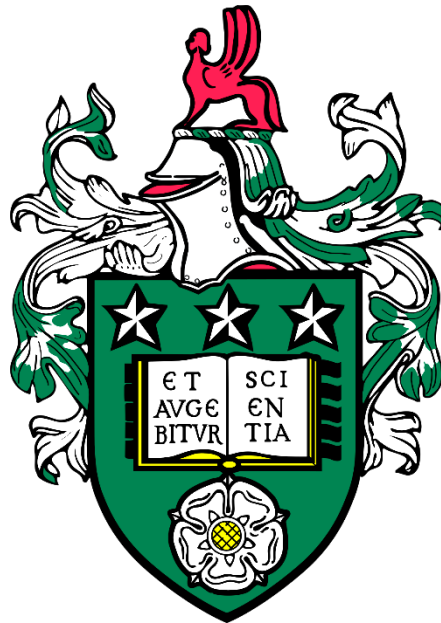# Impacts of survey design and model specification on willingness-to-pay estimates from discrete choice models

Submitted in accordance with the requirements for the degree of

Doctor of Philosophy

by

Jeff Tjiong

The University of Leeds

Institute for Transport Studies

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Intellectual property and publications

The candidate confirms that the work submitted is his own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

The work in **Chapter 2** of this thesis has appeared in publication as follows:

> **Tjiong, J**., Hess, S., Dekker, T. and Cabral, M.O., 2018. Impact of Travel Time Constraints on Taste Heterogeneity and Non-Linearity in Simple Time–Cost Trade-Offs. *Transportation Research Record, 2672(49)*, pp.135-145.

> The main idea for this work was developed together with Stephane Hess, Thijs Dekker and Manuel Ojeda Cabral. I performed the development of simulated choice data, the choice modelling work and wrote the manuscript. Stephane Hess and Thijs Dekker provided recommendations on the modelling and comments on the results. The manuscript was improved by comments from all the co-authors.

The work in **Chapter 3** of this thesis is a manuscript under review:

> **Tjiong, J.**, Dekker, T., Hess, S. and Cabral, M.O., (under review). Analysing the impact of income measures on the cross-sectional income elasticity of the value of travel time and the implications for transport appraisal

> I developed the main idea for this work, under the guidance of Thijs Dekker and Stephane Hess. I performed the expenditure survey data analysis and modelling work, the choice modelling work and wrote the manuscript. The choice modelling work was carried out based on the modelling framework developed for an earlier study conducted at ITS for the UK Department for Transport that involves Stephane Hess, Thijs Dekker and Manuel Ojeda Cabral. My co-authors provided recommendations on the modelling and comments on the results and the manuscript was improved by comments from all the co-authors.

The work **Chapter 4** is a manuscript prepared for submission:

Tjiong, J., Hess, S., Dekker, T., Giergiczny, S., Ojeda-Cabral, M. and Czajkowski, M., (to be submitted). Capturing zero-price effects in stated choice surveys and implications for willingness-to-pay computation

The main idea for this work was developed together with Stephane Hess and Thijs Dekker on the basis of an abstract of an unfinished paper by Marek Giergiczny, Mikołaj Czajkowski and Stephane Hess and an earlier conference presentation by Stephane Hess. I designed the stated choice survey, undertook the modelling work and wrote the manuscript. Marek Giergiczny and Mikołaj Czajkowski coordinated the data collection activities. Stephane Hess, Thijs Dekker and Manuel Ojeda Cabral provided recommendations on the modelling and comments on the results. The manuscript was improved by comments from Stephane Hess, Thijs Dekker and Manuel Ojeda Cabral.

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Abstract

Discrete choice models infer individuals' preferences from observed choices. Analysts can thereby contribute to producing more reliable demand forecasts and assess welfare impacts of policy/scenario changes. However, the risk of model misspecification errors may bias parameter estimates and lead to incorrect demand forecasts and policy recommendations. This thesis examines three types of model misspecifications: i) ignoring travel time constraints, ii) measurement error in the income variable, and iii) ignoring the behavioural phenomenon of the zero-price (ZP) effect. We are particularly interested in understanding the policy implications of these misspecifications on the marginal valuation of qualitative variables. Our analyses are relevant to policy makers as these specification errors prevail in some 'state-of-the-practice' model representations commonly used in support of cost-benefit analyses.

This thesis first examines the issue of ignoring travel time constraints for simple time-cost trade-offs. Analysts may ignore that some alternatives are not available to individuals as the travel times presented could exceed their time allowances for such journey. We find via simulation that the value of travel time (VTT) can be significantly over-estimated when travel time constraints are not accounted for in estimation. More importantly, we identify the confounding issue between travel time constraints and taste heterogeneity.

This thesis then turns to the issue of the measurement error in the income variable. We investigate the extent to which the income measure used in the estimation of choice models contributes to the disparity between the cross-sectional and inter-temporal income elasticity of the VTT. We compile various income measures that are varied in terms of the income re-distribution measures and the intra-household budget allocation based on secondary expenditure data. We empirically test the new income measures based on the modelling framework developed for the 2014/15 UK VTT study. Our results indicate that by additionally accounting for social benefits, the cross-sectional income elasticity of VTT approaches unity. This closes the gap between the cross-sectional and inter-temporal income elasticity. We find the behavioural VTTs, which represent the averages of the VTTs estimated from behavioural models across respondents, to be consistent despite the income variations. However, we find that when moving from the stated choice (SC) to the national travel survey to obtain a nationally representative figure for appraisal, appraisal values diverge as per the income variations due to the sampling bias in the income variable in

behavioural model. We highlight the requirement for the sampling of the income to be consistent between the estimation and implementation tool.

We finally explore the issue of ignoring the ZP effect in choice modelling. ZP effect is a well-established notion in behavioural economics which explains the tendency for individuals to over-react to free alternatives. The lack of attention to the ZP effect in the choice modelling literature is particularly worrying since 'free' status quo (SQ) alternatives are at the heart of many SC surveys, especially outside of transport, and form the basis of contrasting the (policy) 'interventions'. We develop alternative stated survey designs to identify the ZP effect. We find that the observed preference for remaining at the SQ is largely attributed to the ZP effect within our data. We also present experimental design features that allow separation of the ZP effect from the non-linear cost sensitivity. We stress that the prevalence of the ZP effect in observed choice behaviour may introduce bias to the prediction of welfare when the perfect confounding between the ZP and SQ effects is broken.

Overall, this thesis highlights the significant bias on WTP estimates that may be caused by ignoring some basic and fundamental misspecification issues. This thesis closes by suggesting some future improvements required to avoid model misspecification issues identified.

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Chapter 1

Introduction

1.1   Background

Discrete choice analysis has been used extensively for gathering insights into individuals' preferences and choice behaviour across different disciplines including economic research in transport, environment and resource, health, and marketing research. These insights are useful for forecasting market demand for new or modified products or policies, estimation of the welfare effects of policy changes, and identification of the determinants of decision process (Ben-Akiva and Lerman, 1985, McFadden, 2001, Train, 2009).

Within the discrete choice framework, provided individuals' preferences are regular and coherent (see Varian, 1992, Karlström, 2014), utility-maximising choices amongst a finite set of alternatives are empirically analysed based on the random utility maximisation model (RUM) that links individuals' preferences to choice (McFadden, 1974, McFadden, 2001). The conditional indirect utility[1], which is a function of disposable income, prices, quality and individual characteristics, is assumed to be a complete representation of individuals' preferences, subject to budget constraints. A random error (or disturbance) is added to reflect the fact that not all factors explaining choices are observable to analysts. Finally, with choice model specified in terms of the distribution of the random error (e.g. Gumbel, Multivariate Extreme Value) and heterogeneities in tastes, RUM-consistent choice probabilities for a portfolio of choices can be calculated either directly or by integration or simulation (see Train, 2009).

There have been many advances in discrete choice modelling over years. Choice models can now account for more complex error structures, representation of heterogeneity, integration with structural equation models, more efficient estimation techniques, and modelling of discrete-continuous choices (see Hess and Daly, 2014, Train, 2009). While some of these new modelling techniques are already incorporated in recent valuation studies (e.g. Hess et al., 2017), analysts are still faced with some basic and fundamental misspecification

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[1] 'Conditional indirect utility' is abbreviated as 'utility' herein, unless specified otherwise.

issues by adopting the 'conventional' designs and model structures in practice. I posit that these specification errors can bias the estimation of model parameters and can lead to false conclusions with regards to the valuations and their policy implications.

A key theme of this thesis is to compare the marginal valuation of quality variables under different scenarios of (mis)specification of discrete choice models. The marginal valuations of the attribute of interest can be derived from the marginal rates of substitution between attributes of interest and money in this setting. This marginal valuation of quality variable is a key output from most valuation studies, which can be aggregated across population to derive societal level valuation of policy changes (McFadden, 1974, Daly and Zachary, 1975, Small and Rosen, 1981, Karlström, 1999, Hau, 1985, Jara-Díaz and Farah, 1987)

1.2   Model misspecification

1.2.1   Definition of model misspecification

As with most economic models, discrete choice model represents a "theoretical idealisation rather than a practical reality" (Ben-Akiva and Lerman, 1985, p.8). This implies that the representation of the choice behaviour in choice models will inevitably diverge from the true choice behaviour of individuals. Some researchers adopt the view that any divergence of the scenario from the true decision-making process can be generalised as the model misspecification (e.g., Williams and Ortúzar (1979)), which may arise from mistakes made in assuming that the model is a representation of the true data generation process. Some examples in discrete choice analysis include the omission of variables, failure to consider the correlations between variables, or the wrong assumption of the distribution of the disturbance. Alternatively, model may be intentionally misspecified for reasons of parsimony and avoiding computational problems. A common example is the reliance on fixed-taste assumption in choice models while tastes are generally found to be heterogeneous amongst decision-makers.

Model misspecification can also be formalised statistically. Following the RUM approach in discrete choice analysis, indirect utility function can be parametrised and estimated using the maximum likelihood estimation (MLE) approach. A 'true' (or population) maximisation problem in MLE can be generalised as follows:

$$\max LL(\beta) = E_Y \ln f(y|\beta)$$

where a family of distributions representing the true data generation process $f(Y|\beta)$ is defined on Y, with the density determined by a set of parameters β for observations $y_1, \dots, y_N$. This maximisation problem can be approximated using the Sample Average Approximation (SAA) approach to reach an optimal solution (Newey and McFadden, 1994, Equation 1.2):

$$\max \widehat{LL}_N(\beta) = \frac{1}{N} \sum_{n=1}^{N} \ln f(y_n|\beta)$$

For most applications in discrete choice analysis, f has a closed form expression for logit choice probability, or the mixed logit probability which then requires numerical integration or simulation methods like the maximum simulated likelihood method (see Train, 2009, Chapter 10). If the parametric family of distribution f from the SAA problem is not consistent to the density of Y over the population, then the model is said to be misspecified (White, 1982, Mai et al., 2015). Under this circumstance, the pseudo-likelihood function incorporated by the estimator is inconsistent to the true likelihood function, which implies that the parameter estimates will not match the true parameters. In other words, even if the set of parameters β which determines the family of misspecified models f from the SAA problem gives the maximum log-likelihood asymptotically, the optimal solution β would still be misleading.

Assuming the true MLE problem and the SAA approach yield solutions β^* and $\hat{\beta}_N$, respectively. For f to be correctly specified, the estimator is expected to carry the 'information identity':

$$\sqrt{N}(\hat{\beta}_N - \beta^*) \xrightarrow{d} N(0, (-H)^{-1})$$

where N refers to the normal distribution, and $\xrightarrow{d}$ denotes the convergence in distribution. $-H$ is the negative of the Hessian in the population, which is often called the Fisher information matrix. However, if the model is misspecified (as in most cases in practice), the asymptotic covariance matrix would be in the form of $H^{-1}VH^{-1}$, where V is the expectation of the outer product of scores (Train, 2009, p. 200-201). As the key objective of this thesis is to examine the impacts of model misspecification on the marginal valuations of the attributes of interest, this thesis investigates the rationale behind the condition

where $E(\widehat{\beta}_N) \neq \beta^*$, or the departure from the desired condition under which the information identity can be achieved (i.e., inconsistent standard error).

It is emphasised, however, this thesis does not solely focus on the impact of model misspecification on the consistency of parameter estimates (including the function of the parameter estimates, like the ratio of parameters), but also on the impacts on welfare changes as well. Indeed, the severity of the estimation bias, i.e., $E(\widehat{\beta}_N) - \beta^*$, in model estimation due to model misspecification depends on many factors. Some specification issues can be translated into the loss of efficiency only without affecting the consistency of parameter estimates. For instance, consistent and asymptotically normal parameter estimates can still be generated by the so called *quasi-maximum likelihood estimator* when the inter-dependence between responses is ignored, provided the quasi-likelihood function being maximised does correspond to the true marginal likelihood for responses (McFadden, 1999). In other words, while some misspecified models are prone to bias in the inference of the parameter estimates, there are cases where misspecified model might not affect parameter estimates significantly but yet the misspecification could lead to misleading policy implications. This is exemplified in **Chapter 4** that disentangling of the status quo constant from the zero-price effect will not significantly affect the estimates for other parameter estimates within the probabilistic choice model in its linear additive form. However, by additionally capturing the notion of the zero-price effect, the calculation of welfare changes will be affected despite the minimal impacts on the parameter estimates.

1.2.2 Typology of model specification errors

The definition of the model misspecification established above is a broad concept which does not restrict the source for the misspecification. Statistically speaking, the reason why the true likelihood function does not lie within a specified parametric family of probability distributions (i.e. the model) is unclear. A very wide range of misspecification issues can be identified, including the theoretical representation of the decision-making process, alternative functional forms, and model transferability. It is essential to develop a systematic classification of the types of model misspecification, which is specific enough to establish connections with the research objectives in this thesis.

Table 1-1 expands on the typology of model misspecification commonly associated with the discrete choice models by Bates and Terzis (1997) and Manski (1973). Key literature in each

type of model specification and the relevant specification test, if available, are also provided in **Table 1-1**. Two key different sources of model misspecification are classified, namely, data incorporated for choice modelling and the model formulation. The typology is not intended to be exhaustive; many examples and gaps in its coverage of latest research do exist. For example, one can question where endogeneity has to come and look for examples on additive compared to multiplicative errors.

Table 1-1: Typology of model misspecification errors

Type of misspecification	Description	Key literature and evidence base
Data		
Measurement error	This occurs when there is imperfect measurement of the variable of interest; this issue is arguably less relevant to the stated preference (SP) data since the attributes levels are provided directly to the respondent	■ Brownstone et al. (2001)- Found travel time data calculated from loop detector leads are significantly under-estimated and applied multiple imputation of travel times for VTT estimation to adjust for biased travel time ■ Sanko et al. (2014) - Adjusted missing values and measurement errors by treating income as latent variable, in contrast to the conventional imputation method
Response error	This could occur in measuring dependent variables in choice model; this issue is particularly relevant to the stated choice data as responses can be affected by contextual effect (e.g. choice task complexity), inattention, strategic bias, non-trading, lexicographic behaviour etc.	■ Fifer et al. (2014) - Found significant hypothetical bias in model using stated choice data collected for exposure-based charging scheme that largely caused by study design and context ■ Meyerhoff and Liebe (2009) - Examined the rationale of the status quo (SQ) effect and found a protest attitude and attitude toward the good are likely to be the main causes
Sampling bias	Bias in estimation arises when sample is not drawn out from the complete population or under random sampling	■ Manski and Lerman (1977) - devised a weighted exogenous sample maximum likelihood estimator for estimation based on data collected by endogenous sampling (e.g. choice-based sampling)

Model formulation

Omitted / unobserved variable	The vector of attributes which affects decision-makers' responses is incomplete (i.e., missing variables)	■ Guevara (2015) - Demonstrated via Monte Carlo simulation that the endogeneity issue in linear model caused by omitted attribute can be addressed using the Multiple Indicator Solution (MIS) ■ Vij and Walker (2016) - Formalise the setting for the Integrated Choice and Latent Variable (ICLV) framework via Monte Carlo simulation, which can be used to correct for the omitted variable bias
Misspecification of functional form	The form of relationship between dependent and independent variables; this includes the concern when non-linearity in true data generating process is modelled linearly	■ Ben-Akiva and Lerman (1985) - Introduced the piecewise-linear approximation, power series expansion and Box-Cox transformations to the discrete choice modelling framework ■ Zheng (1996) - Established a statistic test of functional form for testing the parametric distribution against non-parametric forms
Unobserved taste variation	Lack of treatment for variations of preferences or unobserved elements between individuals (could also include intra-personal tastes in stated choice data)	■ McFadden and Train (2000) - developed a Lagrange multiplier test of logit and mixed logit models against alternatives with further mixing ■ Hess and Train (2011) - Operationalised a framework to recover both intra- and inter-consumer taste heterogeneity at increase of computational cost
Instrumental variables	Imperfect relationship between instruments (variables related to actual attributes) and attributes	■ Walker and Ben-Akiva (2002) - Developed the modelling framework to combine discrete choice model with a structural equation model that identifies latent attributes based on psychometric indicators ■ Vij and Walker (2016) - Formalised the evaluation criteria for comparison of model performance between the ICLV model and the reduced form choice model

1.3   Rationale for research

Two guiding principles are applied in the narrowing down the research questions in this thesis. First, this thesis turns to the willingness-to-pay (WTP) measure, which is a key input for policy appraisal in many disciplines including transport and environmental economics, as the key measurement of impacts due to model misspecifications. A misspecified WTP measure will have adverse impacts on public decisions. To put the importance of WTP outcomes into perspective, two lessons from past studies which found model misspecifications (i.e., mistakes that analysts should have been avoided) led to biased WTP measures are presented here. Rose and Hensher (2014) postulate that the lack of consideration of the inter-connectivity of tolled and non-tolled road link in a past stated choice (SC) study (i.e. a measurement error) could explain why the value of travel time has been over-estimated by 50% based on findings from an ex-post study. Inevitably, such measurement error would put toll road investment at risk given the perceived travel time benefits are considerably the key driver for travel demand of toll facilities. Similarly, a strong effect of toll saturation (threshold) has been discovered for a toll road study in Australia that challenges the conventional assumption in choice modelling practice where the money budget threshold is ignored. Researchers found without considering the budget threshold in model formulation, VTT can be over-estimated by 50% approximately (i.e. misspecified functional form for cost sensitivity) (Hensher et al., 2016). Similar findings concerning the large impacts of model misspecifications to the WTP measures can also be found in the field of environmental economics (see List et al., 2006).

The second guiding principle points to the deficiencies of the *commonly adopted* model representations in discrete choice analysis. Some legacy choice modelling framework are adopted in practice for maintaining a consistent methodology for comparison of model results. For instance, despite the validity of the simple time and money trade-offs setting in the SC survey for VTT studies has been questioned (Hess et al., 2016), it still plays a key role in providing empirical evidence of the value of travel time (e.g., Arup/ITS/Accent, 2015). This second guiding principle thus aims to provide evidence base of the model misspecification for practitioners to challenge the status quo of some existing modelling frameworks.

1.4 Model misspecification tests

There are two different approaches to test the impacts of model misspecifications that could be implemented. First, synthetic data based on the *a priori* (true) parameters and the underlying data generation process can be generated via a Monte Carlo (MC) simulation process as an analytical proof of the model misspecification. The main advantage of this approach lies in the ability to outright reject the model which departs from theoretical postulate defined by the analysts. On the other hand, further testing using real data is needed to support the proposition that findings or theoretical reasoning from the choice analysis using synthetic data will also be applicable to the real data. However, the more correctly specified model as shown in simulation will likely to fit the real data better than the misspecified model. This can be tested by running hypothesis test or specification test as described next. Simulated data has often been used to demonstrate different concepts of model misspecification. For instance, a seminal paper on the use of simulation by Williams and Ortúzar (1979) involved generating simulated dataset to determine the extent to which alternative assumptions of substitution pattern, satisficing and habitual behaviour could cause misspecification.

Other than employing the simulation technique, a conventional approach to test the misspecification is to test statistically that a model form or parameter estimate is consistent with a given hypothesis. Hypothesis about Individual parameters can be tested using the standard *t*-statistics. A general likelihood ratio test can be employed for testing the "nested" hypotheses where the log-likelihood of the restricted model is compared against the less restrictive one (Train, 2009, p.70). A main drawback of such approach is that one model must be a more restrictive case of the other. For instance, in **Chapter 3** where the main purpose is to assess the impact of income measurement error on the WTP outcomes, same model formulation is retained even though income variables are varied between different scenarios. This precludes the use of the likelihood ratio test and the simple comparison of final log-likelihood is used instead to compare relative model fit. Zheng (2008) further shows that the likelihood ratio test has limited power if the alternative model is misspecified or has difficulty in parametrisation.

Formal specification testing of discrete choice model is important but is seldom applied in practice (Fosgerau, 2008). Some more popular specification tests for discrete choice models include the test for the independence of irrelevant alternatives (IIA) property for

multinomial logit (MNL) model include devised by Hausman and McFadden (1981); a Lagrange multiplier test for testing the need of mixing on top of the MNL model (McFadden and Train, 2000), and; a non-parametric test developed by Zheng (1996) which can be used for the detection of misspecification of functional form. It should be noted, however, that without the knowledge of the true data generating process, it is impossible to determine the true model specification, even after filtering out alternative model according to results given by either by the specification test or hypothesis test.

1.5   Problem definitions and research gaps

1.5.1   Analytical framework

The two guiding principles and two different approaches for testing model specifications described above underpin the development of the research framework in this thesis. **Figure 1-1** illustrates the overall framework for studying the impacts of model misspecification through three selected SC applications, which can be considered as the 'state-of-the-practice' in valuation studies. Each of these applications takes on different misspecification issues. The framework is set out based on the methodology proposed by (Williams and Ortúzar, 1982). Model misspecifications of interest are examined using either simulated SC data (**Chapter 2**) or SC data collected from respondents (**Chapter 3** and **Chapter 4**).

At the outset, the theory of choice behaviour of individuals dictates the choice probabilities produced by true data generating process. For simulated data, it is assumed that individuals follow the neoclassical consumer choice theory, which means that individuals maximise their utilities subject to budget constraint determined by income and prices (Ben-Akiva et al., 2019). While a key objective of our first SC application (i.e. **Chapter 2**) is to test the misspecification when travel time constraint is ignored in choice analysis, constraints are also incorporated to affect simulated choice set when travel time for a particular alternative exceeds one's travel time budget constraint. The simulation process is described in detail in **Chapter 2**.

Beyond simulation, it is likely that heterogeneous decision rules are adopted amongst respondents of the SC surveys, who include either utility maximising choices and or display behaviour which is not universally consistent with the utility maximisation in reality (McFadden, 1999). As in most discrete choice studies, choices made by respondents or pseudo-respondents in simulation are interpreted analytically through the use of standard

RUM-based discrete choice models, irrespective of the possibility of heterogeneous choice behaviour. Therefore, it is a central assumption that all individuals make utility-maximising choices such that the linkage to microeconomics established by the RUM approach is maintained (see Hess et al., 2018). This is essential for the valuations of willingness-to-pay measures and also facilitates calculation of welfare changes in this thesis.

Figure 1-1: Testing of model misspecification using simulation and collected data
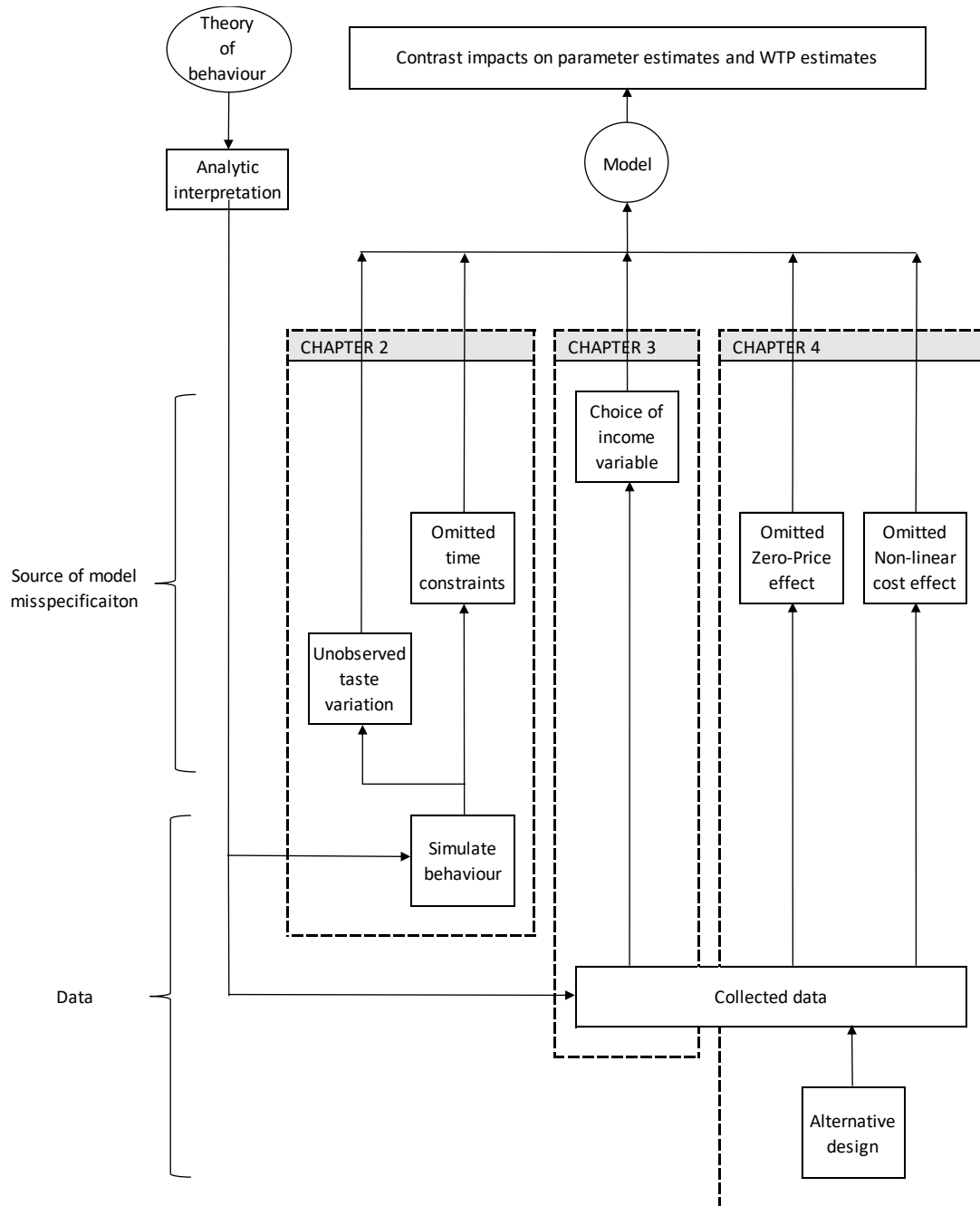
After setting out the theoretical grounding and analytical interpretation of the choice behaviour, the next stage is to generate simulated data or to collect stated choice data. The simulation process, experimental design for SC surveys, choice model formulation and the testing of misspecification are described in detail in later sections. The rest of this section introduces the three types of model misspecification addressed in this thesis. **Table 1-2** presents an overview of the model misspecifications being addressed in each paper.

Table 1-2: Types of model misspecification addressed

Misspecification / Source of error	1 ■ Travel time constraint	2 ■ Income variable	3 ■ behavioural phenomenon of the ZP effect
Measurement error		■ Measurement error in the income variable	
Omitted / unobserved variable	■ Missing availability indicator to account for the impact of travel time constraints on alternative availabilities		■ Missing variable to control for the zero-price effect ■ Missing non-linear specification for cost sensitivity
Unobserved taste variation	■ Preference heterogeneity can pick up for alternative misspecifications and thereby misrepresent the true extent of preference heterogeneity		
Related chapter	■ Chapter 2	■ Chapter 3	■ Chapter 4

1.5.2 Misspecification 1: Travel time constraints

We first examine how ignoring the travel time constraint can affect the derivation of the national non-work value of travel time. In the transportation literature, the value of travel time (VTT) refers to both the willingness to pay for travel time reductions and the willingness to accept longer travel time for less cost (Daly and Hess, 2020). The SC approach to derive VTT estimates by a WTP approach varies across regions. In some European countries including UK, Netherlands, Sweden and Norway, VTT are estimated based on the stated choices that are fixated on a legacy binary time-cost route choice setting. This is in contrast to the more complex choice scenarios as adopted by countries in South America and also Australia (Hess et al., 2016). While there were questions of the reasonableness and reliability

of this simple route choice setting, the lack of explicit treatment to account for the travel time constraint has received less attention.

The importance of the travel time constraint is supported by the theoretical underpinning of VTT in the theories of time allocation linking the VTT to the stringency of time (and money) constraints (see Jara-Díaz, 2000). In empirical measurement of VTT, the specification of the alternative availability in utility is very important for the simple time-cost binary choice setting. When the preferred alternative exceeds respondent's constraint, he/she will be forced to choose the only remaining alternative, which is not compatible with his/her preference. Under normal circumstances, the choice of a faster but more expensive route can be inferred by a choice model as the traveller having a high WTP for transferring 'saved' time for other activities[2]. On the other hand, if the traveller prefers a slower but cheaper route, but was forced to choose the faster but more expensive route as the travel time required for the cheaper route exceeds his/her travel time, then a high WTP can also be inferred erroneously. As most SC studies do not collect direct or indirect indicators of consideration sets (i.e. alternatives that are 'considered' by individuals) as in Capurso et al. (2019), there is a risk of presenting alternatives with too long of travel time which the respondent does not have at his/her disposal. How ignoring the impact of travel time constraint on the inference of VTT in a simple time-cost trade-off is shown below:

> **Remark 1: How the missing indicator of the alternative availability affects the inference of VTT in a simple time-cost trade-off**
>
> *Standard unconstrained condition:*

---

[2] The value of travel time terminology set out by Daly and Hess (2019) is followed here. It is posited that because time "cannot be stored or borrowed", and what travellers could do is to transfer 'saved' travel time for other activities which is more desirable (e.g. leisure). Here the term value of travel time is not determined by the relative tightness of time and money budget constraints (value of time as a resource) only, but also determined by the utility or disutility of the travel itself.

The impact of the missing alternative availability indicator on the conditional indirect utility can be illustrated by an example of route choice between two routes $i = 1,2$. The observed utility formulation, V_i, for route i can be represented by:

$$V_1 = \alpha(24 - T_1) + \beta(Y - C_1)$$
$$V_2 = \alpha(24 - T_2) + \beta(Y - C_2)$$

where:

T_i and C_i are travel time and cost for alternative i, respectively

α and β are the marginal utilities of time and cost, respectively

Y is the income

By assuming respondent is indifferent between the two routes (i.e. $V_1 = V_2$), the inequality gives rise to the marginal rate of substitution (MRS) between time and cost, denoted as ratio of α to β, which is equal to the boundary value of travel time (BVTT) on the right (Fowkes, 2000):

$$\frac{\alpha}{\beta} = \frac{C_1 - C_2}{T_2 - T_1}$$

When both routes are not subject to any travel time constraint (i.e. both routes are considered by respondent) and route 1 is a slower but cheaper than route 2, the choice of the route 1 made during trade-off can be used for inferring the VTT by assuming that MRS perceived by the respondent is lower than the BVTT:

$$\frac{\alpha}{\beta} < \frac{C_1 - C_2}{T_2 - T_1}$$

Missing alternative availability indicator in (time) constrained condition:

Now let's assume that some but not all of the choice tasks presented to respondent are subject to stringent travel time constraints. For instance, when an individual is faced with one of the choice tasks, travel time presented for route 1 is out of consideration because the long travel time (but cheaper) presented is not at his/her disposal. The only option available for this respondent is route 2 in this case, which is the shorter but more expensive option. The choice disclosed by the respondent for this observation thus contradicts with what the true model should predict and may introduce bias in model

estimation. The biased model now reveals that the MRS is higher than the BVTT and gives an opposite sign of the inequality for this particular choice task:

$$\frac{\alpha}{\beta} > \frac{C_1 - C_2}{T_2 - T_1}$$

The modelling of alternative availability is indeed a classic problem of choice set formation in discrete choice modelling. Choice set formation (or generation) refers to the condition when respondents who may restrict their decision-making to a particular subset of full choice set. Different modelling approaches have been suggested to accommodate stochastic choice set formation in the past, which includes a two-stage approach to estimate probabilistic choice set as formulated by Manski (1977) and operationalised by Swait and Ben-Akiva (1987), and the single-stage approach approximate the availability of alternatives in the indirect utility function by adding penalties to utility when attributes fail to comply with thresholds and hence decreased attractiveness of this alternative (Cascetta and Papola, 2001, Martínez et al., 2009, Swait, 2001). Despite these development over years, the treatment of choice set formation are rarely used for derivation of national VTT, or even in discrete choice modelling in general (Swait and Feinberg, 2014).

The unaccounted alternative availability can lead to significantly biased VTT, as exemplified by the Monte Carlo (MC) simulation studies by Cantillo and Ortúzar (2005) and Li et al. (2015).

The effect of the bias in the available choice sets is further complicated for the retrieval of taste heterogeneity across respondents. The confounding of travel time constraint and the taste variation is particularly important nowadays given the increasing popularity of Mixed Multinomial Logit (MMNL) models to retrieve taste heterogeneity (Hess, 2006). That said, to the best of our knowledge, there is no research to date which study whether the MMNL could recover the taste heterogeneity when alternatives in the binary route choice setting are not available due to the travel time constraint.

