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1	Impact of travel time constraints on taste heterogeneity and non-linearity in
2	simple time-cost trade-offs
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## 1 ABSTRACT

- 2 Discrete choice models are a key technique for estimating the value of travel time (VTT). Often,
- 3 stated choice data are used in which respondents are presented with trade-offs between travel
- 4 time and travel cost and possibly additional attributes. There is a clear possibility that some
- 5 respondents experience time constraints, leaving some of the presented options unfeasible. A
- 6 model not incorporating information on these constraints would explain choices for faster and
- 7 more expensive options as an indication that those respondents have a higher value of travel time
- 8 when in reality they may be forced to select the more expensive option as a result of their
- 9 personal constraints. We put forward the hypothesis that this can have major impacts on findings
- in terms of heterogeneity in VTT measures. This paper examines via simulation the bias in VTT
   estimates and especially preference heterogeneity when such constraints are (not) accounted for.
- We provide empirical evidence that preference heterogeneity is confounded with the travel
- 13 budget impact on the availabilities of alternatives, and show that there is a risk of producing
- biased estimates for appraisal VTT if studies do not explicitly model choice set formation. The
- 15 inclusion of an opt-out alternative could be an effective measure to reduce the bias. This paper
- also explores the potential use of non-linear functional forms to capture the time budget impacts.
- 17
- 18
- 18 19
- 20 *Keywords*: value of travel time (VTT), travel time constraints, non-linearities
- 21

### 1 **1 INTRODUCTION**

- 2 Economic theory and empirical findings support the argument that the value of travel time (VTT)
- 3 is directly related to the stringency of time and money (budget) constraints. Recent empirical
- 4 advances explicitly model the impact of constraints through the use of choice set formation (1-3).
- 5 However, such constraints are typically not taken into account in some recent national value of
- 6 travel time studies (4). We hypothesize that not accounting for constraints could create
- 7 significant risks in producing biased VTT estimates based on stated choice (SC) data. In
- 8 particular, let us contrast two situations. If a traveller chooses a faster and more expensive option
- 9 for the reason of wanting to save time for other activities, then this should reasonably be seen as 10 this traveller doing so as his/her VTT is high enough to warrant paying the difference. If on the
- other hand, the traveller is faced with two options departing at the same time and one being faster
- 12 than the other, then he/she might simply be choosing the more expensive and faster option due to
- 13 a constraint on needing to arrive by a specific time. In the majority of stated choice studies, the
- 14 respondent is not given the option of changing his/her departure time and there is thus a
- 15 substantial risk of constraints on timing influencing our findings on the VTT.
- This paper studies the confounding impact on VTT estimates and especially preference 16 heterogeneity findings due to unaccounted (travel) time constraints. This confounding becomes, 17 in our view, even more important given the increasing popularity of Mixed Multinomial Logit 18 (MMNL) models explaining unobserved taste heterogeneity amongst respondents. This paper 19 argues that the estimated variance of the marginal utilities (and hence VTT) captured by the 20 MMNL models could in part be an artefact of constraints (or thresholds) rather than preference 21 heterogeneity. This is tested through the use of simulated data to simulate fixed or random VTT 22 23 amongst the simulated population, who are subject to either fixed or a mix of time budget constraints. Using simulated data, we study the confounding effect that could happen when the 24 choice model is misspecified by ignoring the impact of travel time constraints. In addition, given 25 that the use of non-linear functional forms for utility function does not require any changes to the 26 choice model structure, this paper also illustrates the use of non-linear functional forms to catch 27 the tail of the VTT distributions where attribute levels exceed travel budgets. 28
- This paper is organized as follows. The second section provides a review of existing literature in constrained modelling. The simulated dataset and analytical framework are described in Section 3. Section 4 summarizes model results. Section 5 discusses the implications of including an opt-out option. Section 6 describes the use of non-linearities to capture the time budget effects. Section 7 concludes.
- 34

## 35 2 LITERATURE REVIEW

- 36 Budget constraints in SC experiments
- 37 The empirical measurement of VTT is inextricably linked to the theories of time allocation in
- economics as they provide justification for the VTT concept. By implementing the time
- allocation framework developed by DeSerpa (5) in the empirical random utility model (RUM)
- 40 within the discrete choice setting, the VTT can be estimated as the marginal rate of substitution
- 41 between travel time and cost in the conditional indirect utility function that is linear in income.
- 42 As the utility which appears in the empirical models is the indirect utility, which is a result from
- 43 decisions about consumption that is subject to both money and time budget constraints, the
- 44 budget constraints are implicitly accounted for within the discrete choice models in principle. In
- 45 practice, however, such budget constraints are not observed. This implies that researchers might
- 46 present unfeasible alternatives to respondents in the SC experiment and thus introduce bias when
- 47 unfeasible alternatives are modelled with non-zero choice probabilities. This problem is

- 1 particularly apparent within the SC context due to its hypothetical setting while in revealed
- 2 preference data, the chosen alternatives observed should be within budget unless irrational
- 3 decisions are made. It is hypothesized in this study that money and time budget constraints are
- 4 latent by nature as suggested by Ahmed and Stopher (6) and hence it is inevitable that some
- 5 attribute levels set out by researchers in the SC experiment might exceed some respondents'
- 6 budget constraints.
- 7
- 8 Potential bias due to budget constraint
- 9 The potential bias due to model misspecifications for ignoring the impact of budget constraints
- 10 on the availabilities of alternatives was identified soon after the development of the discrete
- 11 choice modelling framework (7). Since then many studies had provided evidence that suggests
- 12 ignoring the impact of travel (or budget) constraints may lead to biased estimation. Amongst
- 13 these studies, Cantillo and Ortúzar (8) and Li, Adamowicz and Swait (9) estimated the
- misspecified models which also allow for random taste heterogeneity. Cantillo and Ortúzar (8)
   found seriously biased estimates for VTT valuation in the presence of random attribute
- thresholds and concluded that the MMNL model is not capable of capturing the non-
- 17 compensatory behaviour. Li, Adamowicz and Swait (9) assumed fixed tastes in simulated data
- but found welfare measures that are biased even when choice set formation is purposefully
- 19 treated as taste heterogeneity in random parameter logit models. However, none of the above
- have pinpointed the direct confounding issue between the taste heterogeneity and the attribute
- 21 thresholds. As such, this study aims to fill this research gap by allowing for random VTT that
- 22 vary across a simulated population to test the impacts on misspecified models. While our main
- focus is on the impact of retrieving heterogeneity, it should be clear that bias can also arise in
- 24 fixed coefficients models.
- 25
- 26 Implications of budget constraints on choice set modelling tools
- 27 It is anticipated that examination of the potential confounding impacts on taste heterogeneity
- findings due to unaccounted budget constraint effects could provide valuable insights into the
- 29 performance of existing choice set formation models. A full two-stage probabilistic choice set
- 30 model (1; 3) includes modelling a first stage non-compensatory decision-making process in
- 31 which travellers restrict their decisions to a particular subset of a full choice set in order to
- 32 conform to their travel budget constraints. This is followed by a compensatory second stage
- 33 where utilities are maximized within each subset of choice set. We hypothesize that if taste
- 34 heterogeneity is indeed confounded with the budget constraint effect during the choice set
- 35 generation stage, then it could also lead to bias in the choice evaluation stage. It is also
- anticipated that such issues also applies to the single-stage constrained choice set models for
- approximation of the constrained choice sets (2; 10).
- 38

