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Will bus travellers walk further for a more frequent service? A Stated preference investigation

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Abstract

Network planning of bus services requires addressing the trade off between frequency and coverage. Planning for good coverage of bus services using the rule of thumb that people will walk four hundred meters to access bus based public transport services means sharing the available budget between many services. For the same budget, the alternative approach of concentrating frequency on core corridors implies lower coverage and that some travellers would need to walk further to access bus based services. An understanding of to which extent people are willing to walk to a bus stop with higher frequency would provide empirical information for bus network planning.

The research question addressed by this paper is whether travellers are willing to walk further to a more frequent bus service in the context of Australian cities. A Stated Choice Experiment approach is used to elicit the trade off between walking further to access more frequent bus services. In doing so the paper investigates the potential success of reorientating a coverage approach to network planning, prevalent in many Australian cities to one predicated on concentrating frequency in corridors. The results show travellers in Australian capital cities are willing to walk around 206m to 327m further for a ten-minute reduction in bus headways. These research outcomes provide valuable Australian evidence confirming travellers are prepared to walk further to a more frequent bus service.

1. Introduction

Bus network planning often focuses on service coverage to ensure the network provides a minimum accessibility for users. Typically, service coverage is defined by reference to the rule of thumb that the maximum walk distance for bus users is around 400m.

However, recent investigations into how public transport patronage can be increased has identified an important role for service frequency (for example Paulley et al, 2006; Currie and Wallis, 2008). This lends support to an alternative approach to network planning in which resources are concentrated in corridors to provide higher frequency but, for a given budget, necessarily reduces coverage and leads to a longer walking distance to public transport stops. This latter approach has been associated with practice in Europe leading to significant increases in patronage. But European experience will not necessarily translate to the Australian city context which typically has lower density housing and higher car ownership.

The research question addressed by this paper is whether travellers are willing to walk further to a more frequent bus service in the context of Australian cities. This investigation identifies whether providing better network accessibility or higher service frequency is more effective in increasing bus patronage, and quantifies the trade-off between the walk distance to bus stop and service frequency. The research results inform policy on the most successful distribution of public transport services and the best way or planning for bus services in Australia.

To investigate the travellers' choice between trading between the frequency of bus services and the walking distance to bus stops, a state of the art stated preference (SP) experiment is utilised together with choice modelling methods. Whilst the focus of this research is the trade-off between walk distance and bus frequency, the choice models also take account of other variables known to impact on a traveller's behavioural response to bus travel, including journey time and crowding inside the vehicles. The experiment was conducted in the Australian capital cities of Brisbane, Sydney, Canberra, Melbourne, Adelaide and Perth

In this paper, the international evidence of the association between walk distance and service frequency is first reviewed in Section 2. This review identifies the necessity of posing a hypothetical choice to understand the trade-off between walk distance and frequency within a single city context leading to the design of an SP experiment which is introduced in Section 3. Section 4 presents the choice model specifications and estimation techniques the results and their interpretation. The conclusions and the policy implications of this paper are discussed in Section 5.

2. Literature review

Walk is the primary access mode for trips from home to public transport stops, and the walk distance to a public transport stop has shown to be a significant influence on public transport use in the literature. In Sydney, almost 90 percent of bus trips from home and 50 percent of train trips are accessed by walking (Daniels and Mulley, 2011). Ewing and Cervero (2010) reported a meta-analysis with a public transport demand elasticity of -0.29 for distance to the nearest public transport stop, suggesting that a 10 percent increase in distance to the nearest public transport stop is expected to decrease public transport demand by approximately three percent. Agrawal et al. (2008) found that walk distance is the most important factor influencing rail users' route choice to the local rail station in California and

Oregon. The walk distance to public transport stops is related to the public transport network planning, as service planning usually aims to ensure a certain level of accessibility to public transport by making assumptions about walk distance to access public transport stops as “rule of thumb”. Service planning guidelines for Sydney (NSW Ministry of Transport, 2006) specify that 90 percent of households in each of the 15 metropolitan bus contract regions should be within 400m of a rail line and/or bus route during the day, and within 800m of a rail line and/or bus route at night time. Similarly, Vancouver uses 400m (Greater Vancouver Transport Authority, 2004), Helsinki uses 300m (Helsinki City Transport, 2008), while Perth uses 500m (Public Transport Authority, 2003).