1.5.3 Misspecification 2: Income variable

In our second empirical paper, we examine the potential error associated with income variables. A key output from VTT studies is the cross-sectional income elasticity of VTT, which can inform analysts about the relationship between the VTT and income within population

(see Remark 2 below). For non-work trips, economic theory indicates that VTT rises with income level but theory falls short of predicting the size of the income effect on VTT. This is in sharp contrast with the recommendation from the cost savings approach which implies a unit elasticity for business trips (Harrison, 1974, Wardman et al., 2015)

Remark 2: How the marginal utility of income enters the utility for consumer's constrained maximisation by using Lagrange multipliers:

Largely following the notation and formulations in Fowkes (2000), we want to maximise *direct* utility, $U(X_i, t_j)$, which is a function of good or service X_i (with $i = 1, .., I$) consumed and t_j hours spent on activity j (with $j = 1, .., J$). The constrained maximisation is subject to:

- (money) budget constraint m, which equals to the sum of expenditure on each good or service, X_i consumed at cost p_i ($m = \sum p_i X_i$);
- the total time budget in which $t = \sum t_j$, and;
- $t_{1(travelling)} = k + n$, which is a sum of travel time, k, plus non-essential travel time, n

Redefine the objective function form a Lagrange Multiplier, L, for maximisation (Fowkes, 2010, Equation 1):

$$L = U(X_i, t_j) + \lambda\left(m - \sum p_i X_i\right) + \mu\left(T - \sum t_j\right) + \theta(t_1 - k - n)$$

where λ is the marginal utility of relaxing the (money) budget constraint (or the marginal utility of income, MUI), μ is the marginal utility of relaxing the time budget, and θ is the marginal utility of having to spend more time travelling.

Now we derive the first order conditions with respect to X_i, which is represented by:

$$\frac{\partial L}{\partial X_i} = \frac{\partial U}{\partial X_i} - \lambda p_i = 0$$

Rearranging this equality gives this shadow price of the money budget constraint

$$\lambda = \frac{\partial U / \partial X_i}{p_i}$$

Now λ refers to the monetary value of utility of relaxing the budget constraint by one monetary unit for consumption of good or service, X_i. It means that for more income, more consumption is allowed and hence the increase of utility. As per the general assumption of diminishing marginal utility of consumption, the derivative of the marginal utility of consumption becomes negative:

$$\frac{\partial^2 U}{\partial X_i^2} < 0$$

Combine this expression for the diminishing marginal utility of consumption, the assumption that more income implies more consumption, and the marginal utility of income expression. Then it also implies that the marginal utility of income decreases with money budget:

$$\frac{\partial \lambda}{\partial m} < 0$$

Now we derive the first order conditions with respect to travel time, t_i, which is represented by:

$$\frac{\partial L}{\partial t_1} = \frac{\partial U}{\partial t_1} - \mu + \theta = 0$$

Rearranging this equality gives:

$$\frac{\partial U}{\partial t_1} = \mu - \theta$$

This implies that that marginal utility of travel time is the marginal utility of relaxing time budget, minus the marginal utility of spending more time travelling, which can be positive or negative depending on whether this is an 'enjoyment or dislike of travel itself', respectively (Small, 2012). Now we can derive the VTT by dividing the marginal utility of travel time by the shadow price of income, λ, which gives:

$$\text{VTT} = \frac{\mu - \theta}{\lambda}$$

Since marginal utility of income decrease with income, we can derive that VTT increases with increase of income since $\frac{\partial \lambda}{\partial m} < 0$:

$$\frac{\partial \text{VTT}}{\partial \lambda} < 0 \ \text{ and } \ \frac{\partial \text{VTT}}{\partial m} > 0$$

There are two important implications given by this maximisation problem. First, the marginal utility of income depends on the income as money budget. Second, that the economic theory only informs us about the direction of the rate of change of VTT relative to the marginal utility of income, but it does not indicate the size of such income effect.

The cross-sectional income elasticities of VTT as derived through SC studies are often compared to the inter-temporal elasticities estimated from meta-analysis of VTT estimated over years and studies (Abrantes and Wardman, 2011, Wardman et al., 2016). Comparison results point towards lower cross-sectional income elasticities relative to the inter-temporal counterparts. Since economic theory does not give any restriction to the level of income elasticity of VTT, the disparity between the two set of values has been discussed over years but there is still no consensus on the rationale behind to date (Hensher, 2011, Small, 2012). Given that there is an established relationship between the marginal utility of income and the income as we demonstrated above, ceteris paribus, we posit that a potential source of the empirical disparity between the cross-sectional and inter-temporal income elasticities of VTT is the measurement error on income measure. In other words, as different income measures represent different income budget perceived by respondents, the resulting income elasticities of VTT will be different. The key questions here though are how these variations in income representation would also affect the VTT estimates, and which income representation should be recommended for VTT estimation.

Indeed, one can find different types of income variables used in different VTT studies. For instance, household gross income has traditionally been adopted for valuation of travel time in UK (Mackie et al., 2003, Batley et al., 2019) while personal after-tax income has been used in some Scandinavian countries (Fosgerau et al., 2007). These different assumptions of income measures as the money budget raise serious question about the validity of the

comparison of cross-sectional income elasticities as the income measures adopted for VTT estimation might be far from reflecting the true budget constraint perceived by respondents. To date, there is no systematic testing of income measures for any national VTT studies, which could determine how income re-distribution measures (incl. taxes, social benefits) and intra-household composition (incl. personal, household income) would affect the VTT calculations and derivation of the income elasticities. Furthermore, the income elasticities of *behavioural* VTT estimated based on the SC data and behavioural choice model are typically adopted for the basis for coming up with the *appraisal* VTT for a national survey based on sample enumeration approach. If different income measures would lead to different income elasticity of behavioural VTT, then it implies such difference will also affect the computation of the appraisal VTT.

1.5.4 Misspecification 3: Behavioural phenomenon of the ZP effect

Lastly, in our third empirical work, we switch our focus from the VTT studies to a more general SP choice setting that often occurs in economic research in environmental and resource, health and transport. In many SC valuation studies, researchers are interested to derive the WTP for designed policy alternatives over a status quo (SQ) option (Ferrini and Scarpa, 2007). It is a standard practice nowadays to incorporate a constant term to capture the SQ effect (or SQ bias), namely, the preference of the SQ and by respondents who also perceive zero WTP for the designed alternatives. There has been research on pinpointing the rationale behind the SQ effect (Meyerhoff and Liebe, 2009). It has also been shown not capturing the SQ effect will lead to biased welfare estimates (Adamowicz et al., 2011).

Despite the widespread use of this choice setting, the implications of the zero cost on the attractiveness of the SQ has received very limited attention so far. This is contrast to the field of behavioural or experimental economics, where researchers provided amble amount of evidence to show the prevalence of the zero-price (ZP) effect, namely, the extra attractiveness towards the free cost itself (Shampanier et al., 2007, Ariely, 2008, Nicolau and Sellers, 2012). The issue that most concerns us lies in the perfect confounding between the ZP and the SQ effects. If the ZP effect is a real effect, then a minimal change to the status quo could encourage respondents to turn to the designed policy alternatives instead. This significant role of the ZP effect in predicting future demand and welfare changes when the status quote is not free in the future, as the requirement for future scenario to prevent

deterioration of the SQ for instance, is hidden without separating the ZP effect from the SQ effect.

There are also further complications in capturing the ZP effect concerning the non-linear sensitivity to cost (Daly, 2010, Rich and Mabit, 2016). First, it is common to see a price gap between zero cost and the next cost level in experimental designs. This also implies, however, an inadequate number of trade-offs near zero cost levels that are essential for the identification of the ZP effect. Namely, the detection of the disproportionate increase of cost sensitivity from zero cost to near zero cost as exhibited by the ZP effect. Second, it is know that non-linearity in cost sensitivities may erroneously be picked up as ZP effects with linear sensitivities (Hess et al., 2011). All these concerns required a re-thinking of how we develop experimental design and formulate utility whenever respondents could be presented with the ZP alternatives.

1.5.5   Research questions and overall approaches

This thesis aims to examine the impacts of the model specification errors described above on the validity and reliability of the WTP estimates. As shown in **Table 1-2**, this thesis provides a critical assessment of three different model misspecification issues, namely, the lack of explicit treatment of travel time constraint, the measurement error associated with the income variable, and also prevalence of the alternative behavioural phenomenon of the ZP effect. As such, this thesis addresses the following research questions that correspond to each type of model misspecification:

- *Misspecification 1*: What are the impacts of incorrectly accounting for constraints on choice behaviour, such as time constraints, on the retrieval of taste heterogeneity and marginal WTP measures?

- *Misspecification 2*: What are the impacts of measurement error in the income variable on cross-sectional income elasticities of VTT and can it explain the discrepancy between the cross-sectional and inter-temporal income elasticity?

- *Misspecification 3*: What are the impacts of alternative behavioural phenomena, such as the ZP effect, on welfare estimates and what are the implications for study design?

We synthesise these research questions in the hope that we can gather empirical evidence to question the reliability of some standard modelling practices applied for valuation studies

and suggest future improvements required. This overarching objective is achieved in this thesis by undertaking the following approaches specific for each type of model misspecification:

- *Misspecification 1*: Generate simulated SC data where some choices are constrained by the stringency of travel time constraints and whether there is taste heterogeneity across population. The simulated SC data are then used for model estimation but without explicit modelling of the choice set formation.

- *Misspecification 2*: Compile different income measures based on secondary data sources and re-estimate choice models with these newly generated income variables.

- *Misspecification 3*: Develop alternative survey designs to identify the ZP effect and separate it from the SQ effect. Non-linear functional forms are also tested for separation of the ZP effect and non-linearity.

The data gathered in support of our empirical work are described next.

1.6 Data specifications

1.6.1 Stated preference data vs revealed preference data

Both stated preference (SP) data and revealed preference (RP) data can be used for choice analysis in general, and each of them have their pros and cons (Train, 2009, Daly et al., 2014). While there is a growing trend to exploit the RP data for understanding choice behaviour, notably in the use of emerging big data sources (e.g. mobile phones, social media), there remains advantages of using SP data especially in the context of non-market valuation. This is largely because experimental design allows analysts to set out hypothetical menus for abundant independent and exogenous variations in attribute levels for robust statistical efficiency that are otherwise unavailable from a real market condition (Louviere et al., 2000, Ben-Akiva et al., 2019).

To date, SP data continue to be the basis for many valuation studies in support of cost-benefit analysis (CBA). Some relevant examples including the estimation of willingness-to-pay measures for travel time and reliability at national level in transport studies (Axhausen et al., 2008, Batley et al., 2019, Börjesson et al., 2012, Fosgerau et al., 2007), valuation of environmental goods (Adamowicz et al., 2014, Hess and Beharry-Borg, 2012, Meyerhoff,

2013) and measurement of the strength of patient preferences in health economics (Lancsar and Burge, 2014, Lancsar and Savage, 2004, McIntosh, 2006).

Given the widespread use of SP data for valuation studies, it is therefore appropriate for us to rely on the stated choice (SC) data to motivate our discussion in this thesis. SC is a specific type of SP method, where individuals are required to choose the most preferred alternative from a set of available alternatives (see Ben-Akiva et al., 2019, Louviere et al., 2000). However, although the analyses in this thesis are based on the SC data, many of our findings are also relevant to the choice settings where RP data are used.

1.6.2 Data applied in this thesis

A brief description of the data adopted for our analyses is as follows:

Misspecification 1: Travel time constraints

Since this paper is set out to understand the impacts of travel time constraints on taste heterogeneity, a key requirement is to create a set of constrained choices in terms of (un)availability of alternatives. A range of stringency of the travel time constraints are assumed. The use of simulated dataset developed through a Monte Carlo simulation approach appears to be a natural choice such that we can retain full control on the exogenous variations in constrained conditions.

A simple time-cost trade-off binary choice setting is used. This replicates the standard choice sets often seen in some national VTT studies. We first generate a full factorial design, with dominated choices removed. This is followed by the implementation of the choice-rejection mechanism to simulate the unavailability of alternative as per different levels of travel time constraint. This choice-rejection mechanism is set out in a way such that if the travel time attribute presented exceeds the predefined time budget (between 30 minutes and 75 minutes) then the respective alternative is rejected. A total of 2,700 choice tasks amongst 540 pseudo-observed individuals are generated.

Misspecification 2: Income variable

Three sets of data are used for this study. First, we retain the SC data collected for non-work (i.e. non-business) car trips during the 2015 UK VTT study (Arup et al., 2015, Batley et al., 2019, Hess et al., 2017). In particular, we adopted the SC choices for the game SP1 (time-

cost trade-offs) collected from 922 commuters and also 977 travellers who were engaged in 'other non-business' trips. The final questionnaire is presented in (Arup et al., 2015, Appendix E).

We followed the sample enumeration process developed in the 2015 UK VTT to apply the behavioural VTT formulae and the associated covariates on each trip observed in national travel survey to derive the nationally representative VTTs for appraisal. As this case study focuses on the non-work car trips only, we retain the 95,758 commuting trips and 413,198 other non-business trips in the National Travel Survey (NTS) dataset for deriving the appraisal non-work VTTs (DfT, 2014). The NTS survey is a key source of data for understanding individual travel pattern in England, UK, which collects a wide range of travel characteristics and statistics, as well as factors affecting travel.

Finally, as we aim to test a range of income measures based on the 2015 UK VTT modelling framework and examine their impacts on both the behavioural and appraisal VTT estimates, we need to establish a set of conversion factors to convert the household and personal income collected from the 2015 UK VTT SC dataset to different test income measures for choice modelling. The conversion factors were derived based on regression analysis on data from the Living Cost and Food Survey (LCFS) dataset, which is used widely in UK for assessment of the impacts of tax and benefits on household income (ONS, 2015).

Misspecification 3: Behavioural phenomenon of the ZP effect

This paper incorporates SC data collected from 302 students at the University of Warsaw in Poland in late 2017. The data collection was carried out in collaboration with researchers at the University of Warsaw. This survey comprises of three treatments. In the first two treatments, respondents are asked to choose between the existing free Wi-Fi coverage within campus (i.e. the status quo) and two alternatives of 4G LTE data packages for 8 choice tasks in the game. In the third game, respondents are asked to choose between two 4G LTE data packages for 10 choice tasks. The attributes assigned for the 4G LTE data package include the costs, data limits and also whether the 4G services can be accessible for multiple devices. The survey forms are presented in **Appendix F**.

1.7   Thesis outline

This thesis comprises five chapters. The first chapter describes the key objectives of this thesis and provides an overview of the data used to support our analyses. Chapter two addresses the issue of the unaccounted travel time constraints which may affect the availability of alternatives and retrieval of taste heterogeneity. Chapter three examines the impacts of the measurement error in income variable on the income elasticities of VTT and VTT estimates. Chapter four addresses the issue of the unaccounted ZP effect by disentangling the ZP effect from the SQ effect. Chapter five discusses the answers to our research questions, implications of this thesis, limitations of our analyses and future research avenues and concludes.

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Chapter 2

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

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Abstract

Discrete choice models are a key technique for estimating the value of travel time (VTT). Often, stated choice data are used in which respondents are presented with trade-offs between travel time and travel cost and possibly additional attributes. There is a clear possibility that some respondents experience time constraints, leaving some of the presented options unfeasible. A model not incorporating information on these constraints would explain choices for faster and more expensive options as an indication that those respondents have a higher value of travel time when in reality they may be forced to select the more expensive option as a result of their 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 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 generation. The 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.

Keywords: value of travel time (VTT), travel time constraints, non-linearities

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2.1   Introduction

Economic theory and empirical findings support the argument that the value of travel time (VTT) is directly related to the stringency of time and money (budget) constraints. Recent empirical advances explicitly model the impact of constraints through the use of choice set formation (Manski, 1977, Martínez et al., 2009, Swait and Ben-Akiva, 1987b). However, such constraints are typically not taken into account in some recent national value of travel time studies (Hess et al., 2017). We hypothesize that not accounting for constraints could create significant risks in producing biased VTT estimates based on stated choice (SC) data. In particular, let us contrast two situations. If a traveller chooses a faster and more expensive option for the reason of wanting to save time for other activities, then this should reasonably be seen as 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 than the other, then he/she might simply be choosing the more expensive and faster option due to a constraint on needing to arrive by a specific time. In the majority of stated choice studies, the respondent is not given the option of changing his/her departure time and there is thus a substantial risk of constraints on timing influencing our findings on the VTT.

This paper studies the confounding impact on VTT estimates and especially preference heterogeneity findings due to unaccounted (travel) time constraints. This confounding becomes, in our view, even more important given the increasing popularity of Mixed Multinomial Logit (MMNL) models explaining unobserved taste heterogeneity amongst respondents. This paper argues that the estimated variance of the marginal utilities (and hence VTT) captured by the MMNL models could in part be an artefact of constraints (or thresholds) rather than preference heterogeneity. This is tested through the use of simulated data to simulate fixed or random VTT 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 choice model is misspecified by ignoring the impact of travel time constraints. In addition, given that the use of non-linear functional forms for utility function does not require any changes to the choice model structure, this paper also illustrates the use of non-linear functional forms to catch the tail of the VTT distributions where attribute levels exceed travel budgets.

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 2.3. **Section 2.4** summarizes model results. **Section 2.5.1** discusses the implications of including an opt-out option and the use of non-linearities to capture the time budget effects. **Section 2.6** concludes.

2.2 Literature review

2.2.1 SC surveys for national VTT studies

In the transportation literature, the value of travel time (VTT) refers to both the willingness to pay for travel time reduction and the willingness to accept longer travel time for less cost (Daly and Hess, 2020). VTT is an important parameter in transport appraisal, which is arguably as important as the discount rate that underpins most cost-benefit analyses (CBA) (Small, 2012). Therefore, the elicitation and estimation of the VTT have been the key interest for researchers and also to policy makers. Since mid-1980s, national VTT studies started making use of the stated choice (SC) data to measure travellers' VTT rather than based upon the revealed preference (RP) data. There are some practical advantages of the use of SC data for the VTT studies. First, experimental design allows analysts to set out hypothetical menus for abundant independent and exogenous variations in attribute levels for robust statistical efficiency that are otherwise unavailable from real data. Second, data collection cost is considerably lower than the collected RP data. And finally, RP data collected in the past are of poor quality in many cases (see Daly et al., 2014).

To date, SC data continue to be the basis for many valuation studies in support of cost-benefit analysis (CBA), as exemplified by the use of SC data in the most recent national VTT studies in the UK, Netherlands, Sweden and Denmark (Arup/ITS/Accent, 2015, Significance et al., 2013, Börjesson et al., 2012, Fosgerau et al., 2007). Amongst these European countries, the key VTT values are estimated based on the stated choices that are fixated on a legacy binary time-cost route choice setting. This is in contrast to the more complex choice scenarios as adopted by countries in South America and also Australia (Hess et al., 2016). While there was questions of the reasonableness and reliability of this simple route choice setting, the lack of explicit treatment to account for the travel time constraints has received less attention.

2.2.2 Budget constraints in SC experiments

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, 1971) in the empirical random utility model

(RUM) within the discrete choice setting, the VTT can be estimated as the marginal rate of substitution between travel time and cost in the conditional indirect utility function that is linear in income. As the utility which appears in the empirical models is the indirect utility, which is a result from decisions about consumption that is subject to both money and time budget constraints, the budget constraints are implicitly accounted for within the discrete choice models in principle. Within the discrete choice modelling framework, it is a central assumption that decision-maker makes utility-maximising choice within a choice set, which includes the alternatives that are perceived to be feasible and are known to the decision-makers during the decision-making process (Ben-Akiva and Lerman, 1985, p.33). In other words, the availability of an alternative which can be restricted by time constraints (or other physical or monetary constraints) is known to the decision-maker.

In practice, however, such budget constraints are not observed by analysts, as only the final choices given by survey respondents are available but not the feasibility of alternatives. This implies that researchers might present unfeasible alternatives to respondents in the SC experiment and thus introduce bias when unfeasible alternatives are modelled with non-zero choice probabilities. This problem is particularly apparent within the SC context due to its hypothetical setting while in RP data, the chosen alternatives observed should be within budget unless irrational decisions are made. There is an increasing use of referencing or pivot designs for constructing stated choice experiments (Rose et al., 2008, Hess et al., 2008), including SC designs prepared for national VTT studies (e.g., Arup/ITS/Accent, 2015, Fosgerau et al., 2007). Pivoting allows attributes to deviate from travellers' current trips or recent experiences in absolute or relative terms. It is argued that such design can enhance the relevancy in attribute levels by exploiting respondent's knowledge base or existing memory schema, which has its root from the theories in behavioural and cognitive psychology (Hensher, 2010, Starmer, 2000). However, it cannot be guaranteed that the presented variations around the reference time and (or) costs fall within the respondents' respective constraints. Firstly, the positive and negative variations around the reference value are substantial in the GB VTT study. Secondly, even if the presented variations are small, they may still exceed the respective constraint. In fact, there is no evidence to support any linkage between the travel time budget, which is latent by nature (Ahmed and Stopher, 2014), and one's usual travel time.

2.2.3 Choice set formation

The modelling of alternative availability to accommodate the impact of (budget) constraints on attributes is indeed a classic problem of choice set formation in discrete choice modelling.

The potential bias due to model misspecifications for ignoring the impact of budget constraints on the availabilities of alternatives was identified soon after the development of the discrete choice modelling framework. The effects on misallocated alternatives were tested empirically by Williams and Ortúzar (1982), who found bias on parameter estimates and errors in forecasting from a misspecified choice set. (Stopher, 1980) found estimated coefficients in a binary mode choice setting were smaller and less significant in the mis-specified model where all alternatives were given to all individuals, when compared to the "true" model with constrained alternative availability.

The awareness of the potential bias gives rise to the development of modelling approaches to accommodate the choice set formation, which refers to the condition when respondents who may restrict their decision-making to a particular subset of full choice set. Different modelling approaches have been suggested over years to accommodate choice set formation. There is a family of probabilistic choice set models developed based on the two-stage approach formulated by Manski (1977). Here, the decision making strategy is decomposed into two separate and sequential stages, namely, the choice set generation stage, and the choice evaluation stage. Choice set generation is a non-compensatory stage (i.e. strategies that do not involve trade-offs, Payne et al. (1993)) in which individuals limit the decision making to a subset of full choice set. This is followed by the choice evaluation stage, which is a compensatory stage in which individuals select the best alternative amongst a subset of choice set. This probabilistic choice set modelling framework was operationalised by incorporating strict assumptions in the "Independent Availability Logit" model by Swait and Ben-Akiva (1987b) and the "Dogit" model by Gaudry and Dagenais (1979). More recent variations include **Error! Hyperlink reference not valid.** and Cantillo and Ortúzar (2005). There is also another stream of research which aims to develop approach in accommodating constrained choices via a single-stage approach. The basic concept includes approximating the availability of alternatives in the indirect utility function by adding penalties to utility when attributes fail to comply with thresholds and hence decreased attractiveness of this alternative (Cascetta and Papola, 2001, Martínez et al., 2009, Swait, 2001).

It should be noted, however, despite the advance in modelling constrained choices over years, the treatment of choice set formation are rarely used for derivation of national VTT, or even in discrete choice modelling in general (Swait and Feinberg, 2014). Indeed, the potential prevalence of choice set formation can be viewed the "elephant in the living room" of choice modelling (Swait, 2011) which requires attention from choice modellers. This is

especially relevant for national VTT studies, which could produce biased appraisal results when budget constraints are not controlled for in the VTT estimation.

2.2.4 Implications of budget constraints on recovery of taste heterogeneity

The previous section introduces the past studies that suggests ignoring the impact of travel (or budget) constraints may lead to biased estimation. Amongst these studies, Cantillo and Ortúzar (2005) and Li et al. (2015) are the two key studies which estimated the misspecified models which also allow for random taste heterogeneity. Cantillo and Ortúzar (2005) 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-compensatory behaviour, which is caused by the existence of attribute thresholds, as respondents are not able to engage in the presented trade-offs and thereby depart from compensatory choice behaviour, see Payne et al. (1993). Li et al. (2015) assumed fixed tastes in simulated data but found welfare measures that are underestimated by over 30% even when choice set formation is purposefully treated as taste heterogeneity in random parameter logit models.

These two studies had examined the biases in parameter estimates when choice set formation is mistaken or misrepresented as taste heterogeneity. However, many studies have shown the taste are heterogeneous amongst decision-makers (Hensher and Greene, 2003, Hess et al., 2005), which means that the effect of the bias due to budget constraint is further complicated for the retrieval of taste heterogeneity across respondents. The confounding of travel time constraint and the taste variation is particularly important nowadays given the increasing popularity of Mixed Multinomial Logit (MMNL) models to retrieve taste heterogeneity ((Hess et al., 2005)). That said, to the best of our knowledge, there is no research to date which study whether the MMNL could recover the taste heterogeneity when alternatives in the binary route choice setting are not available due to the travel time constraint. Without observing the budget constraints in analysing choice when tastes are varied amongst respondents, there exists a risk that the MMNL model could wrongly capture the budget constraints effect rather than the true taste heterogeneity. As such, this study aims to fill this research gap by allowing for random VTT that 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 fixed coefficients models.

2.3 Empirical setup

2.3.1 Data generating process

Monte Carlo Simulation

Simulated datasets are generated through a Monte Carlo simulation to provide empirical 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 true parameters are available for fair comparisons across different model specifications. In this exercise, we adopt a simple time-cost trade-off exercise, which has been used mostly in the national value of time studies in Western Europe (e.g. Hess et al., 2017) as mentioned in **Section 2.2.1**. The use of simple trade-offs has received increasing criticism as the valuations from more complex SC designs are deemed more reliable. More complex choices are also thought to be more comprehensible to respondents (Hess et al., 2016). Nevertheless, such simple trade-offs are useful in this study to enable us to disentangle the confounding effects, which is more difficult under the presence of more than two attributes. 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 budget constraints at its most extreme condition. The findings from this exercise should provide insights to researchers for further test on designs with more complex choices.

An overview of the simulation process is presented **Figure 2-1**. This illustrates all the key steps involved in the experimental design, and its linkage to the data generating process and model estimation. Each of these three key processes are further described next.

Experimental design

Within the simulated population, all pseudo-observed decision-makers are presented with two alternatives, each with varying levels of travel time between 30 minutes and 75 minutes and travel cost between £3 and £7.5. 10 levels are assumed for each attribute in the experimental design. A full factorial design is first generated, with dominated choices removed. To retain the same number of observations across different budget threshold bands for fair comparisons, the design only allows trade-offs between travel times where at most one alternative exceeds the time budget of 45 minutes. This allows us to compare all the model results across different scenarios (i.e., different assumptions of time constraint)

on a single design, where the model results (e.g. log-likelihood) can be compared directly across scenarios for understanding the impacts of misspecification. 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, with each of the original choice tasks used twice.

Figure 2-1: Overview of the analytical process
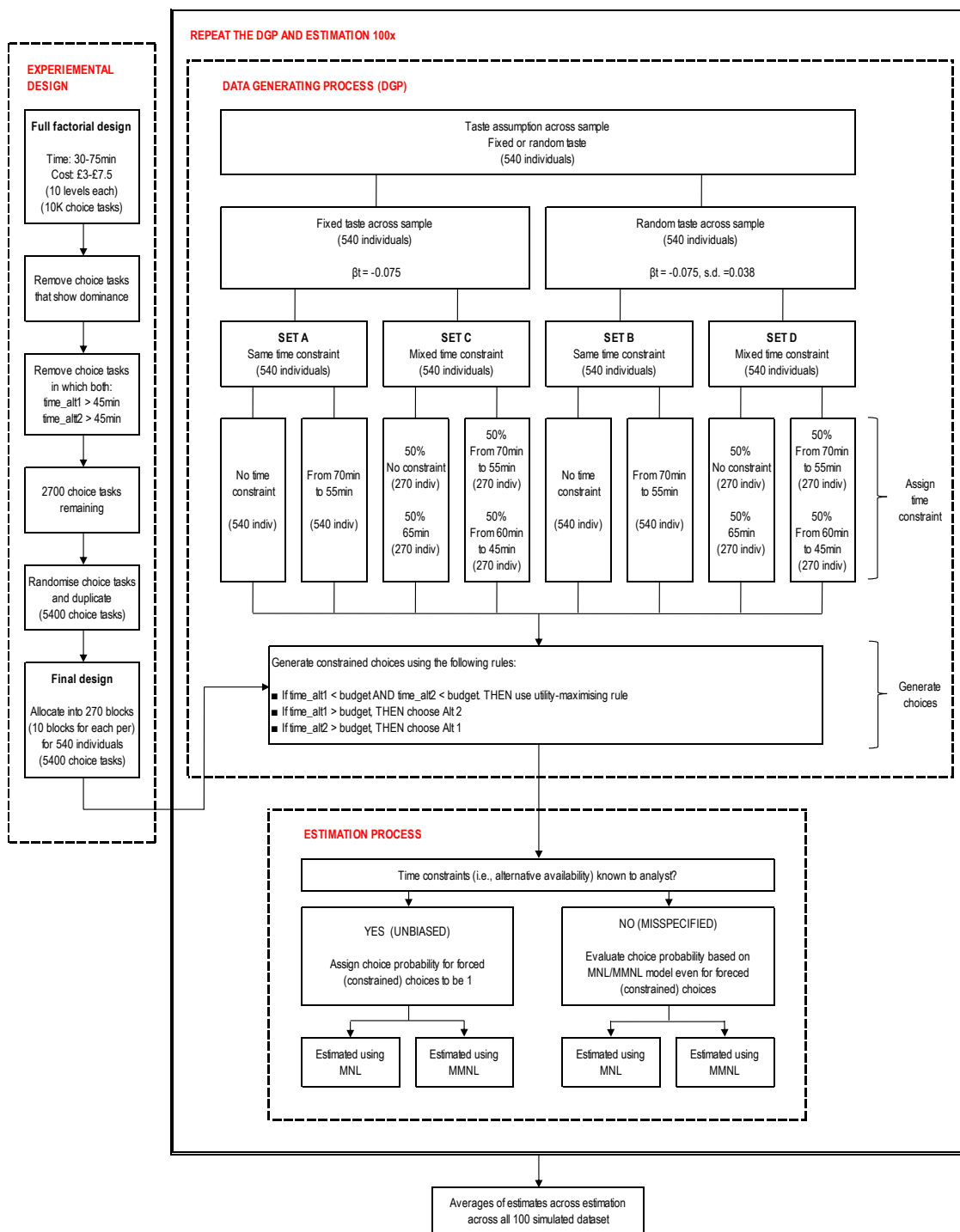
Generation of choices (Data generating process)

The basic process in the data generating process (DGP) is illustrated in **Figure 2-1**. This DGP mainly follows the following few steps:

1. Assign time sensitivities (fixed or random tastes) accordingly across simulated population

2. Make assumption on the variations in time budget (fixed time budget or differential budget at 50/50 split) across simulated population

3. Assign time constraints for each class of simulated population according to the scenario setting, which vary from 70min to 55 min or assuming no constraint at all)

4. Apply choice-rejection mechanisms and retain the alternatives that fall within the travel time budget

5. Identify the chosen alternative from the remaining alternatives based on the notion of utility maximisation

6. Estimate model, with or without the knowledge of the alternative availability (i.e., the knowledge of time constraints)

Using a random utility model, we write the utility $U_{i,n,t}$ that an individual n obtains from 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 trade-offs can simply be written as:

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

where *T* is the time attribute and *C* is the cost attribute, while β_t and β_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:

- Fixed time budget
  - Set A – Fixed and linear time sensitivities of -0.075, where

$$V_{i,n,t} = -0.075T_{i,n,t} - 0.9C_{i,n,t}$$

  - Set B – Negative lognormally distributed time sensitivities with an arithmetic mean of -0.075 and standard deviation of 0.038. This translates into location parameter of 0.259 and shape parameter of 0.472[2], where:

$$V_{i,n,t} = -\exp(2.59 + 0.472r_n)\, T_{i,n,t} - 0.9C_{i,n,t}$$

  r_n is a random draw from a standard normal distribution

- Mixed time budget
  - Set C – Fixed and linear time sensitivities of -0.075, where, for both classes of simulated population:

$$V_{i,n,t} = -0.075T_{i,n,t} - 0.9C_{i,n,t}$$

  - Set B – Negative lognormally distributed time sensitivities with an arithmetic mean of -0.075 and standard deviation of 0.038. This translates into location parameter of 0.259 and shape parameter of 0.472, where, for both classes of simulated population:

$$V_{i,n,t} = -\exp(0.259 + 0.472r_n)\, T_{i,n,t} - 0.9C_{i,n,t}$$

  r_n is a random draw from a standard normal distribution

All the scenarios tested (i.e., including the generation of simulated data and model estimation) based on these four combinations of specifications for time sensitivities and time budget variations are presented in **Table 2-1**.

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. For instance, if individuals from the sample where mixed time budget is allocated across sample, then a random sample of 50% of the simulated population will be subject to 70min of time budget, with the rest of the 50% of population subject to 60min

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[2] The location parameter of μ and shape parameter σ of the lognormal distribution are calculated based on the arithmetic mean of -0.075 and standard deviation of 0.038:

$$\mu = \ln\left(\frac{E[X]^2}{\sqrt{E[X^2]}}\right) = \ln\left(\frac{E[X]^2}{\sqrt{Var[X]+E[X]^2}}\right), \text{ and, } \sigma^2 = \ln\left(\frac{E[X^2]}{E[X]^2}\right) = \ln\left(1 + \frac{Var[X]}{E[X]^2}\right)$$

of time budget. In generating concreated choices, a choice-rejection mechanism is enforced such that if the travel time attribute presented exceeds the predefined time budget, the respective alternative is then rejected. For those choice tasks with both alternatives retained, the simulation assumes that individuals make choices according to the standard random utility maximizing rule

Table 2-1: Overview of test scenarios (binary time-cost trade-offs)

ID	Taste* across sample	Mixed constraint across sample?	Subject to constraint?	# of different Scen	Constraint setting for each class or sub-class	Using MNL — Alternative availability known? (✖ - misspecified if s.t. contraint)		Using MMNL — Alternative availability known? (✖ - misspecified if s.t. contraint)	
SET A	Fixed taste	✖	✖	1	-	✔ A1			
			✔	4	70min, 65min, 60min, 55min	✔ A1	✖ A2		
SET B	Random taste	✖	✖	1	-			✔ B1	
			✔	4	70min, 65min, 60min, 55min			✔ B1	✖ B2
SET C	Fixed taste	✔	50% sample	1	Class 1: - Class 2: 65min	✔ C1	✖ C2		✖ C3
			100% sample	4	Class 1: 70min, 65min, 60min, 55min Class 2: 60min, 55min, 50min, 45min	✔ C1	✖ C2		✖ C3
SET D	Random taste	✔	50% sample	1	Class 1: - Class 2: 65min			✔ D1	✖ D2
			100% sample	4	Class 1: 70min, 65min, 60min, 55min Class 2: 60min, 55min, 50min, 45min			✔ D1	✖ D2

Column group headers: DGP in simulated data (Taste, Mixed constraint, Time constraint: Subject to constraint?, # of different Scen, Constraint setting); Estimation (Using MNL, Using MMNL).

