Preference heterogeneity in mode choice based on a nationwide survey with a focus on urban rail

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Abstract The provision of efficient and effective urban public transport and transport policy requires a deep understanding of the factors influencing urban travellers' choice of travel mode. The majority of existing literature reports on the results from single cities. This study presents the results of a nationwide travel survey implemented to examine multiple modes of urban passenger transport across five mainland state capitals in Australia, with a focus of urban rail. The study aims to explore differences in mode choices among surveyed travellers sampled from the five cities by accounting for two types of factors: service quality and features of public transport, and socio demographic characteristics. A stated preference approach is adopted to elicit people's valuation of specified mode-choice related factors and their willingness to pay. In particular, the availabilities of wireless and laptop stations – two factors rarely examined in the literature, were also considered in the SP survey. The survey data were analysed using mixed logit models. To test for preference heterogeneity, socio-demographic factors were interacted with random parameters, and their influences on marginal utilities simulated. The analysis reveals that intercity differences, user group status, gender, income, and trip purposes partially explain observed preference heterogeneity.

Keywords: rail transit; mode choice; stated preference; mixed logit; Wi-Fi; laptop station

1. Introduction

Identifying factors and their relative importance for choosing rail transit among urban travellers is a pre-requisite for accurate forecasting of urban rail patronage and for the development of effective urban rail policy. Although there is commonly accepted guidance on forecasting rail patronage in practice (e.g., Passenger Demand Forecasting Handbook (PDFC, 2013)), our collective understanding on many factors' influence on public transit demand is inconsistent (see the next section). In addition, potential service factors such as on-board wireless access and laptop stations are rarely discussed in the literature. Moreover, the majority of the literature reports on mode choice heterogeneity within specific cities. In contrast, this paper presents the results of a unique Australia-wide study focused on identifying and quantifying the effects of service quality and demographic factors that influence urban rail patronage. This study was part of a research project funded by the Cooperative Research Centre for Rail Innovation and overseen by an advisory panel consisting of Australian rail operators and government policy advisors (Zheng et al., 2013).

In the Australian urban rail context, recent times have seen urban rail operators confronted with unexpected increases and changing patterns of urban rail patronage. These changes have placed considerable stresses on capacities and service levels in some areas, while resulting in excess capacity in others. These stresses have presented new challenges to rail managers and have resulted in negative community feedback to state governments. Existing travel models and forecasting approaches have failed to adequately predict or explain these changes in rail patronage—for many reasons including omission of potentially important service factors in addition to well-known four step modelling technical limitations. Hence, this project was supported by rail operators as they sought to improve capabilities in understanding and forecasting urban rail trip making behaviour, to focus on urban rail

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and service quality factors, and to develop guidelines for the development of better forecasting and analytical models (Zheng et al., 2013).

The primary objective of this paper was to quantitatively understand how service quality and demographic factors in particular influence urban rail patronage across five Australian capital cities. Specifically, this paper i) makes use of a nationwide comprehensive dataset for mode choices, including many important factors that may influence traveller's mode choices ii) simultaneously tests several random parameter specifications to better explain choice heterogeneity and intercity differences in the SP data; and iii) as one of the first studies, investigates two emerging features' impact on train usage: free Wi-Fi, and laptop stations. Note that some studies in the literature investigated providing Internet access on train and its impact on mode choice. For example, Zhang et al. (2005) focused on paid Internet access on train for business travellers. Similarly, Banerjee and Kanafani (2008) investigated Internet connection's impact on the efficiency of working on train, and studied business travellers' willingness to pay for Internet access. Obviously, these two studies are distinctively different from our study because our study focuses on free Wi-Fi access for all train passengers.

Towards this end, a large-scale, online panel survey was completed by both rail and non-rail users between April and May of 2013 in five Australian state capitals; Sydney, Melbourne, Brisbane, Perth, and Adelaide. This traveller survey focused on urban travel mode choice, including questions on people's current travel behaviours and attitudes, socio-demographics, and a stated preference experiment offering respondents choices among travel modes including car, bus, and train. The stated choice experiment was designed using experimental combinations of levels of service attributes including travel time, fare, fuel cost, parking cost, on-board crowding, and accessibility. To interpret and understand the data collected from these surveys, a set of stochastic mixed logit discrete choice models was carefully estimated.

Methodological development was not the key objective of this paper. Rather, the use of state-of-the-practice random parameters multinomial logit models (mixed logit) using a host of previously untested service quality variables combined with mode choice heterogeneity examined across five Australian cities constitutes the uniqueness of this contribution. In particularly, to better understand possible unobserved heterogeneity, a host of random parameters specifications were tested, including random service quality and demographic parameters. The testing of models with many random parameters (i.e. complex dimensions of unobserved heterogeneity) has rarely been reported in the literature, mainly due to computational problems caused by the high complexity of the random parameter specifications combined with relatively low sample sizes. The relatively large sample size (i.e., over 7000 respondents with more than 42,000 stated choices) of this study enabled to the specification of several random parameters without running into computational difficulty.

The remainder of this paper first briefly introduces the context of urban rail in Australia; then reviews the literature on factors that were previously found to impact urban travel mode choice and (rail) transit ridership. Next, the survey plan, survey instrument development (focusing on the stated choice experiment), and survey administration results are described. A section describing the choice modelling results and interpretations are then presented, followed by some concluding remarks and discussion.

2. Background

Rail is a major public transport mode in many big cities. For example, rail has the largest share of passenger kilometre in the three most populous Australian cities, i.e., Sydney, Melbourne, and Brisbane (BITRE, 2009). Since 2000, several major Australian cities have experienced significant growth in passenger rail demand. For example, Melbourne's urban rail patronage growth between 2004 and 2008 was 47% (Gaymer, 2010) while Sydney's annual rail passenger journeys increased by 5.1 million between 2001 and 2006 (Brooker and Moore, 2008). Rail transport demand in large Australian cities is likely to continue to rise in the future, e.g., BITRE (2013) forecasted urban public transport demand to increase by about a third between 2010 and 2030. Similar trends of passenger rail demand were also observed in other countries, as a global rail revival is happening. In Europe, 160 cities have light rail, 65 of which was built or expanded between 1980 and 2007. In Asia, rail systems are rapidly growing in many countries, e.g., at least 14 Indian cities and 82 Chinese cities have built or are building rail systems. The growth of rail systems is also observed in the North America and Middle East (Newman et al., 2012; Newman et al., 2013).

Catering for increasing demand for rail services whilst maintaining service quality is challenging to Australian state rail authorities and planning agencies with limited funding resources. These agencies must decide how and where to invest among a variety of transport options, including urban rail. Although providing adequate capacity in an urban rail network is important, providing too much excess capacity is not desirable (unless of course demand is increasing very rapidly). Over investment in rail networks implies that funds are inefficiently allocated when they could have been directed to other projects, including other public transport modes. Thus, understanding of factors affecting passengers' rail trip decision-making process is crucial for urban mobility, service delivery, infrastructure planning, and policy formulation.

Factors thought to affect transit ridership can be broadly divided into two categories (Iseki et al., 2009): external (or control) factors exogenous to the transit system and its managers (e.g., service area population and employment), and internal (or policy) factors over which transit managers can exercise some influence (e.g., fares and service levels). Such categorisation is somewhat misleading because external factors related to public policies, such as parking fees, taxes on fuel price, and transit priority, can have a significant impact on transit ridership by influencing transit service quality and travel cost, though these factors are usually not in the direct control of transit managers. Meanwhile, improving the quality of internal factors (such as service levels) can, by making rail travel more attractive, feed back to affect the level of external factors (such as catchment population) by making an area more accessible and therefore attractive to live in. As a result factors that may impact transit ridership are grouped into three categories: quality of service, built environment, and sociodemographics. Most factors in each category have been extensively studied in the literature and thus a comprehensive review of each category is beyond the scope of this paper. Instead, the main factors in each category are briefly discussed here (see Balcombe et al. (2004) and Taylor and Fink (2003) for more comprehensive and detailed reviews).

Quality of service

Rail transit quality of service pertains to a wide spectrum of attributes such as spatial coverage, service time span, service frequency, station accessibility, fare, ticketing policy, reliability, station facilities, traveller information, comfort, safety and security, and customer services (dell'Olio et al., 2010; Eboli and Mazzulla, 2010; European Committee for Standardization, 2002; Hensher et al., 2003; Kittelson and Associates et al., 2003; Litman, 2008). Among these attributes, those related to time (e.g., access and egress time, service frequency, and in-vehicle time) can easily be quantified and incorporated into econometrics models; other qualitative attributes, such as comfort, cleanness, connection convenience, security, are more challenging to quantify and isolate. Table 1 summarises the factors in transit quality of service examined in the literature.

