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Modal image: candidate drivers of preference differences for BRT and LRT

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Abstract The physical image of transport systems, as perceived by users and non users, has long been put forward as a powerful influence on the formation of preferences. One setting for this is in the choice between bus rapid transit (BRT) and light rail transit (LRT) where there appears to be a strong preference in favour of LRT in developed countries and the reverse in developing countries. Using data collected in six capital cities in Australia in 2013, in which individuals rated two BRT and two LRT designs presented as physical images, we develop a full rank mixed logit model to identify candidate sources of influence on image preferences. These provide signals to assist in preparing the ground for a segmented profile for policy makers and politicians to understand how to underpin building a rational debate for modal options in our cities.

Keywords Bus rapid transit · Light rail transit · Modal images · Random parameters · Australian cities

Introduction

Our cities are facing increasing congestion with calls for new public transport infrastructure to cope with the trends of greater urbanization in a more sustainable fashion. Whilst developing countries have achieved considerable success with providing new infrastructure using bus rapid transit (BRT), the call in developed countries is more often to add to what has been seen as a light rail renaissance (Hensher 2007). In both cases, there appears to be a lack of 'agnostic modal approaches' to the question of meeting the

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identified needs of the corridor under question. We know that in many cases bus based systems are less capital intensive to put in place but also rail based systems appear to achieve more buy-in from stakeholders—both policymakers and the general public. We also know that in the right environment, everything about a BRT system can be performed by a light rail transit (LRT) system in terms of capacity and service levels and vice versa (see, for example, Hensher and Waters 1994; Hensher 2007).

Much of the debate between different modal options is presented as being emotional with the 'image' of different modes being given central importance in this argument. Motivated by contributing to a constructive debate on the merits of BRT versus LRT (or vice versa), this paper examines the role of the physical image of different modes to identify the role that image *per se* plays in forming preferences.

In investigating the literature base of 'image' we find the concept of 'image' has long been the source of debate, both in the academic and practitioner literature, and this is elaborated in the next section. Although 'image' has been much discussed, we did not find in the transport—or related literature—evidence of a test of the impact of a physical image on the perceptions of individuals, This paper fills this research gap, with the intention of understanding how a physical vehicle 'image' of LRT and BRT influences perceptions, and identifying candidate influences on differences in image preference.

The paper is organized as follows. We begin with an overview of the literature context, critically reviewing the concept of 'image'. This is followed by a section that sets out the empirical inquiry in order to investigate the role of modal image, followed by a brief overview of the econometric model form, a full ranked (1–4) mixed logit model, used to identify sources of influence on image preference. We then present the model parameter estimates, together with an interpretation of the main results, concluding with comments on the value of the evidence in the development of future marketing and promotional plans designed to better inform the population of the merits of the full set of public transport options.

The literature context

Early contributions in the literature concentrated on the 'image' of public transport in relation to its competitor, the car. Driven by a need to understand why the love affair with the car was so strong, and willingness to use public transport as a mode of choice so weak, the concept of the poor 'image' of public transport was identified as the principal cause. TCRP (2000) defined image as "the set of ideas and impressions, both rational and emotional, which major stakeholders form about the organization or industry" (p. 5). This makes clear that image is not a consequence of hard attributes displayed by a good or service itself but can be indirectly gained through association with similar goods or the service industry.

Studies of perceptions between car and public transport identified many strands that are not so relevant when discussing the difference between modes, as in this paper. However, familiarity with public transport was identified as a key driver of support for public transport as was having what were called 'influentials' or supporters in the debate (TCRP 2000). The marketing literature has also been concerned with the car versus public transport debate, with suggestions that employing 'push' policies (through, for example taxation, and implementing road pricing) are forms of 'de-marketing' the car, where 'de-marketing' is the discouragement of demand for a particular good or service (Wright and Egan 2000). Perhaps more importantly, Ellaway et al. (2003) identified differences in the psychosocial benefits between car drivers and public transport users, with car users gaining more psychosocial benefits (e.g., mastery, self-esteem, protection, prestige) than habitual users of public transport, which would need to be factored into any marketing strategy that involves mode-switch.

Whilst the 1990s and early 2000s were a time when many bus operators undertook vehicle branding with, for example, vehicles being branded for particular routes through colour or specific design (e.g., the route on the outside of the vehicle), the success or otherwise of these branding initiatives has only been reviewed in the management and operations literature. The key question in determining whether or not branding was an operational success depended only on whether the costs of branding (including the necessity to hold potentially more vehicles as spares) outweighed any additional patronage, and not whether or not branding was a more successful form of marketing for public transport. The marketing literature makes a further contribution in terms of understanding how cities create their brand image (Hankinson 2001, 2004) and the way in which different stakeholders hold different brand image perceptions (Virgo and de Chernatony 2006; Merrilees et al. 2009), with quantification of the attributes making a difference through the development of a brand association model (Merrilees et al. 2009).

Underlying all these developments is recognition of the way in which perceptions play a central role. In travel research, positive images reinforce the choice of destination and the way in which the destination image is mediated by the tourists' self-image (Sirgy and Su 2000, as cited by Lin et al. 2007). More recently, the linking of psychological concepts to the analysis of the holding of different perceptions has become central in a number of related disciplines in forming an explanation for the choices and perceptions of individuals or stakeholders. In particular, the distinction between cognitive (or mental load) and affective (or emotional) efforts plays a distinct role in understanding car user's perceptions and how this might be used to market public transport (Stradling 2002; Steg 2005; Beirao and Cabral 2007). The role of image in distinguishing mode choice behaviour between trams and buses is extensively discussed in Ohnmacht (2012) for a number of Swiss cities. This study identifies that a more positive image was promoted by habit and experience/positive feelings, with non-users having smaller differences in their ratings of bus and trams in tram-based cities. Moreover, the study found that vehicle characteristics of seating and space was the second most important factor in choosing bus over tram, but this factor was fifth in the list for preferring tram over bus, suggesting that this is an important characteristic which differentiates quality between the two modes.

