Estimation of new monetary valuations of travel time, quality of travel and safety for Singapore

Stephane Hess (corresponding author)
Institute for Transport Studies & Choice Modelling Centre
University of Leeds
+44 113 343 6611
s.hess@its.leeds.ac.uk

Paul Murphy
Aecom UK
paul.murphy2@aecom.com

Henry Le
Aecom Australia
Henry.Le@aecom.com

Wai Yan Leong
Land Transport Authority
Singapore
LEONG_Wai_Yan@lta.gov.sg

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ABSTRACT

This paper reports the findings of a large scale study in Singapore to estimate 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 and representative sample. The empirical work pushed the boundaries of the international state-of-practice in choice modelling by relying on Mixed Logit models with all model components being random and a full covariance matrix being estimated. We present detailed results and contrast the values to those from the previous study conducted in 2008.

Keywords: value of time (VTT), value of risk reduction, stated choice, Singapore

1. INTRODUCTION

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, social benefits such as travel time savings, reliability improvements, crowding reductions 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 national bodies (see e.g. [1,2,3,4]), LTA makes use of values produced through the estimation of discrete choice models on stated preference (SP) data.

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 means that the values should be updated at regular intervals given not only the changing nature of transport systems and travel behaviour, but also ongoing improvements to survey and modelling approaches.

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

2. SURVEY WORK

2.1. Sampling[1]

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, ensuring sufficiently large sample sizes for the modelling work for each mode as well as representative samples for other dimensions. The study sampled car, motorcycle, MRT (Mass Rapid Transit), bus and taxi users as well as pedestrians and cyclists.

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

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

2.2. Survey contents and design

Stated preference, and in particular stated choice (SC), is a widely used technique for value of time (VTT) research (cf. reviews in [2]). Respondents are faced with a number of carefully designed hypothetical choice scenarios, where in each scenario, two are more alternatives are described by key attributes such as travel time and travel cost, and the respondent is 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 two alternative two attribute (cf. discussions in [2]). On the other hand, work especially in Australia tends to rely on at least three alternatives in each choice task, with often five or six attributes describing them (see e.g. [5]). In our work, we strike a balance between these two extremes. While we retain a binary context, we use a larger number of attributes to describe these alternatives. With substantial differences across the various measures we are interested in (e.g. VTT vs value of safety), we

[1] Details on quotas and socio-demographics in the final sample are available from the first author on request.

however spread the choice tasks for each respondent across different survey contexts, or games, also helping to reduce 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, we sought to increase realism by pivoting the values presented to respondents around the attributes from a recent trip for that respondent. The actual designs were produced using NGene[2], with Bayesian D-efficiency as a criterion for the statistical properties of the designs (cf. [6]), priors coming from the 2008 study ([7]), and avoiding 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. Special attention however is needed for accident games (CA1, MCA1, PA1 and CYA1), crowding games (MT1 and BT1) and the bus excess waiting time game (BT2).

Table 1: Summary of different SC games

Game	Description	Attributes	Choice tasks
CT1	Car: congestion & costs	Free flow travel time, light congestion, heavy congestion; Parking cost, petrol cost, ERP (electronic road pricing) cost	5
CT2	Car: parking choice	Walking time, queuing time, search time; Parking cost	5
CA1	Car: accidents	Fatalities, serious and light injuries per year; Change in annual tax burden	5
MCT1	Motorcycle: congestion & costs	Free flow travel time, light congestion, heavy congestion; Parking cost, petrol cost, ERP cost	7
MCA1	Motorcycle: accidents	Fatalities, serious and light injuries per year; Change in annual tax burden	5
MT1	MRT: time & 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, airconditioned underpass; Covered and uncovered walking time to and from crossing Fare	7
BT1	Bus: time & 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 & 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, airconditioned underpass; Covered and uncovered walking time to and from crossing	7
PA1	Pedestrian: accidents	Fatalities, serious and light injuries per year; Change in annual tax burden	5
CYA1	Cycling: accident	Fatalities, serious and light injuries per year; Change in annual tax burden	5

The purpose of the accident games is to derive a WTP for reducing the number of different types of accidents and hence also the WTP for reducing personal risk. A standard approach (e.g. [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 as e.g. "*Number of deaths per year along the route...*" In [9], this number goes from 0 to 5, which is of course very high for a single road.

