Estimation of New Monetary Valuations of Travel Time, Quality of Travel, and Safety for Singapore

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A large-scale study in Singapore estimated new monetary valuations for travel time, quality of travel, and safety covering different modes and journey components. A wide-ranging stated-choice survey was conducted on a large, representative sample. The empirical work pushed the boundaries of the international state of the practice in choice modeling by relying on mixed logit models with all model components being random and a full covariance matrix being estimated. Detailed results are presented, and the values are contrasted with those from the previous study, conducted in 2008.

The Land Transport Authority (LTA) is the government agency tasked with the development and regulation of Singapore's land transport system. In common with many other such agencies around the world, LTA uses cost–benefit analysis as part of its overall appraisal framework in determining the merits of new transport policies and infrastructure developments. For this analysis, social benefits such as travel time savings, reliability improvements, crowding reduction, and accident cost savings need to be quantified. Willingness-to-pay (WTP) measures are critical inputs into this process, and in common with many other nations, LTA uses values produced through the estimation of discrete choice models on stated-preference data (*1–4*).

With the major societal, economic, and environmental implications of new policy and infrastructure schemes, it is important that these WTP measures have a high level of reliability. This requirement means that the values should be updated at regular intervals given not only the changing nature of transport systems and travel behavior but also ongoing improvements to survey and modeling approaches.

Because the most recent WTP estimates date from 2008, LTA commissioned a new study in 2015, with a large-scale data collection effort and the estimation of advanced choice models; these models offered improvements in flexibility over those used in 2008. What sets the resulting study apart is the relative size of the sample compared with the population of Singapore, the breadth of modes and journey components covered, and the use of a highly flexible treatment of heterogeneity. This last point ensures a methodological contribution in addition to the development of new results for policy work.

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SURVEY WORK

Sampling

A total of 5,000 households were selected for interview between May and November 2015, representing a very large sample from a population of around 5.6 million people. Quotas were developed by travel mode, journey purpose, period of travel, age, and gender; this method ensured sufficiently large sample sizes for the modeling work for each mode as well as representative samples for other dimensions. The study sampled car, motorcycle, mass rapid transit (MRT), bus, and taxi users as well as pedestrians and cyclists.

The vast majority of interviews were carried out in respondents' homes using tablets. These data were supplemented with some observations from an island-wide intercept survey. On successful completion of a survey, each respondent was given a $10 online shopping voucher as a reward.

Before the analysis, the sample was compared with the 2012 household travel survey (HTS) data to test its representativeness. Although this comparison showed small discrepancies, such as a slightly higher percentage of 35- to 54-year-olds and female respondents in the survey, the overall match was also very good in terms of dwelling types, vehicle ownership, ethnic breakdown, employment status, and income distribution.

Survey Content and Design

Stated preference, and in particular stated choice (SC), is a widely used technique for value-of-time (VTT) research (*2*). Respondents are faced with a number of carefully designed hypothetical choice scenarios, in which two or more alternatives are described by key attributes such as travel time and travel cost, and respondents are asked to select their preferred option in each.

There is ongoing debate in the academic literature about the relative merits of simple and complex surveys. Much of the northern European evidence is based on the most simplistic surveys with two alternatives and two attributes [compare with the discussion by Hess et al. (*2*)]. However, the work in Australia especially tends to rely on at least three alternatives in each choice task, with often five or six attributes describing them (*5*). In the current work, a balance was struck between these two extremes. Although a binary context was retained, a larger number of attributes was used to describe these alternatives. With substantial differences across the various measures of interest (e.g., VTT versus value of safety), the choice tasks for each respondent were spread across different survey contexts, or games; this method also helped to reduce the respondent burden.

An overview of the different SC games is given in Table 1, where, for example, car users faced 15 choice tasks spread across three different games. For the majority of attributes, the researchers sought to increase the realism by pivoting the values presented to respondents around the attributes from a recent trip for that respondent. The actual designs were produced by using NGene (http://www.choice-metrics.com) with Bayesian D-efficiency as a criterion for the statistical properties of the designs (*6*), priors coming from the 2008 study (*7*), and avoidance of the inclusion of strictly dominant alternatives by using a regret measure (*8*). The majority of the games are of such standard nature that no details are required beyond those in Table 1. However, special attention is needed for accident games (CA1, MCA1, PA1, and CYA1), crowding games (MT1 and BT1), and the game for bus excess waiting time (BT2).

The purpose of the accident games is to derive a WTP measure for reducing the number of different types of accidents and hence also the WTP measure for reducing personal risk. A standard approach [e.g., that by Hensher et al. (*9*)] involves presenting respondents with a choice between two routes described in terms of travel time, the number of accidents by injury types, and some monetary cost, with the choice framed around a recent journey and accident rates presented, for example, as: "Number of deaths per year along the route." In the work by Hensher et al., this number goes from 0 to 5, which is of course very high for a single road (*9*).

In the case of Singapore, where the total number of accidents is far lower, presenting by road and route rates is even more unrealistic. There is also an issue with exposure because only part of someone's annual travel will be on this route, and a disconnect between the payment mechanism (per trip) and the accident numbers (per year). A per-journey cost also makes the method inapplicable for pedestrians and cyclists. Instead a programmed approach is relied on, in which the choice is between two national safety programs and the payment mechanism is a change in the annual tax burden. The two programs are described in terms of increases or decreases in tax (per year), along with annual figures for fatalities and serious and minor injuries.

MT1 and BT1 consider the sensitivity to in-vehicle travel time in different conditions: waiting time, walking time, and interchanges. Rather than a simple presentation of overall numbers for a journey and a single level of crowding, journeys are broken up into differently sized stages (Figure 1). The presentation allows for changes in crowding that are the result of either changing to a different bus or train or other passengers' joining or leaving the bus or train on which the respondent is already traveling.