It is well established that perceptions of public transport attributes explain user satisfaction (Cirillo et al. (2011); dell'Olio et al. (2010, 2011); Hensher (2014); Eboli and Mazzulla (2010, 2008a, b); Marcucci and Gatta 2007). The Federal Transit Administration (FTA 2009) undertook a significant study in assessing the relative importance of different aspects of image and perception of BRT in the USA. How perceptions of quality of public transport influence its use is also a significant literature although there is evidence to suggest that there are differences between the objective measurement of these elements and the perception of these elements by users (Rietveld 2005). A recent review by Redman et al. (2013) in examining which quality aspects of public transport are attractive to car users, distinguishing between tangible or physical attributes (reliability, frequency, speed etc.) or intangible or perceived factors (e.g., comfort, safety, convenience, aesthetics) concludes that there is, as yet, insufficient research into how to enable public transport services to be perceived as having affective and symbolic value in addition to its functional role.

Salient features from this review include the way in which BRT appears to have gained its image indirectly from its association with bus and that this is tainted by the reputation that bus based modes have in mixed traffic (slow, unreliable etc.). The studies of differing perceptions between car and public transport suggest, drawing a parallel from TCRP (2000) on the importance of familiarity, that LRT is better known than BRT in developed countries, with the reverse being true in developing countries, and this may contribute to understanding what appears as a spatial bias. Despite being focused on travel demand, the work of Ohnmacht (2012) points to the importance of identifying the role of the European experience in assessing perceptions of image, especially in relation to tram and bus systems, and the central role that seats and space play in differentiating between the two modes of tram (light rail) and bus. The suggestion of Redman et al. (2013) that public transport, relative to car, would benefit from the greater symbolic role and affective or emotional connotations (as is evidenced in the positive pictures formed by train travel in film and literature), suggests this is an area worth investigating in respect of the debate between LRT and BRT.

As shown above, the literature has paid significant attention to the concept of ‘image’. Interestingly the empirical investigations (both quantitative and qualitative) have deconstructed this concept into relevant attributes, often using pictorial images to illustrate their points in the methodological discussions or symbolically as part of an experiment (for example, Tirachini et al. 2013). There is no study that we are aware of which has reported the use of physical vehicle images as part of the experimental design and which is the focus of this investigation.

The empirical inquiry setting

We engaged a graphic architect to design four images of BRT and LRT, where the differences relate only to the modal image as shown in Fig. 1. The images are of standard bus, modern bus, standard light rail and modern light rail all set in a dedicated lane. The setting in terms of landscape, traffic in other lanes and the layout of the stations/stops are held constant. Data was collected in six capital cities in Australia in 2013 using a consumer panel (discussed below), in which individuals rated the four design images, two of BRT and two of LRT. The modal image screens were shown as a screen at the end of the online survey after 12 stated preference screens in which respondents were shown four statements about BRT and LRT and asked to indicate which statement is the most preferred and which is the least preferred (see Hensher et al. 2014), but before the socioeconomic screen. The images were shown as a fixed picture, exactly as given in Fig. 1. The picture screen was programmed in a way that enabled the picture to be adjusted in line with the screen used by a respondent.

We selected Sydney, Melbourne, Canberra, Adelaide, Brisbane and Perth, each of which has been exposed to real BRT and/or LRT systems as well as, to varying degrees, the debate on proposals to promote LRT or BRT. Melbourne, for example, has one of the biggest LRT systems in the world and Brisbane has one of the most successful BRT systems of the developed world. The differences in preferences between the six cities is of interest as one way of determining if there exist contextual biases in the preferences of populations towards or against a specific public transport investment for reasons that may or may not be linked to the actual investment in BRT and/or LRT in each jurisdiction.

Given growing evidence that a consumer panel can deliver a representative sample if appropriate quota criteria are applied (see Hatton MacDonald et al. 2010; Lindhjem and Navrud 2011), we have drawn on the Pure Profile panel (www.pureprofile.com) for Australia which has many thousands of participants in the chosen study areas. PureProfile