## 39 **3 EMPIRICAL SETUP**

## 40 **3.1 Data generating process**

- 41 Monte Carlo simulations
- 42 Simulated datasets are generated through a Monte Carlo simulation to provide empirical
- 43 evidence of the impacts of the budget constraints on the availabilities of alternatives. Simulated
- datasets are used for this application as the data generating process is fully controlled while the
- 45 true parameters are available for fair comparisons across different model specifications. In this
- 46 exercise, we adopt a simple time-cost trade-off exercise, which has been used mostly in the
- 47 national value of time studies in Western Europe (4). The use of simple trade-offs has received

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- 1 increasing criticism as the valuations from more complex SC designs are deemed more reliable.
- 2 More complex choices are also thought to be more comprehensible to respondents (11).
- 3 Nevertheless, such simple trade-offs are useful in this study to enable us to disentangle the
- 4 confounding effects, which is more difficult under the presence of more than two attributes.
- 5 Also, it is anticipated that the impact of budget constraints on alternative elimination would be
- the most severe as only one alternative remains in the choice set when the counterpart gets
  eliminated for exceeding the time budget thresholds. As such, we could explore the impact of
- eliminated for exceeding the time budget thresholds. As such, we could explore the impact of
  budget constraints at its most extreme condition. The findings from this exercise should provide
- 9 insights to researchers for further test on designs with more complex choices.
- 10
- 11 *Choice scenarios*
- 12 Within the simulated population, all pseudo-observed decision-makers are presented with two
- 13 alternatives, each with varying levels of travel time between 30 minutes and 75 minutes and
- 14 travel cost between £3 and £7.5. A full factorial design is first generated, with dominated choices
- 15 removed. A choice-rejection mechanism is enforced such that if the travel time attribute
- 16 presented exceeds the predefined time budget, the respective alternative is then rejected. To
- 17 retain the same number of observations across different budget threshold bands for fair
- 18 comparisons, the design only allows trade-offs between travel times where at most one
- 19 alternative exceeds the time budget of 45 minutes. For those choice tasks with both alternatives
- 20 retained, the simulation assumes that individuals make choices according to the standard random
- 21 utility maximizing rule. A total of 2,700 choice tasks are generated, where these choice tasks are
- randomized and organized into 10 choice tasks each for 540 pseudo-observed decision-makers,
- 23 with each of the original choice tasks used twice.
- 24
- 25 Generation of choices
- Using a random utility model, we write the utility  $U_{i,n,t}$  that an individual *n* obtains from
- 27 choosing alternative *i* in choice task *t* as being decomposed into an observed component  $V_{i,n,t}$
- and a random component  $\varepsilon_{i,n,t}$ . The observed component of the utility of the time and cost tradeoffs can simply be written as:
- 30

31  $V_{i,n,t} = \beta_t T_{i,n,t} + \beta_c C_{i,n,t}$ 32

where *T* is the time attribute and *C* is the cost attribute, while  $\beta_t$  and  $\beta_c$  refer to the marginal utilities of time and cost respectively.

Four combinations of specifications for time sensitivities and time budget variations across simulated population are set out to generate choices in this study while cost coefficients are always kept fixed and linear. Mean time and cost coefficients are set as -0.075 and -0.90 respectively, thus resulting in a "true" mean VTT of £5/hr across the simulated population. The four combinations used are as follows:

40 41

42

- Fixed time budget
  - $\circ$  Set A Fixed and linear time sensitivities of -0.075
- 43 o Set B Negative lognormally distributed time sensitivities with an arithmetic mean
   44 of -0.075 and standard deviation of 0.038
- 45 Mixed time budget
  - $\circ$  Set C Fixed and linear time sensitivities of -0.075

- 1 2
- Set D Negative lognormally distributed time sensitivities with an arithmetic mean of -0.075 and standard deviation of 0.038

Two sets of time budgets are tested in this study. The fixed budget assumption as in sets A and B assumes all individuals share the same time budget threshold, which varies from the unconstrained case of 75 minutes to 55 minutes in the most stringent scenario. The mixed budget assumption as in sets C and D assumes that 50% of the simulated population are 10 minutes more restricted in terms of the time budget when compared to the rest of the simulated population.

