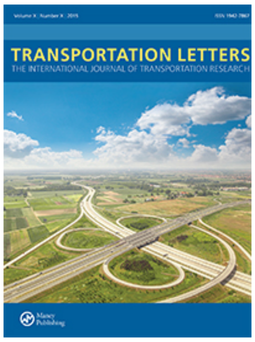

Taylor & Francis
Taylor & Francis Group

Transportation Letters
The International Journal of Transportation Research

ISSN: 1942-7867 (Print) 1942-7875 (Online) Journal homepage: http://www.tandfonline.com/loi/ytrl20

An empirical investigation of values of travel time savings from stated preference data and revealed preference data

Zheng Li, David A. Hensher & Chinh Ho

TRANSPORTATION LETTERS
https://doi.org/10.1080/19427867.2018.1546806

Taylor & Francis
Taylor & Francis Group

An empirical investigation of values of travel time savings from stated preference data and revealed preference data

Zheng Li[a], David A. Hensher[b] and Chinh Ho[b]

[a]School of Finance, Xi'an Eurasia University, Xi'an, China; [b]Institute of Transport and Logistics Studies, The University of Sydney Business School, The University of Sydney, Sydney, Australia

ABSTRACT

A number of studies have found that the willingness-to-pay (WTP) results estimated from revealed preference (RP) and stated preference (SP) data tend to be different. In this paper, we empirically estimate values of travel time savings from an SP data set and an RP data set and compare the findings within this study and between studies. The evidence shows that the design of a stated choice experiment has a significant impact on the ratio of SP and RP WTP values and reveals that presenting a full distribution of travel time to address random travel time variation in the choice scenarios, along with using a real market reference alternative as a pivot in the SP design, significantly reduces the gap between values of travel time savings estimated from SP data and RP data.

KEYWORDS

Travel behavior; stated preference; revealed preference; hypothetical bias; stated choice; value of travel time savings; commuting

Introduction

Revealed preference (RP) and stated preference (SP) data have been used for capturing behavioral responses in choice setting. RP data are typically collected by observing choices made in actual situations or by conducting field experiments. In SP experiments, individuals are usually asked to choose the alternative for a set of labeled nor unlabeled alternative with predefined attributes and levels that they most prefer according to a statistical design. Compared with RP data, SP data have a number of advantages including the ability of predicting responses to new products (e.g. metro) or policies (e.g. congestion charging), as well as providing more robust parameter estimates given sufficient variation in the explanatory variables (Louviere, Hensher, and Swait 2000). Ortúzar and Willumsen (2011) highlighted another limitation of RP; that is, observed behavior may be dominated by a few attributes. However, a major concern about SP data is whether hypothetical choice data can replicate the choice situation observed in real markets (Small, Winston, and Yan 2005).

An important output of both SP and RP studies in the field of transport economics is the value of travel time savings (VTTS), the dominant user benefit in project appraisal. In the transport literature, two influential studies, Small, Winston, and Yan (2005) and Isacsson (2007), have drawn the conclusion that SP delivers lower willingness-to-pay (WTP) values compared to RP. The difference between the results estimated from SP and RP data is commonly referred to as a source of hypothetical bias (Hensher 2010). However, the evidence is mixed in the transport literature (see, e.g. Wardman 1988) and the broader literature (see, e.g. Hensher 2010). Further discussion on this topic is needed, in particular in the context of valuing travel time saving where the empirical findings are limited.

The primary aim of this paper is to add new evidence to this important research topic. Compared to Small, Winston, and Yan (2005) with passenger cars only and Isacsson (2007) with public transport only, this study presents empirical VTTS for both car travel and public transport. In addition, this paper investigates the influence of designing choice experiments on hypothetical bias, especially a pivot design vs. non-pivot design, and with the full illustration of possible travel scenarios for a future trip where each scenario has the minutes of travel time and the associated probability of occurrence vs. without such a full distribution. Last but not least, we have accommodated unobserved between-individual preference heterogeneity within a mixed multinomial logit (MMNL) framework.

This paper is organized as follows: The next section introduces the SP data used in this study, followed by the RP data. The SP and RP models are then estimated separately within an MMNL framework. The comparison of SP and RP findings in this study is presented, followed by a comparison between this study and other studies. The comparison reveals the impact of the design characteristics on hypothetical bias. The final section highlights the key findings of this study.

Stated preference data used in this study

The SP data are drawn from a study (Hensher et al. 2011) undertaken in Sydney in 2009 to identify the patronage potential of a proposed metro rail system for Sydney, where commuting, non-commuting, and employer-business trips were sampled. The SP models in this paper only use the segment of commuters with a sample size of 524, in which the average annual income is AU $68,160.8 in 2009AU$ and the average age is 45.4 years.