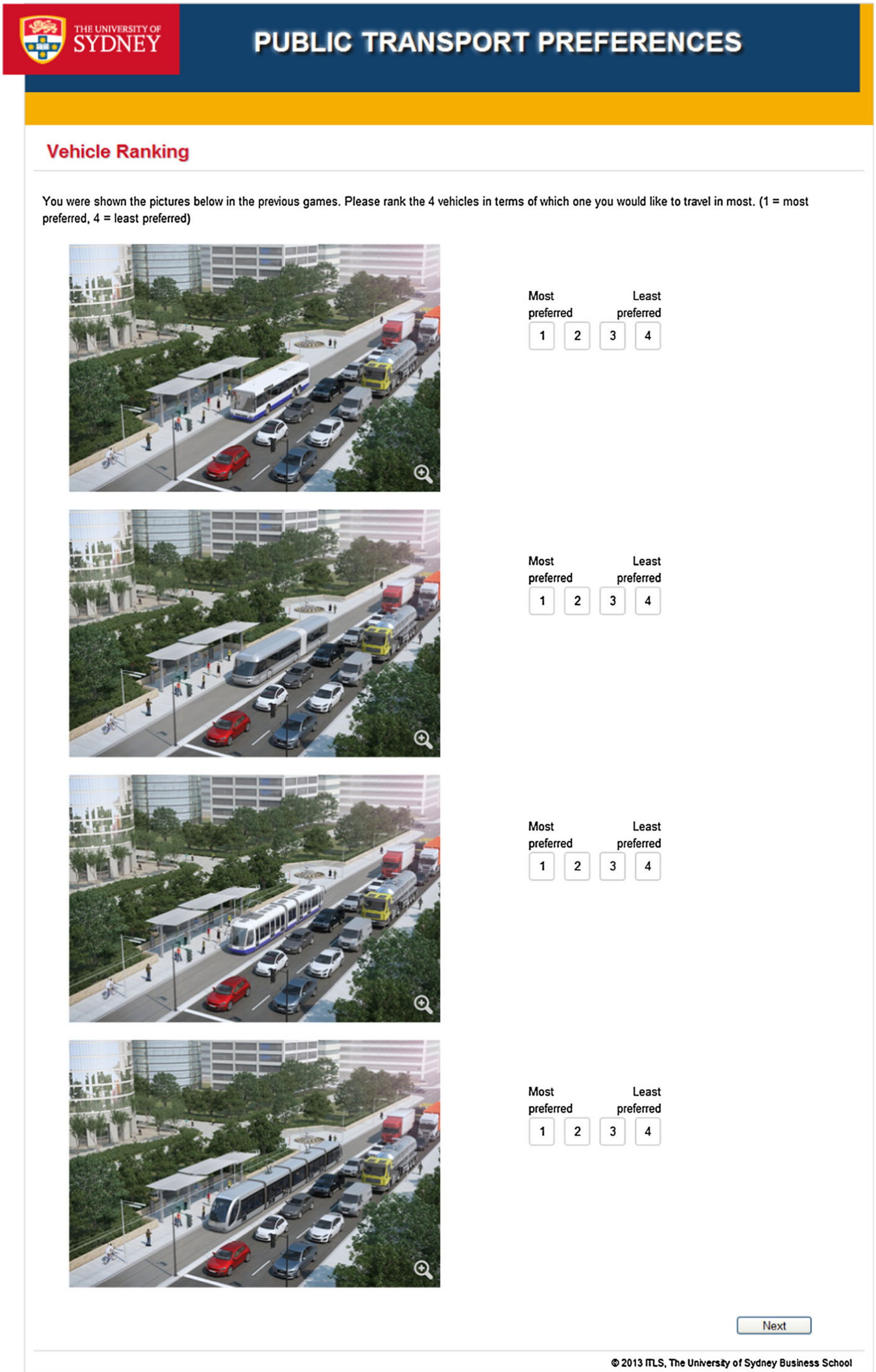

Fig. 1 Survey instrument showing four different images of BRT and LRT vehicles

have over 350,000 individuals in the Australian panel, and will not undertake a project if there is a belief that the target sample is unachievable. Pure Profile paid each respondent $10 for a completed survey.

Questions were asked on recent public transport usage, and socioeconomic descriptors of the respondent and the ranking of the alternative images (as summarised in Table 1). Interviews commenced on 16 May and concluded on 5 June 2013. The final number of interviews are summarised by city in the first row of Table 1.

The socioeconomic profile of the sample across the six cities shows a very similar mix of stakeholders in terms of average age and occupation status. The incidence of males varies from 28.7 percent in Perth to 51.2 percent in Canberra, and average personal income per annum is at the highest level in Canberra ($76,582), dropping to $51,212 per annum in Adelaide, which is in line with the Australian Bureau of Statistics (ABS) 2011 Census. We have a good representation of users and non-users of public transport. The evidence of preferences for each of the four public transport images shows an over-riding preference for modern LRT and this is the focus of our empirical investigation. A Chi square test shows no difference in the shares of the different images between the cities ($p = 0.34$).

Modelling approach

To investigate the candidate sources of influence on individual's preferences for each of the four ranked images in Fig. 1, we have used a discrete choice model of the mixed multinomial logit (MMNL) form. In this section we provide a brief overview of the mixed MMNL model together with the elasticity formulae. Fuller details are given in Train (2009) and Hensher et al. (2005). Assume that a sampled individual q ($q = 1,\ldots,Q$) faces a choice among J modes in each of T choice situations (allowing the possibility of only a single choice situation as in the current application). Individual q is assumed to consider the full set of offered alternatives in choice situation t and to choose the alternative with the highest utility. The utility associated with each alternative j as evaluated by each individual q in choice situation t, is represented in a discrete choice model by a utility expression of the general form in (1).

$$U_{qtj} = \boldsymbol{\beta}_q'\mathbf{x}_{qtj} + \varepsilon_{qtj}. \tag{1}$$

$\mathbf{x}_{qtj}$ is the full vector of explanatory variables, including attributes of the alternatives, characteristics of the individual and descriptors of the decision context in choice situation t. The components $\boldsymbol{\beta}_q$ and ε_{qtj} are not observed by the analyst and are treated as stochastic influences. Individual heterogeneity is introduced into the utility function through $\boldsymbol{\beta}_q$. Thus,

$$\boldsymbol{\beta}_q = \boldsymbol{\beta} + \boldsymbol{\eta}_q, \tag{2}$$

or $\beta_{qk} = \beta_k + \eta_{qk}$ where β_{qk} is the random coefficient associated with $k = 1,\ldots,K$ attributes whose distribution over individuals depends in general on underlying parameters, and $\boldsymbol{\eta}_q$ denotes a vector of K random components in the set of utility functions in addition to the J random elements in $\boldsymbol{\varepsilon}_{qtj}$.