Table 1 Quality of service factors affecting demand for public transit

Factor	Summary findings reported in the literature
Fare	Fare elasticities can change by the time of day and by geography (Balcombe et al., 2004; Litman, 2008); The Simpson-Curtin Rule is ridership increases by 1% for each 3% fare reduction (Pham and Linsalata, 1991).
In vehicle time (IVT)	Balcombe et al. (2004) reported British evidence of IVT elasticities for urban or regional railways were between -0.4 and -0.9. Douglas et al. (2003) estimated that overall, peak, and off peak railway IVT elasticities in Sydney were –0.51, -0.45, and–0.61. IVT elasticities in Australian cities were reported to be between -0.30 and -0.50 (Booz-Allen and Hamilton 2003).
Waiting time	Kittelson et al. (2003) reported that value of waiting time relative to IVT varies significantly, ranging from less than one in very comfortable surrounds to above two

Factor	Summary findings reported in the literature
	in unprotected, unseated environments, while 1.5 is commonly employed in planning studies (Balcombe et al., 2004).
Service frequency	For rail transit in Brisbane, demand elasticities with respect to service interval or headway for the peak and off-peak periods were estimated to be –0.13 and –0.33 respectively. For Sydney CBD railway trips, elasticities for peak and off-peak periods were estimated to be –0.11 and –0.17, respectively (Douglas et al., 2003). Wallis and Schmidt (2003) concluded that typical elasticities in Australian cities for high frequencies (with interval less than every 10 minutes) and for low frequencies were 0.1 to 0.2 and 0.5 to 0.6, respectively. Litman (2008) estimated that the average elasticity of transit service frequency was about 0.5.
Reliability	Wallis and Schmidt (2003) estimated that the elasticity of reliability (measured as the standard deviation of arrival times) was -0.6 to -1.0, around twice of IVT's elasticity.
Transfer	The average penalty of transfer (including walking and waiting times) is equivalent to 21 minutes of IVT of a bus trip, and 37 minutes of IVT of a railway trip (Wardman, 2001; Wardman and Hine 2000). Litman (2008) reported penalties of transfer equivalent to 5 to 15 minutes of IVT. For a typical transit trip, a transfer accounts for approximately one quarter of total generalized costs (or time) (Iseki et al., 2009). Guo and Wilson (2004) argued that transfer penalty for urban rail systems could vary between 1.4 to 31.8 minutes of equivalent IVT in different contexts.
Crowding	Li and Hensher (2011) identified three measures used to value crowding (a time multiplier, a monetary value per time unit, and a monetary value per trip). Douglas and Karpouzis (2006) found that crowded seating increases travel time costs by 17 percent on Sydney railways. The UK Passenger Demand Forecasting Council recommends crowding factor ranges between 0.14 and 0.26 (ATOC, 2014).
Waiting environment	Wardman (2001) derived attribute values for various aspects of bus shelters, seats, lighting, staff presence, closed-circuit TV and bus service information; estimated values for individual attributes of the waiting environment range up to two minutes of IYT per trip. Preston et al (2008) gave more up to date valuations for many aspects of the station environment.
Transit information provision	Most studies related to information provision used stated preference or other attitudinal survey methods and led to different conclusions. However, compared with other factors, generally the resulting attribute weightings are small (Accent, 2002; Balcombe et al., 2004)).
Vehicle or rolling stock	Rolling stock improvements are typically valued at 1-2% of IVT. Refurbishment typically was estimated to be worth 1.5% of the fare, while refurbishment in South-east England was reported to be worth around 2.5% of the fare (Wardman and Whelan, 2001).

Built environment

Built environment attributes influence transit usage because transit trip ends usually involve walking or other forms of active transport. Density, distance to transit, land use diversity, pedestrian oriented design and destination accessibility (the "5Ds") are generally regarded to have significant impacts on travellers' choice of public transit (Ewing and Cervero, 2010). Research has found that built environments characterized by high street connectivity and mixed land uses encourage use of public transport (Cervero and Kockelman, 1997; Cao et al., 2007; Frank and Pivo, 1994; Kitamura et al., 1997; Lee et al., 2009; Kamruzzaman et al., 2013).

Sociodemographics

Sociological and demographic characteristics affect travel mode choice. Interestingly, contradictory findings have been reported. For example, Rosenbloom and Fielding (1998) found that old people are more likely to use transit, while Bonsall (2005) indicated that the senior (either as the driver or as a passenger) rely more on automobiles. It is possible, of course, that differences exist across cities, with a generally positive effect in one city and opposite effect in another. An individual's values and attitudes towards different travel modes (e.g., cars vs. transit) can influence mode choice (Kenyon and Lyons, 2003; Ellaway et al., 2003; Anable, 2005; Paulssen et al, 2014). Blainey et al. (2012) found that cultural barriers to public transit use may exist amongst particular ethnic and faith groups.

Many of the factors for train, bus, and car identified in prior research have been used to design and implement the survey described in the following section. In addition, during discussions with industry partners, free wireless access and laptop stations are two policies that were often discussed for attracting more people to use train. However, these two factors are seldom studied in the literature and thus their effectiveness on increasing train patronage remains elusive. Thus, the availabilities of wireless and laptop stations were also considered in the SP survey.

3. Data collection

3.1 Survey plan

A large-scale survey was implemented to estimate the effects of important factors on the mode choices of both rail and non-rail users in five state capitals in Australia. Information on service quality, public policies, and population characteristics were collected. In particular, both respondent socioeconomic characteristics and responses to stated choice experiments were obtained.

The implemented survey was web-based and utilised a respondent panel approach, arising mainly as a result of logistical, budgetary and sampling integrity considerations. Online surveys have been frequently used in transport research since 2005 with the establishment of panels (e.g., Verhoeven et al., 2007; Cantwell et al., 2009; Clifton et al., 2014). Online surveys are useful for cost-effectively collecting large amounts of data, avoiding cost associated with interviews and postage. The challenges with on-line surveys are associated with non-response of households without internet and self-selection bias. Web access is not a significant issue for this study because web access in Australia is extremely high, e.g., 82.3 out of 100 people in Australia in 2012 have access to the worldwide network (The World Bank, 2014). To minimize self-selection bias, the sample size for each city was proportioned approximately to its population's age and gender profiles according to the latest census results from Australian Bureau of Statistics (ABS, 2012). In other words, gender and age cohorts were sampled to achieve consistency with population statistics.

In this survey, both revealed preference (RP) and stated preference (SP) on urban train usages have been collected. For characteristics of RP and SP data, see Henser et al. (2005). There are two main reasons for us to adopt SP in this study: the first one is the cost (money and time) associated with collecting RP data, and the second reason is that the two new attributes (i.e., free Wi-Fi, and laptop station) do not exist on the trains in any of the cities. In addition, another advantage of adopting SP data collection approach is that using SP has enabled us to investigate participants' sensitivity towards parking and toll fees because most of participants did not pay any parking and tolling fees on the most recent trip. However, SP is less reliable compared with RP because information contained in SP data pertains to hypothetical scenarios (Louviere et al., 2000). SP data represents stated choices in hypothetical situations, where personal constraints are not considered as constraints at the time of 'choice', particularly when the SP task is not taken seriously by respondents. The task of the analyst is therefore to make the hypothetical scenarios as realistic as possible (Hensher et al., 2005). To ensure the reliability of our SP data, we implemented various strategies when we were designing the SP experiments, including: a comprehensive review of similar surveys in this field; reasonable workload (approximately 15 minutes); increasing readability by representing SP experiments in pictograms; SP scenarios were generated using an efficient design; "pivoting off" attribute levels of the most recent trip (rather than arbitrarily providing hard numbers), which can make preference revelation more meaningful because the decision context of the SP experiments is framed within some existing memory schema, see Hensher et al. (2011) for more theoretical justification of this approach; the questionnaire was pre-tested in two pilots and refined accordingly before the main survey, and etc.

3.2 Instrument development

The survey instrument was designed based on experience from previous studies (in total, over 40 similar surveys were analysed and compared) and inputs and feedback from an expert industry advisory group in rail and public transport. Two pilot surveys were conducted to test instrument validity (e.g. response categories, question interpretation, etc.) and to provide prior information for the efficient design of the SP scenarios. Briefly, the survey consisted of five sections: (i) Screening questions and quota selection; (ii) Train riders' most recent travel experience using train; (iii) Non-train riders' most recent travel experience using bus or car; (iv) General questions; and (v) Mode choice SP experiments.