The choice experiment is in the context of modal choice (car vs. public transport such as rail) and a proposed metro as shown to respondents using the screen reproduced in Figure 1. Any one respondent, however, is limited to choosing among a maximum of two existing alternatives plus the proposed metro. The survey itself was undertaken using a computer-aided programmed interview with respondents asked to provide information, either real or perceived, associated with relevant alternatives for a recent trip that they undertook. The SP experiment then 'pivots' the attribute levels of the various alternatives, where a pivot from the reference trips makes sense. The attributes to pivot are the travel times and

CONTACT Zheng Li lzesse@hotmail.com School of Finance, Xi'an Eurasia University, No.8 Dongyi Road, Yanta District, Xi'an, Shaanxi 710065, China

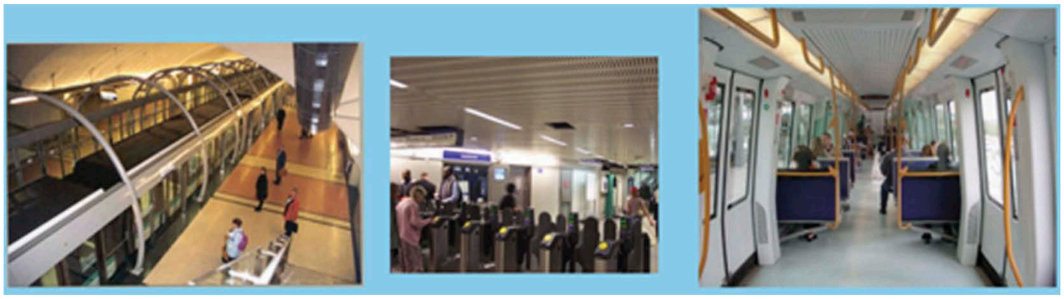

Figure 1. Illustration of proposed metro.

costs. Each sampled respondent evaluated six choice profiles, choosing among a maximum of two stated choice alternatives defined by existing alternatives plus the metro, including car, bus, light rail, cityRail, and the proposed metro. An example choice scenario screen is shown in Figure 2 for metropolitan-wide trips. For a full description of the design and characteristics of the experiment, see Hensher et al. (2011).

In this design, car travel has three scenarios (the length of travel time and the associated probability of occurrence) for a trip – 'quickest travel time,' 'travel time on average' (that is, normal travel time),[1] and 'slowest travel time.' Respondents were advised that *departure time remains unchanged* and that each of the reported trip times is associated with a corresponding probability of occurrence to indicate that travel time is not fixed but varies from time to time. The survey firm that collected the data had an interviewer present to explain what this meant for each respondent. For example, Figure 2 illustrates that if the car mode was chosen, the respondent would face a travel time distribution: 47 min with the probability of occurrence of 0.4, 51 min with the probability of 0.4, and 63 min with the probability of 0.2. The interviewer also explained what this meant for each respondent. For example, the 40% associated with 47-min quickest time for car alternative was explained as 'for every 10 trips you might take, 4 out of the 10 trips had a travel time of 47 min'. For rail modes, a single trip time[2] is emphasized, on the reasonable assumption that the existing rail system and the proposed new metro are not influenced by traffic levels; however, in reality, rail is not 100% reliable in terms of travel time for repeated experiences.

Revealed preference data used in this study

The RP data used for this analysis are the Sydney Household Travel Survey (HTS) pooling from three waves such as 2007/2008, 2008/2009, and 2009/2010. The Sydney HTS, administered by the Bureau of Transport Statistics (BTS), was first conducted in 1997/1998 and has been running continuously since then with approximately 3500 households being surveyed annually in face-to-face interviews. Each wave includes a survey of household

