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Understanding the structure of preference heterogeneity in public transport and air travel using structural choice modelling

By

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Abstract

Explaining and predicting the choices of consumers is perhaps the most enduring research problem faced by the behavioural sciences. Of the range of methods used to gather information about consumers preferences, choice based approaches are common place in both academia and industry. For the most part, consumers preferences from this type of data are typically evaluated assuming preferences for the attributes of alternatives in choice are independent as a necessity due to the limitations of the statistical model. Recent advances in choice modelling however present an opportunity to consider that there may be a latent structure to decision makers' taste sensitivities (preference parameters) and further, behavioural decision theory may be useful in helping the researcher specify that structure. This thesis documents three applications of structural choice modelling that both test behavioural decision theory as well as contribute new interpretations about how behavioural decision theory may manifest as structures within the latent dimensions of consumers utility function. Each application considers the structure of the taste variation (preference heterogeneity) in decision makers' taste sensitivities towards the attributes of transport services. In each case, behavioural decision theory is drawn upon to first predict what structures might be expected, and subsequently structural choice models are specified to represent theory. This unique modelling approach allows the following types of research questions to be addressed:

- How does the nature of the choice environment affect the taste sensitivities in decision makers' preferences for particular product/service attributes?

- Are latent sources of variation in consumers taste sensitivities stable or dynamic?

- What are the drivers of commonalities between the decision makers' taste sensitivities for the attributes of alternatives in choice?
- Is there a relationship between the way consumers think about their priorities and the way consumers make choices?

These questions are explored using so-called structural choice models. Structural choice models are type of factor-analytic choice model (a very general form of mixed logit). The model allows for a parsimonious representation of the ways in which consumers vary in their tastes and preferences. Representing the unobserved sources of taste variation as latent variables and specifying a structure to the latent variables offer great flexibility, including data from the same consumers from different choice tasks. This allows the researcher, for example, to specify latent variables general to several data generation processes and others unique to one particular process. Thus, the extent to which attributes under different scenarios are indeed treated by decision makers' as the same can be assessed. From a policy perspective, the design of more nuanced policy responses may be possible given the insight into the structure of the heterogeneity in decision makers' preferences. The thesis is presented in the following way. Firstly, the introduction provides an overview of behavioural decision theory, choice based methods, structural choice modelling and its general econometric specifications. Next, the empirical results of three separate but related studies are presented. The studies document applications of the structural choice model to representing testing latent variable representations of taste variation. Finally, the conclusion provides a summary of all the results as well as discusses the future of research in this area.

Declarations by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

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Publications during candidature

Journal Articles

Magor, T. and Coote, L. (2014) Latent variables as a proxy for inherent preferences: A test of antecedent volition, *Journal of Choice Modelling*, 13, 24 – 36.

Conference Papers

Coote, L., Magor, T., and Pappu, U. (2015). Market Structure Analysis: Using Arithmetic and Likelihood Approaches in the Classroom, *American Marketing Educators Conference*, August 2015. Chicago, IL., USA.

Coote, L., Towhidul, I., Louviere, J. and Magor, T. (2015). Mixed Logit Specifications for Testing Preference Stability: A Four-Wave Panel Analysis. *International Choice Modelling Conference May 2015*, Austin, TX., USA.

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Contributor	**Statement of contribution**
Thomas Magor	Conception and design (100%)
	Analysis and interpretation (80%)
	Drafting and production (80%)
Len Coote	Conception and design (0%)
	Analysis and interpretation (20%)
	Drafting and production (20%)

Contributions by others to the thesis

With the exception of Study 2 which is co-authored by myself and my primary supervisor, Len Coote, there are no contributions by others.

Statement of parts of the thesis submitted to qualify for the award of another degree

Study 2 of the thesis uses a dataset collected as part of my Bachelor of Business Management (Honours) thesis in 2012. The models, interpretations and conclusions advanced in Study 2 using this dataset are unique. No part of the honours thesis is included in the PhD thesis. Approval for the use of this dataset has been granted by the UQ Graduate School.

Research Involving Human or Animal Subjects

All research involving human or animal subjects requires prior ethical review and approval by an independent review committee. At UQ, the relevant committee for research involving human subjects is the Human Ethics Unit and the relevant committee for research involving animal subjects is the relevant Animal Ethics Committee. Details of ethics approvals obtained including the ethics approval number and name of approving committees are attached in the thesis appendix.

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- ANZSRC code: 1505 Marketing, 100%

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List of Abbreviations and Symbols

Structural choice model parameters

U_i Utility (preference)

V_i Systematic component of utility

x_i Attribute levels (controlled in experimental design of DCE)

μ_ϵ Mean value of parameters representing taste sensitivity

σ_ϵ Standard deviation of parameters representing taste sensitivity

μ_δ Mean value of parameters representing the error component of a latent variable

σ_δ Standard deviation of parameters representing the error component of a latent variable

η_i Sensitivity towards an attribute

$\gamma_{j,i}$ Factor loading of primary preference onto latent variable

ξ_j Latent variable

$\beta_{m,i}$ Factor loading of latent variable onto another latent variable

β_m Factor loading of latent variable onto higher order latent variable

1
Introduction

The way choices we make in the market place is typically thought to be the result of a careful deliberation about the pros/cons of a particular choice using the available information prepared by marketers or shared with us by other people, as well as reflections on own previous experiences, attitudes and norms. However, not all decision makers are the same given the segmented nature of markets characterised by heterogeneous consumers. The order in which preferences are formed will certainly vary not only between people, but between contexts. For example, in transport individuals choices may firstly be based on the characteristics of the product, then also by previous experience, norms, attitudes, perceptions. However, this might change in high stress situations such as when there are many alternatives available (e.g. at a busy bus interchange or transport hub). In other contexts, decision makers may form their preferences on the spot with no prior deliberation. The intention of marketers is influence the behaviour of individuals by optimising the way products/services are configured to increase their probability of being chosen. Marketers also have some input into the design features of decision making environments with the aim to maximise the choice probability of particular targeted products/services, or to permit consumers to efficiently locate their utility maximising choice.