The MMNL class of models assumes a general distribution for β_{qk} and an IID extreme value type 1 distribution for ε_{jtq}. Denote the marginal joint density of $[\beta_{q1},\beta_{q2},\ldots,\beta_{qK}]$ by $f(\boldsymbol{\beta}_q \mid \boldsymbol{\Omega})$ where the elements of $\boldsymbol{\Omega}$ are the underlying structural parameters of the distribution of $\boldsymbol{\beta}_q$, $(\boldsymbol{\beta},\boldsymbol{\Gamma})$. For a given value of $\boldsymbol{\beta}_q$, the *conditional* probability for choice j in choice situation t is multinomial logit, since the remaining error term is IID extreme value:

Table 1 Descriptive overview of total sample and six capital cities (standard deviations in brackets)

	All Cities	Sydney	Melbourne	Canberra	Adelaide	Brisbane	Perth
Sample size	1,372	305	293	78	234	214	248
Used PT in last month (% yes)	55.6	65.5	61.1	37.8	49.1	52.9	49.6
Male (%)	39.8	39.4	42.7	51.2	35.5	38.1	28.7
Annual personal income in $ (standard deviation in $)	58,354 (41,350)	65,267 (45,900)	59,800 (41,800)	76,582 (43,380)	51,212 (36,934)	53,529 (39.2)	54,415 (41.6)
Age in years (standard deviation in years)	44.1 (12.1)	42.8 (13.0)	43.7 (12.8)	44.2 (11.9)	45.3 (13.1)	42.7 (13.3)	43.2 (13.5)
Full time employed (%)	43.1	50.9	49.5	53.9	42.7	44.9	42.3
Part time employed (%)	19.3	22.6	21.1	19.2	21.4	21.9	21.4
Retired (%)	13.1	11.5	10.7	15.3	15.8	14.1	14.9
Student (%)	4.3	4.8	3.6	0.90	3.4	5.7	5.7
Most preferred Image (Fig. 1):							
BRT standard vehicle (%)	9.9	14.5	12.2	10.7	9.9	12.2	5.9
BRT modern vehicle (%)	17.4	19.5	15.4	12.3	18	17.4	16.8
LRT standard vehicle (%)	17.9	16.9	17.9	21.9	16.4	17.1	17.4
LRT modern vehicle (%)	54.8	49.1	54.5	55.1	55.7	53.3	59.9

$$\mathrm{P}_{qtj}(\boldsymbol{\beta}_q|\mathbf{X}_{qtj}) = \exp(\boldsymbol{\beta}_q^{'}\mathbf{x}_{qtj})/\Sigma_j \exp(\boldsymbol{\beta}_q^{'}\mathbf{x}_{qtj}). \tag{3}$$

The *unconditional* choice probability (4) is the expected value of the logit probability over all the possible values of $\boldsymbol{\beta}_q$, that is, it is integrated over these values, weighted by the density of $\boldsymbol{\beta}_q$.

$$P_{qtj}(\mathbf{X}_{qtj}, \boldsymbol{\Omega}) = \int\limits_{\boldsymbol{\beta}_q} P_{qtj}(\boldsymbol{\beta}_q|\mathbf{X}_{qtj}) f(\boldsymbol{\beta}_q|\boldsymbol{\Omega}) d\boldsymbol{\beta}_q. \tag{4}$$

The log likelihood function for estimation of the structural parameters is built up from these unconditional probabilities and can be approximated by simulation. The simulated log likelihood function is:

$$\log \mathrm{L_S} = \sum_{q=1}^{Q} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j}^{J} P_{qtj}^{Y_{qtj}}(\boldsymbol{\beta}_{rq}|\mathbf{X}_{qtj}) f(\boldsymbol{\beta}_q|\boldsymbol{\Omega}), \tag{5}$$

where R is the number of draws in the simulation, and Y_{qtj} is an indicator variable equal to 1 if respondent q was observed to choose alternative j in choice situation t, or 0 otherwise.

The log likelihood is modified when the data consist of a set of ranks. The probability that enters the likelihood is as follows. Suppose there are a total of J ranks provided, and the outcomes are labelled (1), (2),…, (J) where the sequencing indicates the ranking. Thus, alternative (1) is the most preferred, alternative (2) is second, and so on. Assume that there are no ties.[1] Then, the observation of a set of ranks is equivalent to the following compound event:

Alternative (1) is preferred to alternatives (2),…(J),
Alternative (2) is preferred to alternatives (3),…(J),
…
Alternative ($J - 1$) is preferred to alternative (J).

The joint probability is the product of the probabilities of these events. There are $J - 1$ terms in the log likelihood, each of which is similar to the standard log likelihood expression in (5), but each has a different choice set. Combining terms, we have the following contribution of an individual to the log likelihood.

$$Log\, L_q = \sum_{j=1}^{J_q - 1} \log \frac{\exp[\boldsymbol{\beta}^{'} x_{qj}]}{\sum_{z=j}^{J_q} \exp[\boldsymbol{\beta}^{'} x_{qz}]} \tag{6}$$

Note that the number of terms in the denominator is different for each j in the outer summation.

Results

A series of mixed logit models were estimated,[2] and the final model is summarised in Table 3 together with a descriptive profile of the statistically significant variables in Table 2 (defined on the alternative ranked as 1). Table 2 also provides (in italics) the levels

[1] Ties can easily be accommodated.