[2] http://www.choice-metrics.com

In the case of Singapore, where the total number of accidents is far lower, presenting per road/route rates is even more unrealistic. There is also an issue with exposure, as 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. We instead rely on a *programme* approach, where the choice is between two national safety programmes, with the payment mechanism being a change in annual tax burden. The two programmes are described in terms of increases or decreases in tax (per year), along with annual figures for fatalities, serious and slight injuries.

MT1 and BT1 look at the sensitivity to in vehicle travel time in different conditions, waiting time, walking time and interchanges. Rather than simply presenting overall numbers for a journey and a single level of crowding, we show journeys broken up into differently sized stages (cf. **Error! Reference source not found.**). The presentation allows for changes in crowding that are the result of either changing to a different bus/train or other passengers joining/leaving the bus/train the respondent is already travelling on.

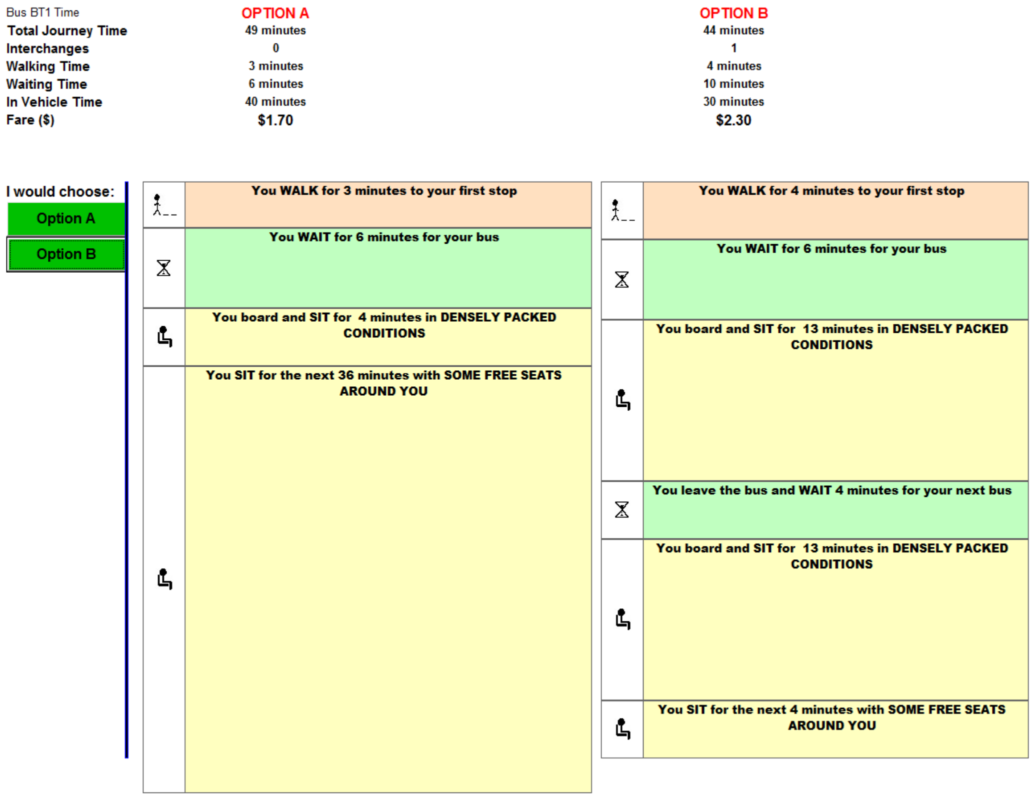

Figure 1: Example choice task for BT1

BT2 is concerned with bus reliability. LTA uses the concept of Excess Wait Time (EWT), where, assuming a uniform arrival rate of passengers, EWT is the average additional wait time actually experienced compared to 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), i.e. EWT = AWT – SWT, with:

$$AWT = \frac{\sum_n actual\ \ headway_n^2}{2 \times \sum_n actual\ \ headway_n};\ SWT = \frac{\sum_n scheduled\ \ headway_n^2}{2 \times \sum_n scheduled\ \ headway_n} \qquad (1)$$

EWT increases if there is bus bunching which results in prolonged waits for the subsequent bus. Respondents had the choice between two future hypothetical bus services (cf. **Error! Reference source not found.**), where the scheduled arrival time of the bus is shown (every 10 minutes), 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.