If the goal of marketers is to be able to have some meaningful input into this process then in order to be efficient and effective in these pursuits requires an understanding of the structure of preference heterogeneity. A limitation of existing approaches to choice modelling consumer heterogeneity is that standard models do not taking into account the complex ways in which sources of heterogeneity may be structured in ways predictable by behavioural theory. In this thesis we seek to understand the structure of preference heterogeneity using specifications of a structural choice model to reflect behavioural theory on how decision makers' taste sensitivities for the attributes of alternatives in choice are correlated. The special forms of the structural choice model reflect the structured ways in which the attributes of alternatives are traded off both at the point of decision making as well as .

Research in marketing typically concerns various phenomena of consumer behaviour as it relates to the way people make choices in markets, what drives those choices or what the impacts of those choices are on consumers and society. By contrast, research in marketing analysis typically relate to the development of metrics or tools designed to measure and forecast behaviour, but rarely to represent the structure of consumers' preferences. The tools used to represent market structure in terms of what are the drivers of consumers' preferences can be specified to represent behavioural decision theory using recent advances in choice modelling. In this thesis, we develop models of the commonalities among decision makers' taste sensitivities that reflect phenomena predicted by behavioural decision theory using these new model forms. Specifically, we explore this in a marketing research contexts that relate to the positioning of transport services, and develop interpretations and recommendations relevant to both marketing research and policy in practice.

The research questions we address are: How does the nature of the choice environment affect the taste sensitivities in decision makers' preferences for particular product/service attributes? Are latent sources of variation in consumers' taste sensitivities stable or dynamic? What are the drivers of commonalities between the decision makers' taste sensitivities for the attributes of alternatives in choice? Is there a commonality between the way consumers' think about their priorities and the way consumers' make choices? The associated phenomena with each of these research questions occurs at different levels of abstraction in the form of correlations among the latent components of decision makers' utility. Structural choice models present a new and unique way to capture these correlations and behavioural decision theory provides a framework in which to explain the behavioural phenomena which give rise to these correlations.

In response to theory about rational choice behaviour, behavioural decision theorists have focussed on challenging normative assumptions about decision making by developing descriptive accounts of behaviour. The parametrising of behavioural phenomena into the flexible econometric models of structural choice modelling allows both a descriptive and quantitative analysis of the way in which the phenomena posited by behavioural decision theory manifests as correlations among the sources of what drives decision makers utility for the attributes of alternatives in choice. In this thesis various behavioural phenomena across different decision making contexts are explored between different decision scenarios, contexts and investigated on several levels of latent abstraction. We contribute to the field of choice modelling by demonstrating how the integration of behavioural decision theory into the specifications of structural choice models provides models that are not only more parsimonious, converge more quickly, and fit better to datasets but are also more readily interpreted with respect to the descriptive theory they are specified to represent. Such models are more useful for policy and strategy development given they reflect the ways in which decisions makers actually behave, rather describing the ways in which decision makers behaviour departs from normative ideals of perfect rationality. The research methods used are new with respect to the literature on behavioural decision theory and the structural choice model forms used are new to the choice modelling literature. To this extent we adopt a multi paradigm perspective (Gioia & Pitre, 1990) to theory development while simultaneously making contributions to method in terms of demonstrating several yet undocumented uses of the structural choice model.

The thesis contributes to the current trend of integrating of theories of behavioural decision making into econometric models of choice and investigating how robust these behavioural phenomena are under different conditions (Simonson, 2014). In doing so, we address some of the criticisms that work published under the banner of behavioural decision theory as lacking econometric rigour (Slovic, Fischhhoff & Lichtenstein, 1977; Kao & Velupillai, 2015; Ross, 2011).

1.1 Behavioural decision theory framework

Early attempts that challenged the normative rules about decision makers as perfectly indefatigable utility maximisers mark the beginning of behavioural economics as a parallel discipline to standard neoclassical economics. The most notable of these is in the seminal work of Simon (1956) on theory of bounded rationality, which posits that decision makers are in fact readily fatigued and face cognitive constraints on the extent to which utility maximising goals can be successfully achieved. This in contrast to view that the apparent randomness in decision makers' choices is due to not having observed enough of information about the systematic components of utility (Marschak, 1959). This theoretical juxtaposition paved the way for researchers from across several of the social sciences to formulate competing rules about judgement and decision making (Bettman, 1979; Payne, 1976; Wright, 1975).

A key characteristic of research into behavioural decision theory are demonstrations of non-utility maximising behaviour. Many of the neoclassical assumptions about utility maximising behaviour stem from Luce's (1959) axioms of choice, which in turn derive from Thurstone's (1927) law of comparative judgement. Violations of these assumptions were well documented in the mainstream economics literature well before the arrival of behavioural decision theory (May, 1954; Strotz, 1953). Edwards (1954) provides an extensive overview of the short comings of strict mathematical models of utility, and sets an agenda for the exploration of non-utility maximising behaviour using experimental approaches in psychology, which continues to this day.

The proceeding decades, most notably the 1970s and early 1980s, saw a proliferation of theory and process oriented work. Seminal articles at this time focus on demonstrating preference reversals (Lichtenstein & Slovic, 1971), the availability heuristic (Tversky & Kahneman, 1973), prospect theory (Kahneman & Tversky, 1979) and behavioural effects such as asymmetric dominance (Huber, Payne & Puto, 1982). At the same time, advances in technical and computational abilities were permitting the estimation of more sophisticated econometric models of choice built upon the utility maximisation framework (McFadden, 1973, 1978, 1980). Also coming to maturity at this time were frameworks for the study of attitudes as predictors of behaviour, specifically with regards to measurement and methods for constructing valid experiments (Ajzen & Fishbein, 1977). In a review of behavioural decision theory conducted at that time, Slovic et al. (1977) note that research on judgement and decision making is being studied by a diverse set of disciplines that conform to either normative or descriptive frameworks (*i.e.* research that describes how decision makers *should behave* versus research describing how decision makers *do behave*).