Although the “rule of thumb” is commonly adopted in the government planning guidelines, international evidence has found that people may walk further to public transport for a better quality of service. O’Sullivan and Morrall (1996) found that people walk further to reach an Light Rail Transit (LRT) station than a bus stop in the city of Calgary, Canada. Alshalalfah and Shalaby (2007) identified that on average people walk around 170m to a bus stop with a service headway more than 15min, whereas the average walk distance to a bus stop is increased to over 200m if the service headway is less than 10min with the difference being more significant in suburban areas than in the inner-city. In Brisbane, Australia, the median walk distance to bus stops is 440m, which is significantly shorter than to train stations (890m) as identified by Burke and Brown (2007). El-Geneidy et al. (2010) found that the 85th percentile of walk distance to public transport stops in Montreal is around 550m for buses and 1,212m for trains. They also identified that the walk distance to public transport stops increases when the stop offers higher service frequency. In Sydney, the average walk distance by public transport users in accessing public transport is 573m with the 75th percentile of walk distance being 824m (Daniels and Mulley, 2011).

The literature discussed above suggests that public transport users are willing to walk further to access public transport with better quality of service, where quality of service is substantially weighted by service frequency from the passengers’ perspective (Currie and Wallis, 2008). Given a constraint of budget for delivering public transport service, expanding the network coverage to achieve the requirement of accessibility inevitably limits the service frequency that can be supplied.

Whilst approaches in cities vary, there is a trade off between coverage and frequency. In NSW, for example, Service Planning Guidelines aim to provide some evenness of coverage, by setting a target for the proportion of households that should be within a distance of 400m or 800m of public transport services, depending on the time of day (NSW Ministry of Transport, 2006). The alternative, evolving from European experience (Nelson et al., 2005) has been to exploit the ‘network effect’ which is identified by concentrating resources and providing high frequency services in corridors. Frequency is particularly important because it reduces wait time, which is heavily weighted in the perception (disutility) of total journey time (Abtrantes and Wardman, 2011).

The studies reviewed above have focused on evidence from people’s revealed behaviour to the frequency and walking distance attributes of quality of service (O’Sullivan and Morrall, 1996; Alshalalfah and Shalaby, 2007; Burke and Brown, 2007; Daniels and Mulley, 2011). However, revealed preference studies are limited by the observed actions of individuals and cannot investigate how people might behave under alternative future service level scenarios. Moreover, many of these previous studies have compared the public transport user’s walking distance to two or more different modes of public transport, providing evidence that users will walk further to railed-based public transport providing more certain and often higher service frequency than traditional buses. The literature provides little evidence on the extent to which people will walk further to the same mode of public transport providing a higher service frequency although one such study in the Netherlands (Brons et al., 2009), has investigated this question in relation to rail services. Brons et al. (2009) found rail demand is induced more by reducing travel time or travel distance to rail station than by improving service frequency, but this is at the cost of opening new stations to provide better accessibility. There is a lack of quantitative evidence investigating the trade-off between the walk distance to bus stops and bus frequency which can be more easily integrated into network planning guidelines given the greater flexibility of bus network.

The important question of preferences in relation to walking further to bus stops with higher frequency services remains and cannot be answered with revealed preference data. The SP experiment presented in this paper investigates this trade off in the Australian context with the results providing an evidence base as to whether the alternative approach of concentrating resources in corridors, commonly used in Europe, would be acceptable to Australians.

3. Survey design, sampling and data structure

3.1 The sample

The data used in this paper were collected in November 2012 and January and February 2013 involving respondents residing in six of the seven capital cities of Australia (Brisbane, Sydney, Canberra, Melbourne, Adelaide and Perth). All these cities have significant and mature public transport systems.

Participants were recruited using an online consumer panel (www.pureprofile.com). The final sample consisted of 836 respondents with over 100 from each city as shown in Table 1. The average age of the sample ranged from 40.93 (Melbourne) to 47.70 (Brisbane) and in all cities the sample consisted of more females than males. The majority of respondents in each city reported being in full time work. The socio-demographic characteristics of the final sample are presented in Table 1.