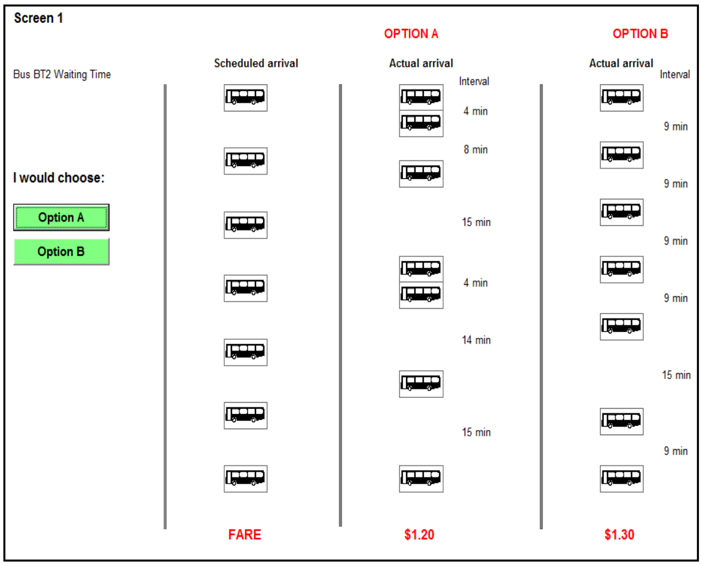

Figure 2:Example choice task for BT2

3. MODELLING FRAMEWORK

In the last 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 (see e.g. [10]). There have as a result 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 GB VTT study [2]. In what follows, we focus only on what’s relevant for the present study, largely for 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 $U_{int} = V_{int} + \varepsilon_{int}$, where noise is independent of observed utility. Recent work by [11] has questioned this and put forward a multiplicative formulation, where errors are proportional to observed utility, with $U_{int} = V_{int} \cdot \varepsilon_{int}$. In practice, this implies more noise on longer trips, a notion which has received empirical support in the Danish [4] and British [2] national studies. We compared the two specifications in early work, and found no evidence of improvements with the multiplicative structure, allowing us to retain the additive structure. Part of the reason could be the smaller size of Singapore and the much reduced heterogeneity in trip distances that results.

We next turn to the specification of the observed component of utility. Using the example of CT1, we would write:

$$V_{int} = \beta_{FF}FF_{int} + \beta_{LC}LC_{int} + \beta_{HC}HC_{int} + \beta_{ERP}ERP_{int} + \beta_{petrol}petrol_{int} + \beta_{parking}parking_{int} \quad (2)$$

where the time attributes are free flow time (*FF*), time spent in light congestion (*LC*), time spent in heavy congestion (*HC*), and the cost attributes are ERP, petrol and parking costs, and where we would estimate six β terms 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 $VTT_{FF,ERP} = \frac{\beta_{FF}}{\beta_{ERP}}$, indicating how much increase in ERP would be acceptable in return for a one minute reduction in free flow time. While these computations are straightforward in models with fixed β, this is no longer the case when allowing for random heterogeneity (cf. [12]). To avoid the need to divide by random coefficients, we instead make use of the mathematically equivalent approach working in WTP space [13], again using ERP as the base cost, such that:

$$\begin{aligned} V_{int} = {} & \beta_{ERP}\left(VTT_{FF,ERP}FF_{int} + VTT_{LC,ERP}LC_{int} + VTT_{HC,ERP}HC_{int} + ERP_{int}\right) \\ & + \beta_{petrol}petrol_{int} + \beta_{parking}parking_{int} \end{aligned} \quad (3)$$

where $VTT_{FF,ERP}$ is now estimated directly.

Each respondent in our surveys was faced with choice tasks from multiple different games. While 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 socio-demographic variables (e.g. income, age) and patterns in VTT were largely unsuccessful, and we suspected that unexplained heterogeneity dominated. Our work in this context relies on Mixed Multinomial Logit (MMNL) models (see e.g. [10], chapter 6), as is now common practice in many national VTT studies (e.g. [1,2,3,4]). Let $P_{int}(\beta)$ give the probability of respondent *n* choosing alternative *i* in choice task *t*, conditional on a vector of parameters β, where, with ε_{int} following a type I extreme value distribution, we have that $P_{int}(\beta) = \frac{e^{V_{int}}}{\sum_{j=1}^{2} e^{V_{jnt}}}$. The probability of the sequence of T_n choices for individual *n* is given by $P_n(\beta) = \prod_{t=1}^{T_n} \frac{e^{V_{i^*nt}}}{\sum_{j=1}^{2} e^{V_{jnt}}}$, where V_{i^*nt} refers to the utility of the alternative *n* actually chose in task *t*.