By the late 1980s and early 1990s, behavioural decision theory was being adopted in the fields of management and marketing sciences, most notably with regards to the manifestation of behavioural decision phenomena in consumers, e.g. (Bettman, Luce & Payne, 1998). The incorporation of prospect theory on how consumers weigh gains more strongly than losses into marketing pricing models (Thaler, 1985) become prominent at this time, as do effects such as the attraction and compromise effect, extremeness aversion (Simonson, 1989; Simonson & Tversky, 1992), regret anticipation (Simonson, 1992), context dependence (Tversky & Simonson, 1993). By the early 2000s, work on behavioural decision theory features prominently in some of the most cited articles in the top marketing journals during that time period.

In 2002 Daniel Kahneman and Vernon Smith were awarded the Nobel Memorial Prize in economics, marking a new acceptance of behavioural decision theory by the mainstream. Specifically, Kahneman is recognised for integrating behavioural decision theory about human judgement and decision making under uncertainty into economic science and Smith for establishing methods of economic experimentation for the study of non-utility maximising behaviour (NobelPrize.org, 2002). Since then there has been somewhat of a hybridisation of normative and descriptive approaches in behavioural decision theory research. For example, Gilovich, Griffin and Kahneman (2002) outline the ways in which consumers' violation of rationality frameworks has negative effects on consumer welfare, and suggest ways in which choice environments might evolve to promote utility maximisation.

Behavioural decision theory continues to evolve over the next decade leading up to the present. Several popular press books are published, most notably Kahneman (2011) and Simonson and Rosen (2014), which are further testament to the fields acceptance both within and outside academia. Simonson and Rosen (2014) posit that the current information-rich socially-intensive environment characterised by a proliferation of digital technologies provides decision makers' with an unprecedented level of information availability and diagnosticity—describing the current era as one of "(nearly) perfect information".

This modern choice environment faced by consumers is argued to permit greater comparison fluency between market offerings due to the abundance of information rich resources now available (Simonson, Bettman, Kramer & Payne, 2013). Supposedly, the increasingly realistic experiences offered through virtual media permit ever more reliable judgements about the subjective quality of products/services before a consumer experiences them. An opposing view is the current information environment is characterised by less information rather than more, due to the "echo chamber" effects of personalised target marketing and consumers' adherence to strongly self-referential social media channels (Pariser, 2011). Rather than creating a more diagnostically rich media environment, this is speculated to promote diffusion of misinformation and further cloud rational decision making abilities (Lewandowsky, Ecker, Seifert, Schwarz & Cook, 2012).

The future of behavioural decision theory presents an interesting research context to explore. It is likely to continue to comprise mapping out the types of information environments that decision makers' face and whether or not they are positively or negatively affected by factors such as information abundance and fluency.

Agenda setting for the future of behavioural decision theory research Simonson (2014) outlines a research agenda for the future of behavioural decision theory with a specific focus on applications in consumer decision making contexts using advanced econometric modelling techniques. Central to this agenda is a need to broaden the research tool kit of researchers of consumer judgement and decision making to adopt the quantitative methods used by researchers in marketing. The simplistic and stylised experimental methods that popularise classic behavioural decision theory research have also long been a source of the field's criticism (Lynch, 1982). In response to Simonson's agenda setting call, Lynch (2015) suggests two ways forward. The first concerns testing theory-based interventions that seek to improve consumer welfare, and the second concerns developing theoretically based explanations of substantive phenomena by integrating and hybridising the approaches of behavioural decision theory with the methods of advanced quantitative analysis in marketing. This thesis will conform more to the latter of these two.

The thesis contributes to this agenda first and foremost by providing new insights into theory. Secondly, the thesis demonstrates a model of consumer choice that is specifically adapted to both incorporate and parameterise behavioural decision theory phenomena. The approach captures behavioural phenomena predicted by behavioural decision theory using methods that are more acceptable to the rigour expected of the econometric sciences. The practical implications from the thesis present a way for policy makers to better account for behavioural phenomena when developing marketing strategy. More generally, the thesis reconciles some of the apparent tensions between behavioural decision theory, choice modelling/economics and marketing using an integrative modelling approach.

1.2 Transport services marketing

This thesis considers how the effects described by behavioural decision theory impact upon consumer behaviour in transportation contexts, specifically air travel and urban public transport. The design of servicescapes (Bitner, 1992) is known to be an important predictor of how consumers interact with products and services. In the transportation planning, the role of a marketing manager is in managing customer experience as well as communicating the benefits and features of services. For example, while targeting aspects of the transit service such as the punctuality of services optimisation of routing may primarily be the responsibility of engineering/timetabling departments, improving the legibility of information dissemination, ensuring comfortable journeys and addressing perceptions about affordability/value are the role of marketing.

Transport marketing plays an important role in attracting travellers, commuters and customers to use transport services. The role of behavioural decision theory in describing how decision makers' behave in these contexts is just as relevant as in other marketing context. This context is argued to carry social and environmental benefits due to the many ways in which consumers' transport choices affect the overall well-being of urban centres (Murray, Davis, Stimson & Ferreira, 1998), as a means to reduce social exclusion (Currie et al., 2010), and as a major contributor to the environmental sustainability of cities (Peattie, 2001; Chapman, 2007). Adequate transport both to and within cities is cited as one of the most important predictors of the health of local economies, and argued it should form an integral part of destination marketing (Guiver & Stanford, 2014).

Transport services are offered as multi-site services, the allocation of capacity for transport services is typically offered on a first come first served basis and the mode of consumption is often collective (Lovelock, 1980), ignoring the obvious exceptions of private modes and ride sharing services. Further, the consumption of transport can never be separated from its production, is intrinsically perishable, is heterogeneous in quality, and while it features tangible elements is essentially intangible as a service concept (Zeithaml, Parasuraman & Perry, 1985). Given these characteristics, the decision environment pertaining to transport services is prone to variability and the preferences of consumers are expected to be highly context dependent for some attributes yet stable for others. For example, consumers taste sensitivity towards their overall comfort during a journey might wane in importance relative to the salience of arriving at destination quickly and efficiently in certain circumstances.

Positioning the challenges of delivering transport as a services marketing problem leads to the question of which components of the servicescape (Bitner, 1992) are most salient in this context. With respect to managing customer experience the legibility and efficient dissemination of information as being critically important in transport contexts (Andreassen, 1995; Edvardsson, 1998). Given the importance of the information environment in this context, the effects of behavioural decision theory are expected to play a significant role in shaping consumer behaviour.