[2] We investigated latent class models, scaled MNL, and exploded random parameter logit, but none of these model forms were a statistical improvement over MMNL.

Table 2 Descriptive statistics for mixed logit model variables (1,373 observations)—mean and (standard deviation) for respondents who chose a specific image as the most preferred

	Bus		Light rail	
	Standard	Modern	Standard	Modern
Personal income ($000s)	54.2 (40.3)	57.5 (37.7)	55.11 (41.1)	*60.02 (42.6)*
Trips in last month by bus	5.73 (14.6)	7.64 (15.3)	*4.23 (10.62)*	*3.35 (9.02)*
Age of respondent (years)	45.29 (13.8)	*40.7 (12.9)*	*46.6 (14.1)*	42.7 (12.7)
Used public transport in last month (1,0)	0.591	*0.660*	*0.542*	*0.539*
Got a seat all the way on bus on last bus trip (1,0)	0.394	0.370	*0.302*	*0.266*
Sydney resident (1,0)	0.285	0.280	*0.218*	*0.207*
Trips in last month by train	*2.97 (7.45)*	*4.79 (10.8)*	4.57 (10.2)	4.62 (12.7)
Number choosing this image as rank = 1	137	100	179	878

of these significant influences for the alternatives in which the variables were not significant as a way of highlighting their levels for all alternatives.

Many of variables have similar means and standard deviations; however of special note is the big difference in the use of bus in the last month (considerably lower for those preferring light rail), but an interesting similarity of preference for light rail and modern bus for individuals who have used the train in the last month. There is a potential impact of personal income with higher incomes favouring light rail, and some similarity in age for those favouring standard over modern bus and light rail. There is a higher incidence of experience in having a seat all the way in favour of bus which is an interesting finding aligning with the literature review (suggesting a relative dislike of the design of rail-based rolling stock designed to have proportionally more standing). In addition, Sydney residents have a slightly higher preference for bus. This might be as a result of Sydneysiders having only limited exposure to LRT, and a public transport network, although dominated by a heavy rail backbone, having large areas only served by bus. These descriptive statistics are interesting, but to assess the systematic variability of these variables in influencing the full rank preferences, we need to estimate the MMNL model.

The overall goodness of fit on the MMNL model in Table 3 relative to equal shares has a pseudo R^2 of 0.577; however when images shares are accounted for through the constants, the pseudo R^2 relative to these shares drops to 0.117. What this suggests is that the constants are accounting for 20.2 % of the pseudo R^2. The contribution of the explanatory variables is however still significant, with four parameter estimates defined as random parameters, highlighting the existence of statistically significant preference heterogeneity. It is worth noting that although the mean parameter estimate for trips in the last month by bus has a t-value of only -0.85 (and is therefore not statistically significant from zero at the mean), the estimate of the standard deviation parameter is highly significant with a t-value of 3.13. It is not uncommon in random parameter models to obtain a significant variance but a non-significant mean estimate. Hence the mean as the only moment is clearly not an appropriate representation of the role of this variable in influencing preferences for specific modal images.

The evidence suggests that experience through use of public transport (bus and/or train) has a statistically significant influence on the probability of preferring specific images. In particular, as the number of monthly trips by bus increases, the utility and hence

Table 3 Mixed logit model for full rank image preferences, 500 Halton draws, unconstrained normal distributions for random parameters

	Alternative image	Parameter estimate	t-value
Random parameters			
Age of respondent (years)	Bus standard	−0.09331	−5.66
Personal income ($000s)	Bus standard and modern	−0.06598	−8.43
Trips in last month by bus	Bus standard and modern	0.01736	−0.85[a]
Personal income ($000s)	Light rail standard	−0.03914	−7.23
Standard deviation of random parameters			
Age of respondent (years)	Bus standard	0.1228	10.7
Personal income ($000s)	Bus standard and modern	0.1131	10.5
Trips in last month by bus	Bus standard and modern	0.0748	3.13
Personal income ($000s)	Light rail standard	0.0696	15.4
Non-random parameters			
Used public transport in last month (1,0)	Bus standard	0.9756	2.80
Bus modern constant	Bus modern	1.3900	2.39
Got a seat all the way on bus on last bus trip (1,0)	Bus standard and modern	0.4437	1.98
Sydney resident (1,0)	Bus standard and modern	0.5686	2.62
Light rail standard constant	Light rail standard	1.9303	3.23
Age of respondent (years)	Light rail modern	−0.0304	−4.36
Light rail modern constant	Light rail modern	3.7971	5.30
Trips in last month by train	Light rail standard and modern	0.0335	2.12
Diagonal values in cholesky matrix			
Age of respondent (years)	Bus standard	0.0916	7.92
Personal income ($000s)	Bus standard and modern	0.1131	10.5
Trips in last month by bus	Bus standard and modern	0.0735	3.05
Personal income ($000s)	Light rail standard	0.0361	7.71
Covariances of random parameters			
Personal income bus and light rail standard	Bus (standard and modern) and light rail standard	0.0067	5.02
Trips by bus and personal income bus	Bus (standard and modern)	0.0016	0.63[a]
Trips by bus and personal income light rail standard	Bus (standard and modern) and light rail standard	0.0007	0.45[a]
Person age bus standard and personal income bus	Bus standard and bus (standard and modern)	0.0080	5.68
Person age bus standard and personal income light rail standard	Bus standard and light rail standard	0.0028	3.38
Person age bus standard and trips by bus	Bus standard and bus (standard and modern)	0.0022	1.16[a]
Sample			
Number of observations	1372		
Goodness of fit			
Log likelihood at zero	−7122.90		
Log-likelihood with constants	−3415.28		
Log likelihood at convergence	−3014.26		