BT2 is concerned with bus reliability. LTA uses the concept of excess wait time (EWT), in which, on the assumption of a uniform arrival rate of passengers, EWT is the average additional wait time actually experienced compared with the expected wait time if buses arrived at regular intervals. It is defined as the difference between actual wait time (AWT) and the scheduled wait time (SWT); that is, EWT = AWT − SWT:

$$\text{AWT} = \frac{\sum_n \text{actual headway}_n^2}{2 \times \sum_n \text{actual headway}_n}$$

$$\text{SWT} = \frac{\sum_n \text{scheduled headway}_n^2}{2 \times \sum_n \text{scheduled headway}_n} \tag{1}$$

EWT increases if there is bus bunching, which results in prolonged waits for the subsequent bus. Respondents had a choice between two future hypothetical bus services (Figure 2), for which the scheduled arrival time of the bus is shown every 10 min, along with the interval between buses for both options and the bus fare. It is assumed that buses arrive frequently enough that users forget the timetable; in other words, their arrival time at the bus stop is completely arbitrary.

TABLE 1 Summary of SC Games

Game	Description	Attributes	Choice Tasks
CT1	Car: congestion and costs	Free-flow travel time, light congestion, heavy congestion, parking cost, petrol cost, ERP cost	5
CT2	Car: parking choice	Walking time, queuing time, search time, parking cost	5
CA1	Car: accidents	Fatalities, serious and minor injuries per year, change in annual tax burden	5
MCT1	Motorcycle: congestion and costs	Free-flow travel time, light congestion, heavy congestion, parking cost, petrol cost, ERP cost	7
MCA1	Motorcycle: accidents	Fatalities, serious and minor injuries per year, change in annual tax burden	5
MT1	MRT: time and crowding	Walking time, waiting time, in-vehicle time in five crowding levels (3 seated, 2 standing), interchanges, fare	7
MT2	MRT: walking	Crossing type (at grade, uncovered bridge, covered bridge without lift, covered bridge with lift, air-conditioned underpass, covered and uncovered walking time to and from crossing, fare	7
BT1	Bus: time and crowding	Walking time, waiting time, in-vehicle time in five crowding levels (3 seated, 2 standing), interchanges, fare	7
BT2	Bus: excess waiting time	Bus arrival times, fare	7
TT1	Taxi: access, time, and costs	Walking time, waiting time, in-vehicle time, prebooked or on street, fare, booking fee	7
PT1	Pedestrian: walking environment	Crossing type (at grade, uncovered bridge, covered bridge without lift, covered bridge with lift, air-conditioned underpass, covered and uncovered walking time to and from crossing	7
PA1	Pedestrian: accidents	Fatalities, serious and minor injuries per year, change in annual tax burden	5
CYA1	Cycling: accidents	Fatalities, serious and minor injuries per year, change in annual tax burden	5

NOTE: ERP = electronic road pricing.

FIGURE 1 Example choice task for BT1.

MODELING FRAMEWORK

In the past four decades, choice models have undergone major developments in terms of flexibility, especially in terms of the presentation of heterogeneity in preferences across individual decision makers (*10*). As a result, there have been substantial improvements to the techniques used in VTT studies, most notably starting with the work in Denmark (*4*) and more recently in the context of the British VTT study (*2*). In what follows, the focus is only on what is relevant for the current study, largely because of space considerations.

In a random utility model, the utility U_{int} that individual n (out of N) obtains from choosing alternative i (out of I) in choice situation t (out of T_n) is decomposed into an observed component V_{int} and a random component ε_{int}. Almost all applications rely on an additive error structure, with $U_{int} = V_{int} + \varepsilon_{int}$, in which noise is independent of observed utility. Recent work by Fosgerau and Bierlaire has questioned this specification and put forward a multiplicative formulation, in which errors are proportional to observed utility, with $U_{int} = V_{int} \cdot \varepsilon_{int}$ (*11*). In practice, this formula implies more noise on longer trips, a notion that has received empirical support in the Danish (*4*) and British (*2*) national studies. The two specifications in early work were compared and no evidence was found of an improvement with the multiplicative structure, so the additive structure was retained. Part of the reason for the lack of improvement could be the smaller size of Singapore and the resulting much-reduced heterogeneity in trip distances.

Next, the specification of the observed component of utility is considered. Using the example of CT1, the following formula would be written:

$$V_{int} = \beta_{\mathrm{FF}}\mathrm{FF}_{int} + \beta_{\mathrm{LC}}\mathrm{LC}_{int} + \beta_{\mathrm{HC}}\mathrm{HC}_{int} + \beta_{\mathrm{ERP}}\mathrm{ERP}_{int} + \beta_{\mathrm{petrol}}\mathrm{petrol}_{int} + \beta_{\mathrm{parking}}\mathrm{parking}_{int} \qquad (2)$$

where

FF = free-flow time,
LC = time spent in light congestion,
HC = time spent in heavy congestion, and
ERP = electronic road pricing.