1.3 Thesis summary

The thesis is organised into three studies that are presented as complete papers prepared as submissions for publication. The papers follow a progression that serves a dual purpose. First, each of the papers generate behavioural insights into the structure of decision makers taste sensitivities in different ways. Second, the order of papers transitions from a focus on a well-documented behavioural phenomenon to testing an emerging view of preference formation, and finally to testing a new behavioural proposition.

Paper 1: A structural choice model of the compromise effect This study consists of two discrete choice experiments; one binary and one trinary choice experiment. Under the trinary choice scenario, theory on compromise effects suggest a middling alternative will be preferred to a utility maximising alternative regardless of the absolute levels of attributes of the alternatives (Simonson, 1989; Simonson & Tversky, 1992; Drolet, Simonson & Tversky, 2000). We test this claim as well as provide additional insights into the effects of this phenomena within the latent dimensions of decision makers' utility functions using structural choice modelling. Specifically, we investigate to what extent the compromise effect accounts for between task stability on attribute taste sensitivity.

Paper 2: Latent variables as a proxy for inherent preferences The emerging view that preferences have both stable and dynamic components (Simonson, 2008) is explored in the context of decision makers' antecedent volition. This concept posits that decision makers' preferences are pre-determined in such a way that the choice set(s) a consumer perceives may not be the same as the choice set(s) available (Swait & Marley, 2013). We bring together these complimentary views into a structural choice model that identifies which components of decision makers' preference remain stable or dynamic under different conditions of task complexity. In doing so we add a particular nuance to our understanding of both the effects of task complexity on decision making, showing that while there are apparent dynamics in decision makers' preferences there are components which remain detectably stable despite increasing choice complexity.

Paper 3: Priority alignment: linking priorities to preferences This study provides a test of theory about priority driven behaviour. The model specification allows for analysis into the extent to which preferences for attributes in a discrete choice experiment are determined by decision makers' priorities as measured using best-worst tasks. Best-worst tasks are rapidly becoming a popular method in both commercial and academic settings as a way to measure consumers attitudes, values and as proxies for consumers' intentions. Accordingly, this study provides evidence about the extent to which such measures are useful for predicting behaviour.

1.4 Methodology

Discrete choice experiments

A discrete choice experiment is a stated preference elicitation task which presents respondents with sets of hypothetical alternatives (choice sets) from which repeated choice observations are made. The available choices in a discrete choice experiment are described by attributes which may have multiple levels. In this thesis the following notation is used: a choice set is C is described by m alternatives which have k attributes which take on l levels (Street, Burgess & Louviere, 2005). Models estimated on stated preference surveys in isolation (i.e. without mixing with revealed preference data) are not recommended for forecasting but are useful for exploring behavioural effects in hypothetical scenarios (Cherchi & Ortúzar, 2006).

The task for a respondent completing a discrete choice experiment is simple. A range of options are presented in a similar fashion to how they might appear on a website or product catalogue, or even how they appear on the shelf in a physical store. The attributes that describe each available option may be explicitly labelled and described with text (e.g. price), or they be represented visually where doing so permits (e.g. the size or colour of an option). The respondent then indicates which of the available options they would choose in a forced choice scenario, or indicate they would choose none of the options available if the researcher wants to make this option available. In the case of a best-worst task, the respondent also indicates which option they would be least likely to select (in addition to which option they would select). After making their choice(s), the respondent progresses to a new choice set comprising a new set of options described by the same attributes but with different levels (e.g. higher/lower prices, different colours, sizes, etc.). An example discrete choice task (one used in Study 2 of the thesis) is shown in Figure 1.1.

The number of choice sets the respondent must complete and the number of attributes/levels that describe the alternatives available is determined by the experimental design. The way in which each of these elements are combined generally follow strict experimental design plans, but may also be generated using *ad hoc* methods. In this thesis a variety of design methods are used to meet the specific purposes of each study, which are outlined in detail for each specific study.

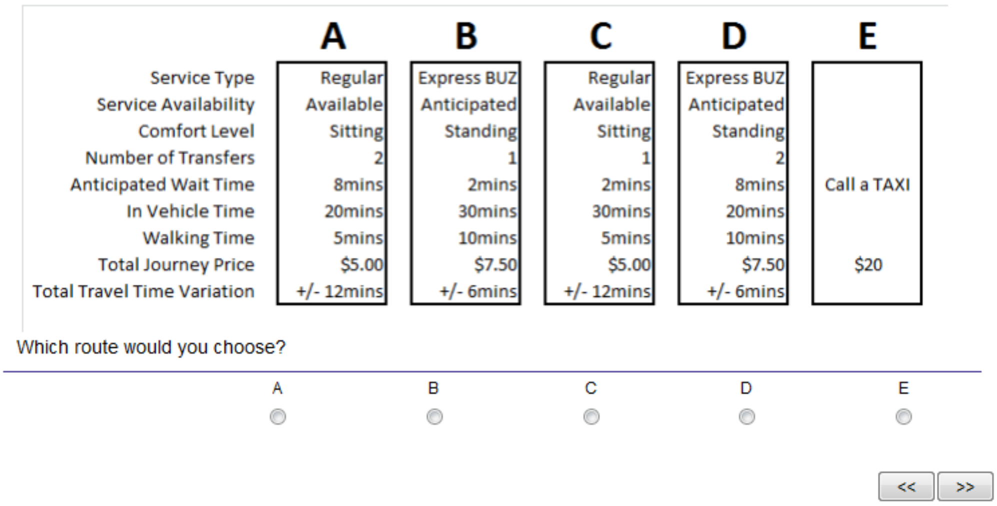

Figure 1.1: Example task from a discrete choice experiment

All data in this thesis are collected using within-subjects choice experiments embedded into online surveys. The unit of analysis is the individual consumer although in each of the three studies aggregated results are reported. Sample sizes in the range of 200 to 300 respondents are used in each study which is sufficient for statistical purposes given the large number of observations generated by each respondent in a discrete choice experiment (Hensher, 1994). Multiple experiments are administered in each survey, and in each study all respondents participate in all conditions to permit within-subjects analysis.