We assume that the vector β follows a random distribution across respondents, with $\beta \sim f(\beta \mid \Omega)$, with Ω a vector of estimated parameters. We then have:

$$P_n(\Omega) = \int_\beta P_n(\beta) f(\beta \mid \Omega) d\beta. \quad (4)$$

Studies using MMNL typically allow for heterogeneity in only some elements of β and impose independence between those. As discussed by [14], the first of these assumptions will invariably lead to lower fit and potential confounding in terms of the source of heterogeneity. The second assumption will also lead to lower fit and may overstate the heterogeneity in relative sensitivities.

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

With *K* elements in β, we would thus estimate *K* mean sensitivities as well as $\sum_{k=1,\ldots,K} k$ 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. We instead turned to Bayesian estimation, as discussed for example by [10] (chapter 13), and specifically the implementation in RSGHB [15].

As already mentioned earlier, our initial explorations on the data failed to retrieve meaningful socio-demographic interactions, and the MMNL models were specified without deterministic heterogeneity on top of the random heterogeneity. After model estimation, we produced posterior estimates (see [10], chapter 11), which are then used in posterior segmentation work to attempt to uncover further deterministic heterogeneity. Let $L(Y_n \mid \beta)$ 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 Bayes rule as:

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

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

$$\widehat{\beta_n} = \frac{\sum_{r=1}^{R} L(Y_n|\beta_r)\beta_r}{\sum_{r=1}^{R} L(Y_n|\beta_r)}, \quad (6)$$

where β_r with $r = 1, \ldots, R$ are *R* independent multi-dimensional draws from $f(\beta \mid \Omega)$.

4. RESULTS

Due to space considerations, we give a detailed account of the results for the CT1 and MCT1 games, along with overview results for other games.

4.1. Detailed results for car and motorcycle in vehicle time games (CT1 and MCT1)

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

Table 2: Estimation results for CT1 and MCT1

	CT1		MCT1	
Respondents	1,192		107	
Observations	5,960		749	
Estimated parameters	27		27	
Log-likelihood	-3,472.68		-318.15	
adj. ρ^2	0.15		0.34	
	posterior mean	posterior std dev.	posterior mean	posterior std dev.
VTT free flow vs ERP (underlying Normal mean for log of coeff)	-2.33	0.20	-2.13	0.30
VTT light congestion shift vs ERP (underlying Normal mean for log of coeff)	-6.33	0.67	-3.47	0.64
VTT heavy congestion shift vs 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

The means of the posterior distributions shown in Table 2 correspond to maximum likelihood estimates of the individual parameters (cf. 10, chapter 13). These relate to the underlying Normal distributions (a Lognormal is given by an exponential of a Normal), where the fifteen elements of the covariance matrix use a numbering reflecting the order of presentation of the mean parameters. With Bayesian techniques, we do not obtain a standard error for individual parameters that would be suited for calculating t-ratios, but instead report the posterior standard deviation 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, we produced VTT measures on the basis of Table 2. The lognormal has a very long tail, and a few outlying values can lead to extreme means (see e.g. [16]). With this in mind, we censored the distributions by removing the 1% of highest values of the WTP distributions. Censoring is a controversial process but is required in some cases (cf. [17]). It is however crucial to ensure that it leads to a distribution that still represents the behaviour in the data. We thus used the censored distributions to recalculate the log-likelihood of the model. For CT1, this led to a minor drop in log-likelihood to -3473.41 (i.e. a drop of 0.73 units), showing very little support in the data for extreme values – i.e. 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, i.e. by 1.19 units. More extreme censoring quickly led to substantial drops in fit, suggesting 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, e.g. the final weighted mean for CT1 travel time is 47c/min, compared to 75c/min.