To avoid potentially biased responses from participants who were younger than 16 years old or who might have a conflict of interest (e.g., those who work for a motor vehicle manufacturer, a public transport provider, city rail company, or the city transport department) these were screened out in section (i). In addition, the self-reported frequency of travelling by train was used to categorise respondent as rail riders and non-riders.

In Section (ii), questions were designed to gather important information on respondents' most recent train trip experience. By designing different questions to target different concerns at different stages of their trip, aspects of the entire journey were assessed; e.g., departure time, station access, crowding level, and destination access. In Section (iii), questions were designed to obtain basic information on the most recent trip of a non-train rider. In particular, reasons for not choosing the train for this trip and perceptions on travelling by train were collected[‡]. In Section (iv), questions were related mainly to attitudes and social-demographic background of respondents. In Section (v), by varying several key attributes (e.g., in-vehicle time, station access, destination access), a series of hypothetical mode choice scenarios were designed to gain additional insights into travellers' mode decision-making process.

Ngene (ChoiceMetrics, 2012), specialised software for designing discrete choice experiments, was used for generating the choice scenarios. For generating the mode choice scenarios for the pilot surveys, an orthogonal design was adopted to achieve balance and independence between the attribute levels. By using parameters of the factors that were estimated based on the data collected from the pilot surveys, the main survey was upgraded via an efficient design, which generated parameter estimates with the smallest standard errors (contingent upon the design), instead of aiming to minimize correlation between attributes. There are several efficiency measures; the commonly-used D-error (i.e., the determinant of the variance-covariance matrix) was deployed in designing our SP experiment (Bliemer and Rose, 2006; Rose et al., 2008).

Furthermore, to make combinations of different attribute levels as realistic as possible to respondents, the choice sets presented to each individual were personalised (see e.g., Hensher et al., 2011) and based on the transport modes available for this respondent's most recent trip. Data obtained from the two pilots were used to determine realistic attribute levels for time to station, waiting time, time in vehicle, time to destination, and fare. To generate an efficient and realistic design, averages of these attributes (except parking and tolls) collected in the pilot surveys were used as baselines and pivoted by plus and minus 50%[§]. Table 2 summarises these attributes and their levels considered in the SP scenarios in the main survey.

[‡] As a reviewer pointed out, we did not check if the person had intermediate stops or activities late on the day that constrain them to use a specific mode.

[§] In our SP experiments, alternatives were personalized. More specifically, based on each respondent's response to the transport modes available for use on the most recent trip, alternatives (i.e., transport modes) that should be included in the SP were then determined accordingly. For other information, such as travel cost, travel time etc., values obtained from the pilot studies were used.

The averages of parking cost and toll from the two pilots were close to zero. Thus, parking and tolls were not pivoted around the averages. To capture respondents' reactions towards a wider range of parking and toll costs, the levels of parking for one day and toll for a one-way trip in the SP survey ranged from zero to 30 Australian dollars (i.e., 0; 10; 20; 30) and zero to 15 Australian dollars (i.e., 0; 5; 10; 15), based on current tolls and daytime parking costs in the five cities. Note that the car cost depends on car occupancy. In our survey, we did not ask car occupancy by assuming only one person in the car.

Train crowding was also considered in the SP survey. Defining crowding can be complex and different methods have been proposed in the literature (see Douglas and Karpouzis, 2006; Hensher and Li, 2012; Lu et al., 2008). To reduce the complexity of SP scenarios (note that the number of possible scenarios increases exponentially as attribute levels increase) and to maintain readability and simplicity, six levels were used to describe crowding in the main survey, uncrowded seats, crowded seats, standing up for 5 minutes prior to finding an empty seat, standing up for 6 to 15 minutes prior to finding an empty seat, standing up for 16 to 25 minutes prior to finding an empty seat, and crush standing.

Table 2 Attributes and their levels considered in the SP survey for each mode

Mode	Time to station (min)	Waiting time (min)	Time in vehicle (min)	Fare (AU$)	Crowding level	Time to destination (min)
Bus	2.5; 5; 7.5	3; 6; 9	16; 32; 48	1.2; 2.4; 3.6	6 levels[#]	2.5; 5; 7.5
Train	5; 10; 15	4; 8; 12	15; 30; 45	1.5; 3; 4.5	6 levels[#]	5; 10; 15
Car	-[&]	-	10, 20, 30	-	-	1; 5; 10
	Free wireless	Laptop station	Fuel cost (AU$)	Daily parking (AU$)	Toll (AU$)	
Bus	Yes; No	Yes; No	-	-	-	
Train	Yes; No	Yes; No	-	-	-	
Car	-	-	Calculated using Equation (1)	0; 10; 20; 30	0; 5; 10; 15	

[#] 1: uncrowded seats; 2: crowded seats; 3: standing up for 5 minutes prior to finding an empty seat; 4: standing up for 6 to 15 minutes prior to finding an empty seat; 5: standing up for 16 to 25 minutes prior to finding an empty seat; and 6: crush standing;

[&] "-" means that this attribute is not applicable to this mode.

To accurately estimate fuel consumption costs, the following Equation (1)[**] from Hensher et al. (2011) was used.

$$Fuel\ cost = ((v/60 \times t)/100) \times e \times p \quad (1)$$

** Essentially this equation is empirical. For a respondent, the trip distance is likely fixed while speed can change. In our study, what we need is an (reasonable) approximation of the fuel consumption. The average speed in these capital cities is well documented. Thus, we used the historical average speed in estimating fuel consumption. By doing so, we essentially treat speed fixed instead of the fixed distance. This is a reasonable twist because from the energy consumption perspective, a trip with a longer distance is equivalent to a trip with a shorter distance at a lower speed.

where t is in-vehicle time (minutes) obtained from the pilot surveys; e is fuel efficiency assumed to be 11 litres per 100 km travelled (ABS, 2010); p is fuel price assumed to be (1.5, 2, and 2.5) Australian dollars per litre; and v is the average speed (km/h) calculated as 35.7 km/h based on the average speeds in QLD, VIC, WA, SA, and NSW in 2010/11 (Austroads, 2013; Vicroads, 2013).

During discussions with industry partners, free wireless access and laptop stations are two policies that were often discussed for attracting more people to use train. However, these two factors are seldom studied in the literature and thus their effectiveness on increasing train patronage remains elusive. Thus, the availabilities of wireless and laptop stations were also considered in the SP survey.

In total 216 mode-choice scenarios were generated. Specifically, we generated 72 scenarios for (Train, Bus), 72 for (Train, Bus, Car), 36 for (Train, Car), and 36 for (Train, Car). To minimise respondent' workload, six scenarios were presented to each respondent. Furthermore, instead of using a tabular form for representing scenarios, which can be difficult and confusing for respondents to read, pictograms were used to present mode choice scenarios. An example of a 3 mode choice pictogram is illustrated in Figure 1.

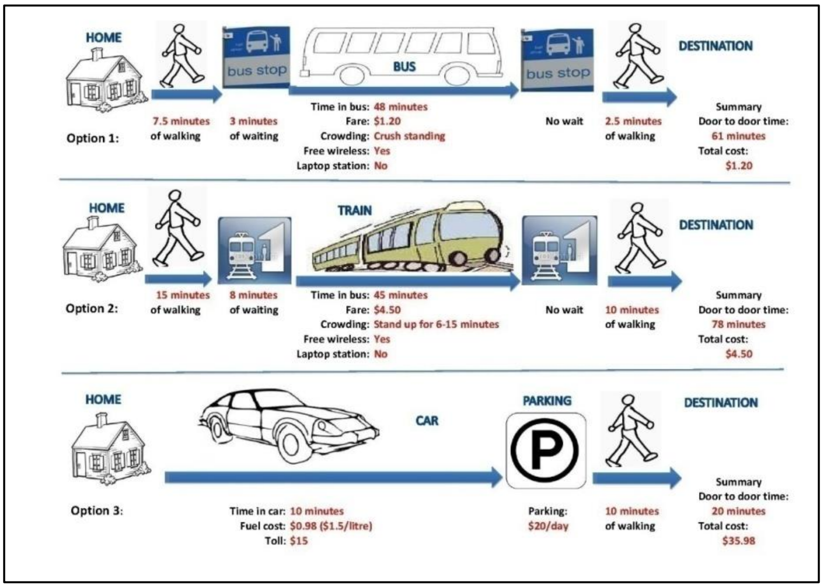

Figure 1 Example pictogram of a mode choice experiment

3.3 Survey administration

Prior to the formal survey, two pilots were implemented to fine-tune the questionnaire. The sample size for the first and the second pilot is 421 and 253, respectively. The main difference between the two pilots is that some questions in pilot 2 were modified according to respondents' feedback from pilot 1 to increase the readability and accuracy. Results from the two pilot surveys revealed large variances and no significant differences across cities for the mean values of the majority of factors (e.g., fare, walking time to station, waiting time, etc. reported for the most recent trips). The results indicated that generating city-specific SP scenarios, which would significantly increase the survey's complexity, was not necessary.