Table 1: Socio-demographic characteristics of the sample

	Sydney	Melbourne	Brisbane	Adelaide	Perth	Canberra
Age (average)	41.33	40.93	47.70	47.59	43.22	42.67
Gender (% female)	57.78%	61.43%	56.28%	59.85%	72.73%	50.83%
F/T	45.81%	57.04%	50.71%	44.81%	36.50%	55.83%
P/T	21.23%	17.78%	22.86%	21.31%	20.44%	17.50%
Retired	14.80%	11.11%	7.86%	16.39%	20.44%	11.67%
Student	4.89%	5.93%	5.71%	7.10%	2.92%	4.17%
Other	13.27%	8.15%	12.86%	10.38%	19.71%	10.83%
Household size	2.72	2.77	2.52	2.47	2.64	2.78
Average number of drivers licences	2.01	2.17	1.89	1.80	2.07	2.01
Number of respondents	135	140	183	137	121	120

3.2 The stated choice experiment

A Stated Choice (SC) experiment was used to collect data to examine the trade off between walking distance to bus stops and the frequency of service at the bus stop. The survey instrument employed was an internet based questionnaire in which the experiment invited respondents to review two hypothetical bus alternatives, or one bus and one train/light rail alternative at a time. The inclusion of non-bus alternatives was used to mask the true focus of the survey from respondents and were removed from the current analysis. The alternatives in each survey task were described by four attributes: distance to bus stop, frequency of service, total journey time, and crowding. The crowding variable was described using pictures showing how many people were seated on each bus, and how many people were standing. Although the overall objective of the study was to determine whether bus users are willing to trade walking distance to the bus stop for frequency of service, the journey time and crowding variables were included partly because these attributes have been shown to be important in the literature and partly because adding in additional attributes prevented respondents guessing the true intention of the survey and introducing bias. Each of these four attributes was then further described by two or more attribute levels, the values as shown in Table 2.

Table 2: Attribute and attribute levels

Distance to stop	4 levels	200m, 400m, 800m, 1000m
Frequency of service	5 levels	Every 5, 10, 15, 20, 30 minutes
Total journey time	5 levels	5, 10, 15, 20, 30 minutes
Crowding	16 levels[1]	(25%,0), (50%,0), (60%,0), (70%,0), (80%,0), (80%,5), (90%,0), (90%,5), (100%,0), (100%,3), (100%,7), (100%,11), (100%,15), (100%,19), (100%,23), (100%,27)

[1] (% of seats occupied, number of people standing)

The response mechanism used a dual response (Rose and Hess, 2009) in which respondents faced both a forced and unforced choice although in this paper, only the unforced choices are modelled and presented. Based on the attribute levels of the alternatives, respondents were asked to select the bus they most preferred, or select a no choice alternative. An example choice set is shown in Figure 1.

The experimental design underlying an SC experiment plays an important role in determining the final results of the study. Given a set of attributes and attribute levels, the problem for the analyst is how best to allocate those levels over the course of the experiment. For this study, an *efficient* design was generated and used. Given a set of attributes and attribute levels, *efficient* designs are constructed such that the levels are allocated to the design in such a way that the elements (or subsets thereof) of the variance-covariance (VC) matrix are expected to be minimised once data is collected.

A single *Bayesian efficient* design was generated for this study and consisted of 48 choice tasks blocked into eight blocks of six questions. In each block, two choice tasks involved a choice consisting of at least one non-bus alternative, which were later excluded from the sample and analysis. The design was optimised for the unforced choice (consistent with the analysis conducted), and assuming an MNL model specification. Constraints were placed on the attribute level combinations throughout the design so that at least one of the two bus alternatives would have a lower walking distance than the other, but could not be better on any of the other attributes (some, but not all attribute levels for the remaining attributes could overlap however). During the survey, respondents were randomly allocated to one of the eight blocks and completed all six choice tasks in that block