* - time senstiivty

2.3.2 Model estimations

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

Fixed and linear time sensitivities

The multinomial logit (MNL) model is used for estimations of the fixed and linear time sensitivities. Let $P_{n,t}(i|\beta)$ give the probability of respondent n (with $n = 1, \dots, N$) for alternative i (with $i = 1, \dots, I$) in choice situation t (with $t = 1, \dots, T_n$), conditional on a vector of taste coefficients β, with $\varepsilon_{i,n,t}$ following a Type I extreme value distribution, distributed identically and independently across alternatives and choice situations. The choice probability given by the 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, conditional on β, is given by:

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

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 β_t/β_c.

Negative lognormally distributed time sensitivities

The MMNL model is used for estimations of the random VTT. In the MMNL model, the vector of the taste coefficients β follows a random distribution across respondents, such that we have $\beta \sim g\left(\beta|\Omega\right)$, with Ω representing a vector of parameters of the distribution of β. In this study we allow tastes to vary across respondents only but stay constant across choice situations (cf. Hess and Train, 2011). The choice probability of the chosen alternative given by the MMNL model for respondent n over a sequence of choices he/she faced becomes:

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

The log-likelihood function is given by:

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

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.

Incorporation of constraints

All scenarios are tested with and without the knowledge of the availabilities of alternatives (due to constraints) for each choice task. The model runs with known availabilities of alternatives are 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 misspecified models.

2.4   Empirical results

We now present the results of the various models, where we look in turn at each simulated data setting. For each model specified for estimation, 100 simulated datasets are generated.

This includes undertaking both the data generating process and model estimation 100 times in total, as illustrated in Figure 2-1. All the model results reported are averages across all 100 simulated datasets.

2.4.1 Linear time sensitivities under fixed time budget

Replication of time and cost sensitivities

When the availabilities of alternatives for all the choice tasks in the SC experiment are known to the analyst, a choice probability of 1 is assigned to the only remaining alternative that falls within the travel time budget. By doing so, 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 2-2. It is also shown that MMNL models (B1) are able to retrieve the true arithmetic mean of -0.075 for time sensitivity and standard deviation of 0.038 from the simulated population with negative lognormally distributed time sensitivities. The true cost sensitivity of -0.9 is also consistently retrieved from the models.

Model fit (ρ^2 and LL)

The unbiased models become more deterministic when alternatives are eliminated due to the 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 in the data generating process, LL is improved from -3,036 to -1,416 (B1) in the unbiased models. The improvement of the final LL is strictly caused by the reduced range of data by eliminating the choice tasks where respondents are forced choose the constrained choices. Since individuals are assumed to make their choices based on RUM-consistent behaviour for the remaining choice tasks that are not eliminated, the true VTT of £5/hr can be retrieved from these choice tasks. These results show that the true values can be replicated when the model structure is properly specified and the availabilities of alternatives are known.

Table 2-2: Estimation results for linear time and fixed time budget in DGP

DGP		Estimation											
Taste	s.t. Constr?	Model for Est	Alt Avail known?	Time Constr (min)	ρ^2	LL	Time sensitivity β_t				Cost sensitivity β_c		VTT (£/hr)	
							Mean	t-stat	SD	t-stat	Est	t-stat	Mean	SD
SET A1														
Fixed	✘	MNL	✔	-	0.21	-2,966.6	-0.075	31.1	-	-	-0.905	31.6	4.99	-
Fixed	✔	MNL	✔	70	0.30	-2,619.8	-0.075	26.7	-	-	-0.896	29.4	5.00	-
				65	0.40	-2,230.4	-0.075	22.5	-	-	-0.900	26.7	4.99	-
				60	0.51	-1,822.4	-0.075	18.0	-	-	-0.899	23.9	5.00	-
				55	0.63	-1,399.6	-0.076	13.7	-	-	-0.905	20.7	5.03	-
SET A2														
Fixed	✔	MNL	✘	70	0.24	-2,843.3	-0.090	34.2	-	-	-0.917	31.8	5.9	-
				65	0.29	-2,650.0	-0.108	37.2	-	-	-0.932	32.0	6.9	-
				60	0.36	-2,382.8	-0.130	38.9	-	-	-0.941	31.1	8.3	-
				55	0.45	-2,057.6	-0.157	38.9	-	-	-0.914	28.5	10.3	-
SET B1														
Random	✘	MMNL	✔	-	0.19	-3,035.9	-0.075	61.4	0.037	14.30	-0.899	29.0	5.02	2.50
Random	✔	MMNL	✔	70	0.29	-2,657.1	-0.075	54.0	0.038	12.50	-0.903	27.2	5.02	2.52
				65	0.40	-2,254.7	-0.076	46.3	0.037	10.00	-0.908	24.9	5.04	2.46
				60	0.51	-1,843.7	-0.074	37.8	0.037	7.60	-0.897	22.3	4.98	2.47
				55	0.62	-1,415.6	-0.075	28.9	0.036	5.20	-0.900	19.1	5.03	2.47
SET B2														
Random	✔	MMNL	✘	70	0.22	-2,924.3	-0.089	70.8	0.028	10.50	-0.906	29.6	5.9	1.90
				65	0.27	-2,722.0	-0.106	75.6	0.018	5.70	-0.904	29.7	7.0	1.20
				60	0.35	-2,431.3	-0.126	76.5	0.004	0.80	-0.899	29.7	8.4	0.30
				55	0.44	-2,078.2	-0.154	71.5	0.000	0.50	-0.890	28.2	10.4	0.00

Biased estimates in MNL models when the availabilities of alternatives are unknown

The fact that the availabilities of alternatives are unknown to the analyst has several implications for the model estimation. First, respondents whose time constraints leave them with only one 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 compared to the estimates in the unbiased scenarios when the availability of alternatives are known to analysts. As shown in

Table 2-2, time sensitivities are overstated significantly by 109% from -0.075 to -0.157 when the time budget is restricted to 55 minutes (A2). VTT is also over-estimated to a similar level, from £5/hr in the unconstrained scenario to £10.3/hr when a time budget of 55 minutes is assumed. These findings of biased estimates for the VTT are in line with the past empirical evidence discussed in **Section 2.2**.

Other than the VTT estimates, it is shown that in general the goodness-of-fit is improved in the constrained (misspecified) condition when the travel time constraint which are unaccounted for becomes more stringent. For instance, there is an increase of ρ^2 and LL from 0.21 and -2,970 in the unconstrained scenario to 0.45 and -2,058, respectively, when the budget is set at 55 minutes.

These model improvements cannot be explained by the reduced number of choice tasks in unbiased scenarios as discussed earlier. Here, the choice probabilities are calculated based on the binary choice sets even when one of the alternatives exceeds people's time budget threshold now. When the travel time constraint becomes more stringent the model attributes this to people being more time sensitive. As a result the choice process becomes more deterministic, which explains the improvement in the rho square and the LL in the constrained scenarios.

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 particular interest to understand whether the MMNL models can fully capture the preference heterogeneity even when some attribute levels exceed the time budget thresholds of respondents. As shown in

Table 2-2, the MMNL models increasingly fail to capture the preference heterogeneity inherent to the true dataset 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 unconstrained scenario to 0.028 and 0.018 when the time budget thresholds are set at 70 minutes 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 MNL model (A2) when the time budget threshold is 55 minutes. This implies that the MMNL model effectively treats all respondents as having high time sensitivities.

To explain this further, let us consider the situation in which people have heterogeneous time sensitivities across the sample. When the time budget constraints are stringent, individuals who have low VTT are forced to choose the fast but expensive alternatives as opposed to the slow and cheap alternatives which they prefer. On the other hand, individuals who have high 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 situations. If, as a result, the choice outcomes are the same between these two groups of individuals who share distinctly different VTT, the MMNL model cannot detect any differences 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 preference heterogeneity, when in fact the preference heterogeneity is simply suppressed by the severe time budget constraints in the model estimations which dominate completely. Similarly, it is also shown that the VTT estimates produced by the MMNL models (B2) align closely with the estimates generated by the misspecified MNL models (A2) at all levels of the time budget constraints. Both the MNL and MMNL models over-estimate the VTT by twofold in the most extreme case, at around £10.3/hr approximately due to the inflated time sensitivities. Cost sensitivities on the other hand are not affected by the time budget constraints and the MMNL models are able to retrieve the true value of -0.90.

2.4.2   Linear time sensitivities under mixed time budgets

Replication of parameters when the availabilities of alternatives are known

It has been shown above that the MMNL models could produce misleading findings with respect to the presence of preference heterogeneity when all respondents share the same time budget thresholds. This section further introduces mixed time budget thresholds to the model 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 the respondents perceive their time budget constraints to be 10 minutes more restrictive in comparison with the rest of the population (e.g., time budget constraints of 60 minutes and 70 minutes perceived by half of the respondents respectively). The objective of this exercise is to 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 data generating process (VTT of £5/hr, mean time sensitivity of -0.075 and cost sensitivity of -0.90) are retrieved (C1 and D1 in **Table 2-3**).

Table 2-3: Estimation results for linear time and mixed time budget in DGP

DGP		Estimation												
Taste	s.t. Constr?	Model for Est	Alt Avail known?	Time Constr (min)	ρ²	LL	Time sensitivity βt				Cost sensitivity βc		VTT (£/hr)	
							Mean	*t*-stat	SD	*t*-stat	Est	*t*-stat	Mean	SD
SET C1														
Fixed	50%	MNL	✓	- & 65	0.30	-2,603.35	-0.075	27.2	-	-	-0.900	29.3	4.99	-
Fixed	100%	MNL	✓	70 & 60	0.41	-2,220.83	-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	-
SET C2														
Fixed	50%	MNL	✗	- & 65	0.24	-2,860.52	-0.089	33.2	-	-	-0.895	31.6	5.95	-
Fixed	100%	MNL	✗	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	-
SET C3														
Fixed	50%	MMNL	✗	- & 65	0.24	-2,858.18	-0.091	77.3	0.014	5.0	-0.920	30.4	5.95	0.9
Fixed	100%	MMNL	✗	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	14.7	3.0
SET D1														
Random	50%	MMNL	✓	- & 65	0.29	-2,641.81	-0.076	54.7	0.037	12.4	-0.904	27.2	5.02	2.5
Random	100%	MMNL	✓	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
SET D2														
Random	50%	MMNL	✗	- & 65	0.22	-2,929.18	-0.091	66.2	0.036	13.6	-0.909	29.5	6.04	2.4
Random	100%	MMNL	✗	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	14.9	3.4

Biased estimates when the availabilities of alternatives are unknown

Similar to the findings from scenarios where fixed time budgets are assumed amongst individuals, the misspecified models over-estimate time sensitivities when the mixed time budget 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 123%, from -0.075 to -0.165 (C2 vs. C1 in **Table 2-3**). 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 biased results. In general, model results show that 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 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 only available option due to the budget constraints, rather than the free alternative that they 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 population instead.

The difficulties of distinguishing whether the variations in choice probabilities are due 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 anticipate that the MMNL model could not fully capture the preference heterogeneity assumed in the simulated dataset when the travel budget constraints are applied, as described in **Section 2.4.1**. 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 time budgets amongst individuals are unknown to the analyst, there is substantial risk that misleading findings of taste heterogeneity can also be attributed to a mix of these two opposite effects. The model results across different levels of stringency of time budgets for simulated data where random time sensitivities and mixed time budgets are assumed are shown in D2 in **Table 2-3**.

2.5   Impacts of opt-out alternative and polynomial functional form

The previous sections had demonstrated the adverse impacts of the unobserved travel time constraints on the VTT estimates and the retrieval of random taste heterogeneity through simulation methods. As discussed in **Chapter 2.2.3**, a few formal choice set formation

models were developed over years to address the issues caused by the exceed budget thresholds. Other than implementation of these choice set formation models, we provide empirical evidence for two suggested practices for the survey development stage that could potentially reduce the impacts of the budget constraints by inclusion of an opt-out alternative and incorporation of non-linear functional form. The opt-out alternative aims to add realism in SC choice tasks by excluding respondent from the trade-off when either one of the travel alternatives exceed his/her time budget threshold. The incorporation of the non-linear functional form aligns with the one-stage choice set formation models (see **Chapter 2.2.3**) in which the utility for the constrained alternative is heavily penalised. We retain our simulation framework for testing these alternative approaches.

2.5.1 Inclusion of an opt-out alternative

The inclusion of an opt-out alternative, or sometimes referred to as the 'no choice', 'neither', 'none of these' or 'status quo' alternative in SC scenarios has been widely discussed in the past. 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. Kontoleon and Yabe, 2003). 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.

Model specifications including fixed time budget thresholds and negative lognormally distributed time sensitivities (B2 in

Table 2-2) are retained as the basis for the new data generating 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 -9.0 is assigned to the opt-out alternative to represent the dis-benefits from not being able to 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 travel alternatives. This setting implies that the dis-utilities of not travelling are slightly larger than the dis-utilities of the travel alternatives in the unconstrained situation, ensuring that the opt-out alternative is not overly attractive relative to the two travel alternatives.

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 the ASC values of -9.0 for the opt-out alternatives are retrieved when the availabilities of alternatives are known to the analyst (B1 in **Table 2-4)**. When the availabilities of alternatives are unknown, taste heterogeneity assumed in the data generating process cannot be retrieved fully (B2 in **Table 2-4**), but the level of bias is not as strong as that in the binary choices examined earlier. When the time budget threshold is set to 55 minutes, the arithmetic mean and standard deviation of the time coefficient change from -0.075 and 0.038 in the unconstrained case to -0.145 and 0.032, respectively, in the model that includes an opt-out alternative. This is compared to the arithmetic mean of -0.154 and a complete loss of taste heterogeneity in binary choices without an opt-out alternative (B2 in

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

Table 2-4: Estimation results for inclusion of the opt-out alternative

DGP		Estimation													
							Time sensitivity β_t				Cost sensitivity β_c		VTT (£/hr)		ASC for Opt-out
Taste	s.t. Constr?	Model for Est	Alt Avail known?	Time Constr (min)	ρ^2	LL	Mean	t-stat	SD	t-stat	Est	t-stat	Mean	SD	Est	t-stat
SET B1																
Random	✗	MMNL	✓	-	0.23	-4568	-0.075	65.1	0.04	20.2	-0.902	34.5	5.0	2.5	-9.03	-36.7
Random	✓	MMNL	✓	65	0.31	-4109	-0.075	52.5	0.04	18.1	-0.903	32.2	5.0	2.5	-9.03	-32.5
				60	0.35	-3875	-0.075	46	0.04	16.8	-0.899	31.0	5.0	2.5	-9.00	-30.2
				55	0.39	-3636	-0.075	39.5	0.04	15.3	-0.899	30.0	5.0	2.5	-8.99	-28.2
SET B2																
Random	✓	MMNL	✗	65	0.24	-4496	-0.105	80.9	0.03	20.3	-0.929	35.5	6.8	2.1	-10.36	-40.3
				60	0.26	-4380	-0.124	84.5	0.03	20.2	-0.927	35.2	8.1	2.1	-11.05	-41.6
				55	0.29	-4219	-0.145	83.1	0.03	19.3	-0.902	33.2	9.7	2.1	-11.67	-41.1

2.5.2   Non-linearities

Replication of parameters when the availabilities of alternatives are known

This section switches our focus to the incorporation of non-linearities in the model specifications to capture potential budget constraint effects. We have demonstrated in earlier sections that the 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 constraints are latent in nature, which are difficult to measure without the use of more complicated probabilistic choice set formation models. It is thus useful to examine whether non-linear functional forms could capture the kink of travel dis-utilities, which could occur when 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 budget thresholds for some decision-makers.

Indeed, this is not new that non-linear functional form could capture the impacts of constraints. As demonstrated in Ben-Akiva and Lerman (1985, p.176), a piecewise linear approximations of the disutility of travel time appears to have captured the impact of non-linear time sensitivities. It has also been suggested by Ben-Akiva and Lerman that a power series expansion can be adopted as well, provided the polynomial of a higher degree "do not exhaust the available degrees of freedom". In practice, however, the polynomial terms are rarely used in VTT studies. While we propose the use of formal choice set generation models to account for the impacts of budget constraints, we suggest that a polynomial functional can be adopted for parsimony, for the detection of any potential influences of budget constraint. A 3rd-degree polynomial functional form for time sensitivities is adopted for testing the use of non-linear functional forms in this study. The 3rd-degree polynomials with the form $\beta_{t1}T + \beta_{t2}T^2 + \beta_{t3}T^3$ specified for time sensitivities are estimated using the MNL models. In terms of 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 $(\beta_{t1} + 2\beta_{t2}T + 3\beta_{t3}T^2)/\beta_c$.

Model results show that the 3rd-degree polynomial functional forms produce very similar cost sensitivities, LL and ρ^2 (E1 in **Table 2-5**) as in the MNL models (A1 in

Table 2-2) 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 second and third

polynomial terms are very small. The true VTT of £5/hr, estimated in quadratic forms as described in **Section 2.3.2**, is retrieved across all levels of the budget thresholds and attribute levels.

Table 2-5: Estimation results for linear time and fixed time budget in DGP but estimated by non-linear functional form

DGP		Estimation													
							Time sensitivity β_t						β_c		VTT
Taste	s.t. Constr?	Model for Est	Alt Avail known?	Time Constr (min)	ρ^2	LL	β_{t1}		β_{t2}		β_{t3}				(£/hr)
							Est	t-stat	Est	t-stat	Est	t-stat	Est	t-stat	
SET E1															
Fixed	✗	MNL	✓	-	0.21	-2,968.33	-0.162	8.1	1.70E-03	8.8	-1.10E-05	46.0	-0.901	29.9	4.79
Fixed	✓	MNL	✓	70	0.30	-2,616.84	-0.129	4.8	1.20E-03	6.4	-8.10E-06	39.1	-0.896	28.3	4.86
				65	0.40	-2,225.71	-0.087	2.8	2.00E-04	4.4	-1.70E-06	27.2	-0.905	26.3	4.96
				60	0.51	-1,819.41	-0.116	1.6	9.00E-04	1.8	-6.10E-06	8.9	-0.902	23.7	4.92
				55	0.62	-1,401.19	-0.021	2.4	-1.30E-03	5.5	1.10E-05	6.0	-0.898	20.7	4.95
SET E1															
Fixed	✓	MNL	✗	70	0.27	-2,728.27	-0.914	112	1.87E-02	606.5	-1.30E-04	174.9	-0.844	28.0	2.65
				65	0.37	-2,347.61	-1.486	103	3.25E-02	256.4	-2.40E-04	343.6	-0.84	26.0	1.80
				60	0.48	-1,943.58	-2.330	222	5.38E-02	984.8	-4.20E-04	187.0	-0.834	23.5	1.89
				55	0.60	-1,507.56	-3.933	349	9.57E-02	273.7	-7.70E-04	490.4	-0.852	21.2	4.78

Biased parameters when the availabilities of alternatives are unknown

Model results estimated when the availabilities of alternatives are unknown to the analyst are summarized in set E2 in **Table 2-5**. The VTT estimates produced by the polynomial utility functional forms are shown to be highly sensitive to the attribute levels of the travel time, as 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 £184/hr when the journey times increase from 65 minutes to 75 minutes, as shown in **Figure 2-2.** These exceptionally high VTT estimates show that respondents are highly unlikely to choose the 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 reflect of the VTT distributions where the attribute levels exceed the travel budgets of the respondents. The lower panel of **Figure 2-2** also shows the utility levels that are related to the travel time components only. It can be 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 polynomial utility function produces a stable utility level for journeys that last between 30 minutes and 55 minutes. Beyond that, the travel time dis-

utilities increase significantly as the time attribute values exceed the designated time budget of 55 minutes. This illustrates the flexibility given by this highly non-linear polynomial functional function. Under the choice-rejection mechanism set out in this simulation, respondents will universally choose the remaining but more expensive alternatives when the travel time budget is binding. This is accommodated by the polynomial functional form applied for the time sensitivities, which allows 1) close to fixed/linear time sensitivity when both alternatives are available, and 2) introduces a sharp increase in time sensitivity when the travel time budget becomes binding. In the latter case the disutility of alternatives with high travel times increases rapidly thereby lowering its choice probabilities.

Figure 2-2: VTT estimates and travel dis-utilities estimated by non-linear functional form
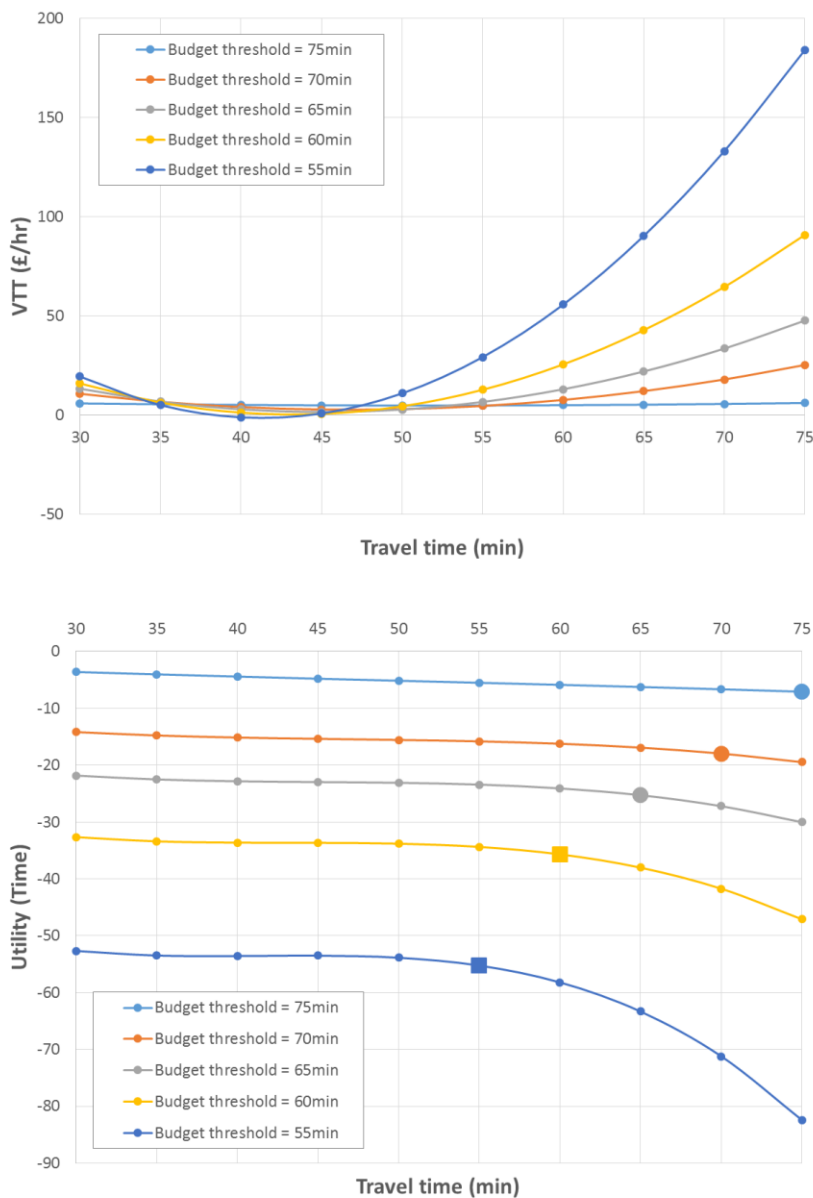
2.6   Conclusions

This paper has sought to provide a detailed assessment of the impact of time budget constraints on the VTT estimates and the identification of preference heterogeneity, when explicit modelling of choice set formation is not involved in a binary choice design with time-cost trade-offs.

We first show that if time budgets are stringent but not accounted for, VTT can be significantly overestimated. Secondly, this paper has provided a 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 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 model could also wrongly attribute the impacts of the mixed time budget constraints to the findings of preference heterogeneity.

We first look into the implications of our findings with respect to the experimental design in particular. It is stressed that while the misspecification error concerning the travel time constraint are relevant to both SP and RP data, this issue is particularly apparent within the SC context. This is because respondents can be presented with unfeasible alternatives in the SC experience which then introduce bias when these unfeasible alternatives are modelled with non-zero choice probabilities. In RP data, the chosen alternatives observed should be within budget unless irrational decisions are made, despite the need to make assumptions on the non-chosen alternatives. It is thus especially important to ensure that the SC design is robust enough for minimising the any impacts due to any misspecification issues.

The design issue with respect to the simple time-cost trade-offs setting lies in the lack of behavioural consideration of the travel time constraint. Indeed, our finding adds further empirical evidence of the literature in questioning the reliability of the VTT estimates derived from simple time-cost trade-offs (see Hess et al., 2016). While there could be merits for this simple design by reducing respondent burden as the original intent (see counter arguments from Chintakayala et al. (2010)), any potential benefits will be outweighed by the significant bias induced by lack of behavioural consideration of the travel time constraint demonstrated in this thesis. While we acknowledge the rising use of the "pivot design" to assign the attribute levels around respondents' current or past travel experiences can enhance the relevancy of attribute levels in the SC design, we posit that it cannot be guaranteed that the

presented variations around the reference time and (or) costs fall within the respondents' respective constraints.

We also found that including an opt-out alternative could potentially help retrieve some but not all preference heterogeneity under the presence of budget constraints. Special attention should be paid to ensure minimal contextual effect will be induced by introducing the opt-out alternative. 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 when subject to binding budget constraints.

Alternatively, there have been numerous methodological advances over years in the modelling choice set formation. This includes the two-stage models to explicitly model the choice set formation (Manski, 1977, Swait and Ben-Akiva, 1987b, Swait and Ben-Akiva, 1987a, Cantillo and Ortúzar, 2005), and the one stage semi-compensatory models for approximation of constrained choice sets (Cascetta and Papola, 2001, Martínez et al., 2009, Paleti, 2015). Clearly, these models can take into consideration the travel time constraints and hence reduce the bias in VTT estimates. However, our results also highlight the confounding issue between the taste heterogeneity and the impacts of travel time constraints. This raises questions whether the confounding problem would also occur in these aforementioned models, which are developed based on the fixed taste assumptions. More recently, Bergantino et al. (2019) take into account of both indicators of consideration including the consideration for alternatives and stated thresholds for attributes and unobserved heterogeneity in mode specific constant to model consideration set generation.

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. Hess et al., 2007). 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 (de Jong and Bliemer, 2015). In this context, we question whether such approaches, especially for the studies which rely on simple time-money trade-offs, could avoid or reduce any potential bias on the VTT estimates that might result from 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 enabling different decision strategies dealing with the budget constraints (e.g. non-compensatory attribute cut-offs by Swait (2001)) instead of the choice-rejection mechanism applied to remove any constrained alternatives completely, and improve realism in the assumption of multiple budget constraints, which assigns different time budget constraints for two classes of the simulated population generated randomly.

Acknowledgement

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Chapter 3

Analysing the impact of income measures on the cross-sectional income elasticity of the value of travel time and the implications for transport appraisal

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Abstract

There is longstanding evidence in the literature about a disparity between the cross-sectional and inter-temporal income elasticity of the value of travel time (VTT). This paper investigates the extent to which the income measure used in the estimation of behavioural choice models contributes to that disparity. Using data from the most recent GB (Great Britain) national VTT study, we focus on two potential sources of measurement errors, namely taxation and within household budget allocation. Our work finds that accounting for the progressive nature of income tax increases the cross-sectional income elasticity and that additionally accounting for social benefits reduces the disparity further. Secondly, we show that the disparity is partially explained by assumptions regarding the within-household budget allocation, albeit the directional change of income elasticity is unclear from the outset. Overall, varying the income measure does not change the average VTT estimated by the behavioural choice model (i.e. behavioural VTT) for the stated choice (SC) sample. However, when moving from the SC data to a nationally representative sample, we obtain significantly different figures for the appraisal VTT, which could have substantial impacts for policy and infrastructure decisions. We also show that the alternative assumptions on the income variable have significant implications to the update of VTT over time with respect to income in that difference in income measurement approaches could provoke diverging VTTs for the future, yet there is no economic theory to suggest any preferred income measure (and hence elasticity of VTT) for non-business trips.

Keywords: value of travel time, income elasticity, income measure, appraisal, non-business

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3.1 Introduction

The value of travel time (VTT) is a key parameter in transport appraisal (Daly and Hess, 2020). Assumptions made regarding the VTT are arguably as important for the outcome of cost-benefit analyses (CBA) of transport infrastructure investments as assumptions made regarding the discount rate (Small, 2012). Most VTT studies account for variations in the VTT across different trip purposes, where the distinction between business and non-business travel (e.g. commute and leisure) is especially relevant. Travel time savings for business travellers have often been connected to the cost-savings approach (CSA) through the wage rate. The benefits of reductions in travel time accrue to the business owners as the saved time can now be used productively.[2] For non-business travel, reduced travel time allows people to use their time for alternative activities (e.g. spending more time with family and friends). It is here that we can make a connection between travel time and income. Travellers may be willing to spend more money on shorter journey times to enjoy more time with others. More formally, the VTT is defined by the ratio of the marginal utility of time over the marginal utility of income (Mackie et al., 2003, p.49, Wardman, 2001). Both the marginal utility of income and time are not considered to be constant entities because of assumed decreasing marginal utility of spending more income and (or) time on given activities. In this paper, we focus on the marginal utility of income, which is generally assumed to be decreasing with income again to the decreasing marginal utility of consumption. Due to the marginal utility of income being in the denominator of the VTT, the conjecture that the VTT increases with income is widespread in the literature.

For appraisal purposes, the relationship between income and the VTT is important for two reasons. First, for deriving nationally representative VTT measures, it is important to understand how the VTT varies across the different income (and other socio-economic) segments (e.g. Börjesson and Eliasson, 2018, Mouter, 2016). Second, CBA exercises require the use of future VTT values to quantify the benefits of travellers up to sixty years in the future. Due to economic growth, future travellers are expected to have higher incomes and

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[2] The most recent UK VTT study (Batley et al., 2019) uses a willingness-to-pay based approach for business travel accounting for the notion that some of the benefits may arise to the business traveller himself. With the increasing blending of work and private activities, this may be a relevant approach. For the purposes of this paper, we however stick to the traditional interpretation of the business VTT and therefore consider it out of scope.

hence higher VTT values than current generations.[3] Limited attention has been paid to how the cross-sectional income elasticity relates to the inter-temporal income elasticity. At first sight, when preferences are not subject to change over time, the two elasticities should be closely related as non-business travellers would simply 'adopt' the preferences of the higher income segment. However, in practice, the cross-sectional and inter-temporal income elasticities are not consistent with each other (see Börjesson et al., 2012, Hensher, 2011, Mackie et al., 2003, Small, 2012, Wardman, 2001).

Economic theory only informs us about the direction of the rate of change of VTT relative to the marginal utility of income but not the size of such income effects (Fowkes, 2000, Hensher, 2011, Hensher and Goodwin, 2004, Small, 2012). Analysts are thus dependent on empirical evidence which typically comes from discrete choice models estimated on stated choice (SC) or more rarely revealed preference (RP) (Daly et al., 2014, Brownstone and Small, 2005, Varela et al., 2018). Whether SC or RP, the data use for such modelling work is typically cross-sectional, i.e. with observations at one point in time, allowing analysts to study the impact of income differences across people, but not the impact of income changes for the same person. Many national VTT studies find significant income effects on VTT in such cross-sectional data. Even excluding outliers, empirical evidence regarding the *cross-sectional* income elasticity for non-business trips ranges from 0.25 to 0.75 (MVA/ITS/TSU, 1987, AHCG, 1996, Arup/ITS/Accent, 2015, Fosgerau, 2005, Gunn, 2000, Wardman, 2001, Mackie et al., 2003, Hensher, 2011). On the other hand, empirical evidence from meta-analyses of VTT estimates indicate that the inter-temporal elasticity of the VTT with respect to GDP (per capita) points towards a unit value (Abrantes and Wardman, 2011, Wardman et al., 2016). The latter evidence base is considered as the state-of-practice for uplifting the VTT over time with applied *inter-temporal* income elasticities between 0.5 and 1, with the lower bound set out for prudency (Sartori et al., 2014, De Jong et al., 2004, Bickel et al., 2006)[4].

The disparity between the cross-sectional and inter-temporal income elasticity on the VTT can occur for three reasons. First, the growth in the VTT over time may not arise entirely due to income effects but rather emerge due to other factors including changes in preferences,

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[3] The Department for Transport in the UK currently adopts an intertemporal income elasticity of one and uplifts the national VTT annually based on long-term expectations in GDP growth (see DfT, 2019, TAG Data Book A1.3.2).

[4] The unit value is in line with the cost savings approach (CSA), which is used for valuing business travel time and implies a unit income elasticity since all the released travel time is assumed to be utilised for productive work (Harrison, 1974, Wardman et al., 2015).

socio-demographics, journey quality, or technological advances over time. The inter-temporal income elasticity inferred from meta-analyses may therefore represent a combination of effects when these confounding factors are not fully disentangled from the income effect (Laird et al., 2013, Arup and Leeds ITS, 2017). Second, the cross-sectional income elasticity may not be constant across income groups, i.e. the differences in VTT that can be linked to differences in income are larger in some parts of the income distribution than in others. This is supported by empirical work. Indeed, by relaxing the conventional assumption of constant income elasticity of VTT, Börjesson et al. (2012) and Börjesson (2014) provide empirical evidence of an income elasticity that increases with income in the pooled data, while the relationship between income and VTT remaining stable between two repeated VTT studies. They concluded that the (non-constant) cross-sectional income elasticity by income group can be used as the inter-temporal elasticity. Replication of this finding in other datasets will be necessary to confirm the appropriateness of the inter-temporal income elasticity set out for updating the VTT over time for income effect. Thirdly, the disparity between the cross-sectional and inter-temporal income elasticity can be the result of measurement error in the income variable used in cross-sectional studies. The marginal utility of income (i.e. the travel budget) is the shadow price of income (i.e. marginal value of relaxing the budget constraint in utility maximisation), and inaccurate representations of the budget constraint may produce biased estimates of the respective income elasticity and the VTT[5]. Four potential sources of measurement error can be identified. First, disposable income can be perceived differently by individuals depending on their knowledge of differences between net and gross income including related social benefits. Second, it is uncertain whether people consider their private or household income, or some alternative allocation of disposable income within the household. Third, it is uncertain how budget is allocated between different classes of spending, including travelling (Deaton and Muellbauer, 1980). Lastly, more data specific reasons exists. Errors can be incurred as income measures are captured only categorically in most surveys, and there is ample anecdotal evidence of survey respondents falsifying the income information they provide.