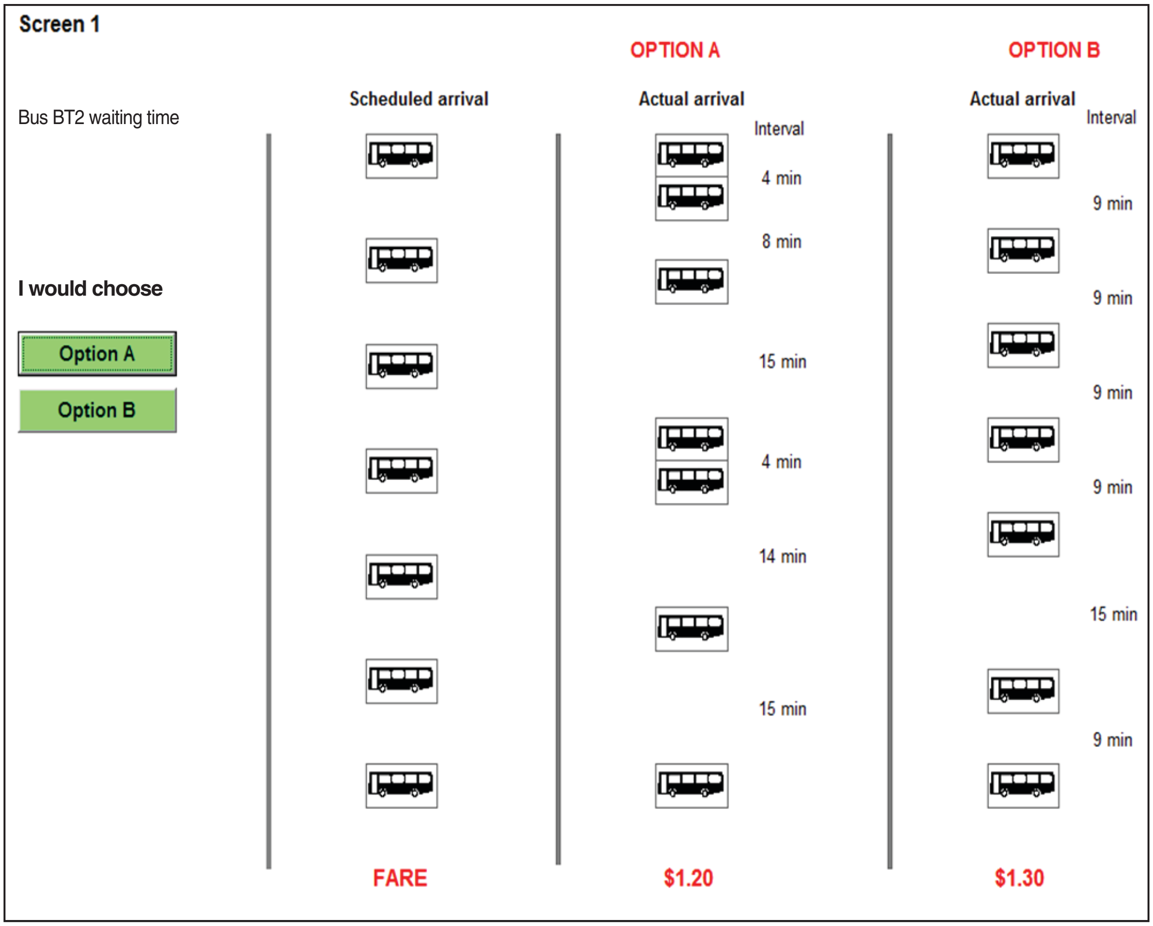

FIGURE 2 Example choice task for BT2 (total journey time = 60 min).

ERP, petrol, and parking costs are cost attributes, and six β-terms would be estimated giving the marginal utilities for the associated attributes.

The VTT in free-flow conditions expressed in terms of ERP cost sensitivity would then, for example, be given by

$$\mathrm{VTT}_{\mathrm{FF,ERP}} = \frac{\beta_{\mathrm{FF}}}{\beta_{\mathrm{ERP}}}$$

This expression indicates how much increase in ERP would be acceptable in return for a 1-min reduction in free-flow time. Although these computations are straightforward in models with fixed β, this is no longer the case when random heterogeneity is allowed for (*12*). To avoid the need to divide by random coefficients, the mathematically equivalent approach working in WTP space is used instead (*13*), again with ERP as the base cost:

$$\begin{aligned} V_{int} = \beta_{\mathrm{ERP}} & \begin{pmatrix} \mathrm{VTT}_{\mathrm{FF,ERP}}\mathrm{FF}_{int} + \mathrm{VTT}_{\mathrm{LC,ERP}}\mathrm{LC}_{int} \\ + \mathrm{VTT}_{\mathrm{HC,ERP}}\mathrm{HC}_{int} + \mathrm{ERP}_{int} \end{pmatrix} \\ & + \beta_{\mathrm{petrol}}\mathrm{petrol}_{int} + \beta_{\mathrm{parking}}\mathrm{parking}_{int} \end{aligned} \tag{3}$$

where $\mathrm{VTT}_{\mathrm{FF,ERP}}$ is now estimated directly.

Each respondent in the surveys was faced with choice tasks from multiple different games. Although joint estimation would be advisable if valuations were consistent across games, preliminary work showed differences in valuations across games (not surprising given the differences in context), and the analysis was carried out on a game-specific level, except for merging MT2 and PT1 in the absence of a cost attribute for the latter.

Initial attempts to unearth links between key sociodemographic variables (e.g., income and age) and patterns in VTT were largely unsuccessful, and it was suspected that unexplained heterogeneity dominated. The work in this context relies on mixed multinomial logit models [see, e.g., Chapter 6 in the work by Train (*10*)], as is now common practice in many national VTT studies (*1–4*). Let $P_{int}(\beta)$ give the probability that respondent n will choose alternative i in choice task t, conditional on a vector of parameters β, where with ε_{int} following a Type I extreme value distribution,

$$P_{int}(\beta) = \frac{e^{V_{int}}}{\sum_{j=1}^{2} e^{V_{jnt}}}$$

The probability of the sequence of T_n choices for individual n is given by

$$P_{int}(\beta) = \prod_{t=1}^{T_n} \frac{e^{V_{i^*nt}}}{\sum_{j=1}^{2} e^{V_{jnt}}}$$

where V_{i*nt} refers to the utility of the alternative n actually chosen in task t.