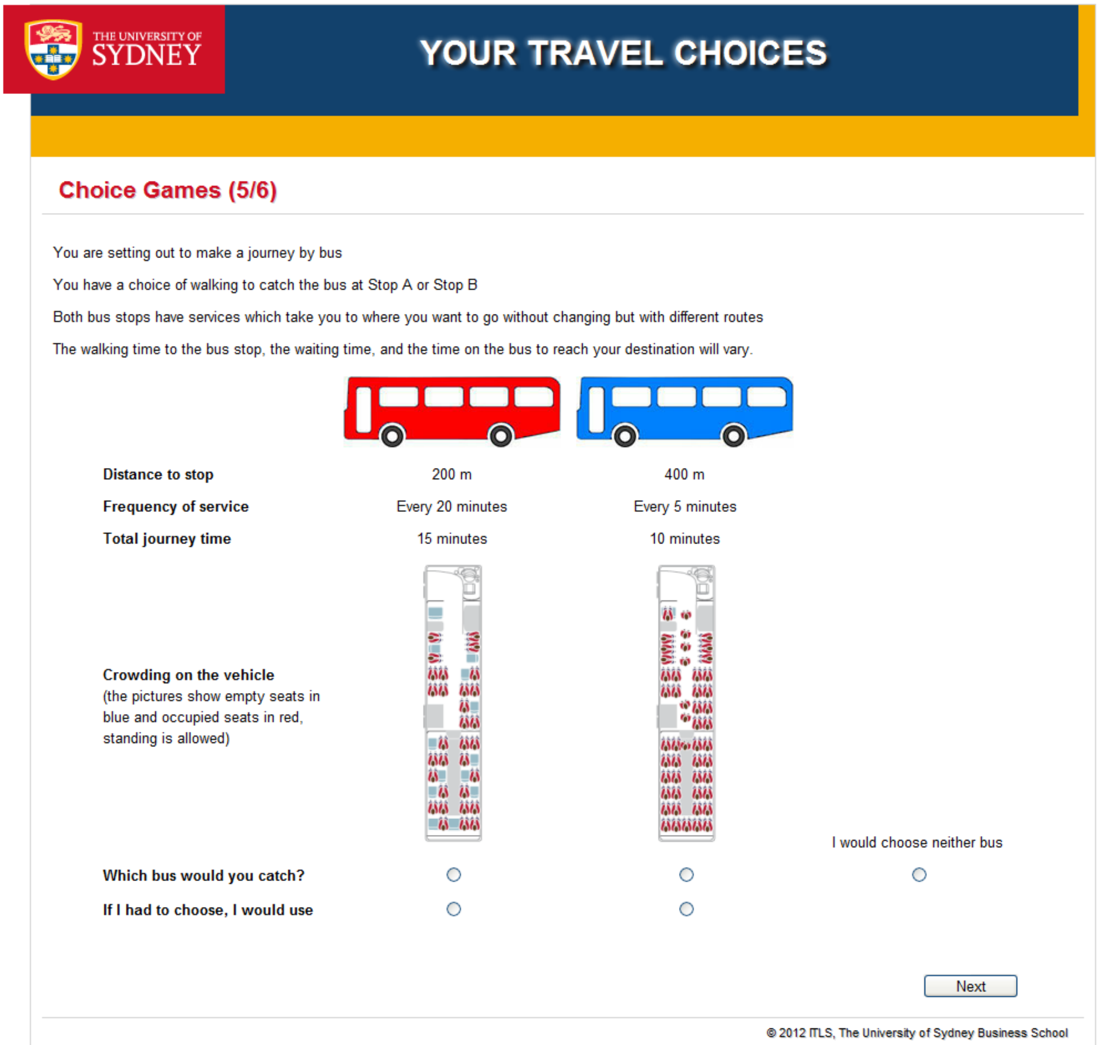

Figure 1: An example of a stated choice screen

As each of the respondents faced six different choice tasks, the final sample of 836 respondents (see Table 1) provided a total of 3,344 choice observations (836×4) after removing the data from the two tasks involving at least one non-bus alternative. Of the 3,344 choice observations, 1282 (38.34%) involved the choice of the bus with the smaller walking distance, 1259 (37.65%) involved the choice of the alternative with a greater walking distance but with at least one of the remaining attribute levels (frequency, crowding or journey time) being better. The no choice alternative was selected 803 (24.01%) of the time.

4. . Model Specification

4.1 Model formulation

The collection of data across a wide number of cities brings about a number of unique modelling challenges.