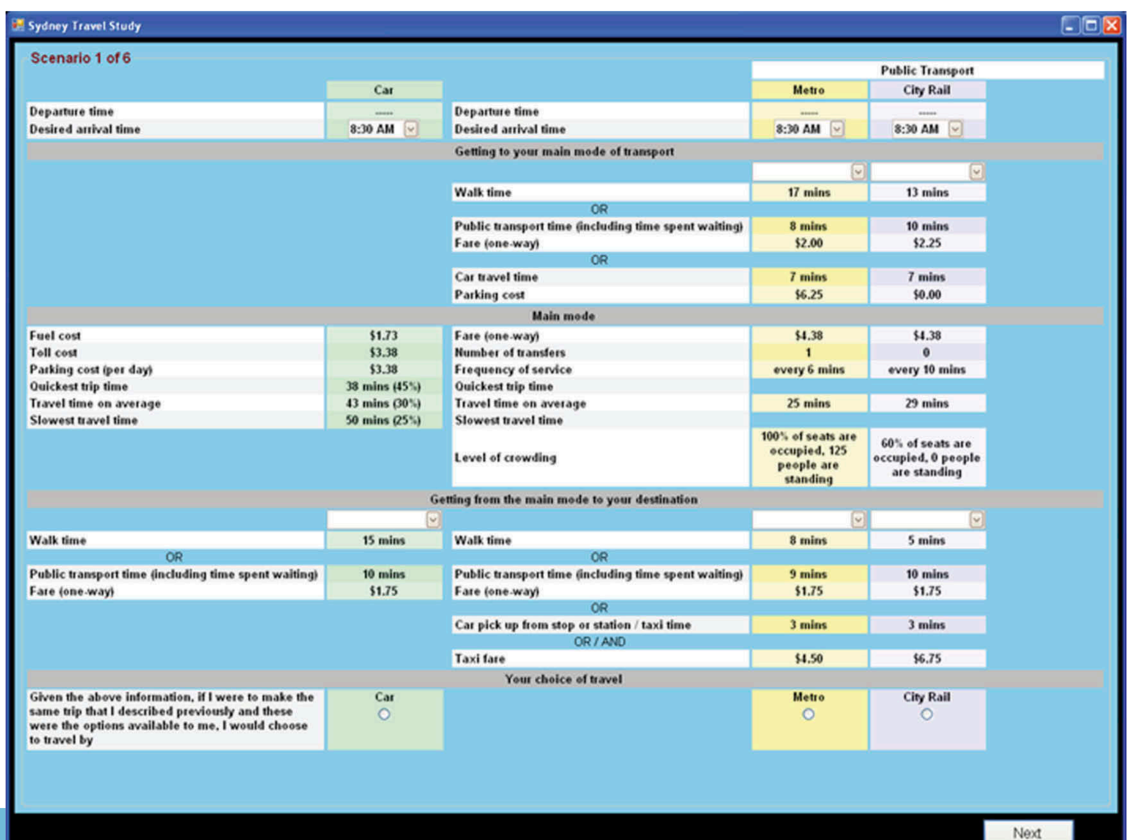

Figure 2. One actual metro-wide choice scenario screen.

characteristics, person characteristics, and a 24-h travel diary for each participant. This website gives full details of sampling, method, and data management (https://www.transport.nsw.gov.au/performance-and-analytics/passenger-travel/surveys/household-travel-survey-hts).

The HTS data are supplemented by data obtained from the Sydney Strategic Travel Model (STM), specifically the level of service including time and cost. This is obtained from the skim[3] matrices which give estimates of inter-zonal travel times and distances on an average weekday for the car mode by four periods of the day (am-peak, inter-peak, pm-peak, and evening) and all public transport-combined modes in am-peak, for 2690 travel zones in the Sydney Metropolitan Area. Technical documentation and standard outputs of the Sydney STM are provided in BTS (2011). Although the Sydney HTS data classify public transport modes into train, bus, ferry, and light rail, the empirical model has been constrained from splitting PT modes by the lack of skim matrices for separate PT mode because the Sydney STM combines all PT modes into one for assignment purposes (i.e. STM uses multi-modal assignment model instead of mode-specific assignment models). After cleaning the data and excluding weekend travel, the three years of pooled data provided 4219 motorized[4] commuting trips for analysis, consisting of 999 PT trips (23.7%) and 3220 car trips (73.6% for the Sydney Metropolitan Area). A full description of the data can be found in Ho and Mulley (2013).

Stated preference and revealed preference results: mixed multinomial logit

Using the SP and RP data sets introduced in the sections on Stated preference data used in this study and Revealed preference data used in this study, the models are estimated within an MMNL framework, with results summarized in Tables 1 and 2, respectively.[5] The MMNL logit model is used to accommodate unobserved between-individual heterogeneity in the travel time parameters for car and public transport. The MMNL or random parameter logit (RPL) model [6] is the dominant approach to reveal unobserved preference heterogeneity, in particular in the transport field. Within a linear utility framework, the utility of alternative j for individual i can be written as:

$$U_{ji} = \alpha_{ji} + \boldsymbol{\beta}_{ji}\mathbf{x}_{ji} + \varepsilon_{ji} \tag{1}$$

where α_{ji} is an alternative-specific constant for alternative j and individual i; x_{ji} is a vector of attributes associated with alternative j for individual i; $\boldsymbol{\beta}_{ji}$ is a vector of parameters; and ε_{ji} is a random component that captures, through a series of assumptions (see below), the unobserved sources of preference heterogeneity that can be ascribed to attributes and alternatives. Within the mixed logit framework, random taste heterogeneity can be aligned to attributes through random parameters and to alternatives through error components.

Table 1. SP model-MMNL for commuting choice.