It is assumed that the vector β follows a random distribution across respondents, with $\beta \sim f(\beta|\Omega)$, with Ω a vector of estimated parameters. Then

$$P_n(\Omega) = \int_{\beta} P_n(\beta) f(\beta|\Omega) d\beta \tag{4}$$

Studies using mixed multinomial logit typically allow for heterogeneity in only some elements of β and impose independence between those. As discussed by Hess and Rose (*14*), the first of these assumptions will invariably lead to a lower fit and potential confounding in terms of the source of heterogeneity. The second assumption will also lead to a lower fit and may overstate the heterogeneity in relative sensitivities.

In this work, all parameters were instead allowed to vary randomly across respondents, with a full covariance matrix estimated between them. To the best of the authors' knowledge, this is the first such application in the context of a national VTT study and is also far beyond the level of flexibility used in the majority of most small-scale academic applications.

With K elements in β, K mean sensitivities would be thus estimated as well as $\sum_{k=1,\dots,K} k$ elements in the covariance matrix of β. This flexibility comes at the cost of increased model complexity, and classical estimation techniques were found to be unsuitable in terms of computational cost and their ability to find meaningful solutions. Instead Bayesian estimation was used, as discussed, for example, by Train (*10,* Chapter 13), specifically the implementation in Resource Systems Group Hierarchical Bayesian (RSGHB) (*15*).

As mentioned earlier, the initial exploration of the data failed to retrieve meaningful sociodemographic interactions, and the mixed multinomial logit models were specified without deterministic heterogeneity on top of the random heterogeneity. After model estimation, posterior estimates were produced (*10,* Chapter 11), which are then used in posterior segmentation work to attempt to uncover further deterministic heterogeneity. Let $L(Y_n|\beta)$ give the probability of observing the sequence of choices Y_n made by respondent n, conditional on a specific value of the vector β. The probability of observing a specific value of β is then given by the Bayes rule as follows:

$$L(\beta|Y_n) = \frac{L(Y_n|\beta) f(\beta|\Omega)}{\int_{\beta} L(Y_n|\beta) f(\beta|\Omega) d\beta} \tag{5}$$

It is then possible to simulate, for example, the most likely value for β for respondent n as follows:

$$\widehat{\beta}_n = \frac{\sum_{r=1}^{R} L(Y_n|\beta_r)\beta_r}{\sum_{r=1}^{R} L(Y_n|\beta_r)} \tag{6}$$

where β_r with $r = 1, \dots, R$ is an R independent multidimensional draw from $f(\beta|\Omega)$.

RESULTS

Because of space considerations, a detailed account of the results for the CT1 and MCT1 games is given, with only overview results for the other games.

Games for Car and Motorcycle In-Vehicle Time: CT1 and MCT1

Negative lognormal distributions were used for the three cost components and the models in WTP space relative to ERP costs for the three time measures; positive lognormal distributions were used, with a full covariance matrix between the six terms. The three VTT measures were specified in an additive manner, such that a positive value of free-flow time, a positive increase in that value for travel in light congestion, and an increase on that value for travel in heavy congestion were estimated.

The means of the posterior distributions shown in Table 2 correspond to maximum likelihood estimates of the individual parameters (*10,* Chapter 13). These relate to the underlying normal distributions (a lognormal is given by an exponential of a normal), where the 15 elements of the covariance matrix use a numbering reflecting the order of presentation of the mean parameters. With Bayesian techniques, a standard error for individual parameters that would be suited for calculating *t*-ratios is not obtained but instead the posterior standard deviation is reported for each parameter. As expected, the relative variation in the posteriors is larger for MCT1 than CT1, given the lower sample size for the former.

As a next step, VTT measures were produced on the basis of Table 2. The lognormal has a very long tail, and a few outlying values can lead to extreme means (*16*). With this in mind, the distributions were censored by removing 1% of the highest values of the WTP distributions. Censoring is a controversial process but is required in some cases (*17*). However, it is crucial to ensure that it leads to a distribution that still represents the behavior in the data. Thus the censored distributions were used to recalculate the log likelihood of the model. For CT1, this calculation led to a minor drop in log likelihood to −3,473.41 (i.e., a drop of 0.73 unit), showing very little support in the data for extreme values. That is, the tail is driven by the overall shape of the distribution rather than the data. For MCT1, there was also only a small drop to −319.34 (by 1.19 units). More extreme censoring quickly led to substantial drops in fit; this result suggests that there is support in the data for the tail of the distribution up to the 99% point. The censoring led to much more realistic VTT measures; for example, the final weighted mean for CT1 travel time is 47 cents/min compared to 75 cents/min.

A wide range of valuations can be calculated from the estimates, as reported in Table 3. These values including the VTT against a weighted cost component, calculated at the level of each individual based on their split in cost components, and the VTT in average travel conditions, calculated for each individual based on their split in travel components observed in the data. With the individual components now all following imperfectly correlated random distributions, the individual mean values cannot be obtained simply as ratios of other means. In addition, the relative VTT in different travel conditions is not constant across the three cost components as a result of the heterogeneity in each component. Finally, with a random coefficients model, it is not appropriate to now calculate simple congestion multipliers.