8 9

## 10 **3.2 Model estimations**

11 A number of different model specifications were tested on the simulated data.

12

13 Fixed and linear time sensitivities

- 14 The multinomial logit (MNL) model is used for estimations of the fixed and linear time
- 15 sensitivities. Let  $P_{n,t}(i|\beta)$  give the probability of respondent n (with n = 1, ..., N) for alternative
- 16 i (with i = 1, ..., I) in choice situation t (with  $t = 1, ..., T_n$ ), conditional on a vector of taste
- 17 coefficients  $\beta$ , with  $\varepsilon_{i,n,t}$  following a Type I extreme value distribution, distributed identically
- 18 and independently across alternatives and choice situations. The choice probability given by the
- 19 MNL model then becomes  $P_{n,t}(i|\beta) = e^{V_{i,n,t}} / \sum_{j=1}^{J} e^{V_{j,n,t}}$ . The log-likelihood (LL) function,
- 20 conditional on  $\beta$ , is given by:

$$LL(\beta) = \sum_{n=1}^{N} \sum_{t=1}^{T_n} \ln\left(P_{n,t}(j_{n,t}|\beta)\right)$$

22

21

where  $j_{n,t}$  is the alternative chosen by respondent *n* in choice situation *t*. Since time sensitivities are specified as fixed and linear in this set of scenarios, VTT can be computed by taking the ratio of the partial derivatives of the utility against time and cost, which is the marginal rate of substitution between time and cost, expressed as  $\beta_t/\beta_c$ .

27

28 Negative lognormally distributed time sensitivities

- 29 The MMNL model is used for estimations of the random VTT. In the MMNL model, the vector 30 of the taste coefficients  $\beta$  follows a random distribution across respondents, such that we
- have  $\beta \sim g(\beta \mid \Omega)$ , with  $\Omega$  representing a vector of parameters of the distribution of  $\beta$ . In this study we allow tastes to very across respondents only but stay constant across choice situations
- 32 study we allow tastes to vary across respondents only but stay constant across choice situations
- 33 (cf. 12). The choice probability of the chosen alternative given by the MMNL model for

34 respondent n over a sequence of choices he/she faced becomes:

35 
$$P_n(\Omega) = \int_{\beta} \prod_{t=1}^{T_n} P_{n,t}(j_{n,t}|\beta)g(\beta|\Omega)d\beta$$

36

37 The log-likelihood function is given by:

38 
$$LL(\Omega) = \sum_{n=1}^{N} \ln\left(\int_{\beta} \left[\prod_{t=1}^{T_n} \left(P_{n,t}(j_{n,t}|\beta)\right)\right] g(\beta|\Omega) d\beta\right)$$

- 1 We have assumed that the time sensitivities are negative lognormally distributed in the model
- estimations where random VTT are estimated. 200 Halton draws are used to approximate the
   integral through Monte Carlo simulation for all the MMNL models.
- 4
- 5 Non-linear time sensitivities
- 6 We finally test non-linear functional forms to catch the tail of the VTT distributions where
- 7 attribute levels exceed travel budgets. As such, the 3rd-degree polynomials with the form  $\beta_{t1}T$  +
- 8  $\beta_{t2}T^2 + \beta_{t3}T^3$  specified for time sensitivities are estimated using the MNL models. In terms of
- 9 the VTT calculations, the partial derivative of the utility also depends on the time attribute due to
- the non-linearities. For the time sensitivities formulated in 3rd-degree polynomial form, the VTT becomes  $(\beta_{t1} + 2\beta_{t2}T + 3\beta_{t3}T^2)/\beta_c$ .
- 12
- 13 Incorporation of constraints
- 14 All scenarios are tested with and without the knowledge of the availabilities of alternatives (due
- 15 to constraints) for each choice task. The model runs with known availabilities of alternatives are
- 16 used for replicating the true parameters in the unbiased models while another set of model runs
- are undertaken for testing the budget constraint impacts in the biased models.
- 18

## 19 4 EMPIRICAL RESULTS

- 20 We now present the results of the various models, where we look in turn at each simulated data
- 21 setting. For each model specified for estimation, 100 simulated data sets are drawn randomly. All
- the model results reported are averages across all 100 simulated data sets.
- 23

## 24 **4.1 Linear time sensitivities under fixed time budget**

- 25 *Replication of time and cost sensitivities*
- 26 When the availabilities of alternatives for all the choice tasks in the SC experiment are known to
- the analyst, the MNL models can replicate the true time sensitivity of -0.075 consistently across
- different levels of thresholds set out in the unbiased models (A1) as shown in Table 1. It is also
- shown that MMNL models (B1) are able to retrieve the true arithmetic mean of -0.075 for time
- 30 sensitivity and standard deviation of 0.038 from the simulated population with negative
- 31 lognormally distributed time sensitivities. The true cost sensitivity of -0.9 is also consistently
- 32 retrieved from the models.
- 33
- 34 *Model fit* ( $\rho^2$  and LL)
- 35 The unbiased models become more deterministic when alternatives are eliminated due to the
- 36 stringency of the time budgets since the probability of observing the chosen alternatives becomes
- one for these choice tasks. It is shown that there is a significant improvement in LL from -2,967
- in the unconstrained scenario to -1,400 when time budget is set at 55 minutes (A1), when fixed
- tastes are assumed in the simulated data. Similarly, when random time sensitivities are included
- 40 in the data generating process, LL is improved from -3,036 to -1,416 (B1) in the unbiased
- 41 models. Since individuals are assumed to make their choices based on RUM-consistent
- 42 behaviour for the remaining choice tasks that are not eliminated, the true VTT of  $\pounds$ 5/hr can be
- retrieved from these choice tasks. These results show that the true values can be replicated whenthe model structure is properly specified and the availabilities of alternatives are known.
- 45
- 46 Biased estimates in MNL models when the availabilities of alternatives are unknown

- 1 The fact that the availabilities of alternatives are unknown to the analyst has several implications
- 2 for the model estimation. First, respondents whose time constraints leave them with only one
- 3 viable option, are then forced to choose the faster but more expensive alternatives. As the time
- constraints are unobserved by the analyst, the choice models consequently over-estimate the time
   sensitivities given that the observed choice probabilities of the faster alternatives are higher
- 6 compared to the estimates in the unbiased scenarios when the availability of alternatives are
- 7 known to analysts. As shown in Table 1, time sensitivities are overstated significantly by 109%
- 8 from -0.075 to -0.157 when the time budget is restricted to 55 minutes (A2). VTT is also over-
- 9 estimated to a similar level, from  $\pm 5/hr$  in the unconstrained scenario to  $\pm 10.3/hr$  when a time
- 10 budget of 55 minutes is assumed. These findings of biased estimates for the VTT are in line with
- 11 the past empirical evidence discussed in Section 2.
- Second, in the unconstrained scenarios when travel times presented are not restricted by 12 time budgets, some respondents would still choose the slower but cheaper alternatives due to any 13 unobserved factors, even when their VTT are higher than the boundary values of time. These 14 unobserved factors, which are represented as random errors in choice models, do not contribute 15 16 to the randomness of choices anymore once the time budget constraints are applied when faster alternatives become the only viable choices. As such, the choice processes are estimated to be 17 more deterministic when the budget constraint impacts enter the model estimations. This 18 explains the increase of  $\rho^2$  and LL from 0.21 and -2,970 in the unconstrained scenario to 0.45 19 and -2,058, respectively, when the budget is set at 55 minutes, even when no choice tasks are 20
- 21 omitted from the LL calculations.
- 22