First, such sampling requires that data for each city be treated as a separate dataset, given possible differences in preference and error that might exist within each sample. If the data are six different datasets then the direct comparison of model, if obtained from independently estimated models is not generally be possible given possible differences in scale (error variance). Likewise, simple comparisons of the log-likelihood functions and other model fit statistics will not possible given the non-nested nature of the datasets. The most common approach to modelling multiple datasets is to use a nested logit (NL) model and using an approach known as the 'Nested Logit trick', the alternatives are grouped into dataset specific nests with any variance and preference differences being simultaneously estimated (Bradley and Daly 1991; Hensher and Bradley, 1993).

Second, SC experiments provide pseudo panel type data. Unlike most data, SC data typically involve the collation of multiple observations from each respondent, albeit during a single session. Failure to properly account for the pseudo panel nature of the data in the econometric modelling will at best affect only the standard errors of the model (and hence tests of parameter statistical significance) and at worst the parameter estimates themselves (see Hess and Rose, 2009). As the NL model fails to account for this aspect of SC data, a panel version of the error component model to approximate the nesting structure of the NL model is used whilst at the same time also accounting for the pseudo panel nature of the data (Hensher et al. 2008). However, this model however assumes heteroskedastic error terms across the subsets of alternatives and this restriction requires that at least one alternative be treated in a separate nest to other alternatives within a dataset for purposes of model identification. In the context of this paper this means that for a given city, a specification with an error component associated with the two hypothetical bus alternatives can be used but assumes the no choice alternative has no associated error component so that the model structure suggests any differences in error variance are between the hypothetical alternatives and the no choice alternative.

Third, some normalisation is required within the model specification for the other treatment conditions when combining datasets. If the no choice alternative is chosen for this normalisation, then the overarching model structure is one in which the error variances for the no choice alternatives for each data sets are constrained to be equal to zero, and empirically different to the error variances of the hypothetical alternatives. As such, the model will account for differences between datasets in terms of the error variances for the hypothetical alternatives whilst constraining the error variances of the no choice alternatives to be the same for all cities.

4.2 Model Estimation

In order to understand the model better, let $U_{nsj|d.}$ denote the utility of alternative *j* obtained by respondent *n* in choice situation *s*, in dataset *d*. =1, 2, ..., 6, where *d* =1 represents the responses associated with Sydney, *d* = 2 with Melbourne, etc (the order of cities is the same as presented in Table 1). To identify potential scale differences, it is necessary to constrain one or more preference parameters to be generic across all data sets. As is common practice, utility is assumed to be described by a linear relationship of observed attribute levels of each alternative, $x_{nsj|d}$ and $z_{nsj|d}$, and their corresponding weights (parameters), β_d and θ. Under this specification, θ represents a vector of parameters which are treated as being generic across each nest within the overall model structure, whilst β_d represent a vector of dataset specific parameters. Alternative specific constants (ASCs), $\alpha_{j|d}$, are estimated for all no choice alternatives and are allowed to vary across the six datasets. In order to account for potential heteroskedastic error between the hypothetical and no choice alternatives, dataset specific error components, $\eta_{n|d}$ are estimated for the two non-no choice alternatives. As is common practice, the error components, $\eta_{n|d}$ are treated as normally distributed random parameters with means of zero. Finally, the unobserved component of each utility, $\varepsilon_{nsj|d}$, is assumed to be independently and identically extreme value type 1 (EV1) distributed. The model specification is shown in Equation (1).

$$U_{nsj|d} = \begin{cases} \exp(\lambda_d)(\beta_d x_{nsj|d} + \theta z_{nsj|d} + \eta_{n|d}) + \varepsilon_{nsj|d}, \forall j \neq \textit{no choice} \\ \exp(\lambda_d)(\alpha_{j|d}) + \varepsilon_{ns,\textit{no choice}|d} \qquad\qquad , j = \textit{no choice} \end{cases} \tag{1}$$

In order to account for potential error variance differences, dataset specific scale parameters λ_d are estimated for data sets *d* = 1 to 5. By taking the exponentials of the scale parameters in model estimation, scale is ensured to be positive and hence consistent with random utility theory. By not estimating a scale parameter for *d* = 6 (Canberra), the remaining scale parameters are estimated relative to this dataset.

Within the model, only the error components are assumed to be randomly distributed. Unlike other models which assume random scale (e.g., the scaled MNL model; see Breffle and Morey, 2000 or Fiebig et al., 2010) scale in this model has fixed parameters with the remaining preference parameters being treated as fixed so as to avoid issues of preference and scale confoundment (Hess and Rose, 2012).