Responses from the two pilot surveys also showed that the parking fees and tolls paid by vehicle users on the most recent trips were extremely small with an average of less than AU$1 in most cities. The low value of parking fees and tolls obtained in two pilots were due to the fact that many vehicle users did not pay for parking or tolls, while a relatively small proportion paid significant sums. Thus, presenting AU$1 parking fee or tolls instead would be pointless. For those who indeed paid parking or tolls in five capital cities, AU$10 to 20 is a reasonable amount for parking and AU$10 for tolls. To introduce more variation, we eventually presented four levels [0, 10, 20, 30] for parking and [0, 5, 10, 15] for tolls. Although currently many drivers do not pay much for parking or tolls, this can have important practical significance. Parking and tolling are often discussed as two options of managing travel demand. Obtaining respondents' sensitivity towards a variety of parking fees and tolling can provide valuable insights to policy makers on how and to what extent these two could discourage car usages. This is an advantage of adopting SP data collection approach because these large parking and tolling fees are rarely observed in RP data. A typical practice of using SP is to provide hypothetical combinations using a range of values to enable sufficient variations in the data to fully capture respondents' potential behavioural responses.

The target sample size of the SP survey was 7000 respondents, half each from train riders and non-train riders. The survey was administrated between April and May 2013. The survey's respondent profile is summarized in Table 3. Income distribution and some main features of their most recent train trip are presented in Appendix.

This table shows that the final sample size was 6731, and that except for train riders in Adelaide, all the quotas for each city and for each user group were achieved. Furthermore, gender and age distributions of the sample were close to those in the census data from ABS (2012) with one notable exception, indicating representativeness of the sample in terms of socio demographic strata. The notable exceptions were the 16-30 years age group that was under-represented in our sample and the 51-60 years age group, which was over-represented in our sample. To remedy this issue, sampling weights were developed based on age strata.

Table 3 Summary of the final survey respondent profile

Gender	Frequency	Breakdown	ABS
Male	3000	45%	49%
Female	3731	55%	51%
Age	**Frequency**	**Breakdown**	**ABS**
16-30 years	1153	17%	23%
31-40 years	1424	21%	21%
41-50 years	1330	20%	19%
51-60 years	1504	22%	14%
60+ years	1320	20%	23%
Rider type	**Regular[††]**	**Non-train rider**	**Target**
Sydney	1000	1000	1000
Melbourne	1000	1000	1000
Brisbane	489	500	500
Adelaide	242	500	500
Perth	500	500	500
Total	3231	3500	3500

4. Mode choice modelling

For each respondent, six SP responses were collected. These responses are likely to be correlated with each other because they are from the same decision maker. Random-effects logit (mixed logit) was employed to fit the stated choice data from the survey.

[††] After extensive discussions with committee members from transit agencies in each city, we classified respondents who used train two times or more last month as regular train users; otherwise, they were classified as non-train users.

As a powerful and flexible tool that can approximate any random utility model (McFadden and Train, 2000; Washington et al., 2011; Zheng et al., 2014), random-effects logit can capture random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over repeated measures (see Train, 2009 or Hensher et al., 2005 for the mathematical details surrounding the random-effects logit model). Nlogit (Greene, 2012), a statistical package for discrete choice modelling, was used to implement the modelling analyses presented in this section.

A large number of models were developed and their performances assessed using standard goodness of fit metrics and logical soundness. The model with the best performance is presented in Table 4. Panel effect is accounted in the random parameters. To increase its readability, distributions of the random parameters and modelling result on heterogeneities of the random parameters are provided in Table 5 and Table 6, respectively.

Table 4 The random-effects logit model

Mode	Attribute	β	z	p
Bus	Constant	.525	4.65	<.001
	Walking time to the stop (min)	-.046	5.75	<.001
	Waiting time (min)[RN]	-3.57	-75.8	<.001
	Time on bus (min)	-.0038	28.65	<.001
	Fare (AU$)	-.261	15.96	<.001
	Crowding level [RN]	-2.33	-18.23	<.001
	Walking time to destination (min)	-.029	-3.35	<.001
Train	Constant	-.021	-.19	.846
	Walking time to the station (min) [RN]	-3.132	-35.26	<.001
	Time on train (min)	-.041	29.6	<.001
	Fare (AU$)	-.274	21	<.001
	Laptop station (Yes; No) [RN]	-.194	-4.05	<.001
	Crowding level	-.068	7.08	<.001
	Walking time to destination (min)	-.048	-11.61	<.001
	wireless	-.025	-.72	.47
Car	Fuel (AU$) [RN]	-2.017	-14.5	<.001
	Parking (AU$)	-.114	57.38	<.001
	Tolling (AU$)	-.125	36.01	<.001
	Walking time to destination (min)	-.04	-7.72	<.001

Model fits: Log likelihood function = -23528.94;
Restricted log likelihood = -36480.04; Significance level <0.001; McFadden Pseudo R-squared=0.36; AIC=47143.9; AIC/N =1.2; Halton sequences used for simulations; RN denotes that this variable's parameter is treated as a random parameter.

Table 5 Distributions of the random parameters

Random parameter	Distribution	Standard deviation	z	p
Bus waiting time (min)	Log normal	4.068	170.25	<.001
Train laptop station	Normal	.777	12.98	<.001
Car fuel cost	Log normal	1.796	19.03	<.001
Train walking time to the station	Log normal	3.523	103.13	<.001
Bus crowding level	Log normal	1.073	10.85	<.001

Table 6 Heterogeneities in the random parameters

<table>
<tr><th>Mode</th><th>Random parameter</th><th>Attribute</th><th>β</th><th>z</th><th>p</th></tr>
<tr><td rowspan="6">Bus</td><td rowspan="4">Waiting time (min)</td><td>Trip for employment</td><td>-.356</td><td>-23</td><td><.001</td></tr>
<tr><td>Low income</td><td>-.375</td><td>-9.39</td><td><.001</td></tr>
<tr><td>Male</td><td>-.343</td><td>20.9</td><td><.001</td></tr>
<tr><td>Train rider</td><td>-1.578</td><td>-13.06</td><td><.001</td></tr>
<tr><td rowspan="2">Crowding level</td><td>Melbourne</td><td>.327</td><td>3.44</td><td><.001</td></tr>
<tr><td>Male</td><td>-.275</td><td>-2.80</td><td>.005</td></tr>
<tr><td rowspan="6">Train</td><td rowspan="4">Walking time to the station</td><td>Adelaide</td><td>.330</td><td>7.83</td><td><.001</td></tr>
<tr><td>Low income[1]</td><td>1.733</td><td>59.02</td><td><.001</td></tr>
<tr><td>Male</td><td>.427</td><td>18.66</td><td><.001</td></tr>
<tr><td>Train rider</td><td>-7.739</td><td>-43.46</td><td><.001</td></tr>
<tr><td rowspan="2">Laptop station</td><td>Trip for employment</td><td>0.1</td><td>1.52</td><td>.1</td></tr>
<tr><td>High income</td><td>-.465</td><td>-5.63</td><td><.001</td></tr>
<tr><td rowspan="4">Car</td><td rowspan="4">Fuel</td><td>Low income</td><td>.247</td><td>2.58</td><td>.01</td></tr>
<tr><td>High income</td><td>-.531</td><td>-4.90</td><td><.001</td></tr>
<tr><td>Male</td><td>.354</td><td>4.28</td><td><.001</td></tr>
<tr><td>Train rider</td><td>1.407</td><td>12.48</td><td><.001</td></tr>
</table>

[1] In this study, the low income group is defined as those participants whose pre-tax household weekly income is less than AU$700.

In this model, coefficients of bus waiting time, bus crowding level, train walking time to the station, car fuel cost were treated as random parameters, following a lognormal distribution. Because lognormals can only be non-negative, the lognormal distribution is widely used in the literature to impose a constraint on the estimate if the expected sign of the estimate is known. Train laptop station's coefficient was also treated as a random parameter, following a normal distribution because of uncertainty of its expected sign.