23 Biased estimates in MMNL models when the availabilities of alternatives are unknown

- Given the popularity of using MMNL models to capture preference heterogeneity, it is of
- 25 particular interest to understand whether the MMNL models can fully capture the preference
- 26 heterogeneity even when some attribute levels exceed the time budget thresholds of respondents.
- As shown in Table 1, the MMNL models increasingly fail to capture the preference heterogeneity
- inherent to the true data set when the time budgets become more stringent (B2). The standard
- deviation of the negative lognormally distributed time sensitivities are reduced from 0.037 in the
- 30 unconstrained scenario to 0.028 and 0.018 when the time budget thresholds are set at 70 minutes 31 and 60 minutes respectively. At the time budget threshold of 55 minutes, the MMNL model fails
- to capture any preference heterogeneity with the arithmetic mean estimated at -0.154. This
- arithmetic mean estimate is similar to the biased marginal time utility estimated at -0.157 by the
- 34 MNL model (A2) when the time budget threshold is 55 minutes. This implies that the MMNL
- 35 model effectively treats all respondents as having high time sensitivities.
- To explain this further, let us consider the situation in which people have heterogeneous 36 time sensitivities across the sample. When the time budget constraints are stringent, individuals 37 who have low VTT are forced to choose the fast but expensive alternatives as opposed to the 38 slow and cheap alternatives which they prefer. On the other hand, individuals who have high 39 40 VTT would also choose the fast but expensive alternatives, either due to their high willingness to pay in the unconstrained choice situations, or due to the budget constraints in the constrained 41 situations. If, as a result, the choice outcomes are the same between these two groups of 42 43 individuals who share distinctly different VTT, the MMNL model cannot detect any differences 44 in tastes between them when the time budget constraints are not accounted for. It demonstrates that the use of MMNL model could potentially produce misleading findings of a lack of 45 preference heterogeneity, when in fact the preference heterogeneity is simply suppressed by the 46
- 47 severe time budget constraints in the model estimations which dominate completely. Similarly, it

- 1 is also shown that the VTT estimates produced by the MMNL models (B2) align closely with the
- 2 estimates generated by the biased MNL models (A2) at all levels of the time budget constraints.
- 3 Both the MNL and MMNL models over-estimate the VTT by twofold in the most extreme case,
- 4 at around  $\pounds 10.3$ /hr approximately due to the inflated time sensitivities. Cost sensitivities on the
- 5 other hand are not affected by the time budget constraints and the MMNL models are able to
- 6 retrieve the true value of -0.90.
- 7

## 8 4.2 Linear time sensitivities under mixed time budgets

- 9 Replication of parameters when the availabilities of alternatives are known
- 10 It has been shown above that the MMNL models could produce misleading findings with respect
- 11 to the presence of preference heterogeneity when all respondents share the same time budget
- 12 thresholds. This section further introduces mixed time budget thresholds to the model
- 13 estimations, which assumes that two randomly selected groups within the simulated population
- share distinctly different perceptions of the time budget constraints. Within this setting, half of
- 15 the respondents perceive their time budget constraints to be 10 minutes more restrictive in
- 16 comparison with the rest of the population (e.g., time budget constraints of 60 minutes and 70 minutes paragived by helf of the respondents respectively). The chieves of this second for the second secon
- 17 minutes perceived by half of the respondents respectively). The objective of this exercise is to 18 examine whether further confounding of preference heterogeneity would occur when budget
- thresholds are not fixed amongst individuals. In the unbiased scenarios where the availabilities of
- alternatives subject to the budget constraints are known to analyst, all true values assumed in the
- 21 data generating process (VTT of £5/hr, mean time sensitivity of -0.075 and cost sensitivity of -
- 22 0.90) are retrieved (C1 and D1 in Table 2).
- 23

24 Biased estimates when the availabilities of alternatives are unknown

- 25 Similar to the findings from scenarios where fixed time budgets are assumed amongst
- 26 individuals, the biased models over-estimate time sensitivities when the mixed time budget
- 27 constraints are stringent. In the most restrictive scenario where half of the respondents perceive
- the time constraints to be either 55 minutes or 45 minutes, time sensitivity is over-estimated by
- 29 123%, from -0.075 to -0.165 (C2 vs. C1 in Table 2). Apart from the inflated time sensitivities
- due to unaccounted time budget constraints, we again test whether the MMNL specification for the model estimations would lead to bioged results. In general, we del would be determined to be a set of the set of
- 31 the model estimations would lead to biased results. In general, model results show that the missnesified MMNL models (C2) pick up preference betwee consists that does not exist in the
- misspecified MMNL models (C3) pick up preference heterogeneity that does not exist in the data generating process. In the scenario where the mixed time budget constraint is the most stringent,
- the misspecified MMNL model estimates the standard deviation of the time sensitivity at 0.037,
- with a *t*-statistic that is significant at 6.5. This provides evidence that the MMNL model could
- potentially misinterpret the effects of mixed budget thresholds as preference heterogeneity. In
- other words, despite the fact that all individuals share the same VTT, choice probabilities for the
- chosen alternatives could still vary significantly across the population according to the mixed
- 39 budget threshold setting.
- To put this issue into context, let us assume a case where all individuals are willing to pay £1.25 to save 15 minutes of travel time (i.e., a VTT of £5/hr). They are then asked to choose between the free alternative, which requires 60 minutes of travel time, and the tolled alternative, which costs £2 for a 45-minute journey. Since the toll charge is higher than the willingness to pay to save 15 minutes of travel time for all individuals, they are likely to choose the free alternative over the tolled alternative. Now assume that some but not all of these respondents are also subject to a time budget threshold of 55 minutes, the tolled alternative then becomes the
- 47 only available option due to the budget constraints, rather than the free alternative that they

- 1 prefer. As the time budget variations amongst individuals are unobserved, the choice models thus
- wrongly attribute such effects to the differences in taste heterogeneity amongst populationinstead.