This paper focuses on examining the impacts of the first and second type of measurement error related to the income variable and the potential impact on the cross-sectional income

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[5] By assuming an income elasticity exists, indirect utility is implicitly assumed to be non-linear in income.

elasticity. More specifically, we test the impact on the VTT estimates and also the income elasticity of VTT by using alternative representations of the income variable (i.e., gross, after-tax or disposable income) and also by household composition and intra-household dynamics (i.e., household, equivalised household and personal income). We base our analysis on the SC survey collected for the 2014/15 GB[6] VTT study (Arup/ITS/Accent, 2015). Given the unavailability of the same survey at different moments in time, we are unable to verify the Börjesson et al. (2012) and Börjesson (2014) argument. We first assess the impacts of varying income variables on the findings obtained from the models estimated on the SC data, where these values are referred to as "the behavioural VTTs". Values for appraisal are in practice then obtained by applying the models to a nationally representative database using sample enumeration (cf. Batley et al., 2019), and we also study the impact on these appraisal VTT measures, compared to the official appraisal values recommended in the 2014/15 GB VTT study.

The remainder of the paper is structured as follows. **Section 3.2** reviews the treatment of income in the VTT literature and provides the essential information regarding the 2014/15 VTT estimation framework which this empirical work is based on. Research questions are also laid out in this section. **Section 3.3** outlines the research methodology, while **Section 3.4** summarises the model results. Finally, **Section 3.5** discusses policy implications and concludes.

3.2 Literature review and research questions

3.2.1 Variations in income re-distribution measures

Fosgerau (2005) is one of the rare studies to have explored the impact of the choice of income variable on the VTT and its income elasticity. This work showed that by replacing gross income with after-tax income, the cross-sectional income elasticity becomes higher and closer to the inter-temporal income elasticity. An argument in favour of this approach is that after-tax income is likely to be a more accurate representation of the budget available for consumption and travel. However, an element not accounted for by Fosgerau (2005) and largely ignored in the literature, is the treatment of social benefits. This practice is

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[6] The 2014/2015 study excluded Northern Ireland, hence GB instead of United Kingdom (UK).

questionable since social benefits (e.g. unemployment, housing subsidy etc.) significantly affect the money budget especially for low income groups.

This paper sets out to account for social benefits in the income variable and is in sharp contrast with VTT studies that have removed observations from the lowest income group during estimation, based on the rationale that income is not a key determinant of VTT for those who rely on benefits (e.g. Börjesson et al., 2012). Statistically speaking, changing the income variable from after to before-tax alters the shape of the income distribution in the sample (and population) and reduces the variation in income across respondents when tax rates are progressive. In terms of modelling implications, the smaller variation that applies in the after-tax income variable needs to explain the same amount of cross-sectional variation in the VTT and thus a higher cross-sectional income elasticity is expected. The same logic can be applied when accounting for social benefits that uplift disposable income at the lower end of the income distribution.

This paper uses the term '*gross income*' to measure the gross earnings from employment and investments only[7]. *After-tax* income accounts for tax deductions from the gross income and *disposable* income additionally takes social benefits into account. Past UK national VTT studies (including the 2014/15 GB VTT study) have used the gross household income in the non-business VTT models. This is as opposed to some other international studies that have adopted the after-tax income (Börjesson et al., 2012, Fosgerau et al., 2007, Ramjerdi et al., 2010). Within this context, we set out the following questions regarding the impacts of the use of after-tax and disposable income as opposed to gross income:

- **Question 1**: Is the cross-sectional income elasticity of VTT based on after-tax income variables higher than the one obtained using the gross income variable under a progressive tax system?
- **Question 2:** Is the cross-sectional income elasticity of VTT based on disposable income variables (i.e. additionally including social benefits and tax deductions) higher than that obtained using either the gross or after-tax income variables?

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[7] This is different to the convention adopted by the UK Office for National Statistics, in which the gross income refers to the *original* income (from labour costs and take-home pay) plus the social benefits (ONS, 2015, p.4).

3.2.2 Variations in household composition and intra-household dynamics

Turning to the second source of measurement error in the income variable, it is reasonable to assume that individuals perceive their money budget differently depending on their household compositions and intra-household dynamics (Mackie et al., 2003, Wardman, 2001). Using the total household income as proxy for the travel budget assumes that household members have access to the income contributed by all household members. Alternatively, individuals can measure their travel budget based on their personal income levels or an uneven allocation of budget across household members. A common approach for dealing with the economies of scale in consumption within a household is to re-scale the household income based on the OECD (Organisation for Economic Co-operation and Development)-modified equivalence scale. The 'equivalised' income measure offers a better assessment of expenditure patterns for households of different size and composition as they require different levels of income to maintain a comparable standard of living (Anyaegbu, 2010). The 2014/15 GB VTT study made use of the household income as proxy for the travel budget for non-business trips[8].

In this context, this paper sets out to answer the following questions:

- **Question 3:** Is there a difference in the cross-sectional income elasticity of VTT when using personal income or household income?
- **Question 4:** Is the cross-sectional income elasticity of VTT when using equivalised household income different from that derived using household and personal income variables?

The potential direction of change in income elasticity is unclear from the outset for both questions since the difference between the perceived budget and respective income variable used may vary across respondents. We have insufficient information on how people allocate budgets within their respective households and are thereby faced by the empirical question of how alternative personal/household income variables potentially contribute towards the disparity between cross-sectional and inter-temporal income elasticity.

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[8] Tests were carried out to determine the most appropriate income variable for given purposes and modes in the early model development stage. Household income is shown to best fit the data for commuting for non-work, with personal income used for business.

3.2.3   2014/15 GB VTT modelling framework

The 2014/15 GB VTT study produced a new set of value of travel time, reliability and other journey quality attributes for the Great Britain to be used in the appraisal of transport investment projects. To arrive at a set of nationally representative VTT measures – the focus of this paper - that vary by mode-purpose segment, an elaborate data collection, estimation and implementation procedure was followed as described by **Figure 3-1**. Firstly, for 11 mode-purpose segments (modes: car, rail, bus, other public transport; purposes: commute, business, and leisure and other non-business travel - excluding the bus-business segment) Stated Choice (SC) data were collected supplemented by a limited amount of Revealed Preference (RP) data on rail operator choice for validation purposes. Advanced choice modelling techniques were applied to understand how the VTT values vary across various trip and traveller characteristics, including the various mode-purpose segments (see Hess et al., 2017).

Figure 3-1: – Overview of the 2014/15 GB VTT modelling framework

Data input	Process	Output
2014 Stated choice (SC) & Revealed preference (RP) data	Behavioural choice model	Behavioural VTTs
2010-2012 National Travel Survey (NTS) data	Implementation Tool (Sample enumeration)	Appraisal VTTs
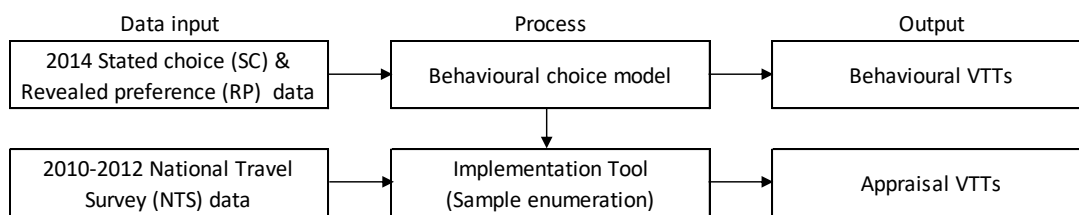
The 2014/15 GB VTT modelling framework incorporates and expands on the latest advances in VTT estimation techniques (see Hess et al., 2017 for details). First, this model framework made use of multiplicative error terms (Fosgerau and Bierlaire, 2009, Fosgerau et al., 2007), which was found to provide better performance and more reasonable results than the additive error structure during the model development. The multiplicative error structure facilities a constant variance for the error term, which is compatible with the general finding that utility variance increases as utility increases, a fact that is important in the context of studies combining short and long journeys. Second, the modelling framework also incorporates reference dependence in the form of size and sign effects relative to the 'reference' trip (De Borger and Fosgerau, 2008). This takes into account the common findings of the asymmetries (sign) of the VTT and also the non-linearities (size) of time or cost changes relative to the reference case (see Daly et al., 2014). Third, the impact of a wide range of trip and socio-economic characteristics on the VTT was examined alongside potential design effects as model covariates. These behavioural elements modelled include time, cost, distance and income elasticities of VTT; SP effects to consider the impact of the

position of attributes and alternatives in the presentation of SC tasks; and finally covariates such as age, gender household composition and car ownership. Fourth, unobserved preference heterogeneity is incorporated in the VTT model, using flexible distributions within a Mixed Logit framework. Finally, data from all three SC games[9] are jointly estimated within a single modelling framework to increase robustness for parameters that are shared across games. The behavioural models directly estimated the VTT and the extent to which it varies with trip and traveller characteristics, including the cross-sectional income elasticity which is of key interest to this paper. Hence, for each observation in the sample we are able to establish a personal (or behavioural VTT) as an output of the choice model.

As is commonly the case, the sampling strategy adopted in the SC survey was not nationally representative and particular segments were oversampled to better understand the key relationships for the VTT under given travel conditions (e.g. long- distance trips) (Arup/ITS/Accent, 2015, p.58). Deriving a nationally representative VTT thus requires applying the behavioural models to a nationally representative sample of trips and then averaging the trip specific VTTs using the necessary population weights accordingly. Data from the National Travel Survey (NTS) over the 2010-2012 period were used for this purpose (DfT, 2014). To facilitate this procedure, a sample enumeration procedure was coded in *R* to connect the NTS data with the behavioural models and conduct the necessary averaging of trip specific VTTS. The output of this *Implementation Tool* was a nationally representative set of VTT for the different mode-purpose segments.

In this paper, we only focus on the commuting and other non-business trip (leisure) purpose segments. As explained in **Section 3.1,** it is in this context were the connection between the VTT and income can be made, whereas in the business segment, there is potential confounding between the attribution of travel time saving benefits to the individual and the firm (see Wardman et al., 2015). The separation of the non-business trips into commute trips and 'other' non-business (non-work) trips is well-established practice in national appraisal guidelines for European countries (see Bickel et al., 2006). We also limit ourselves to a single mode, namely car, to be able to present a focused discussion. Finally, we only rely on estimates generated by SC1 (SC game 1, trade-offs between time and money) following the

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[9] Three experiments are designed to collect trade-offs between time and money in SC1; time, money and reliability in SC2, and; time, money and quality in SC3 (Arup/ITS/Accent, 2015, Batley et al., 2019, Hess et al., 2017).

recommendation for deriving the official appraisal VTT in near term (Batley et al., 2019). All the VTT estimates are in 2014 perceived prices, in £ (pound sterling) per hour.

3.3   Methodology

We re-estimated the behavioural models as used in the 2014/15 GB VTT study (Batley et al., 2019, Hess et al., 2017) on two mode-purpose segments, respectively car-commute and car-other non-business. The key variations that are introduced in this paper are associated with the income variable (nine combinations of gross, after-tax, disposable income; and private, household and household equivalised income, respectively). We will examine the impact of these income variables on the estimated cross-sectional income elasticity, the VTT derived in the SP sample and the appraisal VTT. The latter makes use of the Implementation Tool using the updated model specification and relevant income variables. The remainder of this Section will set out the nine alternative income variables used.

Figure 3-2 provides an overview of the nine alternative income variables and their connections with the research questions to be examined (See **Section 3.2**). The vertical axis depicts the transformation from the gross income to after-tax and disposable income, respectively. These three income measures vary depending on whether tax deductions and provision of social benefits are considered. The horizontal axis presents the variations in the assumption of within- household budget allocation. Notably, the income variable implemented in the 2014/15 GB VTT study for the two mode-purpose segments under considerations was the gross household income (top left).

The 2014/15 GB VTT survey only collected gross household and gross personal income, which was implemented by converting the categorical responses into actual income levels [10]. The transformations of these original income variables into after-tax and disposable income and equivalised household income for the purposes of this paper was more involved. **Appendix A** provides a full description of the necessary transformations, where we only provide a high-level discussion in this section.

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[10] 'Midpoints' of each income category are assumed when converting categorical income variables to continuous variables, with the exception of £130K for the upper bracket, and £7.5K or £5K for the lowest category in the case of household income or personal income, respectively (Arup/ITS/Accent, 2015, p.126). A total of 8 categories were used.

Figure 3-2: Overview of the income measurement approaches and the corresponding research questions
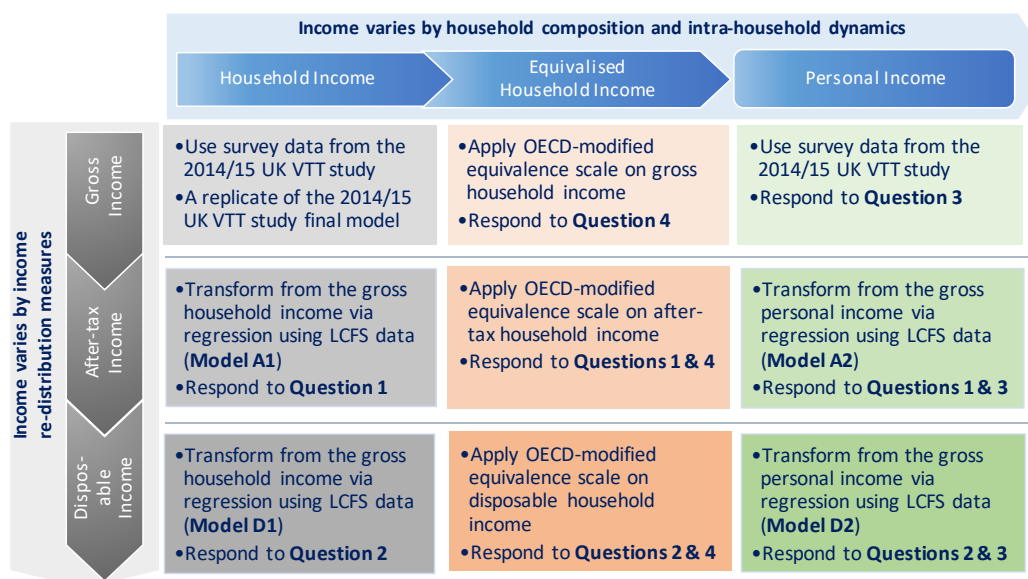
The LCFS is also used to establish conversion factors to move from gross household and personal income (i.e. the top row in **Figure 3-2**) to disposable household and personal income (i.e. the bottom row in **Figure 3-2**). In determining the conversion factors, socio-economic information beyond income is also used to establish whether households or individuals are entitled to social benefits (e.g. child benefits). Households from the lowest income group are estimated to receive 112% additional income (£8.4K approx.) on top of their gross income from cash benefits on average while the top earning households are anticipated to pay 25% of income for tax deduction on average. Again, full details can be found in **Appendix A**.

In moving from the left to the middle column in **Figure 3-2**, the OECD-modified equivalence scale was applied. The measure falls in between household and personal income and assumes that household income is not distributed equally amongst all household members. Instead, the distribution depends on household composition and dynamics. In the UK, the OECD-modified equivalence values for the first adult, additional adult, child aged 14 and over, and child aged 0 to 13 are typically assumed to be 1.0, 0.5, 0.5 and 0.3, respectively (Anyaegbu, 2010, Howell et al., 2015, p.44). These values for children are simplified in our analysis since the number of children by age category is unavailable in the survey data. We therefore rely on the midpoint between the two equivalence values for children, i.e. 0.4. For instance, a family comprising two adults produces an equivalence household size of 1.5 (i.e. 1 + 0.5). Two additional children will push up the equivalence household size to 2.3 (i.e. 1 +

0.5 + 0.4*2). The equivalised income is the total household income divided by the equivalised household size. We apply this conversion factor to gross, after-tax and disposable income.

Figure 3-3 shows that for the car-commute sample the distribution of after-tax household is relatively skewed to the right, corresponding to the progressive tax system. Provision of social benefits, on the other hand, increases the available money budget for the lower income groups and thereby increases the lower bound of the disposable income distribution. Overall, the disposable income variable retains the shape of the gross household income variable but is squeezed inward at both ends, representing a reduced level of income variation within the car-commute sample. Similar effects are observed for other non-business trips. This supports our preliminary hypothesis that after-tax and disposable income measures will result in a higher cross-sectional income elasticity as opposed to its gross income based counterpart.

Figure 3-3 – Distribution of the household income to reference income ratio for commuters

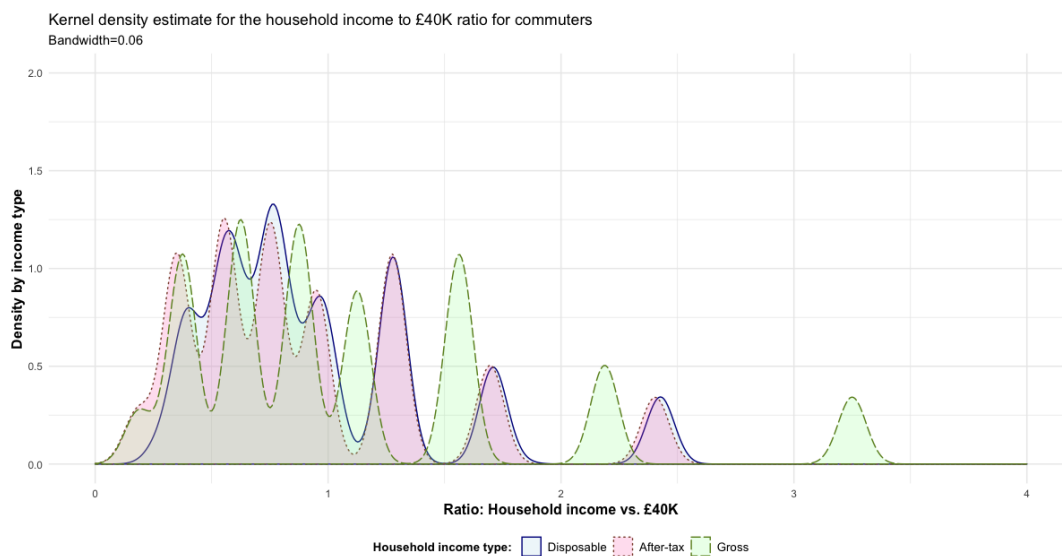**Figure 3-4** presents the income distributions for the gross household, equivalised household and personal income in the car commute sample. Overall, these three income distributions embody different shapes and there is no clear conclusion as to how the household budget allocation assumptions would affect the income elasticity, as previously. This explains the neutral formulation of research questions 3 and 4 in **Section 3.2**.

Figure 3-4 – Distribution of the gross income to reference income ratio for commuters

Kernel density estimate for the original income to £40K ratio for commuters
Bandwidth=0.06
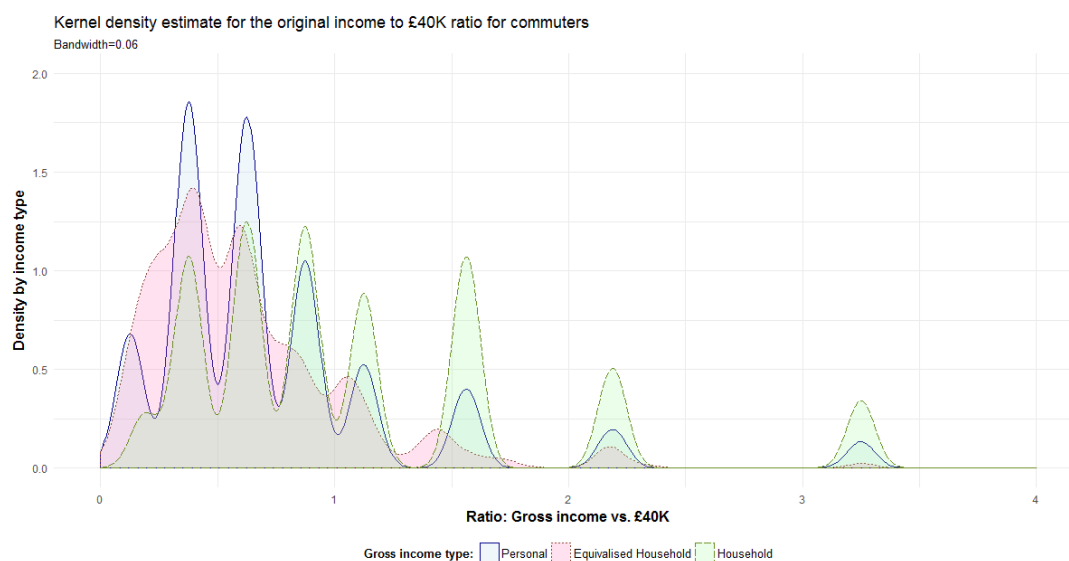
All the 9 income measures that differ in income measurement approaches are incorporated in the 2014/15 GB VTT modelling framework for estimation of (behavioural) VTTs, followed by the compilation of the nationally representative VTTs for appraisal, as described in **Section 3.2.3**. Further details on the interaction between income and the base VTT specified in the behavioural modelling framework and the VTT re-weighting by NTS trips are provided in **Appendix C**.

3.4 Empirical findings

3.4.1 Variations of income elasticities

Table 3-1 reports the eighteen estimated income elasticities based on the nine alternative income variables for the car-commute and car-other non-business samples. The discussion presented here focuses on the commuter trips as similar findings are observed for other non-business trips. The use of gross household income yields an income elasticity of 0.58. This is equivalent to the official income elasticity for commuting car trips recommended in the 2014/15 GB VTT study and forms our basis for comparison. The cross-sectional income elasticity increases as we progress vertically down **Table 3-1**, i.e. from gross income to after-tax income, and then further down to disposable income. When tax payments and social benefits are accounted for in the income variable, the cross-sectional income elasticity increases considerably to 0.64 and 0.78, respectively. This finding supports our hypotheses related to research questions 1 and 2. A similar pattern is observed for the use of equivalised and personal income. For other non-business trips, the income elasticity increases from a higher base of 0.68 to the near-unit elasticity of 0.93.

Table 3-1 – Income elasticities of VTT and final LL on the 2014/15 GB VTT data

Income Measure	Household Income				Equivalised HH Income				Personal Income			
	Final LL	Income Elasticity			Final LL	Income Elasticity			Final LL	Income Elasticity		
		Est	*t*-stat			Est	*t*-stat			Est	*t*-stat	
			vs 0	*vs 1*			*vs 0*	*vs 1*			*vs 0*	*vs 1*
Commuting *(n=922)*												
Gross	-7332.67	0.58	*6.10*	*-4.42*	-7344.37	0.45	*4.84*	*-5.84*	-7356.05	0.32	*3.19*	*-6.80*
After-tax	-7332.74	0.64	*6.09*	*-3.38*	-7346.19	0.47	*4.60*	*-5.17*	-7356.29	0.35	*3.15*	*-5.87*
Disposable	-7332.06	0.78	*6.08*	*-1.71*	-7346.95	0.57	*4.43*	*-3.30*	-7351.96	0.54	*3.78*	*-3.18*
Other non-business *(n=977)*												
Gross	-7585.74	0.68	*7.76*	*-3.62*	-7595.96	0.59	*6.89*	*-4.76*	-7608.36	0.44	*5.96*	*-7.73*
After-tax	-7585.82	0.75	*7.77*	*-2.55*	-7597.58	0.63	*6.78*	*-3.90*	-7608.53	0.48	*5.94*	*-6.49*
Disposable	-7589.81	0.93	*7.35*	*-0.58*	-7598.97	0.83	*6.52*	*-1.29*	-7606.65	0.70	*6.12*	*-2.65*

The observed increase in the cross-sectional income elasticity using after-tax and disposable income can be explained by the fact that we have effectively tightened the income variations to explain the same VTT variations (i.e. trade-offs between time and cost). Comparing the final LLs vertically in **Table 3-1**, it is shown that the model fit remains stable. Indeed, the three behavioural models that incorporate different income measures all explain the same VTT variations, but do so by using different income variables. Since the shape of the income distribution is largely retained except for being squeezed by the income transformation as shown in **Figure 3-3**, the behavioural model gains no additional explanatory power and thus the final LLs remain the same.

Household income consistently produces the highest income elasticities of VTT while personal income gives the lowest income elasticities of VTT overall. Such a finding of a lower elasticity of VTT generated by the use of personal income is contrary to the Scandinavian experience (Algers et al., 1995, Fosgerau et al., 2007, p.29, Ramjerdi et al., 1997, p.57). However, this finding still adheres to our hypotheses 3 and 4, which state that income elasticities can go either way depending on how respondents within the sample perceive their budgets provided the possibility of budget allocation within households.

3.4.2   Impacts on behavioural VTTs

Table 3-2 presents the average (behavioural) VTT for the car-commute and car-other non-business samples in the SC surveys based on the models associated with each of the nine income variables. We see that the average behavioural VTTs do not differ significantly across

these nine income measurement approaches, with a range from £12.25/hr to £13.16/hr for commuters and similarly small variation for the other non-business segment. As we progress vertically down **Table 3-2**, the average VTT estimates remain largely unchanged, despite the increasing cross-sectional income elasticities when tax implications and social benefits are additionally accounted for in the income measurement as described earlier. Comparing the VTT estimates horizontally across **Table 3-2**, the personal income based VTTs are approximately 6% lower for car commute trips compared to the household income based values, which is not significant given the confidence intervals for the VTT[11]. Overall, the small variation in behavioural VTTs indicates that the measurement error due to assumed income variable is limited. For the car-other non-business trips, the average behavioural VTT estimates are comparable across the nine income measurement approaches, also shown in **Table 3-2**.

Table 3-2 – Behavioural VTTs (2014 perceived prices, £/hr)

Journey Type	Income Type	Household Income		Equivalised HH Income			Personal Income		
		Mean VTT	Diff vs. Gross HH Inc	Mean VTT	Diff vs. Gross EqvHH Inc	vs. Gross HH Inc	Mean VTT	Diff vs. Gross Pers Inc	vs. Gross HH Inc
Commuting (n=922)	Gross	13.09	-	12.76	-	-2.5%	12.25	-	-6.4%
	After-tax	13.09	0.0%	12.70	-0.4%	-3.0%	12.25	0.0%	-6.4%
	Disposable	13.16	0.5%	12.75	-0.1%	-2.6%	12.33	0.6%	-5.8%
Other non-business (n=977)	Gross	9.29	-	9.17	-	-1.2%	9.17	-	-1.3%
	After-tax	9.28	0.0%	9.16	-0.2%	-1.4%	9.16	0.0%	-1.3%
	Disposable	9.33	0.4%	9.22	0.5%	-0.7%	9.23	0.7%	-0.6%

3.4.3 Impacts on appraisal VTTs

The nine behavioural models were next applied to the 2010-2012 NTS data to calculate the VTT for each trip within the NTS sample. The sample sizes in the NTS for the car-commute and car-other non-business are 95,758 and 413,198, respectively. Following the specification in the 2014/15 GB VTT study, the appraisal VTTs presented here are derived by weighting

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[11] The 95% confidence intervals for car-commute and car-other non-business journeys are 33% and 70%, respectively. The range of confidence intervals are also results from the flexibility given in behavioural models in terms of preference heterogeneity and functional form (Arup/ITS/Accent, 2015, p.249).

each trip by its corresponding expansion factors provided by the NTS survey[12] and by trip distance. The weighted averages as summarised in **Table 3-3** thus provide a nationally representative appraisal VTT for each mode-purpose segment[13].

Table 3-3 – Mean appraisal VTTs (weighted by NTS expansion factors and trip distance) (2014 perceived prices, £/hr)

Journey Type	Income Type	Household Income		Equivalised HH Income		Personal Income	
		Mean	St. err. Mean	Mean	St. err. Mean	Mean	St. err. Mean
Commuting (n=95,758)	Gross	11.70	*1.96*	11.20	*1.79*	8.97	*1.15*
	After-tax	11.70	*1.95*	11.02	*1.72*	8.97	*1.14*
	Disposable	11.79	*2.03*	11.20	*1.83*	9.23	*1.20*
Other non-business (n=413,198)	Gross	4.91	*1.74*	5.19	*1.79*	3.77	*1.17*
	After-tax	4.89	*1.72*	5.18	*1.77*	3.77	*1.17*
	Disposable	5.02	*1.89*	5.58	*2.02*	3.98	*1.25*

The UK's official appraisal VTT of £11.7/hr for car commuting trips was derived using household income and acts as the point of reference. It can first be seen that all appraisal VTTs presented in **Table 3-3** are lower than their corresponding behavioural VTTs (see **Table 3-2**). For our reference case, the VTT reduces from the behavioural value of £13.1/hr based on the SC sample, to £11.7/hr based on the NTS data. Again, we observe that the VTT hardly changes when we move from the gross household income to the after-tax and disposable income despite the increase in the estimated cross-sectional income elasticity. This picture is consistent across the different assumptions made about the distribution of income within the household. In fact, the equivalised household income case results in highly comparable VTT values to the household income case. The largest discrepancy is, however, observed when applying the personal income variable, where the appraisal VTT drops somewhat unexpectedly to approximately £9/hr, which represents a 22% decrease relative to the

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[12] The NTS expansion factors are provided to re-weight the trip rates to match the frequency of reporting long and short trips in NTS travel diaries to a nationally representative sample; it additionally accounts for non-response and drop-off in reporting trips (Lepanjuuri et al., 2017, Section 5).

[13] The income effect incorporated for deriving appraisal VTTs reflect income distribution of the travelling population, an approach which is recommended for appraisals of all sizes (for small, medium sized and major schemes and policies) in general for the UK (Batley et al., 2019).

official VTT for car commuters. This disparity is also observed for the other non-business trips.

It is not surprising to see that VTT differs between the stated choice and NTS samples, and hence the difference between the behavioural and appraisal VTTs. As noted in **Chapter 3.2.3**, the socio-demographics and travel characteristics for the SC sample cannot be fully representative, despite considerable effort put into representative sampling. Also, some market segments are purposefully oversampled to ensure recruitment of adequate samples of specific groups of target respondents (e.g. long distance car and rail travellers). These residual biases in the sampling are anticipated to be corrected at the implementation stage to re-weight the behavioural VTTs for national representativeness. Given the limited variations in behavioural VTTs across all income measurement approaches, however, one would not expect such large differences in appraisal VTTs across the different income variables. The large difference in appraisal VTTs between the use of personal income and household income warrants further investigation, which is the main focus on this section.

We trace back the potential causes of this discrepancy by providing a breakdown of the appraisal VTT calculation for the different income measures. The final model specification for commuting trips accounts for deterministic heterogeneity in traveller and trip covariates by estimating multipliers on the VTT, one of which is the income effect associated with the selected income variable. By comparing the multipliers on VTT across the model specifications, we can pinpoint the specific multiplier that causes the disparity in appraisal VTTs.

Table 3-4 shows the mean values of the multipliers associated with each of the explanatory variables in the model. Multipliers on VTT for deriving the appraisal VTTs are grouped into 3 categories for presentation: traveller covariates, trip covariates, or elasticity-based multipliers. We first compare the average VTT multipliers for traveller and trip covariates between the SC and NTS data. The covariate effects that relate to the characteristics of travellers and trips are not significantly different between the two data sources and for different income measures. The decrease in average VTT multipliers in the NTS results is consistent amongst income measurement approaches that use gross household, equivalised household and personal income.

Table 3-4 – Mean VTTs and mean VTT multipliers and commuting trips by using gross income (2014 perceived prices, £/hr)

	Gross Household Income			Gross Equivalised Household Income			Gross Personal Income		
	SC	NTS	Diff from SC	SC	NTS	Diff from SC	SC	NTS	Diff from SC
Base underlying VTT	10.19	10.19	0%	12.46	12.46	0%	10.20	10.20	0%
VTT multipliers - traveller covariates									
Aged 17–29 (vs. 30+)	1.07	1.06	-1%	1.06	1.06	-1%	1.06	1.06	-1%
Female (vs. male)	1.17	1.14	-2%	1.16	1.14	-2%	1.20	1.17	-3%
Self-employed (vs. any other)	1.05	1.04	-1%	1.05	1.04	-1%	1.05	1.04	0%
Travel costs paid by company (vs. respondent or other paid)	1.19	1.13	-5%	1.18	1.13	-5%	1.18	1.13	-5%
VTT multipliers - trip covariates									
Travelling with others (vs. travelling alone)	0.94	0.92	-2%	0.94	0.93	-2%	0.94	0.93	-2%
Light / heavy congestion (vs. free flow)	1.31	1.30	-1%	1.33	1.31	-1%	1.35	1.33	-2%
Driving on rural roads (vs. urban or motorway)	0.94	0.94	0%	0.95	0.95	0%	0.96	0.96	0%
VTT multipliers - key elasticities									
Time	0.99	1.52	54%	0.98	1.45	48%	0.98	1.44	48%
Cost	0.96	0.39	-60%	0.95	0.40	-58%	0.96	0.39	-59%
Income	**1.00**	**1.16**	**16%**	**0.76**	**0.89**	**16%**	**0.86**	**0.84**	**-2%**
Behavioural VTT in SC / appraisal VTT in NTS (unweighted)	13.23	9.03	-32%	12.87	8.66	-33%	12.43	6.87	-45%
Appraisal VTT in NTS (weighted)		11.70			11.20			8.97	

With respect to the elasticity-based multipliers, changes in the VTT multipliers for the travel time and cost between the SC and NTS data are quite large, but again consistent across income measures. This is because the commuting journeys in the NTS sample are shorter and cheaper on average. This finding is common in practice and reflects the difficulty in capturing shorter trips in field surveys. As a manifestation of the damping effect on longer trips, the decrease of travel time pushes up the average VTT multiplier for travel time by

54%, from 0.99 to 1.52. In contrast, the decrease in average travel cost in the NTS sample leads to a 60% reduction of the average VTT multiplier for travel cost, from 0.96 to 0.39. Combining these two contrasting effects leads to a net decrease of the VTT in the NTS results relative to the SC results.