In this study, fuel cost, fare, crowding level, waiting time, and walking time to the station were converted to a negative value to make its parameter's expected sign positive, e.g., AU$5 of fuel cost was converted to -5. In addition, as recommended in Bhat (2001), 1,000 random Halton draws were executed in estimating the random parameter to ensure the accuracy of the model results, which consequently requires enormous computing time. As shown in Table 4, all the parameters are alternative-specific with expected signs and most of them are statistically significant at a 99% confidence level; and the overall performance of the model is also significant at a 99% confidence level, with a reasonable McFadden Pseudo R-squared (i.e., 0.36).

(1) Bus and train

Station access time, in-vehicle time, crowding level, fare, and destination access time appear to be significant factors in the mode selection process for both bus and train. Among them, bus fare and train fare display similar effects as evidenced by their almost identical coefficients.

An interesting observation is the complexity of time's influence on utility functions of bus and train. Respondent's disutility of travel time measured across several dimensions (i.e., by station access time, waiting time, in-vehicle time, and destination access time) differed significantly, depending on mode and the trip stage. Furthermore, impact of bus waiting time and train station access time varies across respondents as indicated by the significant standard deviation of their parameters. More specifically, the marginal utility for walking time to the train station is: $-exp[-3.132 + 0.33 \times Adelaide + 1.733 \times (low\ income) + 0.427 \times male - 7.739 \times (train\ rider) + 3.523 \times n]$, where n is from a standard normal distribution. The marginal utility for bus waiting time is: $-exp[-3.57 - 0.356 \times (trip\ for\ employment) - 0.375 \times (low\ income) - 0.343 \times male - 1.578 \times (train\ rider) + 4.068 \times n]$, where n is from a standard normal distribution. Clearly the marginal utilities of train station access time and bus waiting time are linked to trip purpose and socio-demographics of respondents. More discussion on this issue is provided later.

Consistent with the literature (e.g., Hensher et al., 2011), crowding level has significant impact on bus' and train's utilities, respectively. Furthermore, there exists notable heterogeneity in crowding level's impact on bus selection over the sampled population. The marginal utility for bus crowding level is: $-exp[-2.33 + 0.327 \times Melbourne - 0.275 \times male + 1.073 \times n]$, where n is from a standard normal distribution. The marginal utility for bus crowding level is influenced by city and gender. To gain more insight, the willingness to pay for bus crowding level is simulated for 100 randomly selected individuals, as shown in Figure 2. This figure clearly shows that all the individuals are willing to pay for a less crowdedness, while the magnitude of WTP varies significantly across individuals.

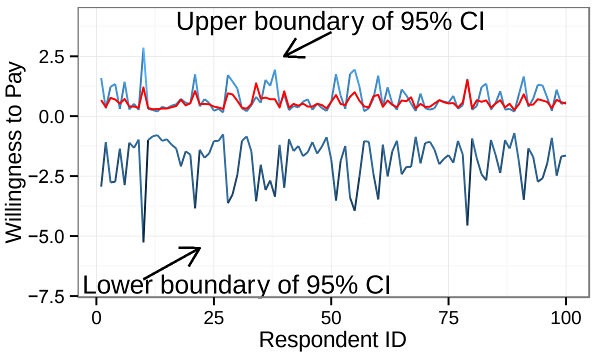

Figure 2 WTP for bus crowding level; CI stands for confidence interval

Perhaps surprisingly, the analysis suggests that providing free wireless access increases neither train's nor bus' utility. This may reflect respondents' fear that providing wireless may result in a fare increase or that wireless serves only a minority of patrons; another possible reason is that the high penetration of smart phones in Australia that often come with a 3G or 4G data plan makes access to wireless less appealing.

The analysis also reveals a mixed effect on utilities of providing laptop station. More specifically, providing laptop station on bus has no significant impact on bus' utility, which is not surprising because respondents may perceive that laptop users and stations utilise more space, leaving less space for passengers; or that laptop stations only serve a minority of 'wealthier' patrons; or that using laptop on bus is likely to be uncomfortable/undesirable for many respondents because of motion sickness, relatively short travel time or other factors. However, respondents' opinions on providing laptop station on train are notably divided as indicated by the significant standard deviation of its parameter, despite its insignificant mean effect. As shown in Table 6, attractiveness of providing laptop station on train differs by trip purpose, and economic status. More specifically, the marginal utility for train laptop station is: $[-0.194 + 0.1 \times (trip\ for\ employment) - 0.465 \times (high\ income) + 0.777 \times n]$, where n is from a standard normal distribution. The marginal utility for train laptop station has been simulated for 100 randomly selected individuals to better understand influence of trip purpose (by holding income constant; similar simulation can be easily implemented for income), as shown in Figure 3. This figure clearly shows strong heterogeneity across individuals regardless of their trip purpose. However, individuals who travel for employment are more attracted to the idea of providing laptop stations on a train than individuals who travel for other purposes. In addition, this figure reveals that many respondents either love or hate the idea of providing laptop stations on a train.

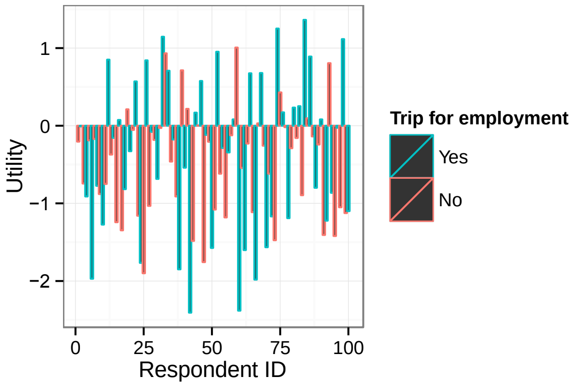

Figure 3 The simulated marginal utility of train laptop station for 100 randomly selected individuals by holding income constant

The willingness to pay for train laptop station is also simulated for 100 randomly selected individuals, as shown in Figure 4. Again, this figure reveals that the mean effect of laptop stations oscillates around zero, and that WTP varies significantly among individuals.

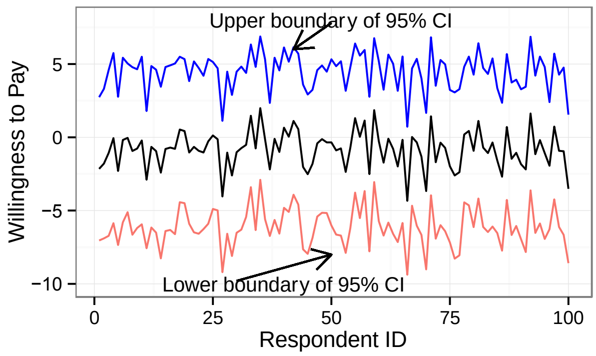

Figure 4 The willingness to pay for train laptop station for 100 randomly selected individuals

(2) Car

For driving, two dominant factors are parking cost and tolls. Meanwhile, fuel cost influences the disutility of driving, and this influence varies across respondents as indicated by the significant standard deviation of the fuel cost parameter. This finding reveals heterogeneity in fuel cost effects on mode choice over the sampled population, and agrees with prior research that has shown heterogeneity in price sensitivities. Note that fuel cost is strongly correlated with in-vehicle time because fuel cost was estimated based on in-vehicle time (see Equation (1)). Thus, in-vehicle time was excluded from the utility function of driving.

The marginal utility for car fuel cost is: $-exp[-2.017 + 0.247 \times (low\ income) - 0.531 \times (high\ income) + 0.354 \times male + 1.407 \times train\ rider + 1.796 \times n]$, where n is from a standard normal distribution. This implies that by controlling randomness and other factors, i) respondents with low income are generally more sensitive to fuel cost; ii) the male are more sensitive to fuel cost compared with their counterpart; iii) train riders are more sensitive to fuel cost of driving a car. More discussion on this matter is provided later.