Assuming that the unobserved components of utility are EV1 IID, the probability, $P_{nsj|d}$, that respondent *n* chooses alternative *j* in choice situation *s* is

$$P_{nsj|d} = \int_{-\infty}^{\infty} \frac{\exp\left(\exp(\lambda_d)V_{nsj|d}\right)}{\sum_{i \in J_{ns|d}} \exp\left(\exp(\lambda_d)V_{nsi|d}\right)} \phi\left(\sigma^2_{\eta|d}\right) d\eta_d \tag{2}$$

where $V_{nsj|d}$ is the modelled component of utility consisting of $\alpha_{j|d}$, β_d, θ, $x_{nsj|d}$, $z_{nsj|d}$ and $\eta_{n|d} \sim N\left(0, \sigma^2_{\eta|d}\right)$.

Let $y_{nsj|d}$. equal one if alternative *j* is the chosen alternative in choice situation *s* shown to respondent *n*, and zero otherwise then the joint probability for respondent *n* making a sequence of choices is

$$P^*_{n|d} = \prod_{s=1}^{S} \prod_{j=1}^{J} \left[P_{nsj|d} \right]^{y_{nsj|d}}. \tag{3}$$

Unlike Equation (2) which represents the choice set specific probability, Equation (3) represents the probability that a particular sequence of alternatives will be observed for each respondent *n*.

The parameters $\alpha_{j|d}$, β_d, θ, and λ_d are unknown and require estimation. Unfortunately, the integral in Equation (2) is mathematically intractable, and in order to estimate these parameters simulated maximum likelihood (SML) techniques are used. In this instance, SML utilises random draws to simulate the error components distributions to calculate the expected value of Equation (2) given $\alpha_{j|d}$, β_d, θ, $x_{nsj|d}$, $z_{nsj|d}$ and the distributional parameters of $\eta_{n|d}$. The parameters can then be estimated by maximizing the likelihood function

$$\log E(L) = \sum_{n=1}^{N} \log E\left(P^*_{n|d}\right). \tag{4}$$

4.3 Model results

Table 3 presents results using the model specification discussed in the Section 4.2 estimated on the data outlined in Section 3. Table 3 presents and the error components model assuming a panel specification. The model was estimated using Python Biogeme (Bierlaire, 2003; 2008) using 500 MLHS quasi Monte Carlo draws (Hess et al., 2005). In order to estimate the model, it is necessary to force at least one parameter to be generic across nests for purposes of identification. After extensive testing it was found that the best parameter for this was the journey time parameter and this is the reason for only a single journey parameter being reported in Table 3.

Table 3 shows the scale parameters for all cities are not statistically significantly different from zero. This suggests that the error variances across the samples are not different and hence the data can be naively pooled with the parameter estimates directly compared. In contrast, the error components for all datasets are statistically significantly different from zero supporting the hypothesis expounded within the literature (and discussed above) that there should exist a greater level of error variance for the hypothetical alternatives of a SC experiment as compared to the status quo or no choice alternative. A statistically significant error component also suggests that there is a higher degree of substitution between the alternatives to which the error component belongs, indicating that respondents, irrespective of which city they live in, are more likely to trade between the two hypothetical alternatives than between one of the bus alternatives and the no choice alternative. Although not shown,

