels: the facility, the transfer zone, the neighborhood catchment, and the region. This extends prior advances in the field that proposed the use of sketch models to capture neighborhood-level effects (Cervero, 2006). The models in this study are pooled for multiple cities and prioritize theoretical validity over predictive accuracy and expediency. While they are not stand-alone forecasting tools, the approach followed to aggregate data could be applied to develop city-level sketch models to assist with predicting the impact of neighborhood interventions on ridership for individual modes. However, careful attention must be paid when developing such models to the conceptual issue of transit supply endogeneity.

This study is the first to collect consistent indicators of neighborhood-level built environment impacts for stations in three networks in different countries. Built environment clusters generated for the three cities were non-uniformly distributed across the three networks. Amsterdam was dominated by a cluster characterized by high quality pedestrian and cycle links, with strong transit ridership. Both Boston and Melbourne had dense ‘downtown core’ clusters with the highest ridership of any mode. However, they were dominated by less permeable, lower- density suburban clusters, characterized by low transit use. These systematic differences in the built environment are expected to produce differences in the underlying demand for transit (Currie et al., 2011; Renne et al., 2016).

Stratified sampling enabled a sample of train, tram and bus locations from across the three cities to be selected so that their locations were balanced across the majority of neighborhood characteristics. This was important, because the built environment characteristics of modes were systematically different according to mode. The use of this stratified sample means the findings are independent of the types of location in which modes are found. In addition, the use of a combined sample for three cities makes the finding robust to many of the differences in the study locations.

The study detected different associations between the built environment and transit use for individual modes. This finding corroborates earlier evidence from Melbourne (Aston et al., 2020b), but this time with three cities in the sample. Local access and pedestrian connectivity are more important for bus use than other modes. Tram is related to commercial density. This finding is consistent for all samples. Land use mix and bicycle connectivity also tend to be associated with higher tram use. Train use is highest where opportunities exist to transfer with bus. Population density is commonly linked to ridership, but its significance varies by mode and network. In contrast, service level is a consistent predictor of ridership across modes. This finding suggests that unlike supply-side characteristics, the built environment determinants of transit use differ by mode.

These findings have important strategic implications for transport and land-use integration. One such application is in sketch planning that seeks to quantify the expected demand increase that might result from modifications to the built environment. The models on which these forecasts are based should enable impacts to be explored on a mode-by-mode basis. Further research is needed to both validate and form behavioral understanding as to why different built environment attributes may impact individual modes, to help shape policy and planning.

6.1. Limitations and further research

This study is inherently limited by its cross-sectional research design, which prevents causal inference from being drawn and which may suffer from endogeneity bias due to the bidirectional relationship of transit supply and demand. We adopted an approach that has gained currency in transit direct demand studies (2SLS) to address the latter concern. However diagnostic tests suggested that this approach did not perform well at addressing endogeneity. This suggests that alternate methods or better instruments are worth exploring to address the persistent conceptual issue of the endogeneity of transit supply and demand. Alternatively, to overcome these limitations of cross-sectional research design, individual-level analysis of time-series data is needed to establish the causal associations between the built environment and mode use.

As with any application of quantitative models, expected results of mode-specific forecasts will be susceptible to external influences and contextual factors. To fully harness the implications of this study's finding, further research should seek to explore the reason why associations differ. One possible explanation, and the impetus for this research, are differences in the ways transit modes interact with their surrounding environment. This is a potential physical or “hard” factor influencing differences by mode. However, there may also be “soft” factors, related to individual perceptions or attitudes, that are also driving the differences observed in this study. Therefore, carefully designed research that links perceptions of the built environment to revealed or stated preferences to travel by modes, may be useful. Mixed-method or interdisciplinary research that compares measured or perceived built environment quality to individual responses or ethnographies may be useful (Scheiner, 2018).

The variables in the model explain 38.9% of variance in bus ridership, compared to 62.9% for tram or light rail, and 76.6% of variance for heavy rail modes. A recent study of bus ridership in US cities Miami, Minneapolis, Portland and Atlanta found an important role for a wider range of demographic variables including age bracket, race, car ownership and as high school educational attainment (as distinct from tertiary educational attainment used in this study) (Berrebi and Watkins, 2020). Levinson and King (2019) posit that factors ranging from in-vehicle ride quality, legibility and payment options; to the intangible aspects of novelty and status ascribed to modes, affect ridership. Much more research is needed across wide subject matter to identify and understand the determinants of bus ridership so that bus transit can provide an attractive and efficient mass transit option for congested cities.

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The data that support this study, as well as supplementary results, are openly available at https://github.com/Laura-k-a/BE-TU_Multi-city_Comparison

Declarations of Competing Interest

None.

Appendix A. Supplementary results

Table 6
Model for transit ridership by mode in Amsterdam including ordinary (OLS) and instrumented models (2SLS) (Significance levels: *: $p < 0.1$, **: $p < 0.05$, *** $p < 0.01$).