4 The difficulties of distinguishing whether the variations in choice probabilities are due 5 to preference heterogeneity or differences in budget thresholds are further complicated when both the budget thresholds and tastes vary amongst individuals. On one hand, we would 6 7 anticipate that the MMNL model could not fully capture the preference heterogeneity assumed in 8 the simulated data set when the travel budget constraints are applied, as described in Section 4.1. 9 On the other hand, we also expect that the MMNL model would wrongly attribute the mixed budget effects as taste heterogeneity when time budgets are very stringent. As the variations of 10 time budgets amongst individuals are unknown to the analyst, there is substantial risk that 11 misleading findings of taste heterogeneity can also be attributed to a mix of these two opposite 12 effects. The model results across different levels of stringency of time budgets for simulated data 13 where random time sensitivities and mixed time budgets are assumed are shown in D2 in Table 14 15 2.

16

## 17 **5 INCLUSION OF AN OPT-OUT ALTERNATIVE**

18 The inclusion of an opt-out alternative, or sometimes referred to as the 'no choice', 'neither',

19 'none of these' or 'status quo' alternative in SC scenarios has been widely discussed in the past.

20 It has been argued that the inclusion of an opt-out alternative increases both the realism of the SC

choice tasks and the statistical efficiency of model estimations (cf. 13). Given the

aforementioned risk of confounding impacts on the taste heterogeneity findings due to

unaccounted budget constraint effects, it is our interest to explore the effectiveness of the opt-out alternative to reduce the bias associated with budget constraints in the valuation of VTT.

25 Model specifications including fixed time budget thresholds and negative lognormally distributed time sensitivities (B2 in Table 1) are retained as the basis for the new data generating 26 27 process to generate choices for the scenarios that include opt-out alternatives. The utility of the new opt-out alternative is represented by an alternative-specific constant (ASC), where a value of 28 -9.0 is assigned to the opt-out alternative to represent the dis-benefits from not being able to 29 30 travel. This results in approximately 25% of individuals choosing the opt-out alternative in the unconstrained scenario, with a choice probability of 37.5% approximately for any of the two 31 travel alternatives. This setting implies that the dis-utilities of not travelling are slightly larger 32 33 than the dis-utilities of the travel alternatives in the unconstrained situation, ensuring that the optout alternative is not overly attractive relative to the two travel alternatives. 34

35 Similar to the unbiased model results presented earlier, all the true values including the arithmetic mean and standard deviation parameters of the time coefficients, cost coefficients, and 36 the ASC values of -9.0 for the opt-out alternatives are retrieved when the availabilities of 37 alternatives are known to the analyst (B1 in Table 3). When the availabilities of alternatives are 38 39 unknown, taste heterogeneity assumed in the data generating process cannot be retrieved fully (B2 in Table 3), but the level of bias is not as strong as that in the binary choices examined 40 earlier. When the time budget threshold is set to 55 minutes, the arithmetic mean and standard 41 deviation of the time coefficient change from -0.075 and 0.038 in the unconstrained case to -42 0.145 and 0.032, respectively, in the model that includes an opt-out alternative. This is compared 43 to the arithmetic mean of -0.154 and a complete loss of taste heterogeneity in binary choices 44 45 without an opt-out alternative (B2 in Table 1). It is noted that the capability of recovering taste heterogeneity under the presence of the opt-out alternative would depend on both the SC design 46 and the value of the ASC assigned. The SC design implemented in this study only allows one out 47

- 1 of two travel alternatives to exceed the budget thresholds. This setting always allows respondents
- 2 to choose between the opt-out alternative and at least one other travel alternative, which
- 3 facilitates the retrieval of the true preference from these trade-offs. In practice, the recovery of
- 4 some taste heterogeneity might be somewhat less effective since the respondents could be forced
- 5 to choose the opt-out alternative only when both the travel alternatives presented exceed their
- 6 budget thresholds. In summary, the inclusion of the opt-out alternative would provide more
- 7 information to the choice model to explain taste heterogeneity but cannot fully eliminate the
- 8 confounding issue when the budget constraints are not accounted for in the choice model.
- 9

## 10 6 NON-LINEARITIES

- 11 Replication of parameters when the availabilities of alternatives are known
- 12 This section switches our focus to the incorporation of non-linearities in the model specifications
- 13 to capture potential budget constraint effects. We have demonstrated in earlier sections that the
- 14 confounding of taste heterogeneity findings due to unaccounted budget constraint effects could
- potentially lead to significant bias in the VTT estimation. We also hypothesize that travel budget
- 16 constraints are latent in nature, which are difficult to measure without the use of more
- 17 complicated probabilistic choice set formation models. It is thus useful to examine whether non-
- 18 linear functional forms could capture the kink of travel dis-utilities, which could occur when
- 19 stringent budget constraints are applied. This could potentially provide useful insights to
- researcher on the possibility that particular attribute levels set out in SC designs are beyond
- 21 budget thresholds for some decision-makers.
- A 3rd-degree polynomial functional form for time sensitivities is adopted for testing the use of non-linear functional forms in this study. Model results show that the 3rd-degree polynomial functional forms produce very similar cost sensitivities, LL and  $\rho^2$  (E1 in Table 4) as in the MNL models (A1 in Table 1) when the availabilities of alternatives are known to the analyst. Overall, it appears that the 3rd-degree polynomial form specified for time sensitivities collapses to a linear form in the unbiased models, as the estimated time coefficients for the
- 28 second and third polynomial terms are very small. The true VTT of £5/hr, estimated in quadratic
- forms as described in Section 3.2, is retrieved across all levels of the budget thresholds and
- 30 attribute levels.
- 31
- 32 Biased parameters when the availabilities of alternatives are unknown
- 33 Model results estimated when the availabilities of alternatives are unknown to the analyst are
- 34 summarized in set E2 in Table 4. The VTT estimates produced by the polynomial utility
- 35 functional forms are shown to be highly sensitive to the attribute levels of the travel time, as
- 36 opposed to the VTT estimates in unbiased models that are stable across attribute levels. For
- instance, when the time budget threshold is set at 55 minutes, the VTT escalates from £91/hr to
- 138 £184/hr when the journey times increase from 65 minutes to 75 minutes, as shown in Figure 1.
- 39 These exceptionally high VTT estimates show that respondents are highly unlikely to choose the
- 40 alternatives where travel times presented are beyond the time budgets, and could become useful
- indicators to highlight the significant impacts of the budget constraints on the VTT valuation.
   Now we examine whether the flexible utility functional forms could capture the tail of
- the VTT distributions where the attribute levels exceed the travel budgets of the respondents.
- Figure 1 also shows the utility levels that are related to the travel time components only. It can be
- 45 seen that the time dis-utilities increase significantly only when time attributes presented are
- beyond the budget thresholds. For instance, when time budget is set at 55 minutes, the
- 47 polynomial utility function produces a stable utility level for journeys that last between 30