We finally look at the last remaining elasticity-based multiplier presented in the table. The income effect appears to have positive influence (+16%) on the base VTT by applying household and equivalised household income to NTS trips while it has limited impact (-2%) when personal income is in use. Given that other VTT multipliers are comparable between different income measurements, we conclude that the income effect is the driving force between the observed discrepancy between the NTS VTT based on household (and equivalised) income and personal income.

A further investigation shows that the differential income effects that affect the appraisal VTTs are a direct result of the sampling bias. As shown in **Figure 3-5**, the SC survey appears to be under-representing household income in general. The mean household income in the NTS data is £56,650, which is 30% higher than the mean household income for SC respondents. The increase of household income translates into a 16% increase of the average VTT multiplier, from 1.0 to 1.16. In contrast, the personal income distribution does not change substantially between the NTS and SC data as shown in **Figure 3-6**. The mean personal income decreases by 2% only, which translates into a 2% decrease in average VTT multiplier, from 0.86 to 0.84.

The mismatch of the household income distribution between the SC and NTS sample raises an important question of which income variable should be used as the basis for the appraisal VTT computation. Economic theory does not provide any guidance as to which income measure (and also the respective income elasticity) is more justified. At best, an assumption can be made on what best represents the travel budget of the traveller. Indeed, there may be a mismatch between the two samples in the household income measure which does not rule out the latter as long as each income category is sufficiently covered in the SC sample. Hence, what we observe here is that the income measure in the SC survey is not sampled representatively and hence leads to diverging appraisal values, but we are unable to make a decision on which income measure is most appropriate, especially not without a new specification search with different income measures.

For completeness, the weighting does not contribute to the disparity between appraisal VTTs as shown in **Table 3-4**.

Figure 3-5 – Gross household income to reference income ratio for commuters (SC vs. NTS)
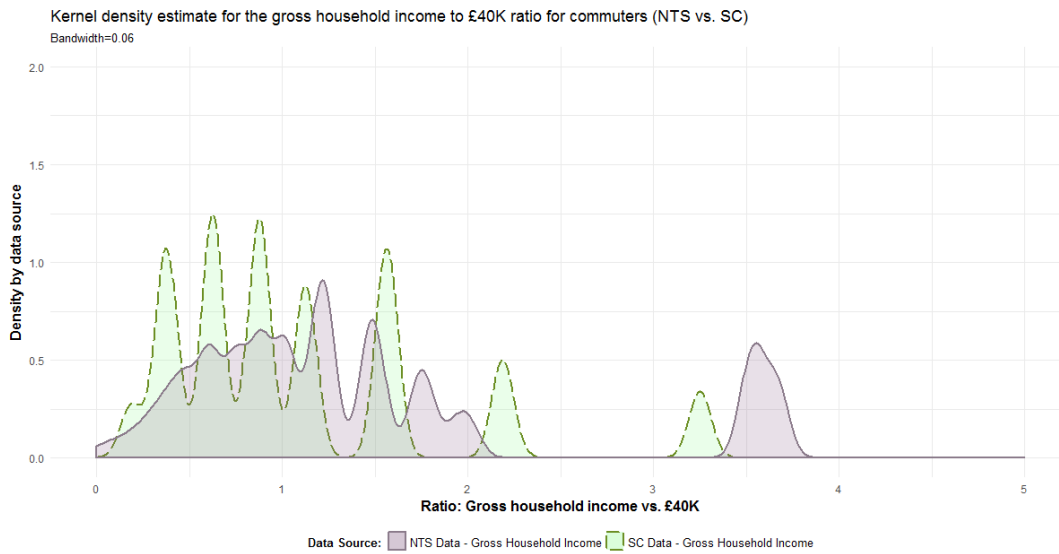

Kernel density estimate for the gross household income to £40K ratio for commuters (NTS vs. SC)
Bandwidth=0.06

Data Source: NTS Data - Gross Household Income   SC Data - Gross Household Income

Figure 3-6 – Gross personal income to reference income ratio for commuters (SC vs. NTS)

Kernel density estimate for the gross personal income to £40K ratio for commuters (NTS vs. SC)
Bandwidth=0.06

Data Source: NTS Data - Gross Personal Income   SC Data - Gross Personal Income
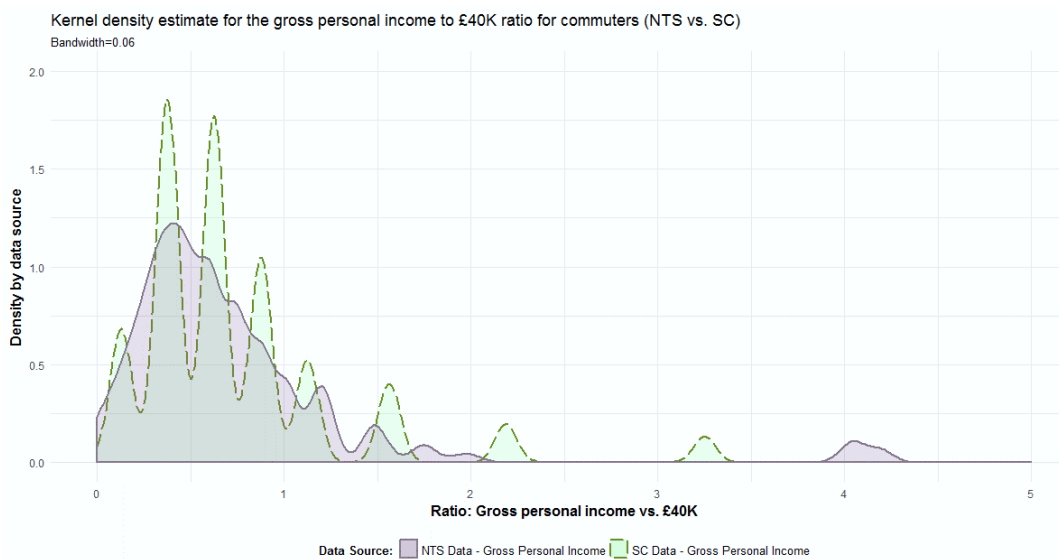
While we expect that the base year appraisal VTT should show little discrepancy irrespective of the income variable used provided the SC survey is sampled representatively, it is important to acknowledge that different income elasticities will, however, induce larger differences over the span of the appraisal period. Impacts of transport investments are typically assessed over a standard 60 years of economic life in the UK (DfT, 2018, TAG A1.1). How the appraisal VTTs are updated annually in relation to income changes will then have significant implications for the future VTT values and the appraisal of transport investment schemes. **Figure 3-7** illustrates the divergence of income-specific VTTs over a 60-year appraisal period. The UK's official appraisal VTT of £11.7/hr for car commuting trips is set as

the common starting point for the base year in 2014. Household and personal income measures are assumed to grow based on the forecast GDP growth rates at household or personal level, respectively (DfT, 2019, TAG Data Book Annual Parameters), and the corresponding income elasticities (see **Table 3-1**). A unit income elasticity of VTT, which reflects the official inter-temporal income elasticity of VTT in the UK, is applied to the projected household income growth as a reference for comparison. The results show that future VTTs are expected to diverge significantly as different income measurement approaches are adopted. By 2074, the appraisal VTTs based on household income are expected to be more than doubled the values calculated based on the personal income. This again highlights the importance of understanding the impacts of income measurement errors on the appraisal VTT.

Figure 3-7 – Mean appraisal VTTs for the commuting trip purpose from 2014 to 2074 (2014 prices)
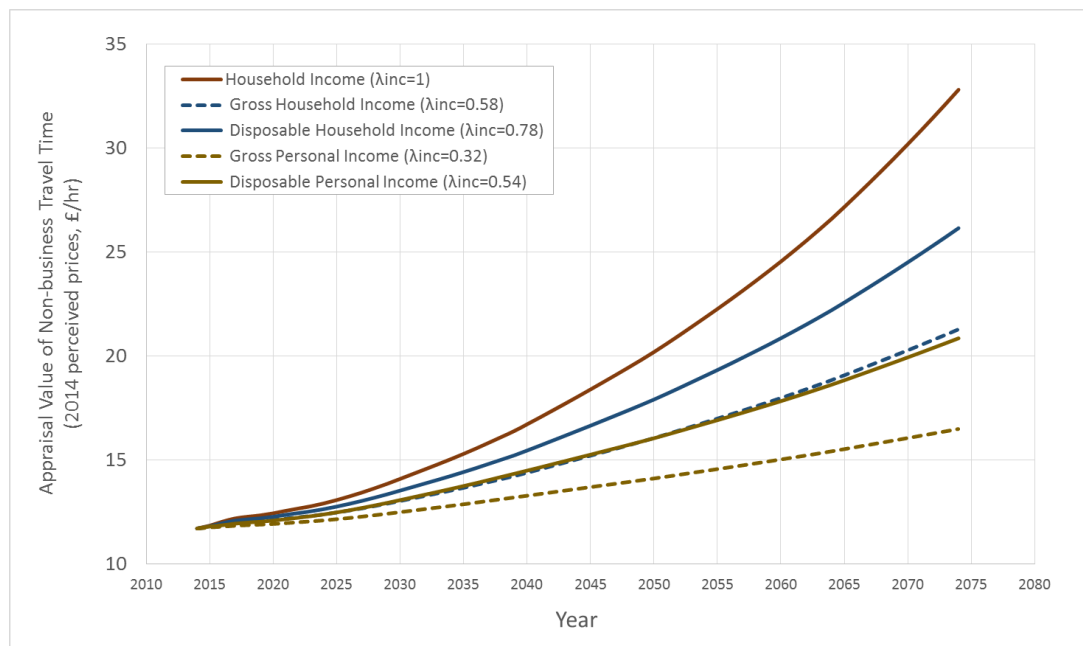
3.5   Summary and conclusions

There has been a long debate in the VTT literature on the empirical disparity between the cross-sectional and inter-temporal income elasticity, where the cross-sectional income elasticity is generally found to be lower. To date, there has been no systematic review of the sources of this discrepancy and its impacts on behavioural and appraisal VTTs. We argue that the disparity between the cross-sectional and inter-temporal income elasticities can be partly explained by the errors incurred in measuring traveller's perceived travel budget, i.e.

the income variable applied. We provide empirical evidence to support this argument by systematically comparing nine different income variables for non-business trips. The nine income measures correspond to a 3x3 matrix based on two dimensions: variation in the income re-distribution measures, and variation in the assumption of within-household budget allocation.

We adopt the modelling framework developed from the 2014/15 GB VTT study to show that the travel budget could potentially be over-estimated if the tax burden is not included in measuring income under a progressive tax system (see also Fosgerau, 2005). We extend this analysis by additionally accounting for social benefits to lower income groups. We demonstrate that the use of the latter disposable income, which has been ignored in the VTT literature, increases the cross-sectional income elasticity of VTT and further reduces the gap between the cross-sectional and inter-temporal income elasticity. This leads to a cross-sectional income elasticity which is not significantly different from the unit value.

We find that the inclusion of income re-distribution measures in the income variable does not affect the base behavioural and appraisal VTT. We therefore conclude that the official behavioural VTTs for non-business trips in the UK remain justified, even when measurement errors could arise due to exclusion of the tax burden and social benefits in the household income. We also examine the impacts that assumptions regarding the budget allocation in the household have on the income elasticity and the VTT. We demonstrate that the use of household income produces the highest income elasticity, followed by the use of equivalised household and personal income. Although this finding is contrary to findings from some Scandinavian studies, which found lower income elasticities by incorporating the household income for VTT estimation, it does not contradict our proposition that changes in the income elasticity can go in either direction since the difference between the perceived travel budget and respective income measure can similarly go either way. Again, behavioural VTTs appear to be unaffected by using any of these 3 income variables.

We do however bring to light a clear divergence in appraisal VTTs between household and personal income measures. We find that appraisal VTTs based on personal income are substantially lower than the (official) VTT based on household income. We disentangle the various VTT multipliers to explain the discrepancy. We first show that the differences in traveller and trip characteristics between data sources lead to lower VTTs for NTS trips than for SC trips. In particular, VTTs are scaled down considerably to adjust for the shorter and cheaper trips in the NTS data. Field surveys typically struggle to capture short distance trips

and these results highlight the impact this can have. More importantly, we show that while high income households are under-sampled in the SC survey, the distribution of personal income is comparable between the two data sources. As a result, the appraisal VTT is adjusted upwards when using household income, whereas the adjustment based on personal income is minimal. We conclude that it is the sampling bias associated with the household income that causes the disparity in appraisal VTTs.

It is important to again stress that there is no economic theory to support any preferred income measure (and hence elasticity of VTT) for non-business trips. Therefore, the answer to the question regarding the choice of income measure is not obvious. Given that the choice of income measure plays an important role in the estimation of the cross-sectional income elasticity and the computation of appraisal VTT, as exemplified by our analysis using the SC data from the most recent GB national VTT study, we highlight the need for testing different income measures to understand their potential impacts on model estimation and sample enumeration. It is also imperative to ensure that the income distribution is sampled representatively for different market segments for VTT estimation to minimise the adversarial income effects on appraisal VTTs that could potentially lead to erroneous outcomes in cost-benefit analyses.

With respect to the issues related to the VTT growth over time, our empirical evidence indicates that error in measuring income can be a potential source of the disparity between the cross-sectional and inter-temporal income elasticities of VTT, as a wide range of cross-sectional income elasticities can be obtained simply by varying income measures. Therefore, we argue that the income variable used needs to be compatible between these two elasticities if an estimate of a cross-sectional elasticity is to be used for the inter-temporal income elasticity, rather than strictly adhering to the near-unity value, which is largely driven by results from meta-analyses. Our suggested approach is similar to Börjesson et al. (2012) who found that the cross-sectional income elasticity is constant over time (but not income), and hence the cross-sectional income elasticity can be applied to changes in the VTT over time. We note that further research using data from repeated VTT studies is needed to confirm the stable relationship between the income measure and income elasticity of VTT over time while allowing us to understand the other potential factors that could contribute to the disparity, whether it is the effect of income distributions or changes in preferences over time. Alternatively, we suggest that additional control variables are required to control for the difference in income measures in the derivation of the inter-temporal income elasticity.

Acknowledgments

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Chapter 4

Capturing zero-price effects in stated choice surveys and implications for willingness-to-pay computation

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Abstract

The zero-price (ZP) effect is a well-established notion in behavioural economics which explains the phenomenon that individuals tend to over-react to free alternatives. Despite the widespread inclusion of zero cost alternatives in choice surveys, especially in the environmental economics and health literature where the 'free' status quo alternatives are often compared against the (policy) interventions, choice modellers have paid little attention to the ZP effect to date. We developed an experimental design that allows separate identification of the ZP effect and the SQ effect. Stated choices made by students between different mobile board packages are analysed. Our analysis shows that ZP effect is significant in our data and the observed preference to remain at the SQ is largely due to the ZP effect. We also present experimental design features that allow separation of the ZP effect form the non-linear cost sensitivity. We stress that the prevalence of the ZP effect in observed choice behaviour may introduce bias to the prediction of welfare when the perfect confounding between the ZP and SQ effects is broken.

Keywords: zero-price effect, status quo bias, willingness-to-pay, non-linearity

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4.1 Introduction

Stated choice (SC) surveys are used extensively to forecast demand and capture welfare effects of policy changes (see Louviere et al., 2000, Ben-Akiva et al., 2019). While it is a common practice to apply random utility maximisation (RUM) models for analysing choice behaviour based on SC data (McFadden, 1986, McFadden et al., 1986, Carson and Louviere, 2011), there has been a growing interest in behavioural phenomena that can imply departures from the RUM framework (Hess et al., 2018, Hensher, 2019).

Amongst these alternative behavioural phenomena, a well-established notion in behavioural economics is that individuals tend to get over-attracted to free alternatives. This psychological mechanism was coined as the zero-price (ZP) effect (Shampanier et al., 2007, Ariely, 2008). The ZP effect has been demonstrated in many different forms. Some examples include the choice of chocolate brands (Shampanier et al., 2007), hotel room bookings in a two-component setting where the breakfast could be free (Nicolau and Sellers, 2012), pseudo-free offers where nonmonetary payments (e.g. time, personal information, privacy) are included as cost components (Dallas and Morwitz, 2018), access to e-services (e.g. music/video streaming services) that could be free (Hüttel et al., 2018), and premiums to health insurance which are subsided by public money (Douven et al., 2019).

Despite a wealth of evidence of the ZP effect in the behavioural economics literature, the choice modelling literature has paid very little attention to this phenomenon, despite the widespread inclusion of zero cost alternatives in surveys, be they status quo alternatives in environmental economics or untolled roads in a transport context. Some exceptions include the inclusion of toll road dummies in transport (e.g. Hess et al. (2008), and Hess and Beharry-Borg (2012). The lack of explicit treatment of ZP effect in discrete choice applications creates significant risks in producing biased parameters and welfare measures, which could lead to inferior policy recommendations. The discussions in Hess et al. (2018) show that it is possible to capture ZP effects without abandoning the RUM framework, but at the potential risk of some extreme values in welfare analysis. However, not accounting for the ZP effect could similarly lead to an overestimation of the cost sensitivity and hence under-estimated willingness-to-pay (WTP) measure.

The lack of attention to the ZP effect in the environmental economics and health literature is particularly worrying since 'free' status quo (SQ) alternatives are at the heart of many SC surveys and form the basis of contrasting the (policy) 'interventions'. Indeed, researchers have conducted in-depth analyses of the over-reaction towards the SQ alternative, namely,

the SQ effect/bias (Samuelson and Zeckhauser, 1988), including the understanding of the behavioural rationale (Meyerhoff and Liebe, 2009, Adamowicz et al., 1998, Zhang and Adamowicz, 2011), econometric issues regarding model specifications for the SQ effects (Scarpa et al., 2005, Oehlmann et al., 2017) and impacts of SQ effect to the welfare analysis (Adamowicz et al., 2011). However, despite the perfect confounding between the ZP effect and the SQ alternative, the ZP effect has rarely been mentioned as a possible behavioural cause for the SQ effect (see discussion in Hess and Beharry-Borg (2012)).

It is particularly important to examine the potential impacts of the ZP effect within the environmental economics context. The reliability and validity of the use of stated preference methods (including both the contingent valuation method and stated choice experiment) for monetary valuation of the environmental goods have long been questioned (Hanley et al., 2001, Carson and Groves, 2011, Lancsar and Swait, 2014, Adamowicz, 2004, McFadden, 2017). Evidence show that hypothetical bias, which refers to the disparity between respondents' expressed preferences and their underlying preferences under real economic condition (Hausman, 2012), may arise when respondents make hypothetical choices on unfamiliar goods in a 'non-market' setting. For most 'non-use' valuations of environmental goods, decision-makers are often more hypersensitive to the framing, contextual effect and cognitive anomalies (Ben-Akiva et al., 2019, McFadden, 2017). It is thus important for environmental economists to assess whether the exceptional attractiveness to the status quo alternatives typically observed in SC studies is largely due to the highly positive *affective* feeling towards the free options during the decision-making process, which could be intensified due to 'non-market' nature of the valuations.

Second, it is well known that people are incentivised to make choices strategically to understate the willingness-to-pay for public goods in order to enjoy the benefits from resources that they do not need to pay for (Samuelson, 1954, Barten and Böhm, 1982, Diewert, 1982, Diamond and McFadden, 1974, Green et al., 1998). It is then reasonable to anticipate that this classic 'free-rider' problem will also occur in the valuation of the environmental goods. For instance, decision-maker might strategically choose not to pay for an environmental mitigation scheme despite his/her positive underlying preferences to pay for the non-use value of the mitigation scheme. This 'free-rider' phenomena can lead to downward bias of the WTP for environmental goods, leading to difficulty in raising sufficient public money (e.g. management policy to prevent natural habitat loss etc.). This again highlights the need to account for the ZP effect in the SC survey design in valuation of environmental goods.

This paper seeks to empirically investigate the role of the ZP effect in a controlled setting. We focus on the impact on WTP calculations as well as the relationship between ZP effects, non-linearity in cost sensitivities and SQ effects. We specifically look at choices made by students between different mobile broadband packages. We chose this context to ensure that survey subjects are familiar with the products or designed policies and can thus be expected to make similar decisions as in reality (Ben-Akiva et al., 2019).

This paper aims to separate the ZP and SQ effects in order to assess how much of the observed preference for maintaining the SQ is influenced by the disproportional attraction to the zero cost only. This is accomplished by re-framing the SQ context such that both free and non-free SQ alternatives are presented to respondents. From a policy perspective, understanding the extent to which ZP effects can affect people's choices is important. In many empirical contexts, maintaining the SQ will be associated with (positive) costs to prevent further deterioration of the SQ (e.g. natural habit loss, worsening traffic). This is particularly relevant to the valuation of environmental goods or health policies. Placing even a minimal cost for maintaining the SQ can significantly reduce its attractiveness in the presence of the ZP effect. Ignoring this effect may thus lead to under-estimation of the acceptability of the designed policy intervention. However, due to perfect confounding between the ZP and the SQ effect in most stated choice surveys, marginal WTP estimates may only be affected to a limited extent and hence the impact of the ZP effect on the welfare changes is hidden from the outset.

We acknowledge that the findings regarding the prevalence of the ZP effect could vary between different types of goods. For instance, we anticipate that the ZP effect could have stronger impact on environmental goods relative to the private goods like the mobile phone data packages. This is due to the tendency of 'free-ride' for public good as mentioned above. That said, the experimental setup and choice modelling technique to separate the ZP and SQ effects should be transferable across disciplines, regardless of the discovery of the ZP effect.

This paper also identifies further complications in capturing the ZP effect that arise where respondents exhibit non-linear sensitivity to cost (Daly, 2010, Rich and Mabit, 2016). We highlight that to ensure that the ZP effect and the non-linear sensitivity can be separated, a sufficient number of small costs need to be incorporated in the design. Second, it is known that non-linearity in cost sensitivities may erroneously be picked up as ZP effects with linear

sensitivities, where the reverse also applies (Hess et al., 2011). Therefore, flexible model specifications are also tested in estimation to minimise the risks of obtaining biased parameter estimates and welfare measures due to utility misspecification.

The remainder of the paper is structured as follows. **Section 4.2** describes the experimental setup. **Section 4.3** outlines the research methodology. **Section 4.4** summarises the model results from the SC data. Lastly, **Section 4.5** discusses policy implications and concludes.

4.2   Experimental setup

4.2.1   Design overview

Our experiment draws on SC data collected from 302 students at the University of Warsaw (Poland) in late 2017. Respondents are asked to choose between retaining the free campus-wide Wi-Fi service (i.e., the SQ alternative) or to purchase a 4G LTE data package which allows access to high speed mobile data beyond the school campus by using a USB dongle. Three attributes are varied amongst choice tasks: monthly costs of the 4G LTE data package and the campus-wide Wi-Fi service, monthly data download limit, and the number of devices that can share bandwidth simultaneously. The cost levels of the 4G LTE data package are set to be lower than the commercial packages typically offered by the major mobile network operators to create incentives for students to consider the mobile data packages. Prior to the stated choice tasks, respondents are required to answer a few basic questions concerning their current internet usage experience, specifications of existing mobile data packages etc.

This experiment is set out to examine the impact of ZP effects on utility via 3 different treatments. The first treatment (SP1) mimics a common format of choice sets in environmental and health economics which includes a SQ alternative with zero price and two experimentally designed alternatives (i.e., the standard '2+*SQ*' format as described in Ferrini and Scarpa (2007)). This is also where ZP and SQ effects are perfectly confounded. It is also similar to many transport SC surveys which look at the choice between a current free road and two hypothetical future toll roads (cf. Hess et al., 2008).

In the second treatment (SP2), both free and non-free SQ alternatives are allowed for separation of the ZP effects from the SQ effects. This is applicable in the environmental and health economics context by assuming an out-of-pocket cost (e.g. entrance fee, tax) that is required to maintain the otherwise deteriorating environment or health condition. Similarly, in a transport setting, other costs (such as fuel) can be included for the SQ alternative.

Finally, the SQ alternatives are dropped in the third treatment (SP3) to focus on the trade-offs between alternatives where zero or near-zero costs are included. Adequate small cost levels are incorporated for better separation of the non-linearity in cost sensitivity and ZP effect econometrically.

These 3 treatments are presented sequentially to each respondent to allow us to observe the variation in terms of the finding of the ZP effect and the resulting WTP measures between treatments. This arguably creates some ordering effects but on balance was a more natural approach than not starting with a scenario that is in line with reality (i.e. free SQ). This is based on the appreciation of the sharp 'reliability gradient' typically exhibited by the use of the stated preference approach, which leads to good predicting of choice behaviour when respondents are dealing with familiar products and information environment which are under aligned economic incentives, and vice versa ((McFadden, 2010)). Gradual changes are introduced to the following second and third treatments such that respondents will not lose their incentives for truthful response from the beginning of the survey

Respondents are required to answer 26 choice tasks in total. This is a large number of choice tasks, but the split into three experiments does go some way towards alleviating fatigue effects. SP1 and SP2 are blocked into 2 sets of 8 choice sets. SP3 consists of 30 choice tasks that are blocked into 3 sets of 10 choice tasks. All 3 treatments are created based on a Bayesian *D*-efficient design. Priors are obtained from pilot surveys and are assumed to be normally distributed. **Table 4-1** provides an overview of the attributes and levels set out for each treatment.

Table 4-1: Overview of attributes

| Treatment | Alt | Monthly fee (zł) | | 4G data limit (GB/month) | 4G data accessibility (# of devices) |
		Wi-Fi (campus)	4G LTE data		
SP1	SQ	0	-	-	-
	Alt 2/3	0	5 / 10 / 15 / 20 / 30 / 40	3 / 5 / 10 / 20	1 / 3
SP2	SQ	0 / 1 / 3	-	-	-
	Alt 2/3	0 / 1 / 3	5 / 10 / 15 / 20 / 30 / 40	3 / 5 / 10 / 20	1 / 3
SP3[3]	Alt 2/3	-	0 / 1 / 2 / 3 / 5 / 8 / 10 / 20 / 30 / 40	3 / 5 / 10 / 20	1 / 3

4.2.2   Individual treatment

SP1 – Zero cost SQ alternatives

All SQ alternatives in SP1 are assumed to be free of charge. The SQ is framed in the way that students would rely on the free Wi-Fi connection already provided by the university. Students are informed prior to the presentation of valuation questions that the university would offer all students both a free SIM card and a USB modem (the size of a dongle/pendrive) with Wi-Fi connectivity for any 4G LTE broadband package chosen, thus enabling the use of high-speed data transfer both within and outside the university. The browsing speed offered by the free Wi-Fi service is known to students to be slower compared to the 4G LTE data connection.

SP2 – Zero and non-zero cost SQ alternatives

Some variations in cost for the SQ alternatives are needed for separating the ZP and SQ effects. Hence, a small charge, either 1 Polish Zloty (zł) or 3zł for the Wi-Fi access (i.e., the SQ alternative), is framed as a mandatory policy. These small costs are described as being required to maintain current service levels of the computer network provision and are presented in 10 out of 16 choice tasks in SP2 while the remaining 6 choice tasks offers free SQ alternatives. Respondents are given the instruction prior to the valuation questions that

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[3] Although there are only two choices presented in SP3, we retain the numbering of the two non-free alternatives for the 4G data package in SP1 and SP2 for consistency in summary of model results. Namely, 'alternative 2' refers to the first 4G data package and 'alternative 3' refers to the second 4G data alternative.

for choosing any of the 4G LTE data packages, the total costs will then include both the minimal charges for the campus-wide Wi-Fi connectivity and the costs of the 4G LTE data package. This implies that the minimal price gap between the 4G LTE data package and the SQ alternatives remains at 5zł, which is the same as in the SP1 (see also **Table 4-1**).

SP3 – No SQ alternative

This treatment presents binary choices between two 4G LTE data packages. The removal of the SQ alternative is designed to ensure that no status quo effect would come into play. Both zero and near-zero cost levels are introduced in this treatment. Respondents are asked to choose between a free and non-free alternative in 3 out of 10 choice tasks and to choose between the non-free 4G LTE data packages in the remaining 7 choice tasks. Small cost levels (1 zł, 2 zł and 3 zł) are introduced in this treatment to allow detection of changes of the marginal cost sensitivity curve at near-zero cost levels in more confidence such that we can better distinguish the ZP effect from non-linearity in cost sensitivity.

Data collection

The SC experiment is carried out through a survey app provided to respondents (see **Figure 4-1**). The presence of the SQ option in SP1 and SP2 creates scope for non-trading, and a follow-up question was used to understand the reasons when this occurs. The rates of SQ non-trading are 11% and 9% in SP1 and SP2, respectively, and the vast majority of the concerned respondents indicated that they are satisfied with the existing services, such that it is unlikely that their behaviour is in protest against the university policy to start charging for the campus-wide Wi-Fi provision.

A pilot survey which surveyed 106 students was carried out prior to the main survey. Model results based on the pilot survey data are reasonable and the parameter estimates are in the right sign. The parameter estimates from the pilot survey are then used for updating the priors assumed in the experimental design for the main survey, which collected responses from 302 students in total.

Figure 4-1: Sample SP1 choice task in the SC survey app

4.3 Methodology

4.3.1 Model specification

The SC data collected are analysed using a standard RUM-based choice model, where the indirect utility U_{jnt} obtained for an individual n (with $n = 1, ..., N$) for alternative j (with $j = 1, ..., J$) in choice task t is decomposed into a deterministic component V_{jnt} and a random component ϵ_{jnt}:

$$U_{jnt} = V_{jnt} + \epsilon_{jnt} \tag{4-1}$$

It is assumed that ϵ_{jnt} follows an extreme value distribution across alternatives. Assuming linear attribute sensitivities for the base specification, the deterministic component of the utility of alternative j applied for all three treatments can be written as:

$$V_{jnt} = \delta_j + \delta_{ZP}(Cost_{jnt} == 0) + \beta_{cost}Cost_{jnt}$$
$$+\beta_{dlim}Dlim_{jnt} + \delta_{dev_j}(Dev_{jnt} == 3) \tag{4-2}$$

where δ_j is a constant associated with alternative j to capture the average effect on utility due to the tendency of choosing a particular alternative. This is normalised to zero for a alternative 3. As the SQ alternative is the left-most alternative (i.e. $j = 1$), δ_1 captures the SQ effects in SP1 and SP2. In addition, δ_{ZP} is a dummy variable estimated in the case where the alternative j is a zero-price alternative; β_{cost} is the marginal utility associated with the

total cost for alternative j, Cost_{jnt}, which includes the costs for both the 4G LTE data package and the Wi-Fi, expressed in Polish złoty (zł)[4]; β_{dlim} is the marginal utility associated with the data limit of the 4G LTE data package, Dlim_{jnt}, expressed in gigabytes (GB) per month; δ_{dev_j} is a dummy variable estimated when the alternative j allows up to 3 devices to access the 4G LTE mobile data ($\text{Dev}_{jnt} = 3$). As we will discuss in latter section, some model specifications allow departures from the base linear-in-attribute specification to include the possibility of non-linear sensitivities to data limit and/or cost attribute by introducing the non-linear transformation of attributes.

Our focus on simple fixed coefficients models is justified in the context of seeking to investigate a very specific behavioural effect.

4.3.2 Modelling non-linearity

A box-Cox transformation (Box and Cox, 1964) is adopted to incorporate the possibility of non-linear sensitivity for the continuous cost attributes. This is a common approach to non-linear treatment (Daly, 2010, Gaudry et al., 1989, Rich and Mabit, 2016), which applies a flexible functional form that estimates the degree of non-linearity in the sensitivity. The transformation of the total cost attribute for alternative j for choice task t, Cost_{jnt} , is given by:

$$\text{Cost}_{jnt} = \begin{cases} \dfrac{\text{Cost}_{jnt}^{\lambda} - 1}{\lambda}, \ \lambda \neq 0; \ \text{Cost} > 0 \\ \ln(\text{Cost}_{jnt}), \ \lambda = 0; \ \text{Cost} > 0 \end{cases} \tag{4-3}$$

where $\lambda = 1$ implies a linear effect while a logarithmic effect is obtained as λ approaches 0.

It is also evident in some earlier model results that respondents show decreasing sensitivity to data limit of the 4G LTE data package presented. Given the non-linearity in sensitivity to data limit, we applied the log-transformation to the data limit attribute, $\ln(\text{Dlim}_{jnt})$, for all model specifications.

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[4] Since the cost items are presented to respondents separately, we also take into consideration that respondents may respond to the costs of Wi-Fi and 4G LTE data packages differently (i.e. different cost sensitivities). However, test results using data SP2 and SP3 indicated that a generic cost sensitivity was appropriate.

Willingness-to-pay measures are generated for the data limit, which represents the marginal rate of substitution between 4G LTE data limit and cost. This is given by the ratio of the partial derivative of the indirect utility function with respect to data limit to the partial derivative with respect to cost. Since a log-transformation of the data limit attribute is applied to all model specifications, the partial derivative with respect to data limit becomes $\beta_{\text{dlim}}/\text{Dlim}$. The partial derivative with respect to cost, however, varies depending on specifications. When cost sensitivity is specified linearly, then the WTP for data limit becomes $\frac{\beta_{\text{dlim}}}{\text{Dlim}}/\beta_{\text{cost}}$. When the possibility of non-linearity in cost sensitivity is incorporated in the utility formulation using a Box-Cox transformation, the WTP for data limit is given by:

$$\text{WTP}_{\text{dlim}} = \frac{\partial V/\partial \text{Dlim}_{\text{LN}}}{\partial V/\partial \text{Cost}_{\text{BC}}} = \frac{\beta_{\text{dlim}}/\text{Dlim}}{\beta_{\text{cost}}(\text{Cost})^{\lambda-1}}$$

(4-4)

where $\lambda \geq 0;\ \text{Cost} > 0;\ \text{Cost}_{\text{BC}} \sim \text{BoxCox}(\text{Cost}; \lambda)$

Equation 4-4 shows that the WTP calculation depends on both the monthly cost and the data limit allowance. A set of reference measures is thus needed for comparing WTP estimates across scenarios, as opposed to simply comparing to an average WTP at sample level in the case where marginal utilities are specified linearly. 2 representative data limits at 5GB and 20GB and 3 representative cost levels at 3zł, 10zł, and 30zł are chosen for summary of model results. This results in 6 reference WTP measures that are compared across all models in this paper. The Delta method was used to obtain the estimates of error in the derived WTP measures (Daly et al., 2012). The computation of standard errors for each of the three cost specifications that vary in the value of λ are outlined in detail in **Appendix E**.