Variable	Mode	Parameter	t-Ratio
Non-random parameters			
Fare (2009AU$)	PT	−0.260	−9.30
Travel cost (2009AU$)	Car	−0.159	−9.03
Headway (minutes)	PT	−0.014	−5.36
Number of transfers	PT	−0.170	−3.57
Crowding (#standing)	PT	−0.004	−6.47
Means for random parameters			
In-vehicle travel time (minutes)	PT	−0.064	−13.81
In-vehicle travel Time (minutes)	Car	−0.060	−3.67
Spreads for random parameters			
In-vehicle travel time (minutes)	PT	0.064	13.81
In-vehicle travel Time (minutes)	Car	0.060	3.67
Model fits			
Log-likelihood at convergence		−1978.63	
McFadden pseudo R-squared		0.55	
Number of observations		3144	

Table 2. RP model-MMNL for commuting choice[7].

Variable	Mode	Parameter	t-Ratio
Non-random parameters			
Travel cost (2008AU$)	PT and car	−0.142	−6.74
No-car household	PT	3.704	7.73
Car-negotiating household	PT	1.330	5.86
Flexible work time	PT	1.382	2.28
PT fare provided	PT	2.861	4.18
Free parking provided	PT	−2.550	−9.26
Fuel cost provided	PT	−4.835	−9.63
License holder	PT	−4.783	−9.76
Constant	PT	5.521	9.75
Means for random parameters			
In-vehicle travel time (minutes)	PT	−0.012	−3.14
In-vehicle travel time (minutes)	Car	−0.057	−8.51
Wait time (minutes)	PT	−0.236	−10.39
Spreads for random parameters			
In-vehicle travel time (minutes)	PT	0.012	3.14
In-vehicle travel Time (minutes)	Car	0.057	8.51
Wait time (minutes)	PT	0.236	10.39
Model fits			
Log-likelihood at convergence		−2309.52	
McFadden pseudo R-squared		0.57	
Number of observations		4219	

The MMNL model with all components in choice setting t is given in Equation (2) (see Greene and Hensher 2007).

$$Prob(y_{it} = j) = \frac{\exp\left[\alpha_{ji} + \boldsymbol{\beta}'_i x_{jit} + \Sigma_{m=1}^{M} d_{jm}\theta_m E_{im}\right]}{\sum_{q=1}^{J_i} \exp\left[\alpha_{qi} + \boldsymbol{\beta}'_i x_{qit} + \Sigma_{m=1}^{M} d_{qm}\theta_m E_{im}\right]} \tag{2}$$

$(\alpha_{ji}, \boldsymbol{\beta}_i) = (\alpha_j, \boldsymbol{\beta}) + \Gamma\Omega_i v_i$ are random alternative-specific constants and taste parameters; $\boldsymbol{\Omega}_i$ = diag(σ_1,…,σ_k); and $\boldsymbol{\beta}$,α_{ji} are constant terms in the distributions of the random taste parameters. Uncorrelated parameters with homogeneous means and variances are defined by $\boldsymbol{\beta}_{ik} = \boldsymbol{\beta}_k + \sigma_k v_k$ when $\boldsymbol{\Gamma}$ = **I**, $\boldsymbol{\Omega}_i$ = diag(σ_1,…,σ_k), x_{jit} are observed choice attributes and individual characteristics, and $\mathbf{v}_i$ is random unobserved taste variation, with mean vector **0** and covariance matrix **I**. This model accommodates correlated parameters with homogeneous means through defining $\boldsymbol{\beta}_{ik} = \boldsymbol{\beta}_k + \Sigma_{s=1}^{k}\boldsymbol{\Gamma}_{ks}v_{is}$ when $\boldsymbol{\Gamma} \neq \mathbf{I}$, and $\boldsymbol{\Omega}_i$ = diag(σ_1,…,σ_k), with $\boldsymbol{\Gamma}$ defined as a lower triangular matrix with ones on the diagonal that allows correlation across random parameters when $\boldsymbol{\Gamma} \neq \mathbf{I}$. An additional layer of individual heterogeneity can be added to the model in the form of the error components. The individual-specific underlying random error components are introduced through the term E_{im}, m = 1,…,M, E_{im} ~ N[0,1], given d_{jm} = 1 if E_{im} appears in utility for alternative j and 0 otherwise, and θ_m is a dispersion factor for error component m.

The random parameters are applied to the travel time variables for car and public transport. With regard to the cost parameter, it can also be random. However, there is a large literature (e.g. Revelt and Train 1998) that argues for keeping one of the parameters fixed in the ratio to derive WTP. Daly et al. (2012) have discussed this recently and have expressed concerns when both the numerator and denominator are random: 'some popular distributions used for the cost coefficient in random coefficient models, including normal, truncated normal, uniform and triangular, imply infinite moments for the distribution of WTP, even if truncated or bounded at zero' (p.19). Given the distributions that provided statistically and behaviorally acceptable parameter estimates (see below), the *cost* parameter is assumed to be non-random in the

MMNL models (both SP and RP) in order to avoid the potential problems associated with taking the ratio of two random variables, following the advice of Sillano and Ortuzar (2005). Different distributions were tested for the random parameters[8]; however, only the constrained triangular distribution[9] delivered behaviorally meaningful VTTS ranges. The MMNL models also take into account the panel nature of the SP data in which a respondent answered six choice tasks (i.e. Panel MMNL).