Sampling Each of the studies in this thesis pertain to market research contexts in public transport or air travel. The motivation to work in these areas is to uncover what are the effects of strategic marketing efforts relating to the design elements of the servicescape on the way consumers make public transport choices. The population of interest are consumers who frequent these services, either for work or leisure travel. It is not the case that in all studies the samples drawn pertain to strictly transport users. To do so would be myopic with respect to the broader goal of increasing the patronage of public transport by consumers who are not current users of a service. As such, the samples drawn for each study vary with respect to the populations that represent ranging from general Australian consumers through to regular users of the public transport in South East Queensland.

Study 1 uses data collected from the Australian Lifestyle Survey panel purchased from Australia Post that is representative of the average Australian consumer. In this case the research context is air travel. Supporting justification is provided in the study to support the claim the average Australian consumer is familiar with air travel and have well-formed preferences in this domain.

Study 2 uses data from the same provider but is restricted to consumers in the South East Queensland Region of Australia. This research context in this study is bus public transport, which is the dominant form of public transportation in the region studied. While the sample does not comprise only regular users of the service, it is argued a general sample of consumers in the region is suitable as many applications in this domain concern attracting new users, as opposed to retaining existing users.

Study 3 uses data collected from a Qualtrics panel representative of frequent (weekly or greater) users of public transport South East Queensland region of Australia. The data in this research context represents current frequent users of public transport (all modes) in the region. The conceptual problem in this research context concerns how the stated priorities of travellers affects their transport choices, hence a representative sample of frequent users is most suitable to determine what factors drive their behaviour.

Choice models

Choice models use data generated by stated or revealed preference methods. In this thesis only stated preference methods including best worst and discrete choice experiments are used to investigate the drivers of decision makers' preferences. The unit of analysis in a discrete choice model can be either the individual decision maker or group of decision makers on aggregate. In this thesis we report only aggregate level results. The response format in a choice experiment is discrete with multinomial outcomes. The dependent variable is binary coded (0,1) for the unchosen and chosen alternatives. The independent variables in a choice model can be continuous (such as price, travel time, etc.), ordinal or categorical. Dummy coding may be used represent the presence or absence of particular attribute levels. The independent variables in a choice model are typically categorical, with dummy coding schemes to represent the presence or absence of particular attribute levels.

The analysis of choice data includes simple arithmetic approaches in addition to inferential statistics. For example, simply frequency counts of how often particular alternatives are chosen without considering the importance of the attributes describing those alternatives is readily applied. Stated preference best-worst scores (Case I) permit simple calculations of implied market share for particular alternatives, as well as analysis about how the frequency and variance of choice given the repeated measures designs typically used. Best-worst is commonly used in marketing studies but is rare in applications in transport.

Regression based models are extensively used in choice modelling and are used to estimate the relative importance of each attribute in terms of the magnitude of their effect on choice from the data. We primarily use three classes of a random utility model in this thesis. First, the fixed parameters conditional logit model (McFadden, 1973) which provides estimates of which attributes are most important to decision makers as fixed coefficients. Second is the random parameters (error components) mixed logit model (McFadden & Train, 2000) which relaxes assumptions about preference homogeneity across respondents and estimates dispersion parameters such that preference heterogeneity can be assessed. Third, the structural choice model (Rungie, Coote & Louviere, 2011, 2012) is a form of mixed logit that allows for the specification of theoretically driven structures amongst the latent dimensions (i.e. error components) of decision makers' preferences. The model is especially designed to incorporate multiple data sources and specifying latent variables such that specific correlations predicted by theory between the sources of taste sensitivity for the attributes of alternative between and within tasks can be considered. In each of our studies latent structures are specified via a structural choice model to both represent and test behavioural phenomena at various levels of latent abstraction.

A brief history of choice modelling Thurstone's (1927) law of comparative judgement leads to the discriminable dispersion model of paired comparison which forms the basis of modern discrete choice modelling and analysis. The discriminable dispersion model posits that the just noticeable difference between particular objects/stimuli A and B is positive in terms of some psychological judgement (*e.g.* responses to items on a rating scale or assessment of one's own latent utility scale), then it follows empirically that $A > B$ in terms of some theoretically relevant measure.

Luce (1959) formalised the discriminable dispersion model into the framework of random utility theory to state rational decision makers will always behave in such a way that attempts to maximise utility or well-being, by always choosing A whenever $A > B$ in terms of preference or liking. To the analyst, the A may appear objectively better than B on important dimension (e.g. price, speed, etc.), yet they observe decision makers' choose B over A in certain circumstance. In such cases decision makers choices may appear random or irrational depending on which assumptions are made about the relationship between those alternatives. First, because not all sources of variation are observed, Marschak (1959) reasoned the source of randomness in decision makers preferences can be decomposed into systematic and random components. To identify and give structure to the systematic component of utility, McFadden (1973) formalised an econometric specification of random utility theory in the equation $U_i = V_i + e_i$ (the multinomial conditional logit model). Utility for some alternative i is comprised of a systematic (observed) component V_i and an unobserved (error) random component e_i, where that systematic component is comprised of the attributes and levels of alternatives that can be readily observed and controlled by the analyst (and most importantly, marketers). Note an index for individuals is suppressed here for ease of expression.

The second view compromises the behavioural explanation that decision makers' rationality is bounded by their ability to process all the relevant and available information needed to inform perfectly rational choice behaviour (Simon, 1956). This behavioural account of rationality is based on information asymmetries (as opposed to unobserved sources of taste variation) which has formed much of the basis of contemporary research into behavioural economics and behavioural decision theory alike. The view can be reconciled with the first by quantifying the effects of things like cognitive burden on choice as part of the systematic component of utility (Swait, 2001). By contrast the structural choice model we use looks for specific hypothesised structures within the random (unobserved) component of utility that can be explained by behavioural phenomena such as those suggested within the framework of bounded rationality (Simon, 1956).