Table 3: Implied in vehicle value of time measures for car and motorcycle (means and standard deviations across the sample)

VTTS (cents/mins)	CAR			MOTORCYCLE		
	Mean	**std. dev.**	**Mean as fraction of wage rate**	**Mean**	**std. dev.**	**Mean as fraction of wage rate**
value of free flow time vs ERP (c/min)	34.32	71.13	0.69	21.20	25.85	0.74
value of light congestion time vs ERP	36.58	73.19	0.74	24.91	26.14	0.87
value of heavy congestion time vs ERP	46.38	86.71	0.94	24.92	26.14	0.87
value of free flow vs petrol costs	52.63	120.60	1.06	23.86	51.02	0.83
value of light congestion time vs petrol costs	61.52	141.14	1.24	27.72	53.33	0.97
value of heavy congestion time vs petrol costs	90.64	223.60	1.83	27.73	53.34	0.97
value of free flow vs parking costs	54.93	139.73	1.11	38.52	108.98	1.34
value of light congestion time vs parking costs	62.78	156.91	1.27	44.03	114.40	1.53
value of heavy congestion time vs parking costs	89.99	233.25	1.82	44.04	114.42	1.54
value of free flow time vs weighted costs	42.48	92.35	0.86	19.73	30.60	0.69
value of light congestion time vs weighted costs	47.35	99.92	0.96	22.92	31.53	0.80
value of heavy congestion time vs weighted costs	65.49	137.33	1.32	22.93	31.53	0.80
value of weighted travel time vs ERP	36.80	73.60	0.74	23.02	26.00	0.80
value of weighted travel time vs petrol costs	61.00	139.40	1.23	25.75	52.14	0.90
value of weighted travel time vs 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
wage rate from sample (SGD/hr)	29.66			17.21		

A wide range of valuations can be calculated from the estimates, as reported in Table 3, 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. Additionally, 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 also not appropriate to now calculate simple congestion multipliers.

We note that the differences across congestion levels is stronger for car, where 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, where the latter is especially low for motorcycle users. Overall valuations are in general below the wage rate from the estimation sample, where exceptions arise in relation to petrol and parking costs, potentially suggesting that respondents did not react to these attributes in a meaningful manner. This 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, we produced posterior distributions, and used the conditional means for further analysis, where we focus on the valuations against ERP. In Table 4, we report only those socio-demographics where 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 in employment, and are also higher for off-peak travel than off-peak, potentially suggesting some self-selection of higher VTT people into the off-peak periods. No clear patterns could be observed in terms of income or group size effects for either mode.

4.2. Summary results for other non-accident games

We now proceed with a summary discussion of the results for the other non-accident games, with results in Table 5. Except where otherwise noted, we relied on positive lognormal distributions for WTP measures and negative lognormal distributions for cost. Except for the different approach in BT2, we always applied a 1% censoring to the lognormal tails. This led to minor drops in fit for BT1 (3.5 units) and MT1 (0.43 units) and small gains in fit for CT2 (0.15 units), TT1 (0.53 units) and MT2/PT1 (5.92 units). Overall, these results confirm little empirical support for the extreme values and justify our censoring approach.

4.2.1. Car out of vehicle time game (CT2)

Respondents are on average most sensitivity to searching time, ahead of walking time and queueing time, where no constraints on the ordering were imposed. The actual valuations are lower than those obtained in CT1, where a possible reason could be that out of vehicle times are on average much shorter (11.8 minutes) than in vehicle times (27 minutes) in our sample. There is substantial empirical evidence elsewhere to support the notion that VTT measures are higher on longer journeys (e.g. [2]).

4.2.2. Taxi game (TT1)

For TT1, a Normal distribution was used for 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 minutes vs 22.6 minutes) and the finding could thus relate to a lower value of small time savings. The actual valuations are higher than the wage rate, but this needs to be placed into the context of taxi journeys being infrequent, and travellers being willing to pay for that service, i.e. we can again link the values to self-selection. As an aside, there is little difference in sensitivities to booking fees and fares.

4.2.3. 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 different in vehicle time valuations, we also calculated a weighted valuations, using the average real world mix of crowding conditions in the time period a given traveller uses. We find that 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 one minute of travel time in average conditions. For bus, there is essentially no difference in valuation across the two lowest levels of crowding, where this extends to all three seated levels for MRT. For bus, the valuation in standing conditions is relatively similar across both levels of crowding, while, for MRT, completely packed conditions are valued substantially more negatively.