The utility functions of bus, train, and car are mathematically given below:

$$V_{bus} = \beta_{b0} + \beta_{b1}(walking\ time\ to\ the\ stop) - \exp[\beta_{bw0} + \beta_{bw1}(trip\ for\ employment) + \beta_{bw2}(low\ income) + \beta_{bw3}male + \beta_{bw4}(rail\ rider) + \beta_{bw5}n] \times (bus\ waiting\ time) + \beta_{b2}fare + \beta_{b3}(in\ vehicle\ time) - exp[\beta_{bc0} + \beta_{bc1}Melbourne + \beta_{bc2}male + \beta_{bc3}n] \times (crowding\ level) + \beta_{b4}(walking\ time\ to\ destination) \quad (2)$$

$$V_{train} = \beta_{t0} - \exp[\beta_{tw0} + \beta_{tw1}Adelaide + \beta_{tw2}(low\ income) + \beta_{tw3}male + \beta_{tw4}(rail\ rider) + \beta_{tw5}n] \times (walking\ time\ to\ station) + \beta_{t1}fare + \beta_{t2}(in\ vehicle\ time) + \beta_{t3}(crowding\ level) + \beta_{t4}(walking\ time\ to\ destination) + [\beta_{tl0} + \beta_{tl1}(trip\ for\ employment) + \beta_{tl2}(high\ income) + \beta_{tl3}n] \times (train\ laptop\ station) \quad (3)$$

$$V_{car} = \beta_{c0}parking + \beta_{c1}tolling + \beta_{c2}(walking\ time\ to\ desti\square ation) - \exp\big[\beta_{cf0} + \beta_{cf1}(low\ income) + \beta_{cf2}(high\ income) + \beta_{cf3}male + \beta_{cf4}(rail\ rider) + \beta_{cf5}n\big] \times (fuel\ cost) \quad (4)$$

In equations (2 ~ 4), βs are coefficients (values of the coefficients in this study can be extracted from Table 4 and Table 6), and n is a parameter drawn from a standard normal distribution.

The modelling result also reveals that all the attributes included in the SP design turned out to be significant except free wireless, which further confirms the validity of the SP design. Discussions on heterogeneity and city differences are provided in the next section.

5. Heterogeneity and intercity comparison

As discussed previously, notable heterogeneity was detected across participants in their mode choice preferences. More specifically, significant heterogeneity was observed for bus waiting time and crowding level effects; for train, walking time to station and laptop station effects; and for vehicle fuel cost effects—all components of generalized cost of travel. The analysis shows that such heterogeneity can be partially explained by socio-demographic variables including intercity differences as elaborated below.

User group status: The status of user group has significant influence on heterogeneity in respondents' sensitivity to car fuel cost, bus waiting time, and walking time to a train station.

The marginal utility of car fuel cost for 100 randomly selected individuals (half are train riders) was simulated by holding income and gender constant. The result is provided in Figure 5, which shows that when other factors are equal, train users are much more sensitive to fuel cost than non-train users. Thus, the marginal disutility of fuel cost for train riders is much larger than that of non-train riders.

The marginal utility for bus waiting time is: $-exp[-3.57 - 0.356 \times (trip\ for\ employment) - 0.375 \times (low\ income) - 0.343 \times male - 1.578 \times (train\ rider) + 4.068 \times n]$, where n is from a standard normal distribution. This marginal utility function reveals that by controlling randomness and other factors, train riders are generally more tolerant of the time they spend on waiting for bus than non-train riders. Similar conclusion can be drawn for walking time to the train station that by controlling randomness and other factors, train riders are generally more tolerant of the time they spend on walking to the train station. This finding is also consistent with our daily experience: public transit users are more likely to be public transit friendly. We did not find significant impact of user group status on travel time, which is probably because waiting and walking are two indicators that can better approximate convenience of using public transit, compared to in-vehicle time, and thus no significant heterogeneity exists in participants' sensitivity towards in-vehicle time.

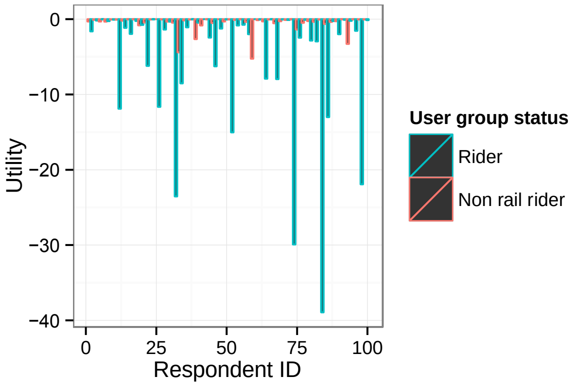

Figure 5 The simulated marginal utility of car fuel cost for 100 randomly selected individuals by holding income and gender constant

Income: Income effects can partially explain preference heterogeneity detected in the marginal utility for walking time to the train station, the marginal utility for bus waiting time, the marginal utility for train laptop station, and the marginal utility for car fuel cost. More specifically, respondents with low income generally are more sensitive to the walking time to the train station, more sensitive to car fuel cost, less sensitive to bus waiting time, and respondents with high income are likely less sensitive to car fuel cost.

Gender: Gender can partially explain preference heterogeneity detected in the marginal utility for walking time to the train station, the marginal utilities for bus waiting time and crowding level, and the marginal utility for car fuel cost. More specifically, males are less sensitive to bus waiting time and crowdedness. However, males are more sensitive to walking time to the train station, and car fuel cost.

Trip purpose: Trip purpose can partially explain preference heterogeneity detected in the marginal utility for bus waiting time, the marginal utility for providing laptop stations. Providing laptop stations is more attractive to trip for employment (see Figure 3). However, it is surprising to see that bus waiting time has less impact on employment related trips.

Intercity differences: Intercity differences also contribute to heterogeneity in individual preferences. More specifically, respondents from Adelaide appear to care more about walking time to the train station (see Figure 6), and respondents from Melbourne care more about bus crowding level (see Figure 7).

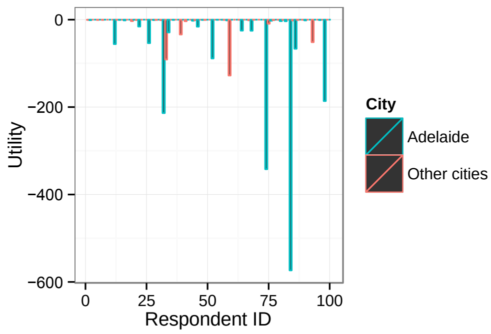

Figure 6 The simulated marginal utility of train station access time for 100 randomly selected individuals by holding income, gender, and user group status constant

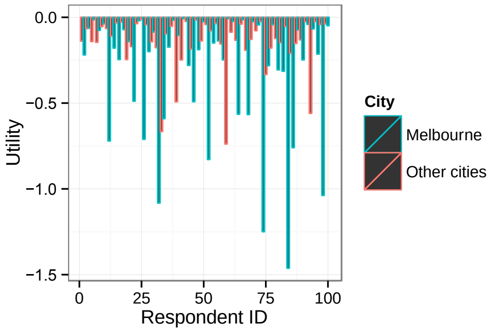

Figure 7 The simulated marginal utility of bus crowding level for 100 randomly selected individuals by holding gender constant

6. Discussion and Conclusions

This paper presents an analysis based on a unique national SP survey focused on urban rail patronage across five Australian capital cities. Results from an SP mode choice experiment were analysed to examine respondents' mode choice behaviour, with particular focus on the effects of service quality, socio-demographics, and inter-city differences. Due to the relatively large size of the sample, unobserved heterogeneity associated with numerous factors was tested using mixed multinomial logit models. Several influential mode-choice factors were identified, and their impacts were quantified.

Regarding public transit, fares are inversely related to the probabilities of choosing bus or train. Service quality was also found to influence demand for urban rail, with crowding consistently revealing negative impacts on the utilities of bus and train across all five cities. For driving, fuel costs, parking costs, and tolls were three important factors inversely related to mode utility. Moreover, the parameter for fuel cost was random—suggesting that individuals respond significantly differently to fuel cost.

Advocacy for providing free Wi-Fi is scattered in the recent literature. Rudnenko and Dauby (2014) argued that, as a lifestyle, rail passengers expect a seamless Internet surfing experience while travelling, thus, Wi-Fi on rail is of paramount importance. Results from their survey on worldwide metro systems reveal that 77% of them provide internet access either in stations (73%) or on-board metro trains (58%), and that 68% of metros plan to expand internet connectivity in the coming 1-3 years. Hartwich and Buckingham (2009) advocated business class rail in New South Wales for attracting business commuters. Wi-Fi and laptop station are two features of the business class rail.