All parameter estimates are statistically significant at the 95% confidence level. The mode-specific constant for all public transport modes (relative to the car-specific constant set to 0) is not statistically significant in the SP model and hence was not reported in Table 1. The parameter estimates are negative as expected which suggests that headway (minutes per service), the number of transfers, crowding in terms of the number of standing passengers in a train/metro carriage or bus, and PT fares are sources of disutility for public transport users, as well as travel time and cost (i.e. fuel cost + toll cost + parking cost) for car users. The focus of this paper is to statistically compare the empirical VTTS values estimated for the SP model (Table 1) and the RP model (see Table 2). Given that SP and RP data were collected in different years: 2009 and 2008, respectively, all original monetary values are converted into a common year of 2016 (2016AU$) based on the Australian Consumer Price Index. On average, each PT user is willing to pay $16.74 in 2016AU$ to reduce one hour's in-vehicle travel time (standard deviation = 7.03), while each car user is willing to pay 2016 AU$26.62 to reduce one hour's in-vehicle travel time (standard deviation = 10.88).

For the RP model, the parameters associated with the time variables were drawn from a constrained triangular distribution with the mean parameter equal to its spread, the same as the SP model. The RP model is shown in Table 2. All estimated standard deviations are highly statistically significant, indicating that the effect of travel time and wait time on the choice of commuting mode varies greatly in the population (preference heterogeneity is present). Also, the likelihood ratio test at the 1% level of significance indicates that the explanatory power of the MMNL is significantly higher than with the standard logit model (with fixed parameters).

We tested alternative-specific cost parameters for car and public transport; however, the estimated cost parameter is not statistically significant, and a generic cost parameter for car and PT delivered a statistically significant parameter estimate. Given this, the RP model treated travel cost as a generic fixed parameter for car and PT travel. The estimated travel cost parameter has the expected sign and is of reasonable magnitude relative to the time parameters. On average, each PT user is willing to pay $6.86 in 2016AU$ to reduce one hour's in-vehicle travel time (standard deviation = 0.14), while each car user is willing to pay 2016 AU $29.71 to reduce one hour's in-vehicle travel time (standard deviation = 2.57).[10] The estimated VTTS for car users are in line with the values derived from RAND's models for STM version 3 in which VTTS for car driver ranges from V16.65 to 29.09 (after converting from 2011AU$ to 2016AU$ using Australia consumer price index) for commuting and work-related purposes (Fox and Bhanu 2015). RAND's estimates of VTTS for bus and train users are higher, at around AU2016$11–12 per hour.

Comparing the stated preference and revealed preference findings

The VTTS estimates from the SP model (Table 1) and the RP model (Table 2) are summarized in Table 3. For car travel, the SP model and the RP model deliver similar mean VTTS values: 2016AU $26.62 and 2016AU$29.71 per person hour, an SP/RP ratio of 0.90. However, for public transport, the mean VTTS estimates from SP and RP are 2016AU$16.74 and 2016AU$6.86 per person hour, respectively, i.e. an SP/RP ratio of 2.44. In the SP experiment, the full distribution of travel time is presented to the choice respondents. Therefore, given a departure time, a car commuter may arrive earlier, on time, or later. However, such information is not shown for rail and metro modes.

For the SP experiments which have not included a full distribution of possible travel scenarios, their estimated VTTS values may be biased (Li 2012). In this study, a full distribution of car travel time is presented to respondents explicitly and appropriately: i.e., multiple travel times for each car trip to reflect the stochastic nature of uncertain travel time and the clear description used to describe the travel time distribution.

Table 3. Comparison of the mean VTTS values from the SP and RP models (2016AU$ per person hour).

SP study Year of study: 2009 Location: Sydney Trip purpose: Commuting		*RP study Year of study: 2008 Location: Sydney Trip purpose: Commuting*	
PT (in-vehicle time per person hour)	Car (in-vehicle time per person hour)	PT (in-vehicle time per person hour)	Car (in-vehicle time per person hour)
2016AU$16.74 (7.03)	2016AU$26.62 (10.88)	2016AU$6.86 (0.14)	2016AU$29.71 (2.57)

The standard deviations of VTTS estimates are given in the parentheses.