Table 3: Model results

	Sydney		Melbourne		Brisbane		Adelaide		Perth		Canberra	
	Par.	(rob. *t*-rat.)	Par.	(rob. *t*-rat.)	Par.	(rob. *t*-rat.)	Par.	(rob. *t*-rat.)	Par.	(rob. *t*-rat.)	Par.	(rob. *t*-rat.)
Error Components Model												
Generic Parameters												
Total journey time	-0.060	(-3.72)	-0.060	(-3.72)	-0.060	(-3.72)	-0.060	(-3.72)	-0.060	(-3.72)	-0.060	(-3.72)
Data Set Specific Parameters												
Constant (ASC)	-8.280	(-2.79)	-11.900	(-2.36)	-8.340	(-2.94)	-10.400	(-2.40)	-9.420	(-2.59)	-6.280	(-6.22)
Distance to stop	-0.003	(-2.33)	-0.003	(-2.06)	-0.003	(-2.43)	-0.003	(-2.03)	-0.002	(-2.25)	-0.002	(-5.25)
Frequency of service	-0.077	(-2.26)	-0.110	(-1.97)	-0.055	(-2.35)	-0.089	(-1.99)	-0.070	(-2.31)	-0.044	(-3.43)
Number of people seated	-1.460	(-1.88)	-1.190	(-1.08)	-2.070	(-2.41)	-2.640	(-1.93)	-3.050	(-2.44)	-0.863	(-1.23)
Number of people standing	-0.062	(-1.96)	-0.082	(-1.74)	-0.071	(-2.17)	-0.114	(-1.85)	-0.051	(-1.73)	-0.058	(-3.19)
Scale parameters												
Scale	-0.074	(-0.18)	-0.560	(-1.24)	-0.056	(-0.15)	-0.336	(-0.74)	-0.083	(-0.19)	0.000	-
exp(scale)	0.929	-	0.571	-	0.946	-	0.715	-	0.920	-	1.000	-
Error components												
Stnd Dev.	3.760	(2.44)	8.080	(2.15)	5.040	(2.62)	6.410	(2.16)	5.420	(2.22)	4.970	(4.97)
Model fits												
LL(0)	-3673.759											
LL(β)	-2514.91											
ρ^2	0.315											
adj. ρ^2	0.279											
Sample statistics												
N	836											
S	3344											

t-tests of statistical differences between the parameter estimates were conducted, with no differences found. This suggests that the heteroskedastic error between the hypothetical and no choice alternatives does not differ across cities.

The ASCs estimated for the no-choice alternatives were found to be negative for each city suggesting that all else being equal, respondents were more likely to select one of the hypothetical alternatives relative to the no-choice alternative. After controlling for scale effects, no differences were found between the city specific ASCs, indicating that the choice shares for the no-choice alternative were similar for each city. Examining the design attributes, the model suggests that respondents prefer shorter distances to bus stops and more frequent service levels in all cities. The influence of the number of people seated however was statistically significant only in Brisbane and Perth, marginally significant in Sydney (*p*-value of 0.063) and Adelaide (*p*-value of 0.056), and not significant for Melbourne (*p*-value of 0.283) and Canberra respondents (*p*-value of 0.222). Nevertheless, despite a pattern of being significant for some cities and not significant for others, *t*-tests of statistical differences suggest no differences exist between the seating parameter (also accounting for parameter covariances). As with the seating parameters, the parameter associated with the number of people standing was found to be statistically significant in some cities but not in others. The number of people standing parameter was found to be statistically significant at the 0.05 level of probability in Sydney, Brisbane and Canberra, and significant at the 0.09 level for Melbourne (*p*-value of 0.085) and Perth (*p*-value of 0.087), and at the 0.07 level for Adelaide (*p*-value of 0.067). Further, as with the *t*-tests of statistical differences for the number of people seated parameters, no differences were found between the parameters for the number of people standing on the bus across the various cities (again after accounting for parameter covariances).

After numerous tests confirmed no differences for this parameter existed across the data sets, prior to estimating the final model reported, the parameter for the total travel time attribute was constrained to be the same across the various datasets, thus allowing for the estimation of dataset scale parameters. In the model, this parameter was found to be statistically significant and negative, suggesting that respondents prefer less travel time to more, consistent with the literature on public transport preferences. Overall, the results of the error component model suggest no differences across the six Australian cities sampled in terms of scale or preference for any of the attributes. The model also suggests that the heteroskedastic error between the hypothetical and no choice alternatives exists, once more consistent with theory and other empirical results.