Few studies have investigated free Wi-Fi's impact on rail ridership. Dong et al. (2014) estimated the impact of free Wi-Fi on rail passengers' trip frequency, based on an onboard survey on all trains of the California Capitol Amtrak, and found some positive impact of Wi-Fi on the self-reported projected trip frequency. In addition, the magnitude of such impact of Wi-Fi depends on trip frequency of participants. More specifically, for participants using CC once a week or more in 2011, the expected number of trips is likely to increase by 6.2% due to free Wi-Fi, while for participants using CC less than once a week in 2011, the impact of free Wi-Fi on the expected number of trips was much less. However, passengers' response to Wi-Fi on train can be influenced by many contextual constraints. As pointed out in Axtell et al. (2008), the usage and usefulness of Wi-Fi on train can be constrained by connectivity, space constraints, noise levels, privacy concerns, and other factors. Thus, the potentially complex interaction effects of Wi-Fi remain unexplored. Despite the intuitive appeal of providing free Wi-Fi and laptop station on trains, there is a great need to systematically investigating free Wi-Fi's and laptop station's impact on rail ridership (and on triggering modal shift), especially considering that transit systems are often under-funded by governments in many countries and providing Wi-Fi and laptop station require additional and significant investment. Such costs should be justified by convincing and evidence-based benefits to increasing ridership.

This study is one of the first studies to investigate Wi-Fi's effect on rail ridership, and examine tradeoffs between Wi-Fi and other attributes. When passengers are choosing among transport modes for their most recent trip, our study found that: the provision of laptop stations and wireless access did not reveal statistically significant positive effects on the utility of public transport, which is consistent with a recent survey of train riders in Denmark (Bjørner, 2015), which found that passengers were frustrated and developed anxiety if the promised Wi-Fi connection on-board was poor or unstable. Overall, the analysis presented here suggests that the impact of providing free Wi-Fi is not as notable as some literature has suggested (Hartwich and Buckingham (2009); Rudnenko and Dauby (2014)). The prevalence of 3G/4G smartphones/ tablets may explain the negligible effect of Wi-Fi on the trains. Moreover, the fixed effect of laptop stations provided on trains was statistically insignificant; however, significant preference heterogeneity existed among respondents, indicating that respondents' preferences regarding laptop stations were polarized: some finding great value while others finding none. While future research is clearly needed to better understand this phenomenon, this finding has practical importance because it implies that prior to introducing this new feature on trains, decision makers need to carefully understand who their target user groups is, and perhaps understand the size of this market so the correct provisioning is provided.

The travel time impacts on transit disutility were more complex than what is often reported and described. The disutility of travel time was observed across several dimensions including station access time, waiting time, in-vehicle time, and destination access time — although the effects differed significantly, depending on mode and trip stage. Although conventional wisdom dictates that travel time has an inverse relationship with mode utility, a growing literature supports that travel time can have positive utility, explained by the proliferation of information and communication technology on the trains. Using data from Great Britain's National Passenger Survey 2010, Susilo et al. (2012) reported that only 13% of travellers regarded their travel time as wasted, and that traveller's value of time was influenced by sociodemographic characteristics, activity engagement, etc. In particular, they found that the ability to work or study on a train might significantly increase an individual's value of time. Similarly, Gripsrud and Hjorthol (2012) analyzed data from a 2008 survey on rail passengers in Norway, and found that value of time on trains is significantly influenced by trip purpose and availability of communication technologies on trains. More specifically, about 25% of the participants regarded their travel time as working hours, while only 10% reported their travel time of no use. Frei et al. (2015) analyzed Chicago transit rider data collected in April 2010, and found that travel attitudes and activity engagement can potentially influence traveller's value of time. Consistent with this literature, the disutility of travel time measured across several dimensions varied significantly across respondents, and was related to socio-demographic factors, such as gender, income, city, and trip purpose.

The importance and urgency of shifting from private to public transport is widely acknowledged in order to achieve the environmental, economic and social sustainability. However, this shift has been proven intrinsically complex due to numerous societal, political and economic barriers (Batty et al., 2015). Even when experiencing large disruptions caused by natural disasters, travellers tend to stick to their normal transport mode (Zheng et al., 2015). This underscores the significant role of habit and its resultant challenge of persuading travellers to switch transport modes (Blainey et al., 2012). Habit or state dependence is an important barrier of modal shift (Thøgersen, 2006), because habit makes people have higher perceptions threshold towards the attractiveness of alternative modes and lower thresholds towards the unattractiveness of alternative modes (Goodwin, 1977). Our analysis confirmed this modal shift difficulty. The analysis here revealed that respondents were more sensitive to the cost (or disadvantages) of the non-chosen transport mode and less sensitive to the cost (or disadvantages) of the chosen mode. It may be critical to change travellers' habitual thinking and travel behaviour by using creative and innovative ways of highlighting the cost/disadvantages of transport modes competing with train, e.g., policy interventions like congestion pricing and parking restriction—and to encourage users to try different modes for short periods of time (e.g. free transit periods, etc.) in order to break habits.

Finally, some studies have attempted to establish relationships between the surrounding built environment and rail ridership (e.g., Loo et al., 2010). These potential links are intuitive, as the "last mile" problem embeds the need to provide transport options from rail stops to trip origins and destinations—and the land use attributes at these trips ends may influence the attractiveness of these journeys. Linking unique characteristics of the transit (urban rail in particular) systems in the five capital cities of Australia to their ridership differences is the subject of ongoing work, and remains as a future research objective.

A limitation of our study is that despite our great effort, the realism of our SP design can be further improved. Meanwhile, the participants' home location and the nearest train station's location can have a large influence on walking time. In reality, a participant's house location is fixed. In our SP design, we specifically instructed each participant to make decisions if walking time is 5 minutes, or 10 minutes, etc. Such SP data can help us to understand the tradeoff and sensitivity related to station/stop accessibility. This can have important implications on transit policy, including decisions such as providing more bus stops, providing bus feeders to train.

Acknowledgements: We would like to thank three anonymous reviewers for their insightful comments, Professors John Rose and Michiel Bliemer, and Dr. Andrew Collins for discussing with us efficient design and Ngene, and Ms Puteri Paramita for helping us produce the figures in the appendix. This study draws on data gathered and analysis undertaken as part of *Project R1.130 Understanding Urban Rail Travel for Improved Patronage Forecasting* funded by the CRC for Rail Innovation (established and supported under the Australian Government's Cooperative Research Centres program).

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Appendix Household income and some main features of the most recent train trip