- 1 minutes and 55 minutes. Beyond that, the travel time dis-utilities increase significantly as the
- 2 time attribute values exceed the designated time budget of 55 minutes. This indicates that the use
- 3 of the 3rd-degree polynomial utility function could become a convenient and effective approach
- 4 to detect the potential budget constraint effects in SC data.
- 5

## 6 7 CONCLUSIONS

7 This paper has sought to provide a detailed assessment of the impact of time budget constraints

- 8 on the VTT estimates and the identification of preference heterogeneity, when explicit modelling
- 9 of choice set formation is not involved. We first show that if time budgets are stringent but not
- accounted for, VTT can be significantly overestimated. Secondly, this paper has provided a
- 11 comprehensive set of empirical evidence to understand the confounding impact on preference
- heterogeneity findings due to the unaccounted budget constraint effects across a range of time hudget stringeney. It is found that the MMANL model fails to continue any professor
- budget stringency. It is found that the MMNL model fails to capture any preference
- heterogeneity and collapses to a MNL model when the travel budget is very binding within a binary choice and deterministic alternative elimination setting. We also found that the MMNL
- 16 model could also wrongly attribute the impacts of the mixed time budget constraints to the
- 17 findings of preference heterogeneity.
- 18 We found that including an opt-out alternative could potentially help retrieve some but 19 not all preference heterogeneity under the presence of budget constraints. Our findings from this
- study also raise some further questions. First, the question arises whether the confounding issue
- also occurs at the non-compensatory stage of the choice set formation models (e.g., the Manski-
- type models). Second, how can we disentangle the confounding effects using real life SC data.
- 23 Third, there is a need for a comparative analysis to assess the differences between the single-
- stage semi-compensatory model for approximation of constrained choice sets (e.g., the
- constrained multinomial logit model) and the simple non-linear functional forms, given that
- simple non-linear functions could potentially capture the kink of the time sensitivities whensubject to binding budget constraints.
- It should be noted that if the SC surveys adequately capture rescheduling by allowing respondents to trade travel time and cost differences against re-timing of their departure and/or arrival times, then many of these aforementioned issues could be avoided or at least reduced (cf. *14*). While there are many VTT studies that have analysed the impact of trip rescheduling, most appraisal VTT measures for national or regional infrastructure projects are estimated without taking into consideration the possibility of trip rescheduling (*15*). In this context, we question whether such approaches, especially for the studies which rely on simple time-money trade-offs,
- 35 could avoid or reduce any potential bias on the VTT estimates that might result from
- 36 unaccounted for travel budget impacts.
- This study represents a key step for extending our knowledge of the impact of budget constraints. Future extensions to the simulation work would include varying number of attribute and alternatives, enabling multiple budget constraints and different decision strategies dealing with budget constraints, and improving realism in the assumption of budget constraints.
- 41

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- 46
- 47 AUTHOR CONTRIBUTION STATEMENT

- 1 The authors confirm contribution to the paper as follows: study conception and design: Tjiong,
- 2 Dekker, Hess; generation of simulated data: Tjiong; analysis and interpretation of results: all
- 3 authors; draft manuscript preparation: all authors. All authors reviewed the results and approved
- 4 the final version of the manuscript.
- 5

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- 47

## 

# TABLE 1 – Estimation results for linear time and fixed time budget in DGP

Budget	ρ²			β	ł		ĥ	Bc	VTT (	E/hr)				
Threshold (min)		LL	Mean	t-stat	SD	t-stat	Est	t-stat	Mean	SD				
	A1 - UNBIASED		DGP: Fixed Time Budget - Linear Time - Fixed $\beta_t$											
AI - UNDIASED		EST: Fixed Time Budget - Linear Time - Fixed βt (MNL)												
75	0.21	-2,966.57	-0.075	31.1	-	-	-0.905	31.6	4.99	-				
70	0.30	-2,619.77	-0.075	26.7	-	-	-0.896	29.4	5.00	-				
65	0.40	-2,230.36	-0.075	22.5	-	-	-0.900	26.7	4.99	-				
60	0.51	-1,822.36	-0.075	18.0	-	-	-0.899	23.9	5.00	-				
55	0.63	-1,399.64	-0.076	13.7	-	-	-0.905	20.7	5.03	-				
B1 - UN		DGP:	Fixed Time B	udget - Li	near Time - Ran	dom $\beta_t$								
BI - UNI	DIASED	EST:	EST: Fixed Time Budget - Linear Time - Random βt (MMNL)											
75	0.19	-3,035.94	-0.075	61.4	0.037	14.3	-0.899	29.0	5.02	2.50				
70	0.29	-2,657.06	-0.075	54.0	0.038	12.5	-0.903	27.2	5.02	2.52				
65	0.40	-2,254.72	-0.076	46.3	0.037	10.0	-0.908	24.9	5.04	2.46				
60	0.51	-1,843.73	-0.074	37.8	0.037	7.6	-0.897	22.3	4.98	2.47				
55	0.62	-1,415.61	-0.075	28.9	0.036	5.2	-0.900	19.1	5.03	2.47				
A2 - BI	ASED	DGP: Fixed Time Budget - Linear Time - Fixed $\beta_t$												
A2 - DI	ASED	EST: Fixed Time Budget - Linear Time - Fixed $\beta_t$ (MNL)												
75	0.21	-2970.04	-0.075	31.1	-	-	-0.901	31.4	5.01	-				
70	0.24	-2843.25	-0.090	34.2	-	-	-0.917	31.8	5.88	-				
65	0.29	-2650.01	-0.108	37.2	-	-	-0.932	32.0	6.94	-				
60	0.36	-2382.77	-0.130	38.9	-	-	-0.941	31.1	8.31	-				
55	0.45	-2057.62	-0.157	38.9	-	-	-0.914	28.5	10.31	-				
B2 - BI	ASED	DGP:	Fixed Time B	udget - Li	near Time - Ran	dom $\beta_t$								
D2 - D1	ASED	EST:	Fixed Time B	udget - Li	near Time - Ran	idom βt (N	MMNL)							
75	0.19	-3035.08	-0.075	61.5	0.037	14.2	-0.900	29.2	5.01	2.5				
70	0.22	-2924.34	-0.089	70.8	0.028	10.5	-0.906	29.6	5.90	1.9				
65	0.27	-2722.02	-0.106	75.6	0.018	5.7	-0.904	29.7	7.01	1.2				
60	0.35	-2431.31	-0.126	76.5	0.004	0.8	-0.899	29.7	8.40	0.3				
55	0.44	-2078.23	-0.154	71.5	0.000	0.5	-0.890	28.2	10.40	0.0				