Mode	Bus		Tram		Train	
Method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Sample size	370		164		33	
	Standardized coefficient (significance level)					
Pop density	0.176***	0.218***				
ln(pop density)			0.195***	0.123*		0.199**
Job density	−0.063		0.201*		0.615***	0.557***
ln(job density)						
Commercial density	0.054		0.248**	0.168*		0.154*
Jobs-housing balance	−0.088	−0.150***	0.212***	0.147*	0.196*	
Land use diversity	−0.119**					
Pedestrian connectivity			−0.100			
Bicycle connectivity					0.314**	0.280**
Destination score	0.012		−0.104*	−0.116*		
Dist. to CBD	−0.110**		0.190**	0.221***		
Prop. employed		−0.062			−0.211	−0.198
Mean hh size	0.091*	0.076*			0.187	0.167
Prop. foreign born	−0.061				0.091	0.082
Prop. tertiary educated	−0.068		−0.083	0.119		
LOS			0.560***	0.801***		
ln(LOS)	0.568***	0.623*			0.401**	0.333**
N bus (overlapping)			0.099	0.111*		
N tram (overlapping)	−0.193***	−0.193***				
N metro (overlapping)	0.081*		0.089			
Intercept (p)		0.039	<0.001**	0.048		−0.093
Residual standard error	1.67	0.747	0.694	0.697	0.335	0.394
df	357	363	152	156	25	25
R^2	0.439	0.416	0.549	0.441	0.825	0.824
Adjusted R^2	0.421	0.406	0.516	0.416	0.776	0.774
Instrument		1		2		3
Instrument test		9.59***		11.4***		28.1***
Wu-Hausmann test		0.036		1.865		0.24

Instrumental variables used to estimate ‘expected’ service level:

1 Log of activity density of intersecting catchments (spatially lagged activity density)
2 Commercial density of intersecting catchments (spatially lagged commercial density
3 Count of buses within transfer zone of stop

Table 7
Model for transit ridership by mode in Boston including ordinary (OLS) and instrumented models (2SLS) (Significance levels: *: $p < 0.1$, **: $p < 0.05$, *** $p < 0.01$).

Mode	Bus		LRT		Metro	
Method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Sample size	2404		62		49	
	Standardized coefficient (significance level)					
Job density						
ln(job density)						
Pop density			0.154**	0.155***	0.107	0.082
ln(pop density)	0.121***					
Commercial density	0.029	0.029	0.219***		0.115	
Jobs-housing balance	0.019	0.032	−0.146*			
Land use diversity		−0.036		0.091**		
Pedestrian connectivity	0.041**	0.033	0.167***	0.159**		
Bicycle connectivity						
Destination score						
Dist. to CBD						
Prop. employed	0.120		−0.131***			
Mean hh size			−0.106**			
Prop. foreign born	0.025	0.074***				
Prop. tertiary educated	−0.091***				0.243**	0.199**
LOS			0.591***	0.681***	0.458***	0.561***
ln(LOS)	0.312***	0.592***				
N bus (overlapping)	−0.127***		0.083	0.136**	0.206*	0.145
N rapid transit (overlapping)	0.058**					
N commuter rail (overlapping)	0.063***	0.054***			0.274**	0.281**
Intercept (p)	<0.001***	> − 0.001	<0.001***	> − 0.001	<0.001***	0.146**
Residual standard error	1.376	0.963	0.446	0.342	0.484	0.598

(*continued on next page*)

Table 7 (*continued*)

Mode	Bus		LRT		Metro	
Method	OLS	2SLS	OLS	2SLS	OLS	2SLS
df	2392	2396	54	56	42	43
R^2	0.175	0.075	0.916	0.887	0.607	0.598
Adjusted R^2	0.171	0.072	0.905	0.877	0.551	0.518
Instrument		4		5		5
Instrument test		277.4***		29.3***		15.5***
Wu-Hausmann Test		22.55***		<0.001		1.05

Instrumental variables used to estimate ‘expected’ service level:
1. Activity density of 200 m ring outside catchment (spatially lagged activity density)
2. Pedestrian connectivity of intersecting catchments (spatially lagged pedestrian connectivity)

Table 8
Model for transit ridership by mode in Melbourne including ordinary (OLS) and instrumented models (2SLS) (Significance levels: *: $p < 0.1$, **: $p < 0.05$, *** $p < 0.01$).

Mode	Bus		Tram		Train	
Method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Sample size	2242		872		107	
	Standardized coefficient (significance level)					
ln(job density)	0.097**					
Pop density		0.061**	0.058*			
Commercial density	0.043**		0.271***	0.193***	0.093	0.102
Jobs-housing balance	−0.068***	−0.046**	−0.065***	−0.047**	−0.114**	−0.093
Land use diversity	0.045**	0.109***			0.090	0.097
Pedestrian connectivity	−0.021			0.077**		−0.092
Bicycle connectivity			0.085***	0.081***	−0.107*	−0.081
Destination score	0.126***		0.108***	0.115***	0.121**	0.122**
Dist. to CBD	0.048**		−0.127***		0.078	
Prop. employed	−0.027	−0.080***	0.028	0.063**	0.099*	
Mean hh size	0.046***	0.029*				−0.098
Prop. foreign born	0.084***		−0.083**		0.191**	
Prop. tertiary educated	0.105***	0.130***	−0.056**	−0.040		−0.115*
LOS			0.576***	0.768***		
ln(LOS)	0.617***	0.901***			0.643***	0.859***
N bus (overlapping)	−0.067***	−0.035*	0.042**	0.054**	0.100**	0.081*
N tram (overlapping)	0.022	0.051***			0.100*	0.083
N metro (overlapping)	0.127***		0.030	0.027		
N commuter rail (overlapping)						
Intercept (p)	<0.001***	−0.008	<0.001***	0.006***	<0.001	> − 0.001
Residual standard error	1.009	0.731	0.606	0.581	0.415	0.445
df	2226	2231	859	861	95	95
R^2	0.563	0.467	0.680	0.655	0.841	0.823
Adjusted R^2	0.560	0.464	0.676	0.650	0.823	0.802
Instrument		6		6		4
Instrument test		37.5***		90.52***		42.6***
Wu-Hausmann Test		4.18**		5.18**		2.69

Instrumental variables used to estimate ‘expected’ service level:
4. Activity density of 200 m ring outside catchment (spatially lagged activity density)
6. Log of activity density of 200 m ring outside catchment (spatially lagged activity density)

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jtrangeo.2021.103136.

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