Comparison with existing evidence

In the transport economics literature, the study by Small, Winston, and Yan (2005) is arguably the most influential study that investigated hypothetical bias empirically.[11] In Small et al.'s RP study, travel information on the free lanes of State Road 91 was collected on 11 different days, and local linear regression was used to smooth data and to estimate the mean and percentiles of the distribution at different times between 06:00 a.m. and 10:00 a.m. It is assumed that the travel time for using tolled lanes is constant (8 min). The median time savings from tolled lanes are estimated relative to using free lanes.

In Small et al.'s RP setting, travel time is presented by the median of the actual distribution, while the unreliability of travel time is measured by the difference between the 80th and the 50th percentiles. For the SP setting, each respondent answered eight choice sets with similar variables to those in the RP survey. Their SP experiments (see Table 4) have the following attributes: usual travel time, toll, and the frequency of being late at the destination by 10 min or more. Small, Winston, and Yan (2005) only presented the scenario of arriving late,

Table 4. A choice example from Small, Winston, and Yan (2005).

Free lanes	Express lanes
Usual travel time: 25 min Toll: none Frequency of unexpected delay of 10 min or more: 1 day in 5	Usual travel time: 15 min Toll: $3.75 Frequency of unexpected delay of 10 min or more: 1 day in 20
Your choice (check one):	
Free lanes	Toll lanes

Table 5. Choice example from Isacsson (2007).

	The bus that departs at 08:30 a.m.	The bus that departs at 08:15 a.m.
Travel time	25 min	40 min
Cost	50 SEK	25 SEK
Your choice		

Table 6. Comparison of three studies.

	This study	This study	Small, Winston, and Yan (2005)	Isacsson (2007)
Mode	Car	PT	Car	PT
SP design	Pivot	Pivot	Non-pivot	Non-pivot
Whether a full travel time distribution shown in SP experiments	Presented	Not presented	Partial distribution (no arriving earlier)	Not presented
SP/RP VTTS ratio	0.90	2.44	0.56	0.47

while the full distribution of possible travel times for a trip is not presented in their SP experiment.

Another study that empirically investigates hypothetical bias is Isacsson (2007). In this study, RP and SP experiments are constructed to compare hypothetical and real choices in the context of bus travel, and a choice example is shown in Table 5. Unlike Small, Winston, and Yan (2005) where a partial travel time distribution is shown as the frequency of being late at the destination by 10 min or more, only one travel time per bus trip is shown in Isacsson's choice experiment. The former is incomplete and the latter is unrealistic given that travel time may vary from time to time resulting in the possibility of arriving earlier, on time, or later than the planned arrival time given a departure time. Both Small, Winston, and Yan (2005) and Isacsson (2007) estimated much lower VTTS estimates when using SP compared to using RP.

Table 6 summarizes the characteristics and findings of Small, Winston, and Yan (2005), Isacsson (2007), and this study. This study is established in the context of car and public transport, while Small et al. focused only on car in a route choice context and Isacson on bus, what makes this research interesting is the focus on mode choice as a way of seeing if the evidence from car and bus only studies has general support in a mode choice context. In terms of the experimental design, this study applies a pivot design (not for metro as it does not exist), in which stated choice alternatives are pivoted around the knowledge base of travelers; however, other two studies are not based on pivot design. Hensher (2010, 735) finds that the role of referencing of an experiment relative to a real experience (including evidence from RP studies), in the design of choice experiments, appears to offer promise in the derivation of estimates of WTP that have a meaningful link to real market activity and strongly suggests that the use of pivot design in choice experiments to reduce the gap between WTP outputs estimated from RP and SP.

In this study's SP experiment, a full travel time distribution is used, which is behaviorally more realistic than Small, Winston, and Yan (2005). The unavoidable variation in travel time is ignored in Isacsson (2007), like public transport in this study, which has a significant impact on travelers' decision-making, and the inappropriate representation or ignorance of it in choice experiments would lead to biased WTP results (Bates et al. 2001; Bhat and Sardesai 2006; Hollander 2006; Asensio and Matas 2008). With respect to the ratio of SP/RP VTTS (SP VTTS divided by RP VTTS), this study produces a value of 0.90 for car travel, which is the closest to '1' among three studies, suggesting the smallest gap between SP and RP WTP estimates, compared to 2.44 for public transport in the current study where travel time variation is ignored, 0.56 for Small, Winston, and Yan (2005) where a partial distribution of travel time is presented, and 0.47 for Isacsson (2007) where travel time variation is ignored. For SP, only the car mode in this study uses a pivot design and shows the travel time distribution simultaneously, so that the SP context herein is closer to the real decision environment compared to the other two studies. This results in a VTTS value from SP that is closest to the RP estimate, an SP/RP ratio of 0.9, which would in turn deliver more realistic forecasts of demand if the RP setting is deemed an appropriate benchmark. Moreover, Table 6 also suggests that a full travel time distribution per trip presented in the stated choice task has a stronger effect on reducing the gap between SP and RP VTTS estimates compared to a pivot design.