## 

# TABLE 2 – Estimation results for linear time and mixed time budget in DGP

Budget	2			ĥ	Bt		βα		VTT	(£/hr)				
$\begin{array}{c c} \text{Threshold} & \rho^2 \\ (\text{min}) & \end{array}$		LL	Mean	t-stat	SD	t-stat	Est	t-stat	Mean	SD				
C1 - UNBIASED		DGP:	Mixed Ti	ne Budge	t (50-50%) -	- Linear Ti	ime - Fixed	β <sub>t</sub>						
		EST: Mixed Time Budget (50-50%) - Linear Time - Fixed βt (MNL)												
75 & 65 0.30		-2,603.35	-0.075	27.2	-	-	-0.900	29.3	4.99	-				
70 & 60	70 & 60 0.41		-0.075	22.9	-	-	-0.894	26.7	5.01	-				
65 & 55	0.51	-1,816.17	-0.074	18.7	-	-	-0.898	24.1	4.97	-				
60 & 50	0.62	-1,404.34	-0.075	14.7	-	-	-0.901	21.1	4.98	-				
55 & 45	0.74	-989.32	-0.075	10.6	-	-	-0.898	17.3	4.98	-				
D1 - UNBL	ASED	DGP:	Mixed Ti	ne Budget	t (50-50%) -	- Linear Ti	ime - Rando	$m \beta_t$						
DI - UNDI	ASED	EST:												
75 & 65	0.29	-2,641.81	-0.076	54.7	0.037	12.4	-0.904	27.2	5.02	2.5				
70 & 60	0.40	-2,244.51	-0.075	47.1	0.037	10.2	-0.905	25.0	4.98	2.5				
65 & 55	0.51	-1,840.67	-0.074	38.5	0.038	8.3	-0.898	22.4	4.99	2.5				
60 & 50	0.62	-1,416.85	-0.075	31.1	0.036	5.7	-0.896	19.6	5.03	2.4				
55 & 45	0.73	-998.14	-0.069	23.5	0.034	5.2	-0.905	16.3	4.97	2.5				
C2 - BIAS	SED	DGP: Mixed Time Budget (50-50%) - Linear Time - Fixed $\beta_t$												
C2 - DIA	360	EST: Mixed Time Budget (50-50%) - Linear Time - Fixed $\beta_t$ (MNL)												
75 & 65	0.24	-2,860.52	-0.089	33.2	-	-	-0.895	31.6	5.95	-				
70 & 60	0.28	-2,689.35	-0.104	35.1	-	-	-0.892	31.2	7.03	-				
65 & 55	0.35	-2,441.55	-0.124	36.7	-	-	-0.877	29.7	8.49	-				
60 & 50	0.42	-2,160.86	-0.144	37.0	-	-	-0.819	26.9	10.58	-				
55 & 45	0.51	-1,833.58	-0.165	36.1	-	-	-0.684	21.0	14.49	-				
C3 - BIAS		DGP:	DGP: Mixed Time Budget (50-50%) - Linear Time - Fixed β <sub>t</sub>											
(MISSPECI	FIED)	EST:	Mixed Ti	ne Budget	t (50-50%) -	Linear Ti	ime - Rando	$m \beta_t (MN)$	INL)					
75 & 65	0.24	-2,858.18	-0.091	77.3	0.014	5.0	-0.920	30.4	5.95	0.9				
70 & 60	0.28	-2,675.94	-0.109	75.9	0.016	5.0	-0.922	29.8	7.07	1.0				
65 & 55	0.35	-2,443.43	-0.129	71.4	0.019	5.4	-0.906	28.3	8.53	1.3				
60 & 50	0.42	-2,152.58	-0.153	63.7	0.025	5.9	-0.858	25.7	10.69	1.8				
55 & 45	0.51	-1,832.06	-0.180	51.8	0.037	6.5	-0.736	20.2	14.70	3.0				
D2 - BIAS	SED	DGP:	Mixed Ti	ne Budget	t (50-50%) -	Linear Ti	ime - Rando	om β <sub>t</sub>						
DZ - DIAGED		EST:	Mixed Ti	ne Budget	t (50-50%) -	Linear Ti	ime - Rando	$m \beta_t (MN)$	INL)					
75 & 65	0.22	-2,929.18	-0.091	66.2	0.036	13.6	-0.909	29.5	6.04	2.4				
70 & 60	0.27	-2,739.95	-0.109	70.0	0.031	11.3	-0.910	29.5	7.17	2.1				
65 & 55	0.34	-2,481.53	-0.130	67.8	0.030	9.7	-0.902	28.0	8.66	2.0				
60 & 50	0.42	-2,169.94	-0.155	61.6	0.034	8.7	-0.859	25.7	10.86	2.4				
55 & 45	0.51	-1,829.64	-0.183	51.2	0.042	7.5	-0.737	20.2	14.90	3.4				