4.4 Empirical results

4.4.1 SP1 – Zero cost SQ alternatives

We start off with a basic utility specification that is commonly applied in practice. Model SP1-L1 relies on two alternative specific constants (ASC), δ_{alt1} and δ_{alt2}, to capture the average of all the effects on utility that are not modelled for an alternative. Cost sensitivity is specified linearly. All parameter estimates presented in **Table 4-2** are statistically significant at 95% confidence level. The SQ constant, δ_{alt1}, is positive, consistent with the notion of SQ effect as respondents show strong preference to remain at the SQ. Since the ZP and SQ constants are perfectly confounded by construct, we cannot exclude the possibility that δ_{alt1} also captures a certain degree of the ZP effects. In line with expectations,

we also see increased utility for larger data limits and the ability to use more devices. We also tested the test the Box-Cox transformation of costs but it only gives marginal improvements in final LL and hence this non-linear specification of cost sensitivity is rejected.

WTP for 4G LTE data derived from the model SP1-L1 varies depending on the data limit level. This results from the first derivatives of both the non-linear marginal utility of data limit and the linear marginal cost utility. Results show that respondents are willing to pay 2.21zł for each additional GB of 4G LTE data for a package that comes with 5GB of data limit. A significantly lower WTP for data limit is estimated at 0.55zł/GB when a higher data limit of 20GB is offered. This 75% decrease in WTP is equivalent to the relative ratio in data limit (i.e., 5GB vs. 20GB), as the WTP is inversely proportional to the size of the data limit. Robust t-ratios for the 6 reference WTP values remain the same as both the standard error (see **Appendix E**) and the WTP (see **Section 4.3.2**) are inversely proportional to the data limit.

Table 4-2: Estimation results for SP1 and SP2

	SP1 - L1 Linear Cost		SP2 - L1 Linear Cost		SP2 - BC1 Box-Cox~(Cost)	
Respondents	302		302		302	
Obs	2416		2416		2416	
Final LL	-2295.33		-2173.93		-2165.67	
AIC	4600.66		4359.85		4345.34	
Adj. ρ^2	0.133		0.179		0.181	
Parameter estimates	est.	rob. t-rat(0)	est.	rob. t-rat(0)	est.	rob. t-rat(0)
ZP (δ_{ZP})	-	-	0.246	3.38	0.083	1.06
SQ$_{alt1}$ (δ_{alt1})	0.737	4.84	0.531	3.03	-1.175	-1.59
ASC$_{alt2}$ (δ_{alt2})	0.085	1.97	0.025	0.53	0.067	1.40
Cost$_{Linear}$ (β_{cost})	-0.097	-16.74	-0.086	-20.36	-	-
Cost$_{Box-Cox}$ (β_{cost})	-	-	-	-	-0.873	-2.05
Lambda$_{Box-Cox}$ (λ)	-	-	-	-	0.261	1.63
Data Limit$_{log}$ (β_{dlim})	1.074	16.82	0.904	15.22	1.038	14.10
Multi-Access (δ_{mdev})	0.412	6.78	0.396	5.54	0.327	4.53

WTP (zł/GB) at reference 4G LTE data limit & total cost

Data Limit (GB)	Cost (zł)	est.	rob. t-rat(0)	est.	rob. t-rat(0)	est.	rob. t-rat(0)
5	3	2.207	17.77	2.110	14.30	0.535	2.04
5	10	2.207	17.77	2.110	14.30	1.304	2.16
5	30	2.207	17.77	2.110	14.30	2.937	2.19
20	3	0.552	17.77	0.528	14.30	0.134	2.04
20	10	0.552	17.77	0.528	14.30	0.326	2.16
20	30	0.552	17.77	0.528	14.30	0.734	2.19

4.4.2   SP2 - Zero and non-zero cost SQ alternatives

Linear cost specification

SP2 is devised to disentangle the ZP and SQ effects by allowing both zero and non-zero costs for the SQ alternatives. Largely based upon the linear-in-cost specification adopted in SP1, the ZP dummy, δ_{ZP}, is now split from the SQ constant, δ_{alt1}, that merely captures the preference of remaining at the SQ even when the SQ alternative is not free. Model results (SP2-L1) are presented in **Table 4-2**. Most parameters are statistically significant at 95% confidence level, except for the constant associated with the middle alternative (i.e. alternative 2). Both the ZP and SQ constants are statistically significant. The result suggests that the extra attractiveness to the SQ alternatives that are not captured by the marginal utilities can be partly explained by the ZP effect, rather than the preference of remaining at SQ at its own. The ZP and SQ constants are estimated at 0.246 and 0.531. Taking ratio of these two constants finds that the SQ effect is approximately 2.2 times the impact of the ZP effect. In other words, Model SP2-L1 implies that the impact of the tendency to remain at the SQ options not related to the attractiveness to the ZP can be over-estimated by 46% if the confounding of the SQ and ZP effects are not disentangled.

Comparing against the model results from model SP1-L1, WTP estimates reduce slightly by 4.4% from 2.21zł/GB and 0.55zł/GB for the alternatives with either 5GB or 20GB data allowance, respectively in model SP1-L1, to 2.11zł/GB and 0.53zł/GB once non-linear cost sensitivities are included in model SP2-L1. The differences in WTP between the two treatments are not statistically significant (*t*-ratio of 0.50), which indicates that the impacts on the contextual difference (e.g. protest behaviour) between SP1 and SP2, namely, the introduction of minimal yet new charges on the Wi-Fi services, do not appear to affect computation of the WTP for 4G LTE data packages.

Non-linear cost specification

A flexible non-linear formulation that adopts a Box-Cox transformation of costs, is also tested to examine whether the presence of the SQ and ZP effects implied by model SP2-L1 are more likely to be contributed by the real behavioural effect, or alternatively, are artefacts of the misspecification of the cost sensitivity. Estimation results from this model SP2-BC1 are summarised in **Table 4-2**.

The final log-likelihood improves from -2,173.93 in model SP2-L1 to -2,165.67 in model SP2-BC1 simply by incorporating non-linearity in cost sensitivity. The Box-Cox parameter λ is close

to zero, implying strong non-linearity. As opposed to the findings from the Model SP2-L1, the ZP and SQ constants are not statistically significant at the 95% confidence interval, indicating that both the ZP effect and the SQ effect are not significant in Model SP2-BC1. This supports the proposition that the ZP and SQ effects captured in the linear-in-cost model in SP2 are partly capturing non-linearities in cost sensitivity due to utility misspecification. It is noted that this finding is based upon the better fit to data shown by specifying cost sensitivity non-linearly. That said, our finding is in line with past literature (Hess et al., 2011) that highlight the risk of obtaining biased estimates for the constant where the utility formulation is misspecified.

WTP also gives a very different picture to the linear-in-cost model as WTP is much smaller at small cost levels, and vice versa for more expensive alternatives. When the cost level is set at 3zł, the WTP reduces by 75% from 2.11zł/GB and 0.53zł/GB in model SP2-LC1 for the alternatives with 5GB and 20GB data limits, to 0.54zł/GB and 0.13zł/GB in model SP2-BC1, respectively. This reflects the damping effect in cost sensitivity facilitated by the Box-Cox transformation, which gives higher cost sensitivity at small cost levels compared to the average cost sensitivity across all cost levels estimated by the linear-in-cost specification. Conversely, the WTP for data package offered at 30zł increases by 39% from 2.11zł/GB and 0.53zł/GB for the alternatives with 5GB and 20GB allowance in the linear-in-cost model SP2-LC1, to 2.94zł/GB and 0.73zł/GB in model SP2-BC1, respectively.

Overall, model results in SP2 suggests that there is no significant ZP effect or SQ effect detected in this treatment after the use of flexible utility formulation to verify the validity of the presence of SQ and ZP effects. That said, there remains a price gap between zero cost and the first cost level of 5zł for the 4G LTE data packages. Therefore, it is still inconclusive whether the non-linearity and ZP effect can be disentangled fully especially near the zero cost. This issue is dealt with explicitly in SP3.

4.4.3   SP3 – No SQ alternative

Linear cost specification

Binary choices are presented in SP3 with the possibility of zero cost in one of the two alternatives available. Respondents are not subject to any SQ effect by design as the SQ alternatives are excluded in SP3. This avoid any confounding between ZP and SQ effects entirely. Very small costs are presented to ensure that the ZP effect can be distinguished from the non-linearity in cost sensitivity near the zero price. This treatment thus represents

the best 'test-bed' for capturing the ZP effect amongst the 3 treatments. Similar to the previous treatments, we first specify a basic linear-in-cost model with a dummy variable to capture any potential ZP effect. Results for this model SP3-L1 are presented in **Table 4-3**. All parameters are statistically significant at 95% confidence level and of the expected sign. A significant positive estimate is obtained for the ZP dummy, suggesting the presence of a ZP effect. The WTP values are reduced by 22% from the linear-in-cost model in SP2 (model SP2-L1), from 2.11zł/GB and 0.53zł/GB for data limit provided at 5GB and 20GB in SP2-L1, to 1.64zł/GB and 0.41zł/GB in SP3, respectively. The lower WTP for 4G LTE data package estimated in SP3-L1 can be attributed to the introduction of the small costs in SP3. This finding is verified by a test model that applies the same specification as with SP3-L1 but with trade-offs involving small costs removed from the model estimation, which produces WTP values that are not statistically different to those obtained in model SP2-L1. Clearly by enriching the experimental design with small costs, we allow the model to identify some high cost sensitivity perceived by respondents at small costs and hence reduce the risk of over-estimating the WTP.

Table 4-3: Estimation results for SP3

	SP3-L1		SP3-BC1	
	Linear Cost		**Box-Cox~(Cost)**	
Respondents	302		302	
Obs	3020		3020	
Final LL	-1553.59		-1509.07	
AIC	3117.18		3030.14	
Adj. ρ^2	0.2554		0.2762	
Parameter estimates	est.	rob. t-rat(0)	est.	rob. t-rat(0)
ZP (δ_{ZP})	0.501	5.78	0.362	3.84
ASC$_{alt2}$ (δ_{alt2})	0.108	2.60	0.073	1.73
Cost$_{Linear}$ (β_{cost})	-0.121	-19.32	-	-
Cost$_{Box-Cox}$ (β_{cost})	-	-	-0.535	-7.74
Lambda$_{Box-Cox}$ (λ)	-	-	0.469	9.90
Data Limit$_{log}$ (β_{dlim})	0.992	13.83	1.181	14.91
Multi-Access (δ_{mdev})	0.299	5.53	0.334	6.04
WTP (zł/GB) at reference data limit & cost				
Data Limit (GB)	Cost (zł)	est.	rob. t-rat(0)	est.	rob. t-rat(0)
5	3	1.642	16.50	0.791	7.55
5	10	1.642	16.50	1.500	7.87
5	30	1.642	16.50	2.689	7.97
20	3	0.410	16.50	0.198	7.55
20	10	0.410	16.50	0.375	7.87
20	30	0.410	16.50	0.672	7.97

Non-linear cost specification

We examine the validity of the findings with respect to the ZP effect from model SP3-L1 by applying a Box-Cox transformation of costs in Model SP3-BC1. As shown in **Table 4-3**, the final log-likelihood improves significantly from -1,553.59 to -1,509.07, which indicates that the specification of non-linear cost sensitivity better fits the SC data. All parameters are statistically significant at 95% confidence level except for the ASC controlling for the preference towards the left-most alternative (i.e., alternative 2), δ_{alt2}. The size and significance of the ZP dummy, δ_{ZP}, reduces once the cost sensitivity takes on a non-linear form. This implies that the ZP effect, albeit still being picked up when cost sensitivity is specified non-linearity, could have been over-stated using a linear-in-cost specification in model SP3-L1 by capturing effects other than the ZP effect. We again find strong non-linearity in the cost sensitivity, as shown by the estimate for λ.

The comparison of the WTP for the 4G LTE data options between linear and non-linear cost models gives a very similar picture as in SP2. WTP values estimated at 3zł and 10zł are significantly lower when cost sensitivity is specified nonlinearly, and vice versa when the 4G LTE package is priced higher at 30zł. In contrast to the model assuming linear cost sensitivity where WTP drops by 22% as mentioned earlier (SP3-L1 vs SP2-L1), differences in WTP computed based on non-linear cost function between SP2 and SP3 are not statistically different across all cost levels, as presented in **Table 4-4**. From a policy perspective, it is clearly more desirable to minimise the bias that is caused by the small cost effect by adopting a flexible functional form for more consistent and robust WTP measures in contrast with the results from using the linear-in-cost specification in our SC data. The insignificant difference in WTP also reassures that the difference in contextual difference of the SC choice format, namely, the removal of the SQ alternative, does not lead to substantial difference in the WTP computation.

Overall, the choice analysis for SP3 provides evidence of a moderate ZP effect in either cost sensitivity specification. By design, this treatment offers the most robust setting for identifying the ZP effect, without the confounding with the SQ effect, while providing abundant information at cost near zero to improve separation of the ZP effect and non-linearity. We highlight the risk of ZP effect being over-stated if non-linearity in cost sensitivity is not incorporated. Also, presentation of small costs in trade-offs also leads to stronger ZP effect detected than in SP2, for both linear and non-linear cost sensitivity specifications.

Table 4-4: WTP differences between SP2 and SP3

Reference cost and data limit		Linear-in-cost model SP3-L1 vs SP2-L1			Non-linear-in-cost model SP3-BC1 vs SP2-BC1		
Data Limit (GB)	Cost (zł)	est.	diff.	rob. *t*-rat (diff)	est.	diff.	rob. *t*-rat (diff)
5	3	2.11	-22%	*2.63*	0.54	48%	*0.90*
5	10	2.11	-22%	*2.63*	1.30	15%	*0.31*
5	30	2.11	-22%	*2.63*	2.94	-8%	*0.18*
20	3	0.53	-22%	*2.63*	0.13	48%	*0.90*
20	10	0.53	-22%	*2.63*	0.33	15%	*0.31*
20	30	0.53	-22%	*2.63*	0.73	-8%	*0.18*

4.4.4 Joint modelling

This paper suggests re-framing the SQ for separating the SQ and ZP effects in SP2 and inclusion of the small costs for distinguishing ZP effect from non-linearity in SP3. This section describes the joint estimation that merges the SC data from all 3 treatments to form a more representative sample for estimation. This allows a consolidated platform that allows separation of ZP effect, SQ effect, and non-linearity in cost sensitivities. Since respondents are exposed to different choice sets across the 2 treatments, the joint model captures the scale difference by incorporating separate scale parameters for each treatment, denoted as μ_{SP1}, μ_{SP2} and μ_{SP3}, for SP1, SP2 and SP3, respectively, where μ_{SP3} is normalised to one. The parameter estimates and WTP measures from the joint-estimation assuming non-linear cost sensitivity (Model Joint-BC1) are summarised in **Table 4-5**. This is based on the previous finding from all individual models that non-linear cost sensitivity gives better model fit.

We retain the ZP dummy and the SQ constant, denoted as δ_{ZP} and $\delta_{alt1,SP2}$, respectively, for capturing the ZP and SQ effects in SP2 while the ZP dummy, δ_{ZP}, is also used for capturing the ZP effect in SP3. The confounding ZP and SQ effects are captured solely by an ASC, denoted as $\delta_{alt1,SP1}$. Two ASCs, $\delta_{alt2,SP1/2}$ and $\delta_{alt2,SP3}$, are assigned to capture the presentation order effect for the middle alternatives in SP1 and SP2, and the left-most alternatives in SP, respectively.

The scale parameters for SP1 and SP2, denoted as μ_{sp1} and μ_{sp2}, are estimated to be lower than one. Since scale parameter is inversely proportional to the random error. Smaller scale parameters estimated for SP1 and SP2 relative SP3 imply that the proportion of the random errors in SP1 and SP2 are relatively larger than the random error in SP3. This suggests less

deterministic behaviour (from the analyst's perspective) relative to SP3. This is not surprising as respondents are required to handle more alternatives in SP1 and SP2. This is in line with the argument that higher level of task complexity can lead to larger variance in random error term (Swait & Adamowicz, 2001).

Table 4-5: Joint estimation results

	Joint - BC1 Box-Cox~(Cost)	
Respondents	302	
Obs	7852	
Final LL	-5982.27	
SP1	-2302.94	
SP2	-2168.74	
SP3	-1510.59	
AIC	11986.5	
Adj. ρ^2	0.190	
Parameter estimates	**est.**	**rob. t-rat(0)**
ZP (δ_{ZP})	0.338	4.46
SQ$_{alt1, SP2}$ ($\delta_{alt1, SP2}$)	-0.418	2.40
ASC$_{alt1, SP1}$ ($\delta_{alt1, SP1}$)	-0.341	-1.89
ASC$_{alt2, SP1/2}$ ($\delta_{alt2, SP1/2}$)	0.068	1.73
ASC$_{alt2, SP3}$ ($\delta_{alt2, SP3}$)	0.058	1.39
Cost$_{Box-Cox}$ (β_{cost})	-0.546	-7.51
Lambda$_{Box-Cox}$ (λ)	0.464	9.68
Data Limit$_{log}$ (β_{dlim})	1.231	17.00
Multi-Access (δ_{mdev})	0.386	8.04
Scale$_{SP1}$ (μ_{SP1})	0.852	16.19
Scale$_{SP2}$ (μ_{SP2})	0.828	17.78
Scale$_{SP3}$ (μ_{SP3})	1.000	-

WTP (zł/GB) at reference data limit & cost

Data Limit (GB)	Cost (zł)	est.	rob. t-rat(0)
5	3	1.035	7.69
5	10	1.700	7.96
5	30	2.673	8.04
20	3	0.259	7.69
20	10	0.425	7.96
20	30	0.668	8.04

The specification of non-linearity in cost sensitivity also leads to decrease in the significance of the ZP effect. This is consistent with the earlier findings that the ZP effect can be over-estimated when it also captures some of the non-linearities in cost sensitivity due to misspecification. By disentangling the ZP and SQ effects, it can be seen that the SQ constant is estimated at -0.418, with a t-ratio of 2.4. Not only that the ZP effects are disentangled

from the SQ effect, but our joint model results based upon non-linear cost formulation indicates that the preferences towards the SQ alternatives are largely due to the ZP effect.

The WTP computed for the joint model largely fall between the values obtained from each treatment and are hence consistent with the previous findings. As shown earlier, the non-linear-in-cost model allows higher cost sensitivity for small cost levels and vice versa for higher costs. This leads to WTP which is 46% lower at small cost level (1.04 vs. 1.93 at 3zł and 5GB; 0.26 vs 0.48 at 20GB) and 39% higher for higher cost level (2.67 vs 1.93 at 30zł and 5GB; 0.67 vs 0.48 at 20GB) when compared to the linear-in-cost specification. Given that the model has shown better fit for the non-linear specification, this suggests that ignoring the non-linearity in cost sensitivity could over-state the ZP effect and also lead to over-estimation of WTP at small costs and alternatively under-estimate WTP at high costs in this SC data.

4.5   Conclusions

This paper develops an experimental design that best allows identification of the ZP effect and the separate identification from SQ effects. Our analysis provides evidence of the presence of the ZP effect and suggests that the SQ effect captured in our SC data can largely be explained by the disproportionate attractiveness of the zero cost alternative, rather than the preference of remaining at the SQ. This finding can potentially affect many commonly studied choice situations where ZP alternatives are presented, yet the impacts of capturing the ZP effect on the valuation studies have been under-examined to date.

The experimental approach discussed herein is a relatively straightforward extension of a conventional experimental design. This includes modifying the framing of the SQ context to include some non-free SQ options, together with the inclusion of trade-offs at small cost levels. Our analysis is based on results from 3 treatments that separately test the impacts of these two design features on the discovery of the ZP effect and WTP measures, and also results from a joint estimation that incorporates the preference data from all 3 treatments. For any prospective choice analyses where ZP effect could potentially come into play, both the inclusion of the non-free SQ alternatives and an adequate number of trade-offs at small costs could be incorporated in the experimental design for capturing any potential ZP effect to avoid biased parameters and WTP measures. That said, the re-framed context of the SQ is arguably not the SQ anymore, which might lead to resulting policy measures that are not compatible with the original intent. Considerable effort should be made to ensure that the SQ context remains largely comparable even when the small out-of-pocket cost is assigned

to the SQ and no significant behavioural change is induced as a result of this change of context. Analysts also need to carefully judge whether the inclusion of the SQ alternative is required in a context where the main interest is on WTP.

We turn to the implications for WTP calculations. If the ZP effect is real behavioural effect, then not accounting for it in the utility specification would lead to an overestimation of the cost sensitivity and hence under-estimated WTP. Since by definition the ZP effect will lead to a disproportionate increase of dis-utility moving from zero cost to *infinitesimal* cost, the ZP effect can be captured by a ZP dummy. This leads to the separation of the ZP effect form the WTP computation. This is supported by our findings that the WTP measures are not affected at all after the ZP effect is split from the SQ effect as both the ZP and SQ effects are separated from the WTP computation. The WTP computed is thus appropriate for policy analysis provided the sole focus is on the marginal rate of substitution between attributes. Without acknowledging the ZP effect, however, analysts could significantly under-estimate the attractiveness of the designed (policy) alternatives when only a slight departure from the zero cost for the SQ alternative may lead to much higher demand for the designed alternatives. Indeed, our model results from the joint model show that the respondents prefer to trade once the SQ is no longer free. This finding from our SC data suggests a significant role of the ZP effect. It is therefore recommended to include the ZP effect in welfare calculation to compensate for the loss of welfare due to simply moving from a free to a non-free option, and conversely for the gain of welfare for moving to a free alternative.

That said, we cannot exclude the possibility that the ZP effect captured could be amplified within a stated choice setting. Namely, the finding of the ZP effect is reinforced by the experimental design which allows more ZP alternatives in choice tasks. Under this circumstance, the ZP effect should be excluded or adjusted accordingly in welfare calculation. The risk of capturing ZP as a survey artefact leads to the recommendation for future research that the ZP effect should also be tested based on revealed preference data, where the ZP effect can be truly isolated from any survey contextual effect. This is indeed feasible in practice. For instance in transport context, one could observe the change of drivers' choices for switching between a free existing road and a tolled facility to detect the presence of the ZP effect. Also, travel dairy can be adopted as the survey instrument to collect past travel choices made for recreational trips. For instance, revealed preferences can be inferred based on travellers' past choices between accessing a local park which is free of charge (i.e. could subject to potential ZP effect) and a national park with entrance fees. Also randomised experiments designed for eliciting online shoppers' preferences have become a standard

marketing technique nowadays. This allows opportunities to replicate the classic experimental setup devised by Shampanier et al. (2007) through big data analysis. In the real choice setting, Shampanier and her colleagues found that individuals are more attracted to a particular chocolate product when its price is reduced to zero, even when the cost differences between alternatives and transaction costs are kept unchanged before and after the price drop.

We also acknowledge the small price setting for teasing out the zero price effect might invoke incompatible cognitive frame. This is a trade-off that analysts might need to make, however. In some cases, it will be difficult to ensure that feasibility of small costs offered for particular goods. For our experimental design, it can be argued that some students could be surprised by the charges (despite being minimal) collected by the university and thus lose the positive incentive for a truthful response (i.e. not incentive aligned). It is also possible that users' preferences might be anchored at small costs presented earlier in the SC experiment. Therefore, analysts need to weigh the conflicting goals of ensuring the market realism of the experimental setup (e.g., feasibility of small costs) with the measures required to avoid serious bias in welfare calculations (e.g. by additionally capturing the ZP effect). Subject training might be useful to enrich the market realism to ensure subject are familiar with the small cost setting, despite it is also difficult to design a training that is "neutral and non-manipulative" (Ben-Akiva et al., 2019). The use of effective design with multiple pilot surveys to examine the realism of responses and refinement of the priors in the efficient experimental design will also help to ensure the utility balance in design (Huber and Zwerina, 1996).

With respect to the low WTP observed in the SP3 using the linear-in-cost model (SP3-L1), it can be argued that the model estimates might be biased by the contextual difference by having forced choices (Boyle and Özdemir, 2009) with the SQ alternatives removed. Namely, respondents who prefer to remain at SQ would choose the 4G LTE data options with lower cost (and hence higher cost sensitivity and lower WTP) as the SQ is no longer an alternative in SP3. This finding is cross-checked with the models specified with the non-linear cost sensitivity which give better model fit and we found no significant difference in WTP between SP2 and SP3.

This paper also implements alternative ways of accounting for the ZP effect in the utility function and impacts on the WTP measures are empirically tested. Our results suggest that respondents' sensitivities to cost decrease with increasing cost levels. This is supported by

the use of Box-Cox transformation of costs that gives significant improvements in model fit. The presence of non-linearities in utility brings complications in the WTP computation. First, small cost levels are required to separate the ZP effect and non-linearity as stated above. We found that the linear-in-cost specification is prone to the small cost effect that WTP would be significantly lowered when more data points allows detection of the higher than average cost sensitivities perceived by respondents at small costs. In contrast, the WTP measures are relatively stable with and without provision of small costs by using a more flexible utility functional form. More importantly, our results show the ZP effect detected in all cases become less significant when non-linear cost sensitivities are specified as opposed to the linear specification which is commonly assumed in many choice analyses. The results suggest that the ZP dummy with the linear-in-cost specification may have captured some of the non-linearities in utility due to utility misspecification. On the other hand, however, if the real source of the retrieved effects is non-linearity in the cost sensitivity rather than a ZP effect, then the inclusion of a ZP dummy with cost sensitivity misspecified linearly may also bias WTP. Our findings strongly support the proposition that flexible utility functions should be tested in capturing any ZP effect.

In conclusion, we demonstrate that capturing the ZP effect requires not only a simple constant term but also a careful experimental design and appropriate estimation techniques to minimise the risk of obtaining biased parameter estimates and WTP measures. Analysts need to tread a fine line between uncovering the full "behavioural effects" and producing results that are useful for policy analysis. Several avenues for further research are identified. These include the testing for the ZP effect in more advanced model structures, such as nesting structures and taste heterogeneity, or a mix of both.

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Chapter 5

Conclusions

5.1 Summary

This thesis has contributed to our understanding of the extent to which parameter estimates are affected by three types of model misspecifications: i) ignoring the travel time constraint, ii) measurement error in the income variable, and iii) ignoring the alternative behavioural phenomenon of the zero-price (ZP) effect. We synthesise three research questions that correspond to each type of model misspecification. We are particularly interested in understanding the implications of these errors on the marginal valuation of quality variables. Our analyses are relevant to policy makers as these marginal valuations support many cost-benefit analyses.

The impacts of the three types of specification error on model outcomes are demonstrated through three separate case studies. The first two model specification errors concerning the travel time constraints and the income variable are examined within the context of the Value of Travel Time (VTT). The third model misspecification associated with the behavioural ZP effect is illustrated within a more generic choice setting when the (policy) 'interventions' are compared against the free status quo alternative. An overview of the model misspecifications, our approaches to the research questions and headline findings are presented in **Table 5-1**.

The rest of the chapters is structured as follows: **Chapter 5.2** provides a detailed discussion regarding our research findings that correspond to each of the research questions specified earlier. This is followed by a consolidated discussion, including research contributions to the choice modelling in general, implications, research limitations and future research avenues in **Chapter 5.3**.

Table 5-1: Overview of the model misspecifications, our approaches and headline outcomes

	1	2	3
Misspecification / Source of error	■ Travel time constraint	■ Income variable	■ Alternative behavioural phenomenon (ZP effect)
Measurement error		■ *Problem:* Measurement error in the income variable ► *Approach:* Compile different income measures based on the secondary data and re-estimate choice models with the new income variables ► *Outcome:* Cross-sectional income elasticity of VTT reaches unity when social benefits are considered in the income variable; behavioural VTT remains consistent despite variations in income but disparity of household income-based and personal income-based appraisal VTTs arises due to sampling bias in the SC data	
Omitted / unobserved variable	■ *Problem:* Missing availability indicator to account for the impact of travel time constraints on availability of alternatives ► *Approach:* Generate simulated SC data assuming some choices are constrained due to the travel time stringency; and estimate models without modelling of the choice set formation ► *Outcome:* VTT can be significantly over-estimated when the impact of travel time constraints on the alternative availabilities are unaccounted for		■ *Problem:* Missing variable to control for the zero-price effect ► *Approach:* Develop alternative survey designs to identify the ZP effect and separate it from the SQ ► *Outcome:* ZP effect can be separated from the SQ effect; ZP effect is the main driver for the preference of the SQ alternative

Table 5-1 (continued)

Misspecification / Source of error	■ Travel time constraint	■ Income variable	■ Alternative behavioural phenomenon (ZP effect)
			■ ***Problem:*** Missing non-linear specification for cost sensitivity
			► ***Approach:*** test alternative non-linear model specifications
			► ***Outcome:*** Non-linearity in cost sensitivity is present but cannot fully control for ZP effect.
Unobserved taste variation	■ ***Problem:*** Preference heterogeneity can pick up for alternative misspecifications and thereby misrepresent the true extent of preference heterogeneity		
	► ***Approach:*** Generate simulated constrained SC data assuming random VTT across respondents; and estimate models without modelling of the choice set formation		
	► ***Outcome:*** Preference heterogeneity cannot be fully retrieved when the travel time constraints are unaccounted for		
Related chapter	■ Chapter 2	■ Chapter 3	■ Chapter 4

5.2 Answers to the research questions

This section revisits the three sets of research question set out in **Chapter 1.5.5**. These research questions correspond to the three types of model specification error. Under the headline research questions for each model specification error, we briefly recall the intuition behind the research questions, our approaches to test our specific hypotheses, the data employed in support of our analysis, and our answers to the research questions.

5.2.1 Misspecification 1: Travel time constraints

What are the impacts of incorrectly accounting for constraints on choice behaviour, such as time constraints, on the retrieval of taste heterogeneity and marginal WTP measures?

In **Chapter 2**, we highlight the impact of ignoring the travel time constraint in a simple time-cost binary choice setting. This binary choice setting, which presents time-cost trade-offs, is a legacy SC design that remains at the heart of many VTT studies. The risk of this design is that when travel time presented is beyond the respondent's perceived time allowance, they will be forced to choose the remaining option. We examine the potential bias via Monte Carlo simulation to attain full control of variations in preferences and travel time constraints. The simulated data are then used for estimation with and without the controlling for the travel time constraints using either logit or MMNL models.

We begin our analysis assuming fixed taste coefficients. Our model results show that the VTT estimates can be significantly overstated when availabilities of alternatives (or any explicit modelling of choice set formation) are not incorporated in estimation. This finding supports our proposition about the upside bias in the VTT estimate when respondents are forced to choose the more expensive but quicker alternative (see discussion in **Chapter 0**). Our empirical results indicate that the MMNL model fails to retrieve the true degree of unobserved taste heterogeneity when travel time becomes stringent. In particular, the MMNL model cannot distinguish between the individuals who have (i) low VTT but is forced to choose the expensive alternatives due to the time constraint, and (ii) high VTT who remain committed to the expensive alternatives. Our empirical tests further show that when time constraints are differently amongst individuals assumed with fixed-taste coefficients, the MMNL model can misinterpret the mixed budget thresholds as taste heterogeneity.

The strong bias in the parameter estimates described above suggests that there is scope for improvement to the current design. Analysts might be motivated to look for extensions to the binary choice design as well as implementing explicit modelling of choice set formation. While the connection of this model specification error to the literature in choice set formation will be discussed in the next section, this thesis also empirically tests the effectiveness of the inclusion of an opt-out alternative as a mean to reduce the bias associated with the travel time constraints. We design an alternative simulation scenario where individuals are allowed to choose between the opt-out option and at least one other unconstrained travel alternative. Our estimation results indicate that some but not all taste heterogeneity are retrieved when respondents are subject to very stringent time constraints. In summary, the over-estimation of the VTT remains an issue by including an opt-out alternative but the bias in model estimates introduced by ignoring the travel time constraints is not as severe as in the binary choice setting.

5.2.2   Misspecification 2: Income variable

What are the impacts of measurement error in the income variable on cross-sectional income elasticities of VTT and can it explain the discrepancy between the cross-sectional and inter-temporal income elasticity?

In **Chapter 3**, we aim to test whether measurement errors in the income variable can partly explain the disparity between the cross-sectional and inter-temporal income elasticities in the VTT literature. Since economic theory does not put any restrictions on the level of the (positive) income elasticity of VTT (see proof in **Chapter 1.5.3**), there has been a long-standing debate over the rationale of observing much lower income elasticities of non-business (or non-work) VTT from cross-sectional studies than the inter-temporal values derived from meta-analyses, which average around unity. We approach this question by generating a wide range of income measures based on survey data on the household expenditure of goods and services in the UK. These income measures are varied in terms their assumptions of the income re-redistribution measures (original, after-tax and disposable income) and intra-household budget allocation (household, equivalised household and personal income). We embed these new income measures in the 'state-of-the-art' choice modelling framework developed for the 2014/15 UK VTT study. A continuous interaction between income and the base VTT is specified for estimation of the income elasticity of the VTT.

By varying our assumptions in terms of the income re-redistribution measures, we find that the income elasticity of VTT estimates become higher when tax implications under a progressive tax system are included in the income variable (i.e. after-tax income). This finding is aligned with the past literature and indicates that travel budget could be over-estimated if tax burden is not included in measuring income. What is more interesting though, is that we identity the first time that inclusion of social benefits (i.e. the true 'disposable' income) to better reflect the travel budget available for low income earners, will further inflate the income elasticity of VTT. Indeed, the disposable income based-income elasticity of VTT is not significantly different to the unit value, and hence closing the gap between the cross-sectional and inter-temporal income elasticities of VTT.