As the research question is to investigate travellers' preferences in relation to walking further to bus stops with higher frequency services or whether travellers are willing to substitute walking distance to a bus stop for frequency of service, the marginal rates of substitution (MRS) are calculated for each of the city samples. Calculated as the ratio of the two parameters, the MRS describes how much of the distance to the bus stop attribute, x_d, would be required to change given a one unit change in an attribute, x_k, to keep total utility U_{nsj} constant. In other words, how much further a respondent is willing to walk for a decrease in another attribute. The MRS for each of the attributes for each of the six cities are presented in Table 4. Also shown are the confidence intervals and *t*-tests, calculated using the Delta method (Bliemer and Rose, 2012; Daly et al., 2012). Focusing on the MRS values

Table 4: Marginal rates of substitution

	Sydney				Melbourne				Brisbane			
	MRS	Low. 95%	Upp. 95%	(rob. *t*-rat.)	MRS	Low. 95%	Upp. 95%	(rob. *t*-rat.)	MRS	Low. 95%	Upp. 95%	(rob. *t*-rat.)
Total journey time	18.323	6.284	30.362	(2.98)	17.887	3.715	32.058	(2.47)	22.425	8.730	36.121	(3.21)
Frequency of service	23.354	17.002	29.706	(7.21)	32.738	21.754	43.722	(5.84)	20.560	12.498	28.621	(5.00)
No. of people seated	445.122	30.850	859.394	(2.11)	354.167	-238.627	946.960	(1.17)	772.388	284.615	1260.161	(3.10)
No. of people standing	18.963	8.460	29.467	(3.54)	24.375	7.246	41.504	(2.79)	26.604	14.164	39.045	(4.19)
	Adelaide				**Perth**				**Canberra**			
	MRS	Low. 95%	Upp. 95%	(rob. *t*-rat.)	MRS	Low. 95%	Upp. 95%	(rob. *t*-rat.)	MRS	Low. 95%	Upp. 95%	(rob. *t*-rat.)
Total journey time	17.471	3.357	31.584	(2.43)	24.631	7.631	41.632	(2.84)	34.343	11.805	56.881	(2.99)
Frequency of service	25.959	17.471	34.447	(5.99)	28.852	20.571	37.134	(6.83)	25.086	12.135	38.036	(3.80)
No. of people seated	767.442	207.707	1327.177	(2.69)	1250.000	648.881	1851.119	(4.08)	493.143	-296.027	1282.313	(1.22)
No. of people standing	33.140	17.376	48.903	(4.12)	20.943	4.428	37.457	(2.49)	33.200	9.327	57.073	(2.73)

for the frequency of service attribute, the MRS for this attribute is statistically different from zero for all six cities suggesting that respondents are on average willing to walk further for a service with a higher frequency of service. On average, for a more frequent bus service represented by a ten minute decrease in headways, respondents are willing to walk an additional 234 meters in Sydney, 327 meters in Melbourne, 206 meters in Brisbane and 260, 289, and 251 meters in Adelaide, Perth and Canberra respectively. This finding confirms that people are willing to walk further to access a more frequent bus service in Australian capital cities, although an examination of the confidence intervals suggests that the MRS between walking distance and frequency of service are significantly different across the various cities in the sample.

5. Conclusions

The research question addressed by this paper is whether travellers are willing to walk further to a more frequent bus service in the context of Australian cities. Using a SP experiment to investigate travellers' trade-off between walk distance to bus stops and bus service frequency, the study finds that there is no significant difference between behaviour in the different Australian capital city samples and that travellers are prepared to trade walking further to bus stops which have higher frequency. The analysis uses an error components model which controls for the scale difference across cities and heteroscedastic error terms of the subsets of alternatives. Although not central to the research question, the estimation confirms travellers are more likely to choose a bus service which provides shorter journey time as well as higher frequency, and that crowding also has a significant impact on respondents' preference of bus travel – all of which is in line with expectations and international experience.

The major contribution of this paper is the quantification of the trade-off between walk distance and bus frequency as identified by the MRS. The results suggest that the travellers are willing to walk further to a more frequent bus service in all Australian capital cities. Travellers in Australian capital cities are prepared to walk further by between 206m and 327m for a ten-minute reduction in bus headways. The policy implications for network planning are that increasing frequency, even if it means travellers have to walk further to bus stops, will attract higher patronage. If budgets are fixed, this suggests that moving from a policy of coverage to the 'European' approach of concentrating frequency in corridors is likely to be a good policy if increasing public transport patronage is desired. Of course, concentrating frequency in corridors will require some travellers to walk further to access bus based public transport and will require policy-makers to consider and implement complementary policies to ensure accessibility is not reduced for those travellers unable to walk the additional distance. This could take the form of lower frequency access services or more flexible services to provide on-demand access to high frequency corridors.

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