Conclusions

Whether SP data and models are associated with hypothetical bias is a hot debate in the literature. The evidence is mixed across studies. Even in this single study, we have contradictory findings by comparing the VTTS values estimated from an SP data set and an RP data set (assuming RP has no hypothetical bias). For the car mode, SP delivers a similar WTP value compared to RP with an SP/RP ratio being 0.90. However, the SP VTTS value is significantly higher than the corresponding RP value for PT modes, which is the opposite of the existing evidence (e.g. Small, Winston, and Yan 2005; with an SP/RP ratio being 0.56 for car and Isacsson 2007; with a ratio being 0.47 for PT). The comparison within this study and between studies indicates that presenting a full distribution of travel time in the choice tasks, along with using a real market reference alternative as a pivot in the SP design, has contributed to closing the gap between the SP and RP WTP values. These two design characteristics appear to play an important role in behavioral realism, which must be addressed simultaneously. The evidence suggests that an SP approach is capable of producing behaviorally meaningful WTP outputs, if the experimental design was conducted in a realistic and relevant manner. Other useful approaches to reduce hypothetical bias are recommended by Hensher (2010), for example, clear explanation of the study objectives, inclusion of null alternative, and inclusion of supplementary questions.

Notes

1. For this study, 'travel time on average' in the choice task should be better represented as 'normal travel time.' For example, for car travel, we use normal travel time in modeling, for example, 51 min as shown in Figure 2, not the calculated average.
2. In reality, the travel time for rail would vary; however, this variation is much less significant compared to road transport such as bus and car.
3. Skim refers to a set of outputs (time, cost, distance, toll, transfer, etc.) generated by Strategic Travel Models when traffic assignment models have converged (equilibrium has been obtained).
4. For long trips, the shares of walk-only and cycling trips are very small; walk-only and cycling trips were removed from the analysis. Walk and cycling as an access or egress mode to PT services are included as a trip legs on PT trips. For long trips, the shares of walk-only and cycling trips are very small.
5. Both the SP and RP models were estimated using Nlogit5, with 500 Halton draws. Starting values for mixed logit are MNL values. The convergence criteria is the gradient g'H$\boldsymbol{g}$ < ε_g where $\boldsymbol{g}$ is the current derivative vector and H is the inverse of the current Hessian.
6. The original formulation of RPL was made much earlier Ortúzar and Willumsen (2011).
7. For example, under the normal distributions, the VTTS range includes negative values, while under the lognormal distributions, the VTTS range for PT travel is also behaviorally implausible (i.e. AU\$0.1–7075.3 per person hour).
8. Let c be the center and s be the spread (i.e. half the range). The density starts at c-s, rises linearly to c, and then drops linearly to c+s. It is zero below c-s and above c+s. The mean and mode are c. The standard deviation is the spread divided by $\sqrt{\sigma}$; hence, the spread is the standard deviation times $\sqrt{\sigma}$. The height of the tent at c is 1/s (such that each side of the tent has area $s \times (1/s) \times (1/2) = 1/2$, and both sides have area $1/2 + 1/2 = 1$, as

required for a density). The slope is $1/s^2$. For a constrained distribution, the mean parameter is constrained to equal its spread (i.e. $\beta_{jk} = \beta_k + |\beta_k|\ T_j$, and T_j is a triangular distribution ranging between −1 and +1), and the density of the distribution rises linearly to the mean from zero before declining to zero again at twice the mean. Therefore, the distribution must lie between zero and some estimated value (i.e. the β_{jk}). When a constrained triangular distribution is used, the reported standard deviation parameter is the spread parameter. The mean and spread are the same under a constrained triangular distribution.

9. There are statistically significant parameter estimates for each mode as alternative specific or as generic parameters. They also have a meaningful sign. What is comforting is the significant absolute higher marginal disutility for waiting time compared to in-vehicle travel time. Also, the VTTS for PT in-vehicle time is in the range that makes sense.
10. Wardman (1988) used a survey conducted in 1983 in which the SP response (873 respondents in total) was based on a five-point scale: definitely prefer coach, probably prefer coach, no preference between coach and train, probably prefer coach, and definitely prefer coach. Wardman compared values of time estimated from the SP and RP models and found that there was no significant difference between RP and SP values of main mode in-vehicle time, but an SP/RP VTTS ratio of 2.24 for other mode in-vehicle time.
11. 'Flexible work time, PT fare provided, Free parking provided, Fuel cost provided' are a set of dummy variables describing the fringe benefits provided to the worker by their employers. For model identification, these variables should be included in either PT or car utility, not both (i.e. they do not vary by alternative mode). We could specify these variables in the car utility, and the sign of the variables will be reversed. The negative parameters associate with 'free parking provided' suggests that when workers are provided with free parking, they are less likely to commute by PT, which is expected. Similarly, license holders are less likely to be PT commuters because its parameter is negative.