Table 3 continued

	Alternative image	Parameter estimate	t-value
Pseudo R^2 relative to equal shares	0.577		
Pseudo R^2 relative to sample shares	0.117		

[a] Indicates parameter value not significantly different from zero at the 5 % level of significance

probability of preferring the bus images increases. The bus use parameter is a random parameter, suggesting significant preference heterogeneity; in contrast the monthly use of trains was found to be significant as a fixed parameter (i.e., no statistically significant standard deviation parameter), suggesting that the probability of preferring the light rail images increases as the experience in using trains increases. This is an important finding, which aligns with the evidence cited in the literature review of the image effect being mediated by experience, and recognises the important role that exposure to specific modes through usage conditions preference for specific modal images.

Personal income and age were the only statistically significant socioeconomic influences on preferences for each image.[3] Specifically, as personal income increases, on average the probability of preferring the bus modal image decreases, as it does for light rail standard, all relative to the preference for the light rail modern image; however the probability decreases at a faster rate for a unit increase in personal income for bus compared to light rail standard. Since personal income is a random parameter for both bus and light rail standard, the full extent of the impact of changes in personal income will vary across the sample of respondents.

To be able to assess the extent of the change, we need to identify the full distribution and impose confidence intervals on the distribution of estimates. We do this below (see Figs. 2, 3, 4 and 5), but before we can present these distribution we have to comment on the role of the covariances of the random parameters, which also play a role in defining the parameter estimate expressions associated with each random parameter. The standard deviation parameter is equal to: $\beta_{\text{diagonal element}} \times f(x_0) + \beta_{\text{off-diagonal element 1}} \times f(x_1) + \ldots + \beta_{\text{off-diagonal element k}} \times f(x_{k\cdot})$, where $f(x_k)$ is a location parameter used to locate individual q on some distribution for each element of the matrix. The location parameter, $f(x_k)$, may take on any distribution, however, it is most common to use the normal distribution. To illustrate this, we present the full expression for personal income for the bus image (linked to both standard and modern bus) and for the light rail standard image.[4] The expressions are (see Hensher et al. 2005 for more details on the decomposition) where marginal utility (MU_i) is the change in total utility resulting from a one unit change in the attribute of interest, holding all other effects unchanged:

[3] The other data available was whether full time, part time employed, student, retired, hours worked per week, gender, number of adults and number of children in household.

[4] The Cholesky decomposition matrix is a lower triangular matrix (meaning the upper off-diagonal elements of the matrix are all zero). When we have more than one random parameter and we permit correlated random parameters then the standard deviations are no longer independent. To assess this we have to decompose the standard deviation parameters into their attribute-specific and attribute-interaction standard deviations. Cholesky decomposition is the method used to do this. The mixed logit model is extended to accommodate this case by allowing the set of random parameters to have an unrestricted covariance matrix. The nonzero off-diagonal element of this matrix carries the cross-parameter correlations.

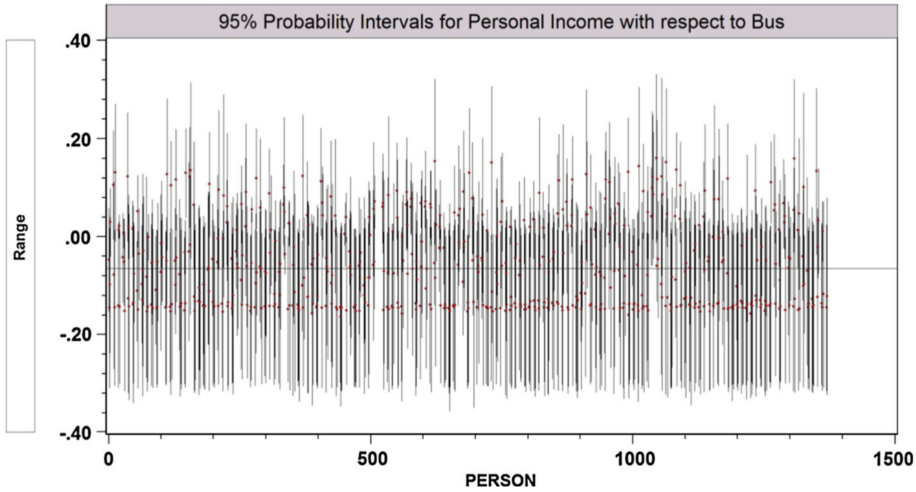

Fig. 2 Confidence intervals for full random parameter expression personal income for bus

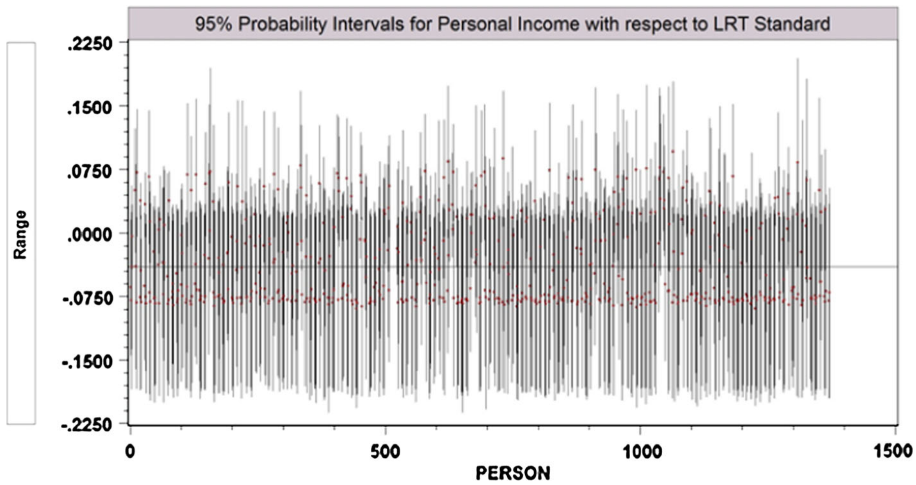

Fig. 3 Confidence intervals for full random parameter expression personal income for light rail standard

$$MU_{bus} = -0.06598 + 0.1131 \times N;\ N \sim (0, 1)$$
$$MU_{LRS} = -0.03914 + (0.0067 + 0.0361) \times N$$