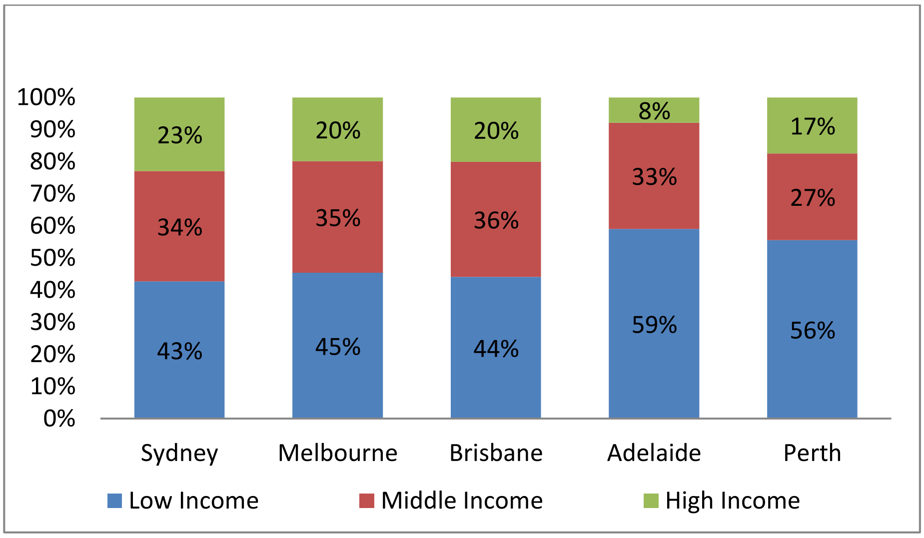

Figure A.1 Household income level

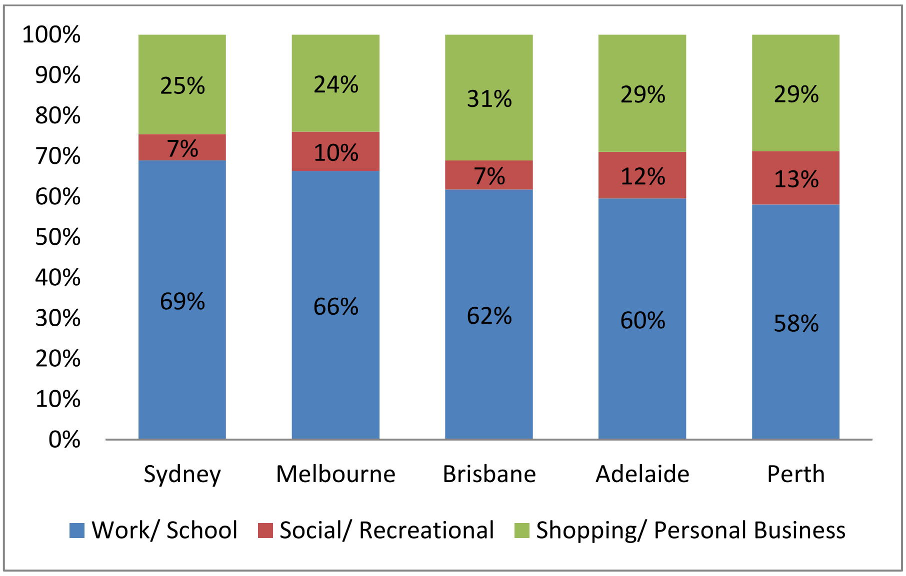

Figure A.2 Main purpose of the most recent train trip

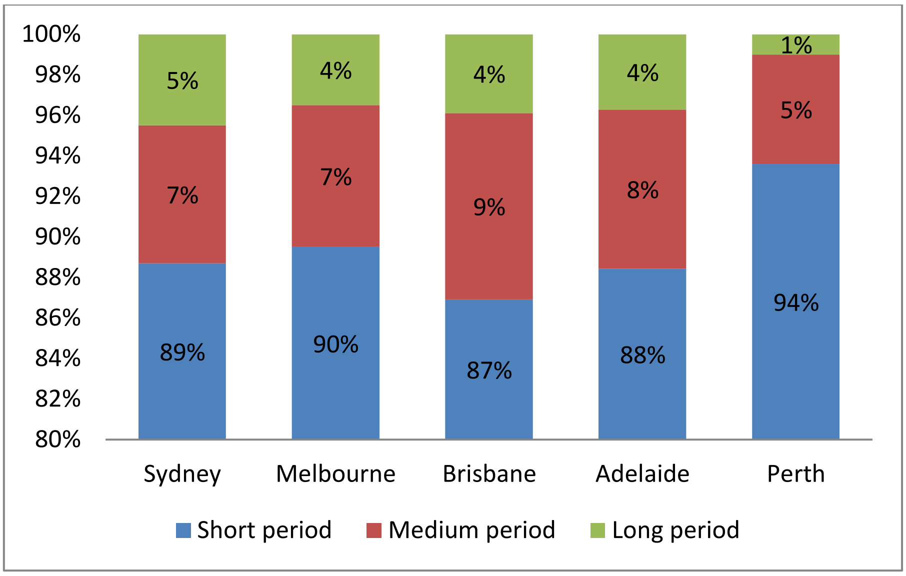

Figure A.3 Waiting time of the most recent train trip; short period for less than 15 minutes, medium period for between 15 and 30 minutes, and long period for more than 30 minutes.

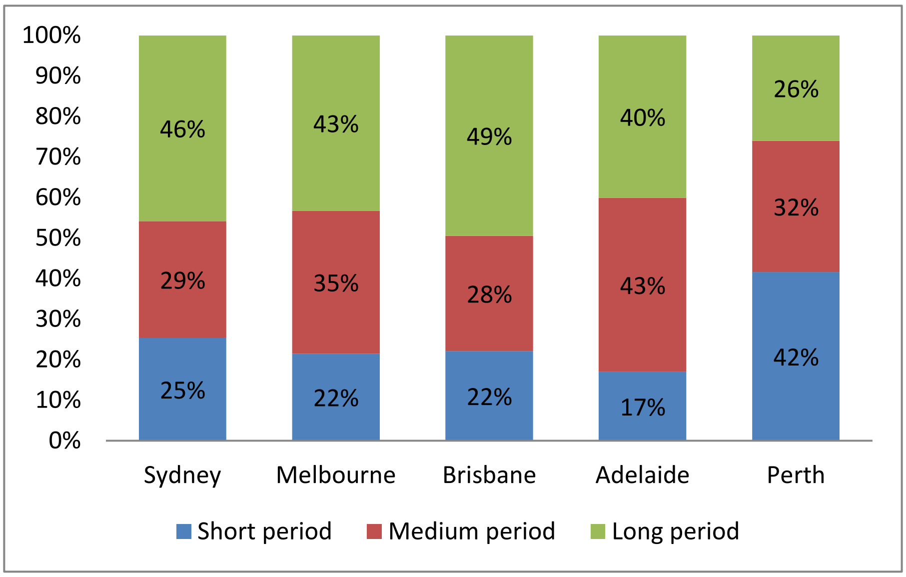

Figure A.4 In-vehicle time of the most recent train trip; short period for less than 15 minutes, medium period for between 15 and 30 minutes, and long period for more than 30 minutes.

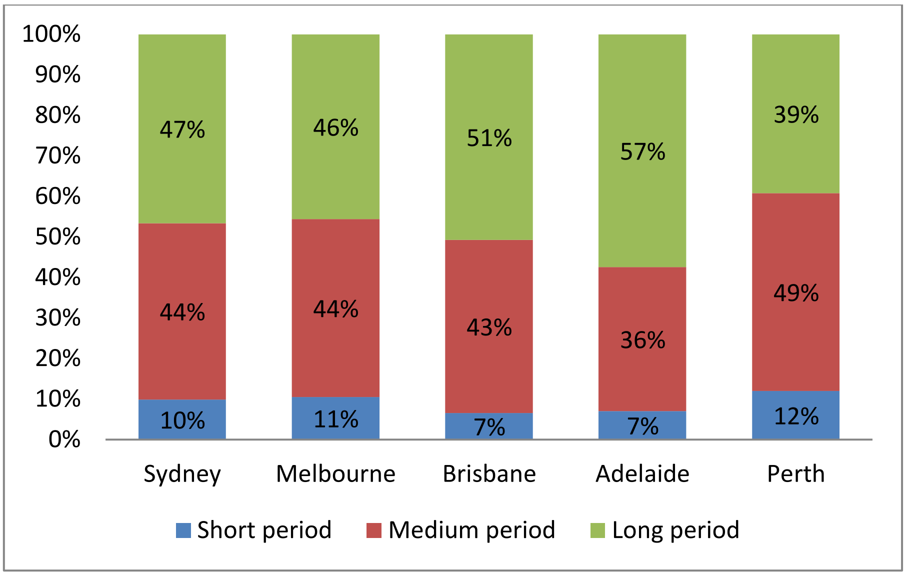

Figure A.5 Out-vehicle time of the most recent train trip; short period for less than 15 minutes, medium period for between 15 and 30 minutes, and long period for more than 30 minutes.

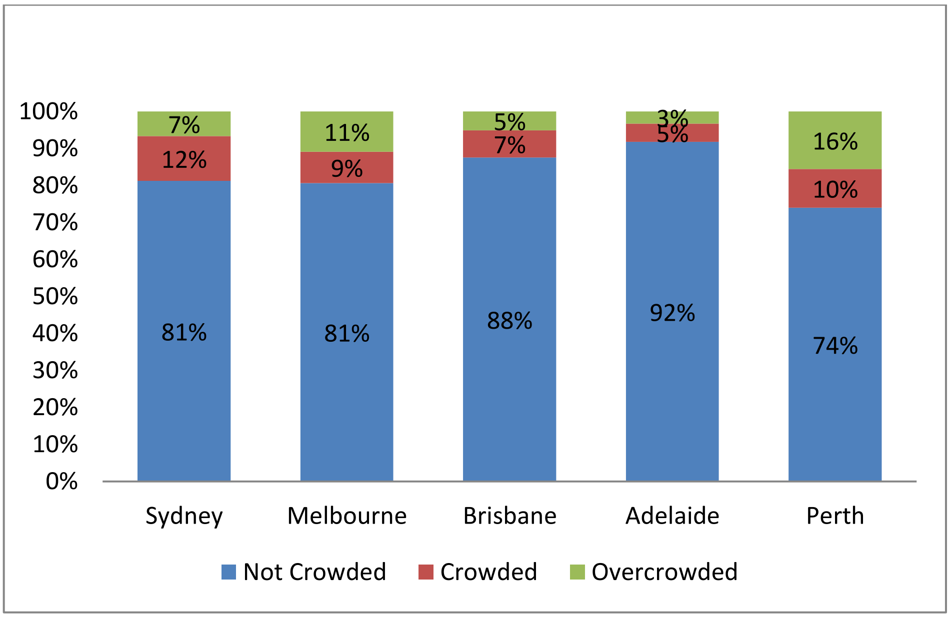

Figure A.6 Crowdedness of the most recent train trip