Model forms which relax various assumptions about decision making are continually being developed. Perhaps most pertinent has been the relaxation of the assumption of the independence of irrelevant alternatives (IIA). The assumption of IIA posits the relative preference between two objects cannot change following the introduction of a third irrelevant alternative (Arrow, 1951). For example, if A is preferred to B in some choice set C, then adding alternative m to the same choice set C should not result in B suddenly being preferred to A. Behavioural decision theorists Amos Tversky and Daniel Kahneman are best known for their demonstration that this axiom of choice is frequently violated by decision makers in many cases, see e.g. Tversky and Kahneman (1973) and Tversky and Simonson (1993).

Models which allow for random taste variation between people fit much better to choice data, provide more behaviourally driven interpretations. The most notable of these models include latent class segmentation models (Kamakura & Russell, 1989; Swait, 1994; Greene & Hensher, 2003) and random parameters mixed logit models (Revelt & Train, 1998; McFadden & Train, 2000). The latter of these has been particularly influential in the way it allows for unrestricted substitution patterns and correlation in unobserved factors (McFadden & Train, 2000). It is possible to estimate the fully parameterised matrix of correlations among the error components specification of utility in the mixed logit, although this is rarely done due to its' computational intensity or perhaps more likely, a lack of theoretical justification.

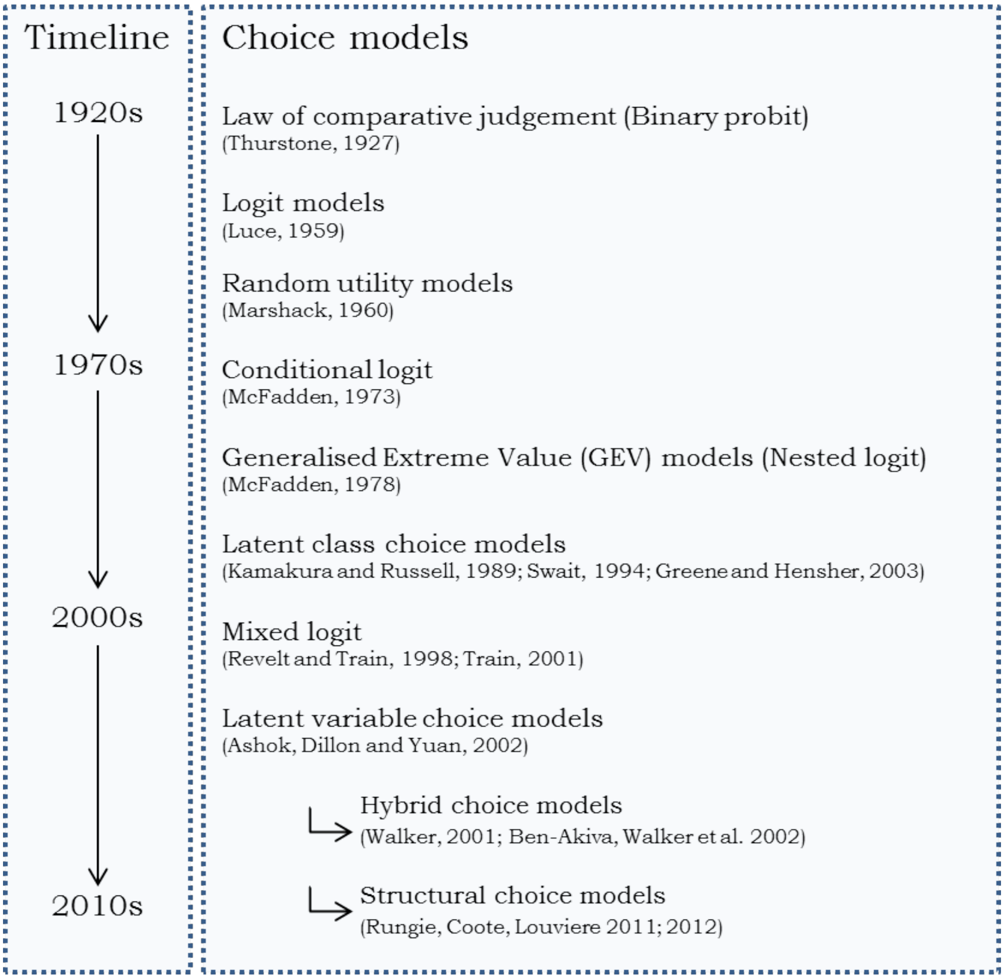

FIGURE 1.2: Time line of developments in choice modelling

Structural choice models Rungie et al. (2011, 2012) provide a more parsimonious version of an error components mixed logit model by only estimating the particular components of the variance-covariance matrix for which there is a theoretical justification to estimate. Particular correlations can be turned on and off in estimation to reflect particular theory about the structure or interrelatedness of particular latent sources of attribute taste sensitivities that arise due phenomena predicted by behavioural decision theory.

Being a more parsimonious model allows for theoretically relevant correlations between particular random components in the model to be investigated in a way that is less computationally intensive than specifying the fully parameterised matrix of correlations among the error components specification of a mixed logit model (McFadden & Train, 2000).

The model is particularly well suited to the testing of behavioural theory about commonalities in the drivers of choice in a way similar to how factor analysis is used in the structural equations modelling to locate items which share common sources of variation. For example, in structural equations modelling a factor analysis of respondents ratings of a brand's perceived trustworthiness, ability, commitment, willingness towards delivering on promises may reveal a unique pattern of correlations that is indicative of the presence of a latent variable that may be labelled "*perceived brand credibility*" (Erdem, Swait & Valenzuela, 2006).

In a structural choice model, a similar approach is used to identify groupings among decision makers preferences for different attributes in a choice experiment which share a common source of variation. The model retrieves the structure of preference heterogeneity by modelling correlations among consumers with similar patterns of substitution. This is different to modelling correlation among multiple choices from the same respondents that is common in studies which use stated preference surveys e.g. (Cherchi & Ortúzar, 2011). Correlations within individuals do not affect the structural choice model coefficients as they are individual specific.