Table 4: Posterior analysis for in vehicle value of time measures for CT1 and MCT1

CT1	**Sample size**	**Value of free flow time vs ERP (c/min)**	**Value of light congestion time vs ERP (c/min)**	**Value of heavy congestion time vs ERP (c/min)**	**Value of weighted travel time vs ERP (c/min)**
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
housewife	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 NA	114	33.14	35.17	43.94	35.37
AM PEAK	454	34.66	36.92	46.62	37.12
PM 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	1141	34.93	37.22	47.07	37.43
Fully or partly compensated	51	42.30	44.78	55.41	44.95
MCT1	**Sample size**	**Value of free flow time vs ERP (c/min)**	**Value of light congestion time vs ERP (c/min)**	**Value of heavy congestion time vs ERP (c/min)**	**Value of weighted travel time vs ERP (c/min)**
No purpose	0	N/A	N/A	N/A	N/A
HBO	18	21.53	25.12	25.13	23.28
HBS	0	N/A	N/A	N/A	N/A
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
housewife	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 NA	3	9.71	13.12	13.13	11.38
AM PEAK	45	20.53	24.25	24.26	22.36
PM 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

4.2.4. Bus EWT game (BT2)

The ranges of EWT presented in the experiment were by definition very narrow, with a maximum and minimum time in between bus arrival times of 4 and 16 minutes, respectively, leading to a maximum EWT of just 1.35 minutes, with an average of 0.66 minutes. With a simple two attribute choice, we can calculate boundary valuations for EWT, and these ranged from 7.69c/min to 4,800c/min. This would be the valuation of EWT 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 75c/min, while the median rejected boundary was 160c/min, with respective means of 114.87c/min and 374.05c/min.

For the valuation of EWT, a different censoring approach was used, based on the work of [17], censoring the lognormal distribution at the highest accepted boundary value, which was 800c/min. This 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 71.74c/min, which is in line with the median accepted trade-off. This is much higher than valuations of in vehicle time from BT1, and exceeds the average wage rate by a factor of more than two. However, it needs to be borne in mind that achieving a minute reduction in EWT is a far bigger step than a one minute reduction in travel time.

4.2.5. Walking games (MT2 and PT1)

For the joint MT2 and PT1 model, we used a Normal distribution 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, where the estimated scale for PT1 is 2.36 (compared to a MT2 base of 1), showing more deterministic choices in PT1. We note that the valuation of uncovered walking time is lower than the valuation of walking time from MT1, possibly due to 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 air conditioned underpass being the base, there is on average a positive willingness to pay for avoiding any of the other crossing types, especially uncovered bridges.

4.3. Summary results for accident games

For accident games, we focus on the car and pedestrian models due to very small sample sizes for the motorcycle and cyclist games. We made use of a negative lognormal distribution for tax increases, along with a positive lognormal distribution for tax reductions, and positive lognormals for the WTP for reductions in accidents (vs 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 PTA1. The resulting monetary valuations are presented in Table 6. For each of the three levels of severity, the average willingness to pay measure is higher in the pedestrian sample than in the car sample. Despite differences in socio-demographics, this is to be expected at least for fatalities, where the presented risk was twice as high in the pedestrian sample than the car respondent sample (at average distances).

Along with the willingness-to-pay measures coming out of the models, we present the implied values of risk reduction (calculated as willingness to pay divided by risk), using actual driving distance for car, and the presented risks from the survey for pedestrians, where no reliable distance estimate was available from respondents.

5. RECOMMENDED VALUES

5.1. Main valuations

Table 7 presents an overview of the key recommended valuations from the various games, where, for car and motorcycle in vehicle time, we 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, giving a VTT of 27.32 cents per minute or $16.39 per hour. This equity value has increased from 18.11 cents per minute in 2008, i.e. an increase by 51%, compared to a GDP per capita growth by just 29%. The higher VTT could be due to the increase of traffic congestion on the road network, and of passenger crowding on the public transport system, where improved survey and modelling methodology can also have affected the values.

Table 5: Summary valuations for non-accident games other than CT1 and MCT1

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

Table 6: Implied WTP values for accident games

	CA1		PTA1	
	mean	**std dev**	**Mean**	**std dev**
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 slight injuries (SGD/injury)	0.17	0.40	0.67	2.77
Risks	risk at 20,000km/year		risk at 500km/year	
Fatality	1/40,000		1/20,000	
serious injury	1/5,000		1/10,000	
slight injury	1/300		1/1,000	
Implied value of risk reduction	using average reported distance (18,850km)		at presented risks (500km/year)	
implied mean value of risk reduction per fatality (SGD/fatality)	4,052,123.50		3,161,602.00	
implied mean value of risk reduction per serious injury (SGD/injury)	16,808.39		65,553.68	
implied mean value of risk reduction per slight injury (SGD/injury)	52.68		674.20	