These expressions result in a distribution of the MU that is likely to move between the positive and negative domains as shown in Figs. 2, 3, 4 and 5, although we note the predominance of negative estimates in Figs. 2, 3 and 5 and positive estimates in Fig. 4.

The remaining explanatory variables are age of respondent for light rail (standard and modern), getting a seat all the way on the last bus trip (bus standard and modern), Sydney resident (bus standard and modern), and a dummy variable taking the value 1 if a respondent used public transport in the last month. We find that Sydney residents are more

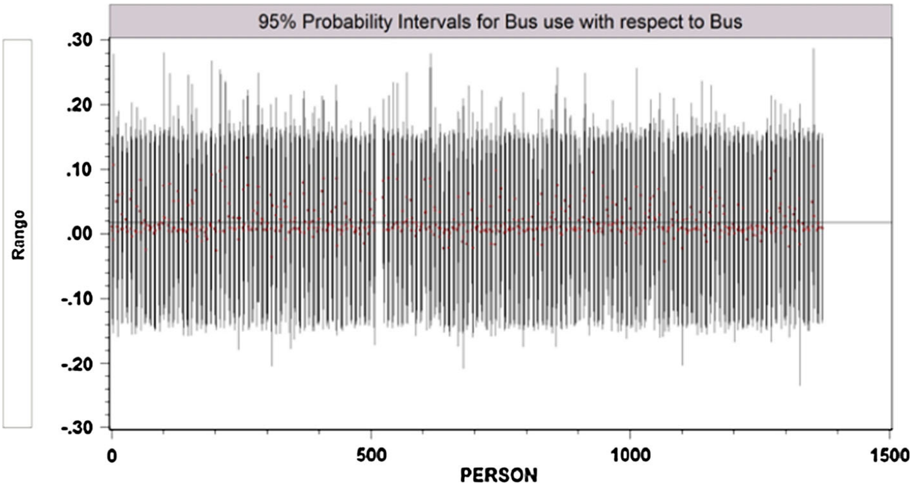

Fig. 4 Confidence intervals for full random parameter expression bus use for bus

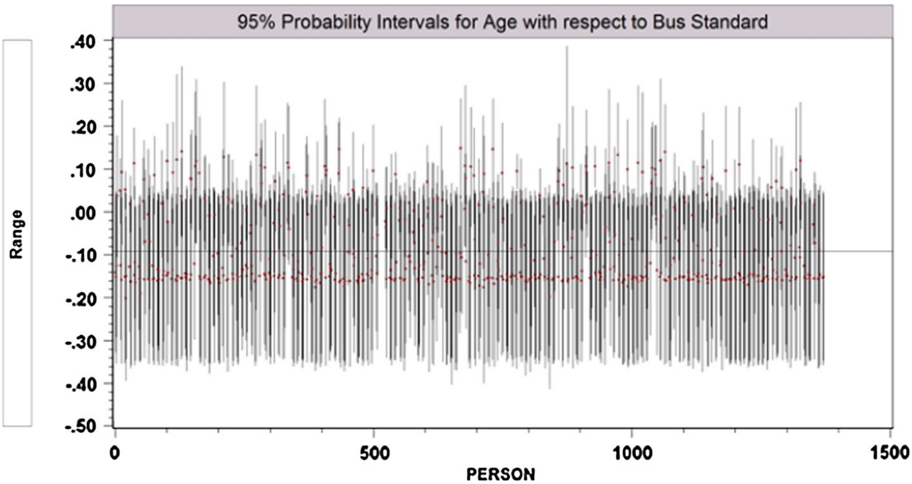

Fig. 5 Confidence intervals for full random parameter expression for age for bus standard

supportive of bus, both standard and modern, compared to the other capital cities, that as an individual ages the preference for light rail modern decreases, getting a seat all the way on a bus in the last month increases the preference for bus (in line with the evidence in Ohnmacht 2012); individuals who have used public transport in the last month in contrast to those who have not, tend to have an increased preference for bus standard. These findings are encouraging for bus and point towards possible promotional segments where greater information on bus based systems is required.

We now examine in more detail the distribution of the four random parameters across individuals. We have for each individual, an estimate of the mean of the conditional distribution of parameters from which their specific vector is drawn. We also have an estimate of the standard deviation of this conditional distribution. As a general result, an interval in a distribution for a continuous random variable defined by the mean plus and minus two standard deviations will encompass 95 % or more of the mass of the distribution. This enables us to form a confidence interval for β_q itself, conditioned on all the information known about the individual. For this level of confidence, the interval $E[\beta_{qk}|$all information on individual $q] + 2 \times$ SD[$\beta qk|$all information on individual q recognising the presence of covariance of random parameters] will contain the actual draw for individual q. The centipede plot feature of PLOT in Nlogit5 allows us to plot the distributions with confidence intervals, for each of the random parameters as shown in Figs. 2, 3, 4 and 5.