A structural choice model produces results similar to a factor analysis of attitudinal statements, but using decision makers choices rather than ratings. For example, in an application to a public transport service, choices of bus routes that are defined by attributes such as in-vehicle time, wait time, egress time and others may reveal a unique pattern of correlations which suggest the presence of a theoretically relevant commonality among these attributes. In some cases, such a latent variable may be readily labelled (*e.g.* "time sensitive" attributes) while in others it may be a source of variation related to some manipulated factor general to a choice task (*e.g.* inclusion of a compromise alternative). In another application, commonalities among the taste sensitivities for attributes in a task may arise due to some characteristic of the task itself (such as being a complex task, or that it contains certain types of alternatives).

Mueller and Rungie (2009) present precursor work in the development of the structural choice model in developing an approach to modelling best-worst scale data using principal components analysis (PCA) to identify structure within the variance-covariance matrix of consumers' utility scores. The interpretation of factor loadings of consumers' preference onto latent variables developed in Mueller and Rungie (2009) inform the way in which we interpret the parameters of the structural choice model. Rungie et al. (2011, 2012) generalise the approach of Mueller and Rungie (2009) to allow regression models to be specified at the level of higher order latent variables, linking them together in ways not possible using regular PCA that are of theoretical interest to the analyst.

We explore a variety of different possible specifications of the structural choice model in this thesis. Each specification allows for various types of theory to be tested. The specifications used in this thesis include those which test the effect of an alternative specific constant on the between task stability of decision makers' latent sources of preference heterogeneity. We also use a specification to test the within-subject stability in their antecedent volition towards attributes under different scenarios of task complexity, which may also be applied to test of temporal stability. In our final study we set up a specification that links the error components of utility in a best-worst task to those in a discrete choice experiment. The behavioural motivation for this specification is to measure the commonalities amongst the sources of preference heterogeneity in consumers priorities and their decision making behaviour with respect to the common attributes included in both tasks.

Comparisons with hybrid choice models A recent trend over the past decade has been to integrate attitudinal latent variables into the explanation of the choice process. There has been a sustained interest in latent variable models of this nature spanning for at least a decade, e.g. (Ben-Akiva, Walker et al., 2002; Ben-Akiva, McFadden, Train & Walker, 2002; Walker, 2001). Models incorporating attitudinal latent variables are most prominently represented in the environmental economics and marketing literatures, e.g. (Ashok, Dillon & Yuan, 2002; Hess & Beharry-Borg, 2012; Paulssen, Temme, Vij & Walker, 2014).

Hybrid choice models have some important similarities and differences when compared to structural choice models. They share the characteristic of capturing "upstream" sources of random taste variation and adding structure to the apparent randomness in decision makers choices when not all sources of a variation are visible (Marschak, 1959). A further similarity is such latent variable models are used to represent the unobserved (latent) characteristics of decision makers as a way to represent the dynamics of market structure (Elrod & Keane, 1995; Keane, 1997).

The most important difference of hybrid choice models compared to structural choice models are in how latent variables are defined. In a hybrid choice model incorporating attitudinal variables, the latent variables are typically exogenously defined via measured indicators per the tradition of structural equations modelling (Joreskog & Sorbom, 1979). In a structural choice model, latent variable are inferred via correlations within the random component of utility (they do not have indicator variables). The latent variables of a structural choice model do not explicitly represent latent attitudes, although depending on the specific groupings they may be used to infer something about attitudes, values, preferences, priorities or other manifestations of behavioural phenomena. The use of indicator variables in hybrid choice models provides readily interpreted theoretical meaning to the latent variables studied, and is known to provide more accurate estimates of choice and are identifiable using similar rules to those of structural equations models (Walker, 2001; Vij & Walker, 2014). Common applications of the hybrid choice model include testing theories about how attitudes might drive preferences for particular attributes (Daly, Hess, Patruni, Potoglou & Rohr, 2011), or how measured decision states affect decision making e.g., Adamowicz and Swait (2012); Swait (1994).

Both hybrid and structural choice models parameterises relationships between latent variables that are of a higher order than the choice itself (Ashok et al., 2002; Maydeu-Olivares & Böckenholt, 2005). In this sense, both models are introducing more information with which to explain the drivers taste sensitivity with decision makers' preferences, but do so through different routes.

Applications of structural choice modelling Structural choice modelling is an established technique for testing behavioural decision theory. Rungie et al. (2011, 2012) provide an overview of the mathematics for the general structural choice model and Sampson, Rungie and Coote (2015) provide valuable guidance to researchers using structural choice models regarding how the specific data requirements and assumptions that should be considered when designing discrete choice experiments to analyse with structural choice models. Specifically, their work simulates various specifications of the structural choice model (*i.e.* with and without latent factors, factor on factor regressions, etc.), using data generated from various design types (efficient, orthogonal, etc.) varying in overall design size and varying sample size. This analysis shows the model is robust to design variations, with greater returns to estimation accuracy coming from larger designs as opposed to larger sample sizes.

Two examples of theory testing using the model are found in Rungie, Scarpa and Thiene (2014) and Thiene, Rungie and Scarpa (2013). Their work tests theory about the influence of individuals in joint decision making scenarios (e.g. household budgeting and leisure travel). The use of a structural choice model in these contexts is particularly well suited to the application as the model allows for the taste sensitivities of both decision makers in a joint decision making context to be regressed on one another. Rungie et al. (2014) provides meaningful insights into what percentage of variance in the level of utility in a couple's jointly estimated preferences is contributed by each member of the couple (*e.g.* man vs. woman). Such a model is useful in a practical way for any application where an analyst may be interested in determining the level of influence of particular decision makers in a joint decision making context.

Wallin and Coote (2014, 2015) consider the effect of missing attribute information in situations where consumers' preferences for a product are considered in isolation (such as on a manufacturer's website) versus when products are displayed together (such as on a comparative website listing many brands together). As different brands decide to display different attributes in their communications with consumers, the levels of some attributes in a comparative setting may appear missing to consumers. Under the single mode of decision making where the product is considered in isolation, the missing information is not immediately apparent, while in a comparative setting the missing information becomes much more salient.

Coote, Rungie and Louviere (2011) tests the stability in consumers preferences for alike environmental attributes between two product categories (attributes used by consumers to achieve carbon mitigation goals in home appliance refrigerators versus air conditioners). This specification is particularly useful as consumers' preferences attributes common to multiple product categories may be correlated. Understanding these correlations aids in determining whether consumers' will be receptive to similar marketing tactics targeting alike attributes across contexts.