The differences across congestion levels are stronger for cars; the lack of difference between light congestion and heavy congestion for motorcycles could reflect that congestion for overall traffic has a reduced impact on motorcyclists. The sensitivity is highest to ERP, followed by petrol costs and then parking costs; the latter are especially low for motorcycle users. Overall valuations are in general below the wage rate from the estimation sample, in which exceptions arise in relation to petrol and parking costs; this finding potentially

TABLE 2 Estimation Results for CT1 and MCT1

Attribute	CT1 Posterior Mean	CT1 Posterior SD	MCT1 Posterior Mean	MCT1 Posterior SD
VTT free flow versus ERP (underlying normal mean for log of coeff.)	−2.33	0.20	−2.13	0.30
VTT light congestion shift versus ERP (underlying normal mean for log of coeff.)	−6.33	0.67	−3.47	0.64
VTT heavy congestion shift versus ERP (underlying normal mean for log of coeff.)	−4.18	0.38	−9.61	1.74
ERP (underlying normal mean for log of negative of coeff.)	−0.51	0.13	0.11	0.18
Petrol costs (underlying normal mean for log of negative of coeff.)	−0.97	0.14	0.39	0.19
Parking costs (underlying normal mean for log of negative of coeff.)	−0.88	0.12	0.24	0.19
cov (1, 1)	3.30	0.84	1.37	0.93
cov (1, 2)	2.57	1.08	0.08	0.62
cov (1, 3)	2.49	1.60	−0.03	0.75
cov (1, 4)	−1.19	0.62	−0.23	0.59
cov (1, 5)	−0.79	0.48	−0.21	0.57
cov (1, 6)	−0.95	0.53	−0.44	0.66
cov (2, 2)	7.33	2.54	0.43	0.43
cov (2, 3)	5.53	1.49	−0.04	0.44
cov (2, 4)	−3.36	0.79	−0.11	0.38
cov (2, 5)	−4.32	1.21	−0.01	0.33
cov (2, 6)	−4.28	1.04	−0.08	0.40
cov (3, 3)	5.18	2.24	0.52	0.75
cov (3, 4)	−2.83	0.86	0.04	0.40
cov (3, 5)	−3.34	0.74	−0.02	0.29
cov (3, 6)	−3.38	0.79	0.02	0.67
cov (4, 4)	1.87	0.48	0.70	0.38
cov (4, 5)	2.15	0.42	0.12	0.30
cov (4, 6)	2.11	0.40	0.10	0.34
cov (5, 5)	3.09	0.64	0.41	0.34
cov (5, 6)	2.94	0.48	−0.06	0.26
cov (6, 6)	3.03	0.51	0.68	0.49

NOTE: Cov = covariance. For CT1: respondents = 1,192; observations = 5,960; estimated parameters = 27; log likelihood = −3,472.68; adjusted $\rho^2 = .15$. For MCT1: respondents = 107; observations = 749; estimated parameters = 27; log likelihood = −318.15; adjusted $\rho^2 = .34$.

TABLE 3 Implied In-Vehicle VTT Measures for Cars and Motorcycles: Means and SDs Across Sample

VTTS (cents/min)	Car Mean	Car SD	Car Mean as Fraction of Wage Rate	Motorcycle Mean	Motorcycle SD	Motorcycle Mean as Fraction of Wage Rate
Value of free-flow time versus ERP (cents/min)	34.32	71.13	0.69	21.20	25.85	0.74
Value of light congestion time versus ERP	36.58	73.19	0.74	24.91	26.14	0.87
Value of heavy congestion time versus ERP	46.38	86.71	0.94	24.92	26.14	0.87
Value of free-flow time versus petrol costs	52.63	120.60	1.06	23.86	51.02	0.83
Value of light congestion time versus petrol costs	61.52	141.14	1.24	27.72	53.33	0.97
Value of heavy congestion time versus petrol costs	90.64	223.60	1.83	27.73	53.34	0.97
Value of free-flow versus parking costs	54.93	139.73	1.11	38.52	108.98	1.34
Value of light congestion time versus parking costs	62.78	156.91	1.27	44.03	114.40	1.53
Value of heavy congestion time versus parking costs	89.99	233.25	1.82	44.04	114.42	1.54
Value of free-flow time versus weighted costs	42.48	92.35	0.86	19.73	30.60	0.69
Value of light congestion time versus weighted costs	47.35	99.92	0.96	22.92	31.53	0.80
Value of heavy congestion time versus weighted costs	65.49	137.33	1.32	22.93	31.53	0.80
Value of weighted travel time versus ERP	36.80	73.60	0.74	23.02	26.00	0.80
Value of weighted travel time versus petrol costs	61.00	139.40	1.23	25.75	52.14	0.90
Value of weighted travel time versus parking costs	62.52	156.11	1.26	41.22	111.58	1.44
Value of time, weighted by conditions and cost components	47.36	99.86	0.96	21.29	31.04	0.74

NOTE: Wage rate from sample [Singapore dollars (SGD)/h]: car = 29.66; motorcycle = 17.21.

suggests that respondents did not react to these attributes in a meaningful manner. The finding is in line with some empirical evidence in other studies showing that respondents do not react realistically to petrol costs in journey-based choice experiments.

After model estimation, posterior distributions were produced and the conditional means were used for further analysis the focus of which is on the valuations against ERP. In Table 4, only those sociodemographics are reported for which a meaningful effect was observed. For car, there is clear evidence to suggest higher VTT measures for home-based-work travel and non-home-based travel, and an indication of higher VTT for those who obtain compensation for their travel costs. For both modes, the values are highest for those who are employed and also higher for off-peak than for peak travel, potentially suggesting some self-selection of higher VTT respondents into the off-peak periods. No clear patterns could be observed in terms of income or group size effects for either mode.