Using Fig. 2 to interpret the graphs, each vertical 'leg' of the centipede plot shows the conditional confidence interval for $\beta pincBus$ for that person. This is the marginal utility for income associated with bus (standard and modern) and uses information on the mean (i.e., −0.06598), the standard deviation (i.e., 0.1131), the covariances of random parameters (i.e., 0.0067, 0.0016, 0.0080). The dot is the midpoint of the interval, which is the point estimate. The centre horizontal bar in the figure shows the mean of the conditional means, which estimates the population mean. This was reported in Table 3 as −0.06598. The upper and lower horizontal bars show the overall mean plus and minus twice the estimated population standard deviation—given in Table 3 as 0.1131. The distributions are all well within the 95 percent confidence interval.

Although the majority of the mean estimates are in the same signed range (i.e., negative in Fig. 2), some are also positive (as high as 0.175) with an unconditional population range of variation estimated to be about −0.35 to 0.30. Thus across the full distribution, increasing personal income will, in the majority of cases, reduce the probability of selecting the bus images as the preferred alternative(s), but some individuals would tend to have a higher probability of selecting the bus image.

In assessing the overall role of each statistically significant influence on preferences for each image, the message emanating from the findings points to the importance of exposure and experience in using public transport as conditioning preferences for bus and light rail options. This experience is reinforced in part by one very specific attribute of service, namely having a seat for the trip by a specific mode in recent use of public transport. In addition, we see an income influence which generally favours LRT as income increases, but especially the modern specification as well as an age influence increasing the preference for bus modern and light rail standard as age increases. This finding on age is interesting, with the growing preference away from the two 'extreme' options of bus standard and light rail modern; however it is offset to some extent by a preference for light rail modern as income increases, which is furthermore modified back towards bus where there has been experience in using public transport (be in bus and/or train). Finally we note that Sydney residents (relative to the other five cities) tend to have a strong relative preference for bus; although we cannot definitely explain the reasoning, the recent press on the high costs of rail and the recent success in improving the frequency and network coverage of bus services may have a role.

Discussion and conclusions

This paper has used specially designed pictures of public transport modes, against a common background, to investigate the role of physical image in defining preferences for public transport. This has allowed the concept of image to be examined without deconstruction into a set of attributes for respondents to consider. This focus is especially pertinent when establishing the perceptions of specific modes that appear to be a driver of potential prejudices towards or away from a given modal technology.

Using a mixed logit model to identify the preferences for the full rank of four modal images, the findings suggest considerable support for many of the ideas identified in the literature. It would appear that ‘bus’ has a relatively bad image, and that BRT suffers from its indirect association with bus,[5] with a very high preference for non-bus images. This also supports the broader literature (e.g., Merrilees et al. 2009) on the symbolic and affective impact of images on respondent’s choices.

Surprisingly, we found that there is no strong evidence to support the view where BRT is more widespread than LRT (as in Brisbane and Adelaide), independent of real experience in using the available modes, that this is likely to be a strong factor supporting BRT. BRT’s negative image, due to the proximity of ‘Bus’ and BRT, can in part be explained by the representativeness heuristic of Tversky and Kahneman (1974). It is also in line with the results of Barlach et al. (2007) who found a negative image of bus relative to rail in an intercity corridor in Israel, despite similar travel times; and also Innocenti et al. (2013) who found a strong car image causing myopic mode choices in the laboratory, even when an LRT alternative had a better level of service and when respondents receive immediate feedback on the results of their choices through experience.

A key finding of our study, however, is that the image effect is mediated by previous usage experience of specific modes. If a positive experience is attributed a priori to an alternative, the evidence suggests that the image is less dominant in preference revelation (implying that the service levels are a defining influence). The proximity to experience with close modes, as in LRT and train (and bus and BRT) is also an important finding. The challenge, where there is evidence of the role of a positive (i.e., real) experience (for bus and BRT) as a mediating factor on image, is to pick this message up and reinforce it.

Income, a variable not given much attention in the image literature, also plays a role. Increases in personal income are associated with an increasing preference, relative to BRT (standard and modern), for the LRT modern and standard images even though in the latter case there is a decreasing preference for the light rail standard image.

Apart from investigating the role of image in forming preferences, the results of this investigation offers understanding to policymakers (and politicians) of the role of image in the community’s view of different modal options. Specifically, this research shows that it is important to take account of image in the promotion of different modal options and that information to inform might be best undertaken by segmenting the market by experience, income, and age as well as the physical attributes of the vehicles. In general, the role of experience and learning on travel choices has been long identified as an ongoing gap in the transportation literature, including in particular the travel demand modelling field. The results reinforce the existence of this gap and show the necessity for more research.

In terms of specific directions for ongoing research, a mixed methods approach might be value adding. The addition of open ended questions, delving more deeply into the reasons for the preference for a particular image could be addressed not only quantitatively, as in this paper, but in association with qualitative tools (e.g., semantic text analysis) where the issues can be further explored in interviews or focus groups. Alternatively, a focus group approach, prior to a survey could lead to the design of an improved survey strategy including the open ended questions. This mixed approach would offer policy makers not only the fact that image is important, that image is mediated by experience and that

[5] In various seminars, Hensher has suggested a name change to ‘Dedicated Corridor Rapid Transit’ (DCRT) in order to emphasise the key features of the modal service, avoiding the use of the word ‘bus’.

preferences are clearly different in different community segments but also why these differences occur.

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