In contrast, the variation in terms of the assumption of the intra-household budget allocation does not give clear directional change of the income elasticity from the outset. Based on our SC data, we find that the use of household income leads to the highest income

elasticity of VTT, followed by the use of the equivalised household[1] and personal income. This finding is contrary to findings from some Scandinavian studies (Algers et al., 1995, Fosgerau et al., 2007, Ramjerdi et al., 1997); however, we stress that the income elasticity can go either direction since the difference between the perceived travel budget and respective income measure can go either way. In summary, we show that different measurement of the money budget for travel will lead to different income elasticities of VTT, and the use of disposable income in particular for our SC data can bridge the gap between the cross-sectional and inter-temporal income elasticities of VTT.

Despite the changes in the income elasticities by varying the income variable, we find that the behavioural VTT, which is the average VTT across all respondents derived from the SC data, appear to be unaffected by the size of the measurement errors in the income variable. Therefore, this finding does not invalidate the finding of the behavioural VTT from the 2014/15 UK VTT study, where the original household income was used for the VTT estimation.

However, in the translation of the behavioural VTTs into the values for use in appraisal (i.e. the appraisal VTT) issues arise. This translation is achieved via a sample enumeration approach to apply the behavioural VTT formulae and the associated covariates on each observed trip within the NTS sample. We bring to light a clear divergence in appraisal VTTs between the use of household and personal income. By disentangling the various VTT multipliers to explain the discrepancy, we show that the disparity is caused by the sampling bias in the SC sample. In particular, we find that the high income households are under-sampled in the SC survey. Therefore, even though the behavioural VTTs seem not affected by the size of the measurement error of the income variable, the measurement error of the income variable may affect the derivation of the appraisal VTTs when sampling of the income variable is not representative. In other words, in order to avoid the differential appraisal VTTs due to the sampling bias of the income, analysts need to ensure income distribution is sampled representatively for different market segmentations for both the model estimation and sample enumeration.

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[1] The equivalised income measure considers the expenditure patterns for households of different size and composition and thus is made equivalent for all household sizes and composition

In summary, we show that measurement errors in the income variable can explain the discrepancy between the cross-sectional and inter-temporal income elasticity. While the measurement errors in the income variable does not appear to affect the behavioural VTT in estimation, sampling bias of the income distribution for VTT estimation may lead to adversarial income effects on appraisal VTTs. Full behavioural model results are presented in **Appendix D**.

5.2.3   Misspecification 3: Behavioural ZP effect

What are the impacts of alternative behavioural phenomena, such as the ZP effect, on welfare estimates and what are the implications for study design?

In **Chapter 4**, we aim to test whether alternative behavioural phenomena such as the ZP effect can affect the welfare estimates. The ZP effect refers to the phenomenon that individuals perceive extra attractiveness towards the free alternative. Despite the widespread inclusions of zero cost alternatives in survey, the choice modelling literature has paid very little attention to this behavioural phenomenon. This is particularly relevant to the environmental economics and health literature, where the (policy) 'interventions' are often compared against the free SQ option. This thesis focuses particularly on the issue of the perfect confounding between the ZP effect and the SQ alternative in this context. As such, an experimental design which comprises three treatments is developed that best allows identification of the ZP effect and the separate identification from SQ effects. Stated choices made by students between different mobile board packages are analysed by choice models assuming fixed taste coefficients.

We stress that due to the perfect confounding between the ZP and the SQ effect in most stated choice surveys, marginal WTP estimates may only be affected to a limited extent. This is because both ZP and SQ alternatives can be captured by constants and are thus excluded from the computation of the marginal WTP. However, the prevalence of the ZP effect in observed choice behaviour implies that a minimal charge on the SQ option, as the requirement for future scenario to prevent deterioration of the SQ for instance, may introduce bias to the prediction of welfare. Therefore, there is a need to separate the ZP effect from the SQ effect and to assess the size of the ZP effect, which is only feasible by re-framing the SQ context such that both free and non-free SQ alternatives are presented to respondents. Indeed, our model results show that respondents prefer to remain at the SQ largely due to the ZP effect.

Chapter 4 also takes non-linear cost-sensitivity into consideration. We highlight that a sufficient number of small costs levels need to be incorporated in the experimental design to separate the ZP effect from non-linear cost sensitivity. Therefore, in capturing the ZP effect, a flexible functional form for the specification of cost sensitivity is also required to minimise the risk of obtaining biased parameter estimates and the welfare measures. Our joint model results confirm that individuals do respond to cost non-linearly in addition to the ZP effect.

In summary, we separate the ZP effect from the SQ effect and show that ZP effect is a significant effect in our data. This is achieved by re-framing the SQ effect to include also non-free SQ alternatives. The prevalence of the ZP effect also affects welfare analysis as it implies a disproportional loss of welfare even a minimal charge is placed on the SQ.

5.3 Implications and directions for future research

This section first describes the implications of our findings for each of the three misspecifications. We also suggest future research avenues to further extend our knowledge of the impacts of the model misspecification on model outcomes and policy recommendations.

5.3.1 Misspecification 1: Travel time constraints

Our examination of the impacts of ignoring the travel time constraints shows that significant bias, in terms of over-estimation of VTT and difficulties in retrieval of taste heterogeneity, can be introduced if the travel time constraints are not account for in a binary choice design with time-cost trade-offs. As we mentioned earlier, there is scope for improvements which can include moving beyond the simple design and also the implementation of more advanced choice modelling techniques to model the impacts of the travel time constraints. They are described in more detail here.

We first look into the implications of our findings with respect to the experimental design in particular. It is stressed that while the misspecification error concerning the travel time constraint are relevant to both SP and RP data, this issue is particularly apparent within the SC context. This is because respondents can be presented with unfeasible alternatives in the SC experience which then introduce bias when these unfeasible alternatives are modelled with non-zero choice probabilities. In RP data, the chosen alternatives observed should be within budget unless irrational decisions are made, despite the need to make assumptions

on the non-chosen alternatives. It is thus especially important to ensure that the SC design is robust enough for minimising the any impacts due to any misspecification issues.

The design issue with respect to the simple time-cost trade-offs setting lies in the lack of behavioural consideration of the travel time constraint. Indeed, our finding adds further empirical evidence of the literature in questioning the reliability of the VTT estimates derived from simple time-cost trade-offs (see Hess et al., 2016). While there could be merits for this simple design by reducing respondent burden as the original intent (see counter arguments from Chintakayala et al. (2010)), any potential benefits will be outweighed by the significant bias induced by lack of behavioural consideration of the travel time constraint demonstrated in this thesis.

Our results shown that introducing an opt-out alternative (i.e. not travelling) can reduce estimation bias, especially for improving the retrieval of taste heterogeneity. Special attention should be paid to ensure minimal contextual effect will be induced by introducing the opt-out alternative. Second, our findings can further connect with the wider literature in the trip-scheduling/re-timing choice modelling. As such, departure time choices can be modelled by using the scheduling model (Small, 1982, Small and Verhoef, 2007) based on the bottleneck theory (Vickrey, 1969). While this method can largely reduce the misspecification issue of ignoring the travel time constraint, the survey context and the modelling techniques will be rather different compared to the modelling framework applied in conventional national VTT studies.

Alternatively, there have been numerous methodological advances over years in the modelling choice set formation. This includes the two-stage models to explicitly model the choice set formation (Manski, 1977, Swait and Ben-Akiva, 1987a, Swait and Ben-Akiva, 1987b, Cantillo and Ortúzar, 2005), and the one stage semi-compensatory models for approximation of constrained choice sets (Cascetta and Papola, 2001, Martínez et al., 2009, Paleti, 2015). Clearly, these models can take into consideration the travel time constraints and hence reduce the bias in VTT estimates. However, our results also highlight the confounding issue between the taste heterogeneity and the impacts of travel time constraints. This raises questions whether the confounding problem would also occur in these aforementioned models, which are developed based on the fixed taste assumptions. More recently, Bergantino et al. (2019) take into account of both indicators of consideration including the consideration for alternatives and stated thresholds for attributes and unobserved heterogeneity in mode specific constant to model consideration set generation.

We have also identified future extensions to the simulation work, which would include enabling different decision strategies dealing with the budget constraints (e.g. non-compensatory attribute cut-offs by Swait (2001)), and improve realism in the assumption of multiple budget constraints.

5.3.2 Misspecification 2: Income variable

We demonstrate that economic theory does not provide any guidance in terms of the size of the cross-sectional income elasticity of VTT, as discussed in **Chapter 1.5.4**. This is the reason why there has been long-standing debate about the disparity between cross-sectional and inter-temporal income elasticities (Börjesson et al., 2012, Hensher, 2011, Mackie et al., 2003, Small, 2012, Wardman, 2001). We contribute to this literature by pinpointing the cause of the disparity that is partly due to the measurement errors in the income variables. We also provide evidence to support our proposition that including the social benefits to reflect the realistic travel (money) budget will lead to even higher income elasticity compared to the consideration of the tax implications only (Fosgerau, 2005). By varying different income measures, we do not see any significant differences in the calculation of the behavioural VTTs. This is assuring as it implies that measurement error income budget would lead to limited impact to the behavioural VTT estimates.

Our findings provide useful insights in particularly in the requirement of survey undertaking. First, if it is the main goal of analysts to best estimate the cross-sectional income elasticity of VTT (i.e. minimising the measurement error in the income variable), then more detailed information regarding individuals' income are required. This includes the tax implications and the social benefits, and also the household structure and budget allocation mechanism, if possible. Clearly, analysts should beware of the potential contextual problem (Swait and Adamowicz, 2001) and strike a balance between the length of the survey and the quality of the behavioural responses. We emphasise again the importance of ensuring income distribution to be sampled representatively for different market segmentations for both the model estimation and sample enumeration. This is to avoid any disparity of the appraisal values caused by the sampling bias in income from the SC survey. We further note that Börjesson et al. (2012) has provided an alternative explanation to the disparity between the cross-sectional and inter-temporal income elasticity using panel survey data. They find the income elasticity varies amongst population and the income elasticity of VTT is considerably higher than one for higher income groups. However, we do not find clear indication of directional changes in terms of the size of elasticities by income groups based on our cross-sectional data.

Our analysis examines the impacts of two out of four types of measurement error on the cross-sectional income elasticity. These two types of measurement error in the income variable are related to the perception of budget which might or might not include tax implications and social benefits, and the degree of budget allocation within households. Therefore, we also suggest future research to investigate the impacts of the rest of the measurement errors, either due to the budget allocation between different classes of spending (Deaton and Muellbauer, 1980), or due to the categorical income captured in most surveys.

5.3.3   Misspecification 3: Behavioural ZP effect

Despite the vast amount of evidence of the ZP effect in behavioural economics, the impacts of the ZP effect have been over-looked by choice modellers (Hess and Beharry-Borg, 2012). This is particularly problematic for many SC studies in environmental or health economics where the policy interventions are compared against the SQ options (see Ferrini and Scarpa, 2007). Our model results add empirical evidence to the literature in the SQ bias (Adamowicz et al., 1998, Oehlmann et al., 2017, Zhang and Adamowicz, 2011), by clearly pointing out that ZP effect is a possible behavioural cause for the SQ effect. We emphasise that the finding of the ZP effect does not affect the calculation of the marginal WTP. However, bias will be introduced to the welfare analysis if the size of the ZP effect is not estimated appropriately. This is because a minimal charge on the SQ will lead to welfare loss for individuals remaining at the SQ, and thus under-estimate the welfare gain of project that often improves the SQ at a cost if the ZP effect is not accounted for.

Our findings shed some light on the requirements for the experimental design to separate the ZP effect from the SQ effect. First, we need to ensure that some but not all SQ alternatives are not free. This is the basic requirement for separating the two effects. Special attention should be paid to ensure no contextual effect is induced (e.g. protest behavioural). Small costs are also required in order to separate the ZP effect and the non-linearity in cost sensitivity, which is a commonly observed (Daly, 2010). Other than the design criteria in separating the ZP effect from the SQ effect, we also recommend the use of the flexible functional form for the costs sensitivity to ensure that the ZP effect captured is not the artefact of the non-linearity of the cost sensitivity that is misspecified linearly in the utility formulation.

We have identified several avenues for future research. First, more advanced model structures, such as incorporation of the nesting structure (Scarpa et al., 2005) and random

taste heterogeneity (Train, 2009) can be tested. Second, welfare changes which also considers the ZP effect can be computed based on the approach by Karlström and Morey (2004), which allows separation of the compensating variation (CV) measures depending their choices before and after the policy change. This is important because the ZP effect will affect the CV calculation for the individuals who switch between free and non-free goods only. Finally, we also note that the ZP effect might arguably be amplified due to the SC setting. Further research on exploring the impact of the ZP effect on WTP should then be carried out using the RP data, where we could then avoid all the survey artefacts.

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Appendix A

Additional notes on income transformations (Appendix to Chapter 3)

From gross income to after-tax income

The conversion from gross income to after-tax household income is straightforward as the amount of tax deduction depends largely on the income level. Income is, however, taxed at the personal level and not at the household level in the UK. Hence, we rely on a regression analysis on data from the *Living Cost and Food Survey* (LCFS) to establish conversion factors for each household income band between gross and after-tax income. LCFS is the primary data source in the UK for assessment of the effects of tax and benefits on household income (ONS, 2015, p.26). A simple linear regression model was developed to regress the after-tax household income on the gross household income over 5,130 income profiles in the 2014 LFCS.

[Model A1]

$$AfterTaxInc_h = \sum_{i=1}^{8} \left(\beta_i * GrossInc_h * (GrossIncCat_h == i) \right) + C + \epsilon_h$$

The weekly gross income, $GrossInc_h$ represents the total gross earnings for household h before deduction of any payments of direct taxes and receipt of any cash benefits. The gross income term interacts with an indicator which is equal to 1 when the observation belongs to income group i ($h \in i$, with $i = 1, ..., 8$), and 0 otherwise. Weekly after-tax income, $AfterTaxInc_h$, represents the remaining income after taking into account income taxes, National Insurance (NI) and local taxes (e.g. council taxes). In this specification, β_i is the parameter estimated for income group i, C is the intercept and ϵ_h is the error term for household h. In the conversion of income in the SC data, the transformation function (i.e., β_i and C) is applied to 853 car commuters and 864 other non-business car drivers who have reported their income levels in the UK VTT sample. The results from the regression model and the income transformation in the SC data are summarised in the left part of **Table A.1**. The transformed income shows that the average tax burden rises with income, which is expected due to the progressive nature of the income tax in the UK.

Similar procedure is set out to transform the gross personal income to after-tax personal income. Instead of applying the official income tax rates to gross personal income as in Fosgerau (2005), and Börjesson et al. (2012), we apply the linear regression to establish the transformation function for personal income (Model A2). This allows us to derive realistic representation of the combined tax deductions applied to taxpayers, which includes different types of direct taxes including income tax, council tax and Employees' National Insurance (NI). The specification of the regression model to regress the after-tax personal income on the gross personal income for person p as follows:

[Model A2]

$$AfterTaxInc_p = \sum_{i=1}^{8} \left(\beta_i * GrossInc_p * \left(GrossIncCat_p == i \right) \right) + C + \epsilon_p$$

All parameter estimates in Model A2 are significant at the 95% level of confidence, as shown in the right part of **Table A.1**. Average personal tax burden is estimated to increase from 4% for individuals who earn less than £10K to 31% for the highest income group. Both R-squared values for Models A1 and A2 are very high at 0.98, which is not surprising for a society with progressive tax rates that closely link to income level.

Table A.1 – Regression results - After-tax income

Income group i		Model A1					Model A2			
		Regression		Implied average			Regression		Implied average	
		Est	t-stat	Commute	Other		Est	t-stat	Commute	Other
	C	11.2617	4.18			C	1.7991	2.84		
1 <£10K	β_1	0.9047	35.12	2%	2%	β_1	0.9375	127.38	4%	4%
2 £10K-£20K	β_2	0.8956	80.67	7%	7%	β_2	0.8724	281.75	12%	12%
3 £20K-£30K	β_3	0.8631	124.17	11%	11%	β_3	0.8245	381.14	17%	17%
4 £30K-£40K	β_4	0.8434	164.33	14%	14%	β_4	0.7995	414.63	20%	20%
5 £40K-£50K	β_5	0.8307	193.11	16%	16%	β_5	0.7823	420.10	22%	22%
6 £50K-£75K	β_6	0.8072	281.31	18%	18%	β_6	0.7578	455.51	24%	24%
7 £75K-£100K	β_7	0.7685	316.11	22%	22%	β_7	0.718*	-	28%	28%
8 >£100K	β_8	0.735*	-	26%	26%	β_8	0.686*	-	31%	31%
		R-squared: 0.9758					R-squared: 0.9816			

Interpolated

**Average tax burden =1-After-tax Income ∕ Gross Income

From gross income to disposable income

Another set of regression models is estimated to transform the gross income to disposable income. In contrast to the after-tax income model (Models A1 and A2), where only the gross income is used as a regressor, the eligibility to social benefits depends also on socio-demographics. The linear regression models developed to relate the disposable income to the gross household income is specified as follows:

[Model D1]

$$DispoInc_h = \sum_{i=1}^{8} \left((\alpha_i + \gamma_i Kid_h + \theta_i Old_h) * GrossInc_h * (GrossIncCat_h == i) \right) + C + \epsilon_h$$

where Kid_h represent the number of children within household h; Old_h refer to the number of seniors (65+) within household h; α_i, γ_i and θ_i are the parameters estimated for income group i; C is the intercept and ϵ_h or ϵ_p refer to the error term for household h and person p, respectively. The regression results for disposable income are shown in the left part of **Table A.2.** By applying the transformation function (with α_i, γ_i, θ_i and C) on the SC data, it is shown that households which earn less than £20K are estimated to receive net gain in salary due to the receipt of social benefits. Households from the lowest income group are estimated to receive 112% additional income (£8.4K approx.) on top of their gross income from cash benefits on average while the top earning households are anticipated to pay 25% of income for tax deduction on average.

A similar model specification is set out for transforming the gross personal income to the disposable personal income:

[Model D2]

$$DispoInc_p = \sum_{i=1}^{8} \left((\alpha_i + \gamma_i Kid_h + \theta_i Old_h) * GrossInc_p * (GrossIncCat_p == i) \right) + C + \epsilon_p$$

As shown in the right part of **Table A.2**, the *R*-squared value of 0.84 indicates that the regression model provides a lower fit by using personal income to predict amounts of social benefits, compared to the use of household income (with an adjusted *R*-squared value of 0.92). This finding is reasonable since eligibility of many types of social benefits including the housing benefits and child benefits, are dependent on household income rather than personal income.

Top coding for after-tax income

It is assumed that there are 52 weeks per year and 4.35 weeks per month in converting between weekly and annual income. The conversion factor for households who earn more than £100K per annum ($i = 8$) cannot be estimated since the top 4% of earners (GSS, 2014, p.22) are capped at the cut-off value in the LCFS to protect confidentiality. An assumption of the conversion factor for this group of households is thus needed. We base this on the conversion factor β_7 in Model A-1, which is estimated for households with annual salary between £75K and £100K ($i = 7$). The conversion factor β_8 is set such the ratio of the after-tax incomes between the top two income groups ($i = 7 \ and \ 8$) in the LCFS matches the equivalent ratio observed from the tax burden implied by the official marginal tax rate for the tax year 2014/2015[1].

Cash benefits provided by the UK government primarily include tax credits (child tax credit and working tax credit), housing benefit, state pension, child benefit, and employment and support allowance (Hood and Keiller, 2016, Table 3.1). For our study, it is impossible to approximate every single cash benefit as we are constrained by the limited number of socio-demographic characteristics collected in the SC survey and the NTS. We regress disposable income on two important explanatory variables. Benefit for families with children, which covers the child benefits and child tax credit, is represented as a function of the number of children within household Kid_h in Model D1 and D2. Its effect on disposable income for each income group i is represented by γ_i. Benefits for seniors, which includes tax allowance and state pensions for pensioners, is represented as a function of the number of overaged persons within household Old_h. Employment and support allowance, which is eligible for job seekers who are unemployed, is captured partly in the intercept term C. Other than cash benefits, the effects of direct taxes on disposable income are represented as the proportionate effect α_i for each income group i.

The top-coding issue described earlier is also applied here for households which earn more than £100K. Conversion factor α_7 is then interpolated to create α_8 for the top earning

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[1] The average tax burden for personal income bands £50K-75K (*i*=6), £75-£100K (*i*=7) and greater than £100K (*i*=8), are calculated as 26%, 30% and 33%, respectively, using the midpoints of each income category (HM Treasury, 2014).

household group based on the ratios of the tax burden implied by the official marginal income tax rates.

Table A.2 – Regression results – Disposable income

Income group i		Model D1				Model D2			
		Regression		Implied average tax		Regression		Implied average	
		Est	t-stat	Commute	Other NB	Est	t-stat	Commut	Other
	C	255.10	57.99			C 132.50	79.45		
1	<£10K	α_1 -0.2511	-4.15	-112%	-93%	α_1 0.2057	8.28	-79%	-82%
2	£10K-£20K	α_2 0.1538	6.89	-23%	-20%	α_2 0.4781	50.40	1%	-1%
3	£20K-£30K	α_3 0.3755	27.91	2%	1%	α_3 0.5643	83.30	16%	13%
4	£30K-£40K	α_4 0.4883	50.01	11%	12%	α_4 0.6105	116.04	19%	18%
5	£40K-£50K	α_5 0.5525	67.40	13%	14%	α_5 0.6317	125.09	21%	20%
6	£50K-£75K	α_6 0.6010	114.86	18%	18%	α_6 0.6409	142.16	25%	24%
7	£75K-£100K	α_7 0.6293	155.86	22%	22%	α_7 0.636*	-	29%	29%
8	>£100K	α_8 0.645*	-	25%	25%	α_8 0.629*	-	32%	32%

Effect on disposable income as per the number of children within household h

1	<£10K	γ_1 0.6761	20.31			γ_1 0.3025	19.05		
2	£10K-£20K	γ_2 0.3087	22.56			γ_2 0.0694	9.15		
3	£20K-£30K	γ_3 0.1170	13.13			γ_3 0.0145	2.57		
4	£30K-£40K	γ_4 0.0444	6.69			γ_4 -	-		
5	£40K-£50K	γ_5 0.0239	3.90			γ_5 -	-		
6	£50K-£75K	γ_6 0.0071	2.22			γ_6 -	-		

Effect on disposable income as per the number of seniors (65+) within household

1	<£10K	θ_1 0.1112	1.91			θ_1 0.4399	20.87		
2	£10K-£20K	θ_2 0.0737	4.85			θ_2 0.2031	20.88		
3	£20K-£30K	θ_3 0.0413	4.62			θ_3 0.1442	16.54		
4	£30K-£40K	θ_4 0.0396	5.03			θ_4 0.1167	12.01		
5	£40K-£50K	θ_5 0.0332	4.30			θ_5 0.1297	12.79		
6	£50K-£75K	θ_6 0.0422	8.54			θ_6 0.0827	7.32		
7	£75K-£100K	θ_7 0.0185	2.39			θ_7 0.082*	-		

Adjusted R-squared: 0.9205	Adjusted R-squared:

* - Interpolated

** - Disposable income vs. original income; (+): tax burden; (-): net benefits

Cash/social benefits Disposable income

The OECD-modified equivalence scale is applied to rescale both the gross and the newly transformed after-tax and disposable household income. The proportional effect of the tax payments and cash benefits on the equivalised income are shown in **Table A.3**. Similar to the previous findings, the lowest income group is shown to receive net income support while households are taxed progressively alongside income increase. The average tax burden implied by the equivalised household income lies between the household and personal income.

Table A.3 – Average tax burden implied by the equivalised household income

Gross equivalised household income	Implied average tax burden (UK VTT SC data)			
	After-tax equivalised household income*		Disposable equivalised personal income**	
	Commute *(n=853)*	Other NB *(n=864)*	Commute *(n=850)*	Other NB *(n=861)*
<£10K	6%	5%	-54%	-58%
£10K-£20K	12%	11%	5%	3%
£20K-£30K	15%	15%	14%	13%
£30K-£40K	17%	17%	17%	16%
£40K-£50K	19%	19%	19%	18%
£50K-£75K	24%	22%	23%	22%
£75K-£100K	25%	25%	24%	25%
>£100K	26%	26%	25%	25%

* Average tax burden= 1- After-tax equivalised HH Income / Gross equivalised HH Income

** Average tax burden = 1-Disposable equivalised HH Income / Gross equivalised HH Income; (+): tax burden; (-) net benefits

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Appendix B

Model estimation and sample enumeration (Appendix to Chapter 3)

Model estimation

A continuous interaction between income and the base VTT is specified in the 2014/15 UK VTT behavioural framework to directly estimate a constant cross-sectional elasticity of VTT with respect to changes in income, given by the following functional form:

$$f(inc, VTT) = \theta_0 \left(\frac{inc}{inc_{ref}} \right)^{\lambda_{inc}} \qquad\qquad (\text{B-5})$$

where $f(inc, VTT)$ is the income elasticity formulation associated with the base underlying VTT, θ_0, as part of a range of interactions of VTT with different covariates (see **Appendix C** for the full formulation). Observed income and reference income are represented as inc and inc_{ref}, respectively; λ_{inc} refers to the cross-sectional income elasticity of VTT. Income is divided by a reference income of £40K to ensure that the base VTT corresponds to the respondent with an annual income of £40K. This specification is retained across all income measurement approaches for a fair comparison of the income elasticity estimates. The selection of the reference income does not affect the model fit or estimation of the income elasticity. For each of the 9 income measurement approaches, the designated income measurement for modelling, either collected by the 2014/15 UK VTT survey or generated by the income transformation, replaces the income variable inc in **Equation B-5**. Valuations of time for each respondent are averaged across the SC data to generate an average behavioural VTT value across sample.

Sample enumeration

The Implementation Tool that make use of the sample enumeration approach is retained in our analysis to compute the mean VTT across the NTS sample and the different confidence measures across different segments. This process involved calculation of the appropriate valuations (of time, reliability, etc.) for each NTS trip in the sample while acknowledging the relevant covariates, and the weighted averages over the sample to derive a nationally representative value. The NTS trips are weighted by both the expansion factor provided with the NTS data and also the trip distance. This implies that the VTT

generated by the Implementation Tool is at an average kilometre basis. This process can be generalised as follows (see Hess et al., 2017, Equation 36):

$$\overline{VTT} = \frac{\sum_i w_i l_i E(VTT_i)}{\sum_i w_i l_i}$$

<div align="right">(B-6)</div>

where w_i represents the expansion factor provided in the NTS data for trip i; l_i represents a trip distance for the NTS trip i for distance weighting, and $E(VTT_i)$ is the valuation formula from the behavioural model, which is as function of covariates, including the income elasticity of VTT (see **Appendix C** for the full formulation).

Appendix C

VTT formulations (Appendix to Chapter 3)

All the 3 SC games are estimated jointly within a single framework to increase robustness for parameters that are shared across games including a series of covariates that are used for explaining deterministic heterogeneity and the set of parameters for explaining random heterogeneity. With the joint modelling framework, different valuations across games are related to the base underlying VTT θ_0 using separate game-specific multipliers, $\zeta_{SPx,VTT}$[1]. The VTT for game x is specified as follows (Hess et al., 2017, Table 2):

$$VTT_{SPx} = \theta_0^{\kappa_{SPx,VTT}} \zeta_{SPx,VTT} \prod_m z_m^{\lambda_m} \prod_n \zeta_n^{z_n} |\Delta t|^{\kappa_{SPx,VTT}-1} \qquad (\text{C-1})$$

where: λ_m represents the elasticity for a continuous covariate z_m (income, time, cost and distance in this case); ζ_n refers to the multiplier applied for a discrete covariate z_n when its value is 1. All covariates are generic across the 3 SC games, meaning that their impacts to the base θ are the same across games. $|\Delta t|^{\kappa_{SPx,VTT}-1}$ is the game specific multiplier related to non-linear relationship between VTT and the change in time[2]. Δt is chosen to be 10 min based on analysis of the empirical evidence from the past UK and recent Scandinavian studies. The VTT is estimated in 2014 perceived prices.

The impact of the continuous interaction between the income measure and the underlying VTT θ_0 is estimated with an 'elasticity specification' set out as follow (Hess et al., 2017, Eq.25):

$$\left(\frac{inc}{40}\right)^{\lambda_{inc}} \delta_{\text{income\_reported}} + \zeta_{\text{not\_stated}} \delta_{\text{income\_not\_stated}} + \zeta_{\text{unknown}} \delta_{\text{income\_unknown}} + \zeta_{\text{refused}} \delta_{\text{refused}} \qquad (\text{C-2})$$

where λ_{inc} is the estimated income elasticity in relation to the continuous income variable; ζ_{not_stated}, $\zeta_{unknown}$ and $\zeta_{refused}$ are the three additional multipliers on the underlying VTT for respondents with unreported income. δ is the corresponding dummy variable denoting whether income is reported or not. Following this specification, we set the

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[1] 6 separate θ measures are estimated across 3 games:
[2] $\kappa = \frac{1-\beta_t}{1-\beta_c}$ where β controls the non-linear sensitivities of gains and losses (i.e., size effects) in the dbf function (see De Borger and Fosgerau, 2008)

reference value of 40 as the denominator for all the different income variables tested in this study such that the base VTT, θ, is estimated based on the preferences of the household/person with annual income of £40K. The reference denominator of the elasticity does not affect the income elasticity calculations and model fit (Hess, 2006). Out of the 977 commuters who responded to the SC survey, 79 of them refused to disclose their income, 34 of them did not state the income or their income is unknown, with the income for the remaining 864 respondents are used to interact with VTT continuously.