Summary Results for Other, Nonaccident Games

The results for the other, nonaccident games are discussed next (Table 5). Except where otherwise noted, positive lognormal distributions were relied on for WTP measures and negative lognormal distributions for cost. Except for the different approach in BT2, a 1% censoring was always applied to the lognormal tails. This procedure led to minor drops in fit for BT1 (3.5 units) and MT1 (0.43 unit) and

TABLE 4 Posterior Analysis for In-Vehicle VTT Measures for CT1 and MCT1

Variable	Sample Size	Value of Free-Flow Time versus ERP (cents/min)	Value of Light Congestion Time versus ERP (cents/min)	Value of Heavy Congestion Time versus ERP (cents/min)	Value of Weighted Travel Time versus ERP (cents/min)
CT1					
No purpose	4	27.86	30.65	43.02	30.91
HBO	352	34.34	36.46	45.72	36.68
HBS	171	29.88	31.70	39.74	31.92
HBW	327	37.29	39.84	50.68	40.04
NHB	338	37.01	39.48	49.98	39.68
Work FT, PT, or SE	737	36.88	39.35	49.92	39.55
Homemaker	139	31.15	32.97	41.02	33.20
Student	165	32.76	34.75	43.45	34.96
Retired	37	35.63	38.38	50.13	38.73
Unemployed or work not applicable	114	33.14	35.17	43.94	35.37
a.m. peak	454	34.66	36.92	46.62	37.12
p.m. peak	293	34.38	36.62	46.22	36.84
Combined peak	747	34.55	36.80	46.46	37.01
Off peak	445	36.40	38.78	49.04	38.99
Not compensated	1,141	34.93	37.22	47.07	37.43
Fully or partly compensated	51	42.30	44.78	55.41	44.95
MCT1					
No purpose	0	na	na	na	na
HBO	18	21.53	25.12	25.13	23.28
HBS	0	na	na	na	na
HBW	57	23.25	26.96	26.96	25.07
NHB	32	19.50	23.29	23.30	21.36
Work FT, PT, or SE	96	22.92	26.65	26.66	24.75
Homemaker	3	12.22	15.60	15.61	13.87
Student	3	19.12	23.00	23.01	21.02
Retired	2	6.74	9.98	9.98	8.33
Unemployed or work not applicable	3	9.71	13.12	13.13	11.38
a.m. peak	45	20.53	24.25	24.26	22.36
p.m. peak	24	18.55	22.20	22.21	20.33
Combined peak	69	19.84	23.54	23.54	21.65
Off peak	38	25.47	29.21	29.22	27.31
Not compensated	96	22.14	25.84	25.85	23.95
Fully or partly compensated	11	19.26	23.03	23.04	21.11

NOTE: HBO = home-based other; HBS = home-based shopping; HBW = home-based work; NHB = non–home based; FT = full time; PT = part time; SE = self-employed; na = not applicable.

TABLE 5 Summary Valuations for Nonaccident Games Other Than CT1 and MCT1

Variable	Mean	SD	Mean as Fraction of Wage Rate
CT2 (cents/min)			
Value of walking time	36.39	142.66	0.74
Value of queueing time	32.62	132.12	0.66
Value of searching time	40.02	186.07	0.81
TT1 (cents/min)			
Value of walking time	54.97	102.89	1.28
Value of in-vehicle time	55.27	85.34	1.28
Value of waiting time	61.59	133.90	1.43
BT1 (cents/min except where indicated)			
Value of walking time	15.96	30.76	0.53
Value of waiting time	15.06	34.85	0.50
Value of interchanges (cents/interchange)	40.82	122.89	na
Value of in-vehicle time, seated, with empty seats	10.67	25.34	0.35
Value of in-vehicle time, seated, quite packed	10.88	25.42	0.36
Value of in-vehicle time, seated, completely packed	13.01	25.60	0.43
Value of in-vehicle time, standing, quite packed	16.55	30.38	0.55
Value of in-vehicle time, standing, completely packed	17.01	30.66	0.56
Value of vehicle time weighted by crowding conditions	11.73	25.39	0.39
MT1 (cents/min except where indicated)			
Value of walking time	22.83	46.67	0.67
Value of waiting time	17.00	32.91	0.50
Value of interchanges (cents/interchange)	68.16	287.24	na
Value of in-vehicle time, seated, with empty seats	17.39	43.20	0.51
Value of in-vehicle time, seated, quite packed	17.78	43.39	0.52
Value of in-vehicle time, seated, completely packed	18.01	43.44	0.53
Value of in-vehicle time, standing, quite packed	22.08	48.39	0.65
Value of in-vehicle time, standing, completely packed	24.50	50.40	0.72
Value of vehicle time weighted by crowding conditions	20.71	46.21	0.61
BT2			
Value of EWT (cents/min)	71.74	144.75	2.38
MT2 and PT1 Combined			
Value of uncovered walking time (cents/min)	15.47	27.43	0.51
Value of covered walking time (cents/min)	5.71	10.93	0.19
Value of crossing time (cents/min)	10.79	22.73	0.36
WTP for avoiding covered bridge with lift versus air-conditioned underpass (cents/crossing)	13.56	16.74	na
WTP for avoiding covered bridge without lift versus air-conditioned underpass (cents/crossing)	24.68	40.44	na
WTP for avoiding uncovered bridge without lift versus air-conditioned underpass (cents/crossing)	52.11	45.27	na
WTP for avoiding road crossing versus air-conditioned underpass (cents/crossing)	13.96	20.60	na

NOTE: na = not applicable.

small gains in fit for CT2 (0.15 unit), TT1 (0.53 unit), and MT2-PT1 (5.92 units). Overall, these results confirm little empirical support for the extreme values and justify the censoring approach.

Car Out-of-Vehicle Time Game (CT2)

Respondents are on average most sensitive to searching time ahead of walking time and queueing time, in which no constraints on the ordering were imposed. The actual valuations are lower than those obtained in CT1; a possible reason is that out-of-vehicle times are on average much shorter (11.8 min) than in-vehicle times (27 min) in this sample. There is substantial empirical evidence elsewhere (*2*) to support the notion that VTT measures are higher on longer journeys.