Recommended values and international comparison					
Type of injury	Singapore		Australia[3]	UK[4]	US[5]
	($2015)	($2008)	($2007)	($2014)	($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
Slight injury	40,521	18,740	17,098	31,015	38,070

5.2. Values of risk reduction

In terms of recommended value of risk reduction (VRR) for different types of accident, we believe that those coming out of CA1 are more realistic, largely also because of a more accurate estimate of the exposure risk. This would lead to a value of risk reduction for a fatality of SGD 4,052,123.50. However, the corresponding values for serious and light injuries (SGD 16,808.39 and SGD 52.68) are very low, possibly suggesting that respondents were focussed on the number of fatalities. Ratios of 13% (for serious injury) and 1% for light injury were obtained from [18], and applied to the VRR for fatalities to derive the VRR for serious and slight injuries respectively. This leads to the results at the bottom of Table 6, which also shows a comparison against 2008 and values from other developed countries. While the US value is on the upper range and the 2008 Singapore value is on the lower side, overall, the recommended VRR for Singapore are sensible and within an accepted range.

6. CONCLUSIONS

This paper has summarised the work carried out to update a large number of WTP measures used in transport policy and infrastructure scheme appraisal in Singapore. The work made use of a distinctively 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 coming out of the analysis are in line with expectation in terms of relationships across modes (showing evidence of self selection) as well as across journey components (e.g. effects of

[3] cf. [19]
[4] cf. [20]
[5] cf. [21]

crowding/congestion). Insights can be gained into differences across modes in terms of the relationship between congestion levels (e.g. bigger effect for car than motorcycle) and crowding (bigger effect for bus than MRT).

Table 7: Recommended values across modes

	CAR	MOTORCYCLE
value of free flow time vs ERP (c/min)	34.32	21.20
value of light congestion time vs ERP (c/min)	36.58	24.91
value of heavy congestion time vs ERP (c/min)	46.38	24.92
value of weighted travel time vs ERP (c/min)	36.80	23.02
value of walking time vs parking cost (c/min)	36.39	-
value of queueing time vs parking cost (c/min)	32.62	-
value of searching time vs parking cost (c/min)	40.02	-
	TAXI	
value of walking time vs fare (c/min)	54.97	
value of in vehicle time vs fare (c/min)	55.27	
value of waiting time vs fare (c/min)	61.59	
	BUS	MRT
value of walking time (c/min)	15.96	22.83
value of waiting time (c/min)	15.06	17.00
value of interchanges (c/interchange)	40.82	68.16
value of in vehicle time, seated with empty seats (c/min)	10.67	17.39
value of in vehicle time, seated, quite packed (c/min)	10.88	17.78
value of in vehicle time, seated, completely packed (c/min)	13.01	18.01
value of in vehicle time, standing, quite packed (c/min)	16.55	22.08
value of in vehicle time, standing, completely packed (c/min)	17.01	24.50
value of in vehicle time weighted by crowding conditions (c/min)	11.73	20.71
value of EWT (c/min)	71.74	
	WALKING	
value of uncovered walking time (c/min)	15.47	
value of covered walking time (c/min)	5.71	
value of crossing time (c/min)	10.79	
WTP for avoiding covered bridge with lift vs air conditioned underpass (c/crossing)	13.56	
WTP for avoiding covered bridge without lift vs air conditioned underpass (c/crossing)	24.68	
WTP for avoiding uncovered bridge without lift vs air conditioned underpass (c/crossing)	52.11	
WTP for avoiding road crossing vs air conditioned underpass (c/crossing)	13.96	

Our work uncovered extensive amounts of random heterogeneity in valuations across respondents, showing clear advantages over models assuming homogeneous preferences. Interestingly, it was not possible to link much of this to observed respondent characteristics, though some insights were gained from posterior analysis. This suggests that, at least with this sample, much of the heterogeneity relates to intrinsic preferences rather than differences in socio-demographics. 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.

The valuations are overall substantially higher than those from the 2008 study. While some of this can be attributed to changes in the transport system and increased congestion/crowding, the use of more advanced survey design and modelling 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. Our work also uncovered differences in VTT measures depending on which cost attribute is used (e.g. ERP vs petrol) and we recommend to base the core values for car and motorcycle on ERP.

Finally, our work has put forward a different approach for SC surveys for safety, and especially in the context of small areas with low numbers of fatalities, the approach seems preferable to a route based approach.

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