#### 

Budget Threshold	ρ <sup>2</sup>	LL	βι				βc		VTT (£/hr)		ASC for Opt- out Option	
(min)			Mean	t-stat	SD	t-stat	Est	t-stat	Mean	SD	Est	t-stat
B1 – UNBI	ASED	DGP:	Fixed Tin	ne Budget	- Linear T	Time - Rai	ndom $\beta_t$					
(W/ OPT-	OUT)	EST:	Fixed Tin	ne Budget	- Linear 🛛	Time - Rai	ndom β <sub>t</sub> (1	MMNL)				
75	0.23	-4567.86	-0.075	65.1	0.037	20.2	-0.902	34.5	5.00	2.50	-9.027	-36.7
65	0.31	-4108.58	-0.075	52.5	0.038	18.1	-0.903	32.2	5.01	2.52	-9.028	-32.5
60	0.35	-3875.24	-0.075	46.0	0.038	16.8	-0.899	31.0	5.03	2.52	-9.002	-30.2
55	0.39	-3635.90	-0.075	39.5	0.038	15.3	-0.899	30.0	5.00	2.52	-8.988	-28.2
B2 – BIA	SED	DGP:	Fixed Time Budget - Linear Time - Random $\beta_t$									
(W/ OPT-	OUT)	EST:	Fixed Time Budget - Linear Time - Random $\beta_t$ (MMNL)									
75	0.23	-4574.10	-0.075	65.1	0.038	20.4	-0.901	34.7	5.03	2.5	-9.01	-36.9
65	0.24	-4495.65	-0.105	80.9	0.033	20.3	-0.929	35.5	6.82	2.1	-10.36	-40.3
60	0.26	-4379.86	-0.124	84.5	0.032	20.2	-0.927	35.2	8.05	2.1	-11.05	-41.6
55	0.29	-4218.61	-0.145	83.1	0.032	19.3	-0.902	33.2	9.68	2.1	-11.67	-41.1

TABLE 3 – Estimation results for inclusion of the opt-out alternative

# TABLE 4 – Estimation results for linear time and fixed time budget in DGP but estimated by non-linear functional form

Budget	ρ <sup>2</sup>		βι							c			
Threshold		LL	β <sub>t1</sub>		βt	β <sub>t2</sub>		β <sub>t3</sub>		4 - 4 - 4	VTT (£/hr)		
(min)			Est	t-stat	Est	t-stat	Est	t-stat	Est	t-stat	( <b>«/III</b> )		
E1 - UNBIASED		DGP:	Fixed Time Budget - Linear Time - Fixed β <sub>t</sub>										
EI - UNDIA	SED	EST:	: Fixed Time Budget - Non-linear Time (3 <sup>rd</sup> -degree polynomials) - Fixed $\beta_t$ (MNL)										
75	0.21	-2,968.33	-0.162	8.1	0.0017	8.8	-1.1E-05	45.98	-0.901	29.9	4.79		
70	0.30	-2,616.84	-0.129	4.8	0.0012	6.4	-8.1E-06	39.07	-0.896	28.3	4.86		
65	0.40	-2,225.71	-0.087	2.8	0.0002	4.4	-1.7E-06	27.19	-0.905	26.3	4.96		
60	0.51	-1,819.41	-0.116	1.6	0.0009	1.8	-6.1E-06	8.92	-0.902	23.7	4.92		
55	0.62	-1,401.19	-0.021	2.4	-0.0013	5.5	1.1E-05	5.95	-0.898	20.7	4.95		
E2 - BIAS	ED	DGP:	Fixed Time Budget - Linear Time - Fixed $\beta_t$										
E2 - DIAS	ED	EST:	Fixed Time Budget - Non-linear Time (3 <sup>rd</sup> -degree polynomials) - Fixed $\beta_t$ (MNL)										
75	0.21	-2,965.66	-0.164	7.6	0.0018	8.2	-1.2E-05	44.5	-0.901	30.1	4.78		
70	0.27	-2,728.27	-0.914	112	0.0187	606.5	-1.3E-04	174.9	-0.844	28.0	2.65		
65	0.37	-2,347.61	-1.486	103	0.0325	256.4	-2.4E-04	343.6	-0.840	26.0	1.80		
60	0.48	-1,943.58	-2.330	222	0.0538	984.8	-4.2E-04	187.0	-0.834	23.5	1.89		
55	0.60	-1,507.56	-3.933	349	0.0957	273.7	-7.7E-04	490.4	-0.852	21.2	4.78		

1 2

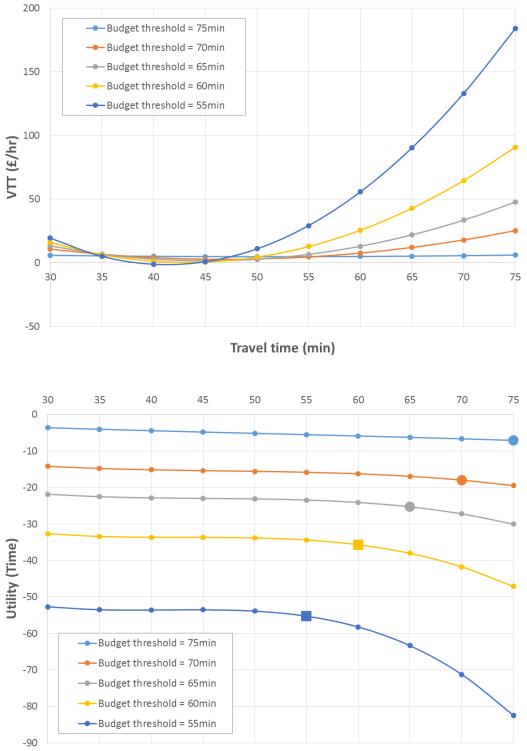


Figure 1 –VTT estimates and travel dis-utilities estimated by non-linear functional form

Travel time (min)