Taxi Game (TT1)

For TT1, a normal distribution was used as the constant for booked taxi services, and no constraints on ordering were imposed. Respondents are on average most sensitive to waiting time, with no difference between in-vehicle time and walking time in the mean, although the latter has a higher standard deviation. Walking time is on average much shorter than in-vehicle time in this sample (1.8 min versus 22.6 min), and the findings could thus relate to a lower value of small time savings. The actual valuations are higher than the wage rate, but this finding needs to be placed in the context that taxi journeys are infrequent, and travelers are willing to pay for that service; that is, the values can again be linked to self-selection. As an aside, there is little difference in sensitivities to booking fees and fares.

Core Bus and MRT Games: BT1 and MT1

For BT1 and MT1, the five in-vehicle VTT measures were specified in an additive manner, thus imposing an ordering. Alongside the valuations of out-of-vehicle time and the five in-vehicle-time valuations, a weighted valuation was also calculated using the average real-world mix of crowding conditions in the time period used by the given traveler. Walking time is valued more highly than waiting time, especially for MRT. It is also valued more highly than seated travel time for both modes, and the valuation is only exceeded by both valuations of standing time for bus and the valuation of standing in packed conditions for MRT. For both modes, the monetary valuation of an interchange is over three times as high as the valuation of 1 min of travel time in average conditions. For bus, there is essentially no difference in valuation across the two lowest levels of crowding; this finding extends to all three seated levels for MRT. For bus, the valuation in standing conditions is relatively similar across both levels of crowding, whereas for MRT, completely packed conditions are valued substantially more negatively.

Bus EWT Game: BT2

The ranges of EWT presented in the experiment were by definition very narrow, with a maximum and minimum time between bus arrival times of 4 and 16 min, respectively, leading to a maximum EWT of just 1.35 min with an average of 0.66 min. With a simple two-attribute choice, boundary valuations can be calculated for EWT, and these ranged from 7.69 cents/min to 4,800 cents/min. This boundary valuation would be the one a respondent would need to have to choose the more expensive option (with a lower EWT) in a given choice task. The median accepted boundary was 75 cents/min, and the median rejected boundary was 160 cents/min, with respective means of 114.87 cents/min and 374.05 cents/min.

For the valuation of EWT, a different censoring approach was used based on the work of Börjesson et al. (*17*), censoring the lognormal distribution at the highest accepted boundary value, which was 800 cents/min. This finding led to a drop in log likelihood by 58.65 units, which corresponds to 1.9% and is a much bigger drop than in other games but was needed in order to obtain reasonable results. The resulting average valuation of EWT is 71.74 cents/min, which is in line with the median accepted trade-off. This result is much higher than valuations of in-vehicle time from BT1 and exceeds the average wage rate by a factor of more than 2. However, achieving a minute's reduction in EWT is a far bigger step than a 1-min reduction in travel time.

Walking Games: MT2 and PT1

For the joint MT2 and PT1 model, a normal distribution was used for the crossing-type constants, and no constraints were imposed on the ordering of the three time components. The model allowed for scale differences between MT2 and PT1, in which the estimated scale for PT1 is 2.36 (compared with an MT2 base of 1), showing more deterministic choices in PT1. The valuation of uncovered walking time is lower than the valuation of walking time from MT1, possibly because of the inclusion of the PT1 data. Uncovered walking time is valued much more highly than covered walking time, with crossing time in between, and with an air-conditioned underpass being the base, there is on average a positive WTP for avoiding any of the other crossing types, especially uncovered bridges.

Summary Results for Accident Games

For accident games, the focus is on the car and pedestrian models because of the very small sample sizes for the motorcycle and cyclist games. A negative lognormal distribution for tax increases was used, with a positive lognormal distribution for tax reductions and positive lognormals for the WTP for reductions in accidents (versus tax increases). The 1% censoring of the lognormal distributions led to drops in log likelihood by 3.26 units (0.16%) for CA1 and 2.09 units (0.24%) for PA1. The resulting monetary valuations are presented across a number of tables. Table 6 presents the implied WTP measures, and Table 7 summarizes the presented risks. Table 8 then shows the implied values of risk reduction, which are contrasted with international results in Table 9. For each of the three levels of severity, the average WTP measure is higher in the pedestrian sample than in the car sample. Despite differences in sociodemographics, this finding is to be expected at least for fatalities, for which the presented risk was twice as high in the pedestrian sample than in the car respondent sample (at average distances).

TABLE 6 Implied WTP Values for Accident Games for Cars and Pedestrians

	CA1		PA1	
Variable	Mean	SD	Mean	SD
Value of reducing fatalities (SGD/fatality)	95.48	357.67	158.08	626.70
Value of reducing serious injuries (SGD/injury)	3.17	7.79	6.56	16.77
Value of reducing minor injuries (SGD/injury)	0.17	0.40	0.67	2.77

TABLE 7 Presented Risks for Accident Games for Cars and Pedestrians

Outcome	Risk at 20,000 km/year	Risk at 500 km/year
Fatality	1/40,000	1/20,000
Serious injury	1/5,000	1/10,000
Minor injury	1/300	1/1,000

TABLE 8 Implied Values of Risk Reduction for Accident Games for Cars and Pedestrians

Variable	Implied Value of Risk Reduction: Per Average Reported Distance (18,850 km)	Per Presented Risks (500 km/year)
SGD, fatality	4,052,123.50	3,161,602.00
SGD, serious injury	16,808.39	65,553.68
SGD, minor injury	52.68	674.20

Along with the WTP measures resulting from the models, the implied values of risk reduction are presented (calculated as willingness to pay divided by risk) by using actual driving distance for car and the presented risks from the survey for pedestrians, for which no reliable distance estimate was available from respondents.