Coote, Islam, Louviere and Magor (2015) apply the structural choice model to a longitudinal dataset and find stability in the latent drivers of consumers' preference sensitivities across each waves. These findings suggest consumers employ a consistent decision making strategy in each wave. This study also plots the factor loadings of a structural choice model to provide a longitudinal preference map which is context independent.

Bowe, Rungie, Lee and Lockshin (2016) investigates the stability of consumers' taste sensitivities towards the country of origin (COO) attribute of two disparate product contexts. They investigate Chinese consumers' perceptions of Australian wine and seafood in a market research context, using a unique specification of the structural choice model that estimates the correlation of the COO attribute between both contexts.

1.5 General econometric specifications

Random utility theory

McFadden (1973) formalized random utility theory into a well-known econometric specification which states that for an individual n alternative k has a utility Ui with a systematic component V_i and an idiosyncratic identically independently distributed (IID) random component e_i, given by:

$$U_i = V_i + e_i \tag{1.1}$$

For ease of expression, here the subscripts for the individual n, the choice set C, and alternative k are omitted. The systematic component of utility Vi is observed in the form of choices made from k alternatives that are described by covariates $x_1 \dots j$ chosen by the analyst.

Structural choice model specification

The estimated parameters are regression coefficients representing factor loadings on/between the error components of decision makers utility functions. A stronger/weaker taste sensitivity means someone is more/less sensitive to changes in that attribute, or changes related to a latent variable (e.g. the presence/absence of a compromising alternative or the level of task complexity). Hence we call these parameters “taste sensitivities”. This term is more accurate than a term like “attribute preference” which does not describe the structure of the heterogeneity related to preferences for the attributes in the choice model. Taste sensitivities have a specific behavioural interpretation related to some unobserved source of heterogeneity, such as compromising, an antecedent volition or alignment with priority goals.

The model is a random utility model and which V_i is specified as the linear combination of covariates X_i as a row vector, weighted by regression coefficients i as a column vector. These regression coefficients are typically denoted β in standard econometrics, however are denoted η here maintaining the conventions structural equation models (SEMs), hence:

$$V_i = \eta_1 x_{i,1} + \ldots + \eta_j x_{i,j} \tag{1.2}$$

Equation (1.3) specifies η as a linear function of m a latent variables ξ multiplied by a regression coefficient γ (which can be turned on or off in estimation) and random (error) components ϵ for which either means and/or standard deviations can be estimated. As a linear in parameters model the estimates are robust and stable (Sampson, 2017) although we do note that non-linear models have been shown to perform better than linear models in transport studies, e.g. (Cherchi & Ortúzar, 2002; Cherchi & de Dios Ortúzar, 2006)..

These error components represent the antecedent sources of what drives decision makers' sensitivity towards changes in the levels of a particular attribute, hence the term “taste sensitivity”. The model is equivalent to a fixed coefficient specification of conditional logit when γ coefficients are not estimated, and only μ_ϵ is estimated and is equivalent to the random coefficients mixed logit model when μ_ϵ and σ_ϵ are both estimated. When one or more ξ variables are specified with γ coefficients turned on for every attribute the model is conceptually equivalent to an exploratory factor analysis. The standard deviation of the error components of decision makers taste sensitivities reflect the distribution of preference heterogeneity in the sampled data towards an attribute, hence:

$$\eta_j = \gamma_{i,1}\xi_1 + \ldots + \gamma_{j,m}\xi_m + \epsilon_j \tag{1.3}$$

The latent variable(s) ξ are unobserved source(s) of random taste sensitivity. They are unlike the formative latent variables of a hybrid choice models which have exogenous and theoretically meaningful indicators. Instead, the ξ in a structural choice model is reflective per the definition of (Bollen, 1989; Bollen & Lennox, 1991), and are specified such that the latent variable determines its' indicators, in this case decision makers' taste sensitivities. The regression coefficients are denoted γ which represent the strength of association between a taste sensitivity and the specified latent variable. The regression coefficients give structure to the observed preference heterogeneity in relation to the attributes of the choice alternatives.

The regression coefficients are interpreted as factor loadings, and are used to represent commonalities among the attributes in a choice experiment in terms of the drivers of decision makers' taste sensitivities towards them. Different attributes may share a common source of heterogeneity for a variety of theoretically interesting reasons. For example, commonalities between attributes may arise due to some behavioural phenomena such as compromise effects or decision rules to deal with choice complexity or when they might be considered substitutes within a task. Multiple latent variables ξ common across multiple choice experiments may also be considered which allows for commonalities between the drivers of taste sensitivities for the both alike or different attributes across contexts/time.

Equation (1.4) regresses one latent variable onto another such that a ξ may be exogenously defined by another ξ. In this specification a sensitivity parameter β is estimated which denotes the strength of association of one latent variable with another. The random component δ is a normally distributed (i.e. Gaussian) variable for which either a mean and/or standard deviation can be estimated, hence:

$$\xi_j = \beta_{i,1}\xi_1 + \ldots + \beta_{j,m}\xi_m + \delta_j \tag{1.4}$$

This specification allows for further flexible specifications of the model which may be of theoretical interest. For example, links can be made between latent variables both unique to one choice experiment, and common across multiple choice experiments. This allows for tests of whether a latent variable common to all attributes in one task predicts a latent variable common to all the attributes in another task (global stability test). Alternatively, latent variables unique to each attribute across multiple tasks can be specified which can be linked in similar ways to form attribute specific between-task stability tests for alike attributes.

The structural choice model has parallels with random coefficient and latent class specifications of conditional logit (Kamakura & Russell, 1989; McFadden & Train, 2000). In a structural choice model, the latent variables represent unobserved sources of preference heterogeneity in relation to the taste sensitivities for the attributes of a choice alternative. In this sense, these latent variables conceptually can be interpreted as having a moderating type of the effect of the systematic component V_i of utility on the random component of utility, in the sense it is determinant of the strength of association between observed attribute levels and decision makers' preferences (i.e. the structural choice model uncovers the drivers of decision makers' taste sensitivities).