Acknowledgments

We thank NSW (New South Wales) Bureau of Transport Statistics for allowing us using the RP data set. We also thank Professor John Rose for his innovative stated choice design. This paper is funded by Xi'an Eurasia University Research Group Foundation. The valuable comments of the editor and reviewers significantly improve this paper.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Asensio, J., and A. Matas. 2008. "Commuters' Valuation of Travel Time Variability." *Transportation Research Part E* 44 (6): 1074–1085. doi:10.1016/j.tre.2007.12.002.

Bates, J., J. Polak, P. Jones, and A. Cook. 2001. "The Valuation of Reliability for Personal Travel." *Transportation Research Part E* 37 (2-3): 191–229. doi:10.1016/S1366-5545(00)00011-9.

Bhat, C. R., and R. Sardesai. 2006. "The Impact of Stop-Making and Travel Time Reliability." *Transportation Research B* 40 (9): 709–730. doi:10.1016/j.trb.2005.09.008.

BTS. 2011. *Sydney Strategic Travel Model (STM): Modelling Future Travel Patterns*. BTS, Sydney, Australia: NWS Government.

Daly, A.J., S. Hess, B. Patruni, D. Potoglou, and C. Rohr. 2012. "Using Ordered Attitudinal Indicators in a Latent Variable Choice Model: a Study Of The Impact Of Security on Rail Travel Behaviour." *Transportation* 39 (2): 267–297. doi:10.1007/s11116-011-9351-z.

Fox, J., and P. Bhanu. 2015. "STM3 2011 Base Frequency, Mode-Destination and Car Ownership Models." No. RR-1125-BTS. Cambridge, UK: RAND Corporation.

Greene, W. H., and D. A. Hensher. 2007. "Heteroscedastic Control for Random Coefficients and Error Components in Mixed Logit." *Transportation Research Part E* 43 (6): 610–623. doi:10.1016/j.tre.2006.02.001.

Hensher, D. A. 2010. "Hypothetical Bias, Choice Experiments and Willingness to Pay." *Transportation Research Part B: Methodological* 44 (6): 735–752. doi:10.1016/j.trb.2009.12.012.

Hensher, D. A., J. M. Rose, and A. T. Collins. 2011. "Identifying Commuter Preferences for Existing Modes and a Proposed Metro in Sydney, Australia With Special Reference to Crowding." *Public Transport-planning and Operations* 3 (2): 109–147. doi:10.1007/s12469-010-0035-4.

Ho, C., and C. Mulley. 2013. "Multiple Purposes at Single Destination: A Key to a Better Understanding of the Relationship between Tour Complexity and Mode Choice." *Transportation Research Part A: Policy and Practice* 49 (1): 206–219.

Hollander, Y. 2006. "Direct versus Indirect Models for the Effects of Unreliability." *Transportation Research Part A* 40 (9): 699–711.

Isacsson, G. 2007. *The Trade-off between Time and Money: Is There a Difference between Real and Hypothetical Choices?* Borlange, Sweden: Swedish National Road and Transport Research Institute.

Li, Z. 2012. "The Role of Alternative Behavioural Theories in Valuing Travel Time Savings and Travel Time Variability." PhD Thesis, University of Sydney.

Louviere, J. J., D. A. Hensher, and J. Swait. 2000. *Stated Choice Methods: Analysis and Applications*. Cambridge: Cambridge University Press.

Ortúzar, J., D. de, and L. G. Willumsen. 2011. *Modelling Transport*. 4th ed. Chichester, UK: Wiley.

Revelt, D., and K. Train. 1998. "Mixed Logit with Repeated Choices: Households' Choices Of Appliance Efficiency Level." *Review Of Economics and Statistics* 80 (4): 647-657. doi:10.1162/003465398557735.

Sillano, M., and J. de Dios Ortúzar. 2005. "Willingness-To-Pay Estimation with Mixed Logit Models: Some New Evidence." *Environment and Planning A* 37 (3): 525–550. doi:10.1068/a36137.

Small, K. A., C. Winston, and J. Yan. 2005. "Uncovering the Distribution of Motorists Preferences for Travel Time and Reliability: Implications for Road Pricing." *Econometrica* 73 (4): 1367–1382. doi:10.1111/j.1468-0262.2005.00619.x.

Wardman, M. 1988. "A Comparison of Revealed Preference and Stated Preference Models of Travel Behaviour." *Journal of Transport Economics and Policy* 22 (1): 71–91.