RECOMMENDED VALUES

Main Valuations

The final recommended values are summarized in cents per minute across a number of tables: Table 10 shows the values for cars and motorcycles, Table 11 for taxis, Table 12 for buses and MRT, and Table 13 for walking (the last four rows of Table 13 are in cents per crossing). Car and motorcycle in-vehicle time values rely solely on valuations against ERP. An equity value of travel time was also calculated by using the values of in-vehicle time by mode weighted by travel conditions and by the island-wide daily mode share estimated from the 2012 HTS model; the VTT was 27.32 cents/min or $16.39/h. This equity value has increased from 18.11 cents/min in 2008, an increase of 51%, compared with a gross domestic product per-capita growth by just 29%. The higher VTT could be due to the increase in traffic congestion on the road network and passenger crowding on the public transport system, in which improved survey and modeling methodology can also have affected the values.

Values of Risk Reduction

In terms of the recommended values of risk reduction (VRRs) for different types of accidents, those coming from CA1 are believed to be more realistic, largely because of a more accurate estimate

TABLE 10 Recommended Values for Cars and Motorcycles

Variable (cents/min)	Cost: Car	Motorcycle
Value of free-flow time versus ERP	34.32	21.20
Value of light congestion time versus ERP	36.58	24.91
Value of heavy congestion time versus ERP	46.38	24.92
Value of weighted travel time versus ERP	36.80	23.02
Value of walking time versus parking cost	36.39	na
Value of queueing time versus parking cost	32.62	na
Value of searching time versus parking cost	40.02	na

NOTE: na = not applicable.

of the exposure risk. This finding would lead to a VRR for a fatality of 4,052,123.50 Singapore dollars (S$1 = $.72 in June 2017). However, the corresponding values for serious and minor injuries (S$16,808.39 and S$52.68) are very low, possibly suggesting that respondents were focused on the number of fatalities. Ratios of 13% (for serious injury) and 1% for minor injury were obtained from the U.S. Department of Transportation (*21*) and applied to the VRR for fatalities to derive the VRR for serious and minor injuries, respectively. This calculation leads to the results in Table 9, which also shows a comparison against 2008 values and values from other developed countries. Although the U.S. value is in the upper range and the 2008 Singapore value is on the lower side, overall the recommended VRRs for Singapore are sensible and within an accepted range.

CONCLUSIONS

The work carried out to update a large number of WTP measures used in transport policy and infrastructure scheme appraisal in Singapore is summarized. The work used a distinctly large sample (relative to the population) and covered a wide variety of modes and variables. The work also pushed the methodological boundaries by using mixed logit models with a full specification of heterogeneity.

The values from the analysis are in line with expectations in terms of relationships across modes (showing evidence of self-selection) as well as across journey components (e.g., effects of crowding and congestion). Insights can be gained into differences across modes in

TABLE 9 Comparison of Risk Reduction Valuations with International Results

Type of Injury	Singapore (2015 $)	Singapore (2008 $)	Australia[a] (2007 $)	UK[b] (2014 $)	United States[c] (2015 $)
Fatality	4,052,124	1,874,000	6,579,854	3,580,305	12,690,000
Serious injury	526,776	243,600	320,532	402,326	1,332,450
Minor injury	40,521	18,740	17,098	31,015	38,070

[a]Hensher et al. (*19*).
[b]UK Department for Transport (*20*).
[c]U.S. Department of Transportation (*21*).

TABLE 11 Recommended Values for Taxis

Variable (cents/min)	Cost
Value of walking time versus fare	54.97
Value of in-vehicle time versus fare	55.27
Value of waiting time versus fare	61.59

TABLE 12 Recommended Values for Buses and MRT

	Cost	
Variable (cents/min)	Bus	MRT
Value of walking time	15.96	22.83
Value of waiting time	15.06	17.00
Value of interchanges (cents/interchange)	40.82	68.16
Value of in-vehicle time, seated, with empty seats	10.67	17.39
Value of in-vehicle time, seated, quite packed	10.88	17.78
Value of in-vehicle time, seated, completely packed	13.01	18.01
Value of in-vehicle time, standing, quite packed	16.55	22.08
Value of in-vehicle time, standing, completely packed	17.01	24.50
Value of in-vehicle time weighted by crowding conditions	11.73	20.71
Value of EWT	71.74	na

terms of the relationship between congestion levels (e.g., a bigger effect for car than motorcycle) and crowding (a bigger effect for bus than MRT).

This work uncovered extensive amounts of random heterogeneity in valuations across respondents and showed clear advantages over models assuming homogeneous preferences. Interestingly, it was not possible to link much of these results to observed respondent characteristics, though some insights were gained from posterior analysis. This finding suggests that, at least with this sample, much of the heterogeneity relates to intrinsic preferences rather than differences in sociodemographics. In this context, the representativeness of the sample is of crucial importance, but with the use of posterior estimates, the possibility of course also remains open for reweighting of results.

TABLE 13 Recommended Values for Walking

Variable	Cost
Value of uncovered walking time (cents/min)	15.47
Value of covered walking time (cents/min)	5.71
Value of crossing time (cents/min)	10.79
WTP for avoiding covered bridge with lift versus air-conditioned underpass (cents/crossing)	13.56
WTP for avoiding covered bridge without lift versus air-conditioned underpass (cents/crossing)	24.68
WTP for avoiding uncovered bridge without lift versus air-conditioned underpass (cents/crossing)	52.11
WTP for avoiding road crossing versus air-conditioned underpass (cents/crossing)	13.96

The valuations are overall substantially higher than those from the 2008 LTA study. Although some of these findings can be attributed to changes in the transport system and increased congestion and crowding, the use of more advanced survey design and modeling approaches may also play a role. This update is thus of high importance to ensure continued reliability of the cost–benefit appraisal work conducted by LTA. This study also uncovered differences in VTT measures depending on which cost attribute is used (e.g., ERP versus petrol) and it is recommended that the core values for car and motorcycle be based on ERP.

Finally, this study has put forward a different approach for SC surveys for safety; especially in the context of small areas with a low number of fatalities, the approach seems preferable to a route-based approach.

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