References

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Appendix D

Full model results (Appendix to Chapter 3)

Type of non-work journeys	Commuters		Commuters		Commuters		Commuters		Commuters		Commuters	
Income type by intra-household budget allocation	Household Income		Household Income		Household Income		Equiv HH Income		Equiv HH Income		Equiv HH Income	
Income type by income re-distribution measures	Original		After-tax		Disposable		Original		After-tax		Disposable	
Respondents	922		922		922		922		922		922	
Observations	4610		4610		4610		4610		4610		4610	
Final log-likelihood	-7332.67		-7332.74		-7332.06		-7344.37		-7346.19		-7346.95	
	est	rob t-rat	est	rob t-rat	est	rob t-rat	est	rob t-rat	est	rob t-rat	est	rob t-rat
parameters of base Θ_0 distribution (rob t-rat vs. 0)												
a_log(Θ_0) - min value of the underlying dist	-0.3559	-1.74	-0.2794	-1.38	-0.2990	-1.48	-0.2370	-1.14	-0.1818	-0.87	-0.1583	-0.75
b_log(Θ_0) - range of the underlying uniform dist	3.7060	15.62	3.7058	15.63	3.7016	15.61	3.7491	15.32	3.7561	15.26	3.7565	15.26
game specific Θ_0 multipliers (rob t-rat vs. 1)												
SP1 travel time	1	-	1	-	1	-	1	-	1	-	1	-
SP2 travel time	1.5988	4.05	1.6288	4.29	1.6191	4.21	1.6753	4.55	1.7005	4.70	1.7106	4.76
SP2 std dev of travel time	0.5803	-4.75	0.5981	-4.46	0.5951	-4.51	0.6183	-4.10	0.6330	-3.85	0.6408	-3.73
SP3 free flow	0.6968	-2.26	0.7178	-2.07	0.7127	-2.08	0.7610	-1.63	0.7821	-1.45	0.7936	-1.34
SP3 light congestion	0.9770	-0.14	1.0066	0.04	1.0017	0.01	1.0619	0.35	1.0911	0.50	1.1071	0.57
SP3 heavy congestion	1.8557	2.98	1.9122	3.14	1.9026	3.05	2.0065	3.17	2.0601	3.25	2.0893	3.21
key elasticities (rob t-rat vs. 0)												
income elasticity (λ_{income})	0.5797	6.10	0.6432	6.09	0.7806	6.08	0.4534	4.84	0.4707	4.60	0.5733	4.43
distance elasticity ($\lambda_{distance}$)	-	-	-	-	-	-	-	-	-	-	-	-
cost elasticity (λ_{cost})	0.6790	3.70	0.6795	3.71	0.6936	3.78	0.6536	3.55	0.6537	3.54	0.6589	3.57
time elasticity (λ_{time})	-0.6241	-2.62	-0.6248	-2.63	-0.6383	-2.67	-0.5632	-2.36	-0.5572	-2.33	-0.5611	-2.35
traveller covariate (multipliers on Θ unless stated) (rob t-rat vs. 1)												
unstated income ($\zeta_{income not stated}$)	2.4775	0.65	2.2281	0.60	1.2116	0.37	1.9637	0.53	1.8075	0.49	0.9162	-0.19
unknown income ($\zeta_{income unknown}$)	1.4264	1.16	1.2821	0.85	1.3444	0.98	1.1435	0.47	1.0547	0.19	1.0311	0.11
refused income ($\zeta_{income refused}$)	0.7697	-1.30	0.6918	-1.91	0.7256	-1.62	0.6112	-2.61	0.5629	-3.09	0.5496	-3.21
female (base=male)	1.3674	2.26	1.3687	2.27	1.3476	2.17	1.3527	2.16	1.3503	2.15	1.3311	2.06
aged 17-29 (base=30+)	1.3645	1.76	1.3645	1.76	1.3507	1.72	1.3425	1.65	1.3326	1.61	1.3315	1.61
aged 17-39 (base=40+)	-	-	-	-	-	-	-	-	-	-	-	-
household with 2+ adults (base=1 or no adults)	-	-	-	-	-	-	-	-	-	-	-	-
1+ car owned (base=no cars)	-	-	-	-	-	-	-	-	-	-	-	-
2+ motorcycles owned (base=1 or 0 motorcycles)	-	-	-	-	-	-	-	-	-	-	-	-

(Continued)

Type of non-work journeys	Commuters		Commuters		Commuters		Commuters		Commuters		Commuters	
Income type by intra-household budget allocation	Household Income		Household Income		Household Income		Equiv HH Income		Equiv HH Income		Equiv HH Income	
Income type by income re-distribution measures	Original		After-tax		Disposable		Original		After-tax		Disposable	
traveller covariate (multipliers on Ө unless stated) (rob t-rat vs. 1) (continued)												
self-employed (base=any other)	1.6669	1.97	1.6670	1.97	1.5746	1.80	1.6418	1.91	1.6361	1.90	1.5735	1.78
Travel costs paid by company (base=respondent or other paid)	2.2194	3.09	2.2194	3.09	2.2399	3.15	2.1916	3.02	2.1913	3.01	2.1975	3.03
1+ nights away (base=day return)	-	-	-	-	-	-	-	-	-	-	-	-
travelling with others (base=travelling alone)	0.6690	-3.37	0.6689	-3.37	0.6599	-3.47	0.6866	-3.05	0.6887	-3.01	0.6840	-3.05
driving on rural roads (base=urban or motorway)	0.8119	-1.31	0.8113	-1.32	0.8265	-1.19	0.8345	-1.10	0.8359	-1.09	0.8500	-0.98
light congestion (base=free flow)	1.4025	1.57	1.4017	1.57	1.4194	1.62	1.4443	1.67	1.4495	1.69	1.4652	1.72
heavy congestion (base=free flow)	1.5604	1.78	1.5608	1.78	1.5728	1.80	1.5639	1.76	1.5668	1.76	1.5696	1.76
trip with London base origin & destination (base=any other)	-	-	-	-	-	-	-	-	-	-	-	-
design covariates (multipliers on Ө unless stated) (rob t-rat vs. 1)												
SP1 cheap option on left (multiplicative effects coding)	0.8842	-3.26	0.8842	-3.26	0.8848	-3.24	0.8836	-3.28	0.8837	-3.28	0.8838	-3.27
SP3 cheap option on left (multiplicative effects coding)	0.9282	-1.37	0.9283	-1.37	0.9287	-1.36	0.9261	-1.41	0.9259	-1.41	0.9259	-1.41
SP1 time shown above cost (multiplicative Effects coding)	-	-	-	-	-	-	-	-	-	-	-	-
SP2 scale (μ_{sp2}) multiplier if SP2 before SP3 (multiplicative Effects coding)	0.8938	-2.63	0.8937	-2.63	0.8944	-2.62	0.8932	-2.64	0.8930	-2.65	0.8933	-2.64
scale parameters (rob t-rat vs. 0)												
μ_{sp1}	1.1975	14.71	1.1973	14.71	1.1999	14.67	1.1970	14.66	1.1978	14.66	1.1975	14.58
μ_{sp2}	7.7383	18.05	7.7381	18.05	7.7488	18.07	7.7445	18.06	7.7463	18.06	7.7530	18.09
μ_{sp3}	5.6636	14.65	5.6636	14.66	5.6472	14.50	5.6785	14.22	5.6766	14.12	5.6700	13.91
dBF parameters (rob t-rat vs. 0)												
$\beta_{t, sp1}$	-0.4000	-3.64	-0.4003	-3.64	-0.4027	-3.65	-0.3860	-3.46	-0.3835	-3.43	-0.3862	-3.44
$\beta_{t, sp2}$	-0.1564	-2.84	-0.1564	-2.84	-0.1567	-2.81	-0.1542	-2.82	-0.1534	-2.80	-0.1542	-2.81
$\beta_{c, sp1}$	-	-	-	-	-	-	-	-	-	-	-	-
$\Upsilon_{t, sp1}$	-0.2127	-3.52	-0.2129	-3.52	-0.2123	-3.49	-0.2098	-3.51	-0.2089	-3.50	-0.2093	-3.48
$\Upsilon_{t, sp2}$	-	-	-	-	-	-	-	-	-	-	-	-
$\Upsilon_{c, sp3}$	-	-	-	-	-	-	-	-	-	-	-	-
$\eta_{t, sp1}$	0.2573	4.34	0.2573	4.34	0.2559	4.33	0.2580	4.35	0.2578	4.35	0.2573	4.34
$\eta_{t, sp2}$	0.0874	1.43	0.0874	1.43	0.0886	1.46	0.0790	1.30	0.0786	1.29	0.0781	1.29
$\eta_{c, sp1}$	0.1267	2.18	0.1268	2.18	0.1272	2.19	0.1250	2.15	0.1246	2.14	0.1254	2.15
$\eta_{c, sp2}$	-	-	-	-	-	-	-	-	-	-	-	-
$\eta_{c, sp3}$	0.2771	1.51	0.2768	1.51	0.2830	1.51	0.2890	1.47	0.2916	1.46	0.2985	1.45
	Commuters		Commuters		Commuters		Other trips		Other trips		Other trips	

Type of non-work journeys

Income type by intra-household budget allocation	Personal Income		Personal Income		Personal Income		Household Income		Household Income		Household Income	
Income type by income re-distribution measures	Original		After-tax		Disposable		Original		After-tax		Disposable	
Respondents	922		922		922		977		977		977	
Observations	4610		4610		4610		4885		4885		4885	
Final log-likelihood	-7356.05		-7356.29		-7351.96		-7585.74		-7585.82		-7589.81	
	est	rob t-rat	est	rob t-rat	est	rob t-rat	est	rob t-rat	est	rob t-rat	est	rob t-rat
parameters of base Θ_0 distribution (rob t-rat vs. 0)												
a_log(Θ_0) - min value of the underlying dist	-0.4137	-1.87	-0.3545	-1.60	-0.2981	-1.35	-0.8840	-2.65	-0.7851	-2.35	-0.8136	-2.43
b_log(Θ_0) - range of the underlying uniform dist	3.8178	14.64	3.8186	14.64	3.8077	14.64	3.7141	19.16	3.7154	19.15	3.7182	19.24
game specific Θ_0 multipliers (rob t-rat vs. 1)												
SP1 travel time	1	-	1	-	1	-	1	-	1	-	1	-
SP2 travel time	1.6304	4.11	1.6500	4.28	1.6622	4.42	2.1875	5.52	2.1928	5.74	2.1918	5.66
SP2 std dev of travel time	0.5973	-4.38	0.6098	-4.18	0.6225	-4.01	0.8118	-1.48	0.8341	-1.29	0.8264	-1.34
SP3 free flow	0.7541	-1.58	0.7701	-1.46	0.7843	-1.36	0.5008	-4.43	0.5145	-4.20	0.5027	-4.37
SP3 light congestion	1.0557	0.29	1.0781	0.40	1.0981	0.49	0.8801	-0.90	0.9042	-0.70	0.8872	-0.84
SP3 heavy congestion	1.9814	2.79	2.0232	2.88	2.0621	2.96	1.9955	4.05	2.0500	4.22	2.0212	4.13
key elasticities (rob t-rat vs. 0)												
income elasticity (λ_{income})	0.3192	3.19	0.3491	3.15	0.5438	3.78	0.6819	7.76	0.7526	7.77	0.9269	7.35
distance elasticity ($\lambda_{distance}$)	-	-	-	-	-	-	-	-	-	-	-	-
cost elasticity (λ_{cost})	0.6631	3.54	0.6639	3.55	0.6537	3.49	1.0492	6.56	1.0500	6.57	1.0299	6.33
time elasticity (λ_{time})	-0.5577	-2.29	-0.5577	-2.29	-0.5608	-2.29	-0.9273	-4.72	-0.9283	-4.73	-0.8769	-4.39
traveller covariate (multipliers on Θ unless stated) (rob t-rat vs. 1)												
unstated income ($\zeta_{income\ not\ stated}$)	0.7603	-0.59	0.7019	-0.79	0.6777	-1.16	1.0117	0.03	0.8937	-0.29	0.9735	-0.07
unknown income ($\zeta_{income\ unknown}$)	0.8934	-0.34	0.8259	-0.59	0.7502	-0.93	0.2998	-5.89	0.2648	-6.97	0.2755	-6.62
refused income ($\zeta_{income\ refused}$)	0.7466	-1.41	0.6898	-1.81	0.6329	-2.31	0.8643	-0.77	0.7634	-1.49	0.8034	-1.18
female (base=male)	1.4326	2.40	1.4308	2.40	1.4573	2.52	-	-	-	-	-	-
aged 17-29 (base=30+)	1.3377	1.59	1.3346	1.58	1.3761	1.72	-	-	-	-	-	-
aged 17-39 (base=40+)	-	-	-	-	-	-	1.4530	2.52	1.4525	2.51	1.3221	1.96
household with 2+ adults (base=1 or no adults)	-	-	-	-	-	-	0.6980	-3.47	0.6977	-3.48	0.7312	-2.97
1+ car owned (base=no cars)	-	-	-	-	-	-	2.6826	1.91	2.6790	1.90	2.5416	1.83
2+ motorcycles owned (base=1 or 0 motorcycles)	-	-	-	-	-	-	0.4668	-1.65	0.4652	-1.66	0.4871	-1.50

(Continued)

Type of non-work journeys	Commuters		Commuters		Commuters		Other trips		Other trips		Other trips	
Income type by intra-household budget allocation	Personal Income		Personal Income		Personal Income		Household Income		Household Income		Household Income	
Income type by income re-distribution measures	Original		After-tax		Disposable		Original		After-tax		Disposable	
traveller covariate (multipliers on Ɵ unless stated) (rob t-rat vs. 1) (continued)												
self-employed (base=any other)	1.6478	1.87	1.6471	1.87	1.6370	1.84	-	-	-	-	-	-
Travel costs paid by company (base=respondent or other paid)	2.1951	3.05	2.1956	3.05	2.1914	3.07	-	-	-	-	-	-
1+ nights away (base=day return)	-	-	-	-	-	-	1.5522	2.14	1.5525	2.14	1.5396	2.09
travelling with others (base=travelling alone)	0.6921	-2.98	0.6923	-2.98	0.6910	-3.02	-	-	-	-	-	-
driving on rural roads (base=urban or motorway)	0.8614	-0.88	0.8609	-0.89	0.8689	-0.84	-	-	-	-	-	-
light congestion (base=free flow)	1.4795	1.73	1.4804	1.73	1.4706	1.71	1.3554	1.51	1.3546	1.51	1.3688	1.57
heavy congestion (base=free flow)	1.5996	1.80	1.6000	1.80	1.6044	1.81	1.4621	1.57	1.4649	1.57	1.3916	1.39
trip with London base origin & destination (base=any other)	-	-	-	-	-	-	-	-	-	-	-	-
design covariates (multipliers on Ɵ unless stated) (rob t-rat vs. 1)												
SP1 cheap option on left (multiplicative effects coding)	0.8863	-3.23	0.8863	-3.23	0.8867	-3.23	0.9259	-2.00	0.9259	-2.00	0.9266	-1.97
SP3 cheap option on left (multiplicative effects coding)	0.9260	-1.39	0.9260	-1.39	0.9267	-1.37	0.9537	-0.85	0.9536	-0.85	0.9516	-0.89
SP1 time shown above cost (multiplicative Effects coding)	-	-	-	-	-	-	-	-	-	-	-	-
SP2 scale (μ_{sp2}) multiplier if SP2 before SP3 (multiplicative Effects coding)	0.8914	-2.69	0.8914	-2.70	0.8919	-2.68	-	-	-	-	-	-
scale parameters (rob t-rat vs. 0)												
μ_{sp1}	1.2149	14.88	1.2149	14.87	1.2171	14.99	1.3014	16.53	1.3015	16.53	1.3009	16.51
μ_{sp2}	7.7336	17.98	7.7340	17.98	7.7293	18.01	7.5389	16.92	7.5391	16.92	7.5271	16.85
μ_{sp3}	5.6316	13.34	5.6315	13.34	5.6237	13.36	5.9410	17.07	5.9401	17.07	5.9374	17.09
dBF parameters (rob t-rat vs. 0)												
$\beta_{t, sp1}$	-0.3496	-3.10	-0.3496	-3.09	-0.3461	-3.08	-0.1366	-1.91	-0.1364	-1.91	-0.1368	-1.91
$\beta_{t, sp2}$	-0.1500	-2.61	-0.1498	-2.61	-0.1526	-2.67	-0.2435	-4.96	-0.2435	-4.97	-0.2443	-4.91
$\beta_{c, sp1}$	-	-	-	-	-	-	0.1032	1.78	0.1031	1.78	0.1061	1.83
$\Upsilon_{t, sp1}$	-0.1962	-3.41	-0.1963	-3.41	-0.1949	-3.40	-0.1075	-2.75	-0.1075	-2.75	-0.1063	-2.71
$\Upsilon_{t, sp2}$	-	-	-	-	-	-	-0.0606	-1.79	-0.0606	-1.79	-0.0608	-1.79
$\Upsilon_{c, sp3}$	-	-	-	-	-	-	-	-	-	-	-	-
$\eta_{t, sp1}$	0.2573	4.41	0.2572	4.41	0.2575	4.42	0.2237	4.20	0.2237	4.20	0.2233	4.19
$\eta_{t, sp2}$	0.0889	1.45	0.0888	1.45	0.0916	0.00	-	-	-	-	-	-
$\eta_{c, sp1}$	0.1195	2.10	0.1195	2.10	0.1185	2.09	-	-	-	-	-	-
$\eta_{c, sp2}$	-	-	-	-	-	-	0.2244	2.88	0.2247	2.89	0.2247	2.87
$\eta_{c, sp3}$	0.3084	1.41	0.3086	1.41	0.3067	1.41	-	-	-	-	-	-

Type of non-work journeys	Other trips		Other trips		Other trips		Other trips		Other trips		Other trips	
Income type by intra-household budget allocation	Equiv HH Income		Equiv HH Income		Equiv HH Income		Personal Income		Personal Income		Personal Income	
Income type by income re-distribution measures	Original		After-tax		Disposable		Original		After-tax		Disposable	
Respondents	977		977		977		977		977		977	
Observations	4885		4885		4885		4885		4885		4885	
Final log-likelihood	-7595.96		-7597.58		-7598.97		-7608.36		-7608.53		-7606.65	
	est	**rob t-rat**	**est**	**rob t-rat**	**est**	**rob t-rat**	**est**	**rob t-rat**	**est**	**rob t-rat**	**est**	**rob t-rat**
parameters of base Θ_0 distribution (rob t-rat vs. 0)												
a_log(Θ_0) - min value of the underlying dist	-0.9496	-2.84	-0.8807	-2.63	-0.8533	-2.54	-1.0318	-3.06	-0.9440	-2.80	-0.8551	-2.52
b_log(Θ_0) - range of the underlying uniform dist	3.7337	19.10	3.7392	19.09	3.7292	19.19	3.7909	18.68	3.7915	18.68	3.7774	18.69
game specific Θ_0 multipliers (rob t-rat vs. 1)												
SP1 travel time	1	-	1	-	1	-	1	-	1	-	1	-
SP2 travel time	2.1929	5.43	2.1979	5.60	2.1963	5.64	2.2166	5.25	2.2153	5.45	2.2179	5.65
SP2 std dev of travel time	0.8028	-1.56	0.8197	-1.41	0.8192	-1.41	0.8109	-1.48	0.8284	-1.34	0.8417	-1.23
SP3 free flow	0.4905	-4.55	0.5001	-4.38	0.4937	-4.46	0.4917	-4.56	0.5023	-4.39	0.5064	-4.31
SP3 light congestion	0.8645	-1.01	0.8816	-0.88	0.8747	-0.93	0.8666	-1.00	0.8851	-0.86	0.8975	-0.76
SP3 heavy congestion	1.9605	3.91	1.9991	4.04	1.9926	4.00	1.9632	3.96	2.0051	4.13	2.0406	4.28
key elasticities (rob t-rat vs. 0)												
income elasticity (λ_{income})	0.5915	6.89	0.6346	6.78	0.8346	6.52	0.4352	5.96	0.4781	5.94	0.6976	6.12
distance elasticity ($\lambda_{distance}$)	-	-	-	-	-	-	-	-	-	-	-	-
cost elasticity (λ_{cost})	1.0565	6.52	1.0594	6.52	1.0355	6.30	1.0846	6.66	1.0866	6.67	1.0554	6.49
time elasticity (λ_{time})	-0.9475	-4.75	-0.9508	-4.76	-0.9090	-4.51	-0.9549	-4.76	-0.9573	-4.77	-0.9105	-4.55
traveller covariate (multipliers on Θ unless stated) (rob t-rat vs. 1)												
unstated income ($\zeta_{income\ not\ stated}$)	0.7875	-0.63	0.6990	-0.99	0.6678	-1.27	0.5231	-2.42	0.4689	-2.97	0.4384	-3.53
unknown income ($\zeta_{income\ unknown}$)	0.2320	-8.12	0.2058	-9.36	0.1890	-10.30	0.2641	-7.29	0.2368	-8.35	0.2190	-9.25
refused income ($\zeta_{income\ refused}$)	0.7068	-1.93	0.6304	-2.64	0.5907	-3.00	0.7802	-1.36	0.6997	-2.01	0.6459	-2.52
female (base=male)	-	-	-	-	-	-	-	-	-	-	-	-
aged 17-29 (base=30+)	-	-	-	-	-	-	-	-	-	-	-	-
aged 17-39 (base=40+)	1.5798	2.92	1.5881	2.94	1.5087	2.71	1.4849	2.61	1.4850	2.61	1.4491	2.49
household with 2+ adults (base=1 or no adults)	0.9170	-0.74	0.9390	-0.53	1.0428	0.33	0.9078	-0.84	0.9080	-0.84	0.9048	-0.87
1+ car owned (base=no cars)	2.9969	2.04	3.0288	2.05	2.9201	2.00	2.9335	2.08	2.9354	2.08	2.8284	2.04
2+ motorcycles owned (base=1 or 0 motorcycles)	0.4988	-1.47	0.5009	-1.46	0.5266	-1.32	0.4352	-1.78	0.4351	-1.78	0.4411	-1.74

(Continued)

Type of non-work journeys	Other trips		Other trips		Other trips		Other trips		Other trips		Other trips	
Income type by intra-household budget allocation	Equiv HH Income		Equiv HH Income		Equiv HH Income		Personal Income		Personal Income		Personal Income	
Income type by income re-distribution measures	Original		After-tax		Disposable		Original		After-tax		Disposable	
traveller covariate (multipliers on Ɵ unless stated) (rob t-rat vs. 1) (continued)												
self-employed (base=any other)	-	-	-	-	-	-	-	-	-	-	-	-
Travel costs paid by company (base=respondent or other paid)	-	-	-	-	-	-	-	-	-	-	-	-
1+ nights away (base=day return)	1.5638	2.16	1.5661	2.16	1.5493	2.11	1.5749	2.19	1.5766	2.19	1.5557	2.15
travelling with others (base=travelling alone)	-	-	-	-	-	-	-	-	-	-	-	-
driving on rural roads (base=urban or motorway)	-	-	-	-	-	-	-	-	-	-	-	-
light congestion (base=free flow)	1.3622	1.52	1.3614	1.51	1.3801	1.59	1.3540	1.50	1.3544	1.50	1.3485	1.49
heavy congestion (base=free flow)	1.4435	1.51	1.4448	1.51	1.3763	1.35	1.4197	1.45	1.4212	1.45	1.3958	1.39
trip with London base origin & destination (base=any other)	-	-	-	-	-	-	-	-	-	-	-	-
design covariates (multipliers on Ɵ unless stated) (rob t-rat vs. 1)												
SP1 cheap option on left (multiplicative effects coding)	0.9269	-1.98	0.9271	-1.98	0.9273	-1.96	0.9289	-1.95	0.9289	-1.95	0.9299	-1.92
SP3 cheap option on left (multiplicative effects coding)	0.9568	-0.79	0.9569	-0.78	0.9569	-0.79	0.9497	-0.93	0.9497	-0.93	0.9496	-0.93
SP1 time shown above cost (multiplicative Effects coding)	-	-	-	-	-	-	-	-	-	-	-	-
SP2 scale (μ_{sp2}) multiplier if SP2 before SP3 (multiplicative Effects coding)	-	-	-	-	-	-	-	-	-	-	-	-
scale parameters (rob t-rat vs. 0)												
μ_{sp1}	1.3059	16.52	1.3065	16.52	1.3058	16.49	1.3098	16.57	1.3099	16.57	1.3091	16.58
μ_{sp2}	7.5407	16.92	7.5407	16.92	7.5289	16.87	7.5239	16.86	7.5238	16.86	7.5272	16.87
μ_{sp3}	5.9269	16.97	5.9249	16.95	5.9201	16.96	5.9217	16.96	5.9216	16.96	5.9087	16.96
dBF parameters (rob t-rat vs. 0)												
$\beta_{t,\,sp1}$	-0.1382	-1.94	-0.1378	-1.94	-0.1407	-1.97	-0.1264	-1.76	-0.1264	-1.76	-0.1266	-1.76
$\beta_{t,\,sp2}$	-0.2460	-5.02	-0.2461	-5.03	-0.2482	-5.01	-0.2454	-5.00	-0.2455	-5.00	-0.2434	-4.94
$\beta_{c,\,sp1}$	0.1013	1.75	0.1009	1.74	0.1040	1.80	0.0919	1.56	0.0920	1.56	0.0914	1.55
$\gamma_{t,\,sp1}$	-0.1082	-2.77	-0.1081	-2.77	-0.1079	-2.75	-0.1055	-2.75	-0.1054	-2.75	-0.1061	-2.77
$\gamma_{t,\,sp2}$	-0.0572	-1.69	-0.0569	-1.68	-0.0566	-1.67	-0.0558	-1.63	-0.0558	-1.63	-0.0563	-1.64
$\gamma_{c,\,sp3}$	-	-	-	-	-	-	-	-	-	-	-	-
$\eta_{t,\,sp1}$	0.2209	4.17	0.2207	4.16	0.2195	4.14	0.2243	4.21	0.2242	4.21	0.2240	4.21
$\eta_{t,\,sp2}$	-	-	-	-	-	-	-	-	-	-	-	-
$\eta_{c,\,sp1}$	-	-	-	-	-	-	-	-	-	-	-	-
$\eta_{c,\,sp2}$	0.2225	2.86	0.2225	2.86	0.2221	2.85	0.2185	2.77	0.2186	2.78	0.2178	2.77
$\eta_{c,\,sp3}$	-	-	-	-	-	-	-	-	-	-	-	-

Appendix E

Calculating errors for WTP measures (Appendix to Chapter 4)

Following the notation as in Daly et al. (2012), we define Φ as a differentiable and invertible function of a number of model parameters β. Applying the Delta method, the variance of the function Φ is equal to:

$$\text{var}(\Phi) = \sum_{l=1}^{L} \phi_l'^2 \omega_{ll} + 2 \sum_{l=2}^{L} \sum_{m=1}^{l-1} \phi_l' \phi_m' \omega_{lm}$$

CASE 1 $(\lambda > 0)$: When data limit is log-transformed and cost is Box-Cox transformed, function Φ becomes:

$$\Phi = \frac{\partial V / \partial \text{Dlim}_{LN}}{\partial V / \partial \text{Cost}_{BC}} = \frac{\beta_{dlim}}{\text{Dlim}\,\beta_{cost}(\text{Cost})^{\lambda-1}}$$

Individual elements Φ', which is the first derivative matrix of Φ, and the variance of Φ are given by:

$$\phi_k' = \frac{\partial \Phi}{\partial \beta^*}$$

For $\beta^* = \beta_{dlim}$: $\quad \phi_1' = \frac{1}{\text{Dlim}\,\beta_{cost}(\text{Cost})^{\lambda-1}}$

For $\beta^* = \beta_{cost}$: $\quad \phi_2' = -\frac{\beta_{dlim}}{\text{Dlim}\,\beta_{cost}^2(\text{Cost})^{\lambda-1}}$

For $\beta^* = \lambda$: $\quad \phi_3' = -\frac{\beta_{dlim}(\lambda-1)}{\text{Dlim}\,\beta_{cost}\text{Cost}^{\lambda}}$

$$\text{var}(\Phi) = \phi_1'^2 \omega_{11} + \phi_2'^2 \omega_{22} + \phi_3'^2 \omega_{33} + 2(\phi_2'\phi_1'\omega_{21} + \phi_3'\phi_1'\omega_{31} + \phi_3'\phi_2'\omega_{32})$$

CASE 2 $(\lambda = 0)$: When data limit is log-transformed and cost is log-transformed, then Φ, Φ_k', and $\text{var}(\Phi)$ are given by:

$$\Phi = \frac{\partial V / \partial \text{Dlim}_{LN}}{\partial V / \partial \text{Cost}_{LN}} = \frac{\beta_{dlim}\text{Cost}}{\beta_{cost}\text{Dlim}}$$

For $\beta^* = \beta_{dlim}$: $\quad \phi_1' = \frac{\text{Cost}}{\beta_{cost}\text{Dlim}}$

For $\beta^* = \beta_{cost}$: $\phi'_2 = -\dfrac{\beta_{dlim} Cost}{\beta^2_{cost} Dlim}$

$$\text{var}(\Phi) = \phi'^2_1 \omega_{11} + \phi'^2_2 \omega_{22} + 2\phi'_2 \phi'_1 \omega_{21}$$

CASE 3: When data limit is log-transformed, while cost is linear, Φ, Φ'_k, and var(Φ) become:

$$\Phi = \frac{\partial V/\partial Dlim_{LN}}{\partial V/\partial Cost_{linear}} = \frac{\beta_{dlim}}{\beta_{cost} Dlim}$$

For $\beta^* = \beta_{dlim}$: $\phi'_1 = \dfrac{1}{\beta_{cost} Dlim}$

For $\beta^* = \beta_{cost}$: $\phi'_2 = -\dfrac{\beta_{dlim}}{\beta^2_{cost} Dlim}$

$$\text{var}(\Phi) = \phi'^2_1 \omega_{11} + \phi'^2_2 \omega_{22} + 2\phi'_2 \phi'_1 \omega_{21}$$

References

Daly, A., Hess, S. & de Jong, G. 2012. Calculating errors for measures derived from choice modelling estimates. *Transportation Research Part B: Methodological,* 46**,** 333-341.

Appendix F

Stated choice survey forms (Appendix to Chapter 4)

Start menu (in Polish)

English translation:

Dear Sir/Madam

You are presented with a survey form that aims to collect data on young people's preferences for internet services.

The study consists of three parts. Each of them has 8 to 10 situations in which you will be asked to indicate the offer that you think is best for you.

The data collected will be used for scientific purposes only. Your individual answers will not be disclosed to anyone - the results of the study will be presented in the form of summary statements.

In case of problems or irregularities in using the application, please contact Dr Marek Giergiczny, mig@wne.uw.edu.pl

Background questions (in Polish):

English translation:

A1. Do you have internet access at home?

- Wireless router/modem VDSL/ADSL
- Ethernet
- WiFi and Ethernet
- I don't have

A2. How often do you stream or download TV/movies

- Every two weeks
- About 1 time per two weeks
- 1 per month
- 1 per 6 months
- Less frequently
- Never

A3. Do you have a mobile phone? Yes/No

A4. What is your approximate mobile data transfer limit? (It is about the amount of data that can be downloaded or sent without limiting the speed of transfer)

- _____GB/month (value must be greater than 0, or may be in fractions, e.g. 0.5)

- I have unlimited data access
- I don't know / hard to say

A5. What is the approximate cost of your cellular data package?

- _____ zł /month (value must be greater than 0)
- I don't know / hard to say

A4) Do you have a laptop: Yes/No

A5) Do you have a tablet: Yes/No

Treatment 1: Instructions (in Polish)

English translation:

Imagine that University of Warsaw would offer all students access to a free or paid (depending on the variant) service to broadband Internet (4G LTE) inside and outside the University.

LTE is a technology for wireless mobile data transmission, which is the fastest amongst those currently available in Poland and in the world.

How fast is LTE?

LTE throughput is in practice around 4MB/s (download) and 2 MB/s (sending). This means that a HD movie (about 2.5GB) could be downloaded in about 10 minutes. Faster data

transmission allows for trouble-free use of e.g. video conference, watching live movies, exchanging larger amounts of data, online games, etc.

People who would decide to purchase the service would receive a **free SIM card** that will allow them to use the service on smartphones and a **USB modem** (the size of a pendrive) that would allow the use of broadband Internet (4G LTE) using laptops, tablets and desktops in any place in Poland within the range of this technology.

The service, depending on the variant chosen, could allow the simultaneous use of one, two or a maximum of three devices (smartphone, tablet, laptop, desktop computer, etc.).

Unlike the university's wireless Wi-Fi network, which has no limit on data transfer, and still will not have any limit, the service of access to broadband Internet (4G LTE) **will have a monthly limit on data transfer**

We would like you to indicate now the variant that you would choose, if such a service were available. In each of the following selection situations, you can also indicate that you would not decide to use this service, if there would be such variants - please select the option: *Current situation*.

Please treat each of the 8 subsequent situations independently.

Treatment 1: Sample choice task (in Polish)

English translation:

University WI-FI network

- Monthly cost (Current situation / Package A / Package B)

Access to broadband internet (4G LTE)

- Monthly cost (Package A / Package B)

- Monthly data transfer limit (Package A / Package B)

- Maximum number of devices (Package A / Package B)

Treatment 1: Follow-up questions for non-traders

English translation:

Please select the best answer:
- I do not use 4G data outside campus
- The 4G data package offered here is too expensive
- The 4G data package offered here does not give me enough data limit
- I am happy with my existing 4G data access
- I cannot switch mobile companies/packages anytime soon as I have signed up for a fixed contract already
- These 4G data packages are confusing
- Other, please specify: _____

Treatment 2: Instructions (in Polish)

English translation:

Now imagine that the University of Warsaw would introduce a mandatory monthly fee for access to a wireless WiFi network. In addition, (over the basic fee) it would be possible to purchase access to broadband Internet (4G LTE).

We would like you to indicate now the variant which you would choose in such a situation. Please note that in this situation, choosing the current option would mean paying the monthly cost of accessing the University's wireless network

Please treat each of the 8 subsequent situations independently.

Treatment 2: Sample choice task (in Polish)

Karta D2/2/1		Obecna sytuacja	Pakiet A	Pakiet B
Uniwersytecka sieć WiFi	Miesięczny koszt	1 zł	1 zł	1 zł
Dostęp do szerokopasmowego Internetu (4G LTE)	Miesięczny koszt	-	30 zł	40 zł
	Miesięczny limit transferu danych	-	5 GB	10 GB
	Maksymalna liczba urządzeń	-	3	1
		Najlepsza	Najlepsza	Najlepsza
			Dalej	

Biorąc pod uwagę miesięczny koszt i pozostałe cechy ofert proszę wybrać najlepszy Pani/Pana zdaniem wariant

English translation:

University WI-FI network

- Monthly cost (Current situation / Package A / Package B)

Access to broadband internet (4G LTE)

- Monthly cost (Package A / Package B)
- Monthly data transfer limit (Package A / Package B)
- Maximum number of devices (Package A / Package B)

Treatment 2: Follow-up questions for non-traders (in Polish)

English translation:

Please choose the best answer:

- I do not use 4G data outside campus

- The 4G data package offered here is too expensive

- The 4G data package offered here does not give me enough data limit

- I am happy with my existing 4G data access

- I cannot switch mobile companies/packages anytime soon as I have signed up for a fixed contract already

- These 4G data packages are confusing

- I am against the policy that University should charge for Wi-Fi connection at all

- Other, please specify: _____

Treatment 3: Instructions (in Polish)

Mobile 2017 X					_ ◻ ✕
Podaj numer swojego indeksu oraz inicjały:					
Indeks: 1	Inicjały - (I)mię (N)azwisko: XX	Wskaż płeć: M ▾		Połącz z serwerem	

Część 3

Wyobraź sobie, że Uniwersytet Warszawski zaoferowałby wszystkim studentom kartę sim oraz modem USB z funkcją WiFi, umożliwiające korzystanie z szerokopasmowej sieci 4G LTE na terenie Uniwersytetu i poza nim.

Dodatkowo, Uniwersytet utrzymywałby bezpłatną sieć WiFi (jak obecnie). Dlatego nawet jeżeli ktoś wyczerpałby limit transferu danych szerokopasmowego Internetu (4G LTE), **na terenie Uniwersytetu** nadal miałby **nieograniczony dostęp do Internetu** przez sieć WiFi.

Chcielibyśmy, aby wskazał(a) Pan(i) teraz wariant dostępu do szerokopasmowego Internetu (4G LTE), który uważa Pan(i) za najkorzystniejszy dla siebie.

Każdą z 10 kolejnych sytuacji wyboru proszę traktować niezależnie.

Dalej

English translation:

Imagine that the University of Warsaw would offer all students a sim card and a USB modem with Wi-Fi function, enabling the use of 4G LTE broadband network within and outside the University

In addition, the University would maintain a free Wi-Fi network (as it is now). Therefore, even if someone cuts out the data transfer limit of the broadband internet, the university still has unlimited access to the internet via the Wi-Fi network.

We would like you to indicate the broadband access variant you consider the most rewarding for you.

Treatment 3: Sample choice task (in Polish)

	Karta D3/1/2	Pakiet A	Pakiet B
	Miesięczny koszt	1 zł	40 zł
Dostęp do szerokopasmowego Internetu (4G LTE)	**Miesięczny limit transferu danych**	10 GB	20 GB
	Maksymalna liczba urządzeń	1	3
		Najlepsza	Najlepsza

Biorąc pod uwagę miesięczny koszt i pozostałe cechy ofert proszę wybrać najlepszy Pani/Pana zdaniem wariant

Podaj numer swojego indeksu oraz inicjały: Indeks: 1 Inicjały - (I)mię (N)azwisko: XX Wskaż płeć: M Połącz z serwerem

English translation:

Access to broadband internet (4G LTE)

- Monthly cost (Package A / Package B)
- Monthly data transfer limit (Package A / Package B)
- Maximum number of devices (Package A / Package B)

Follow-up questions (in Polish)

English translation:

In each question, select 1 (strongly disagree) to 7 (strongly agree)

1. I love having unlimited data access as I am a heavy internet user
2. Whenever I go to places where there is no free Wi-Fi connection, I try to restrict myself from downloading big files to save mobile data usage
3. I often reach (or almost reach) my monthly mobile data limit
4. I had been looking for good or better deals for mobile data package recently
5. The idea of being able to connect to internet with laptop and all my mobile devices outside campus seems pleasant to me
6. Do you agree that the 4G data package presented in this survey is attractive compared to what the market is currently offering?
7. Please provide any additional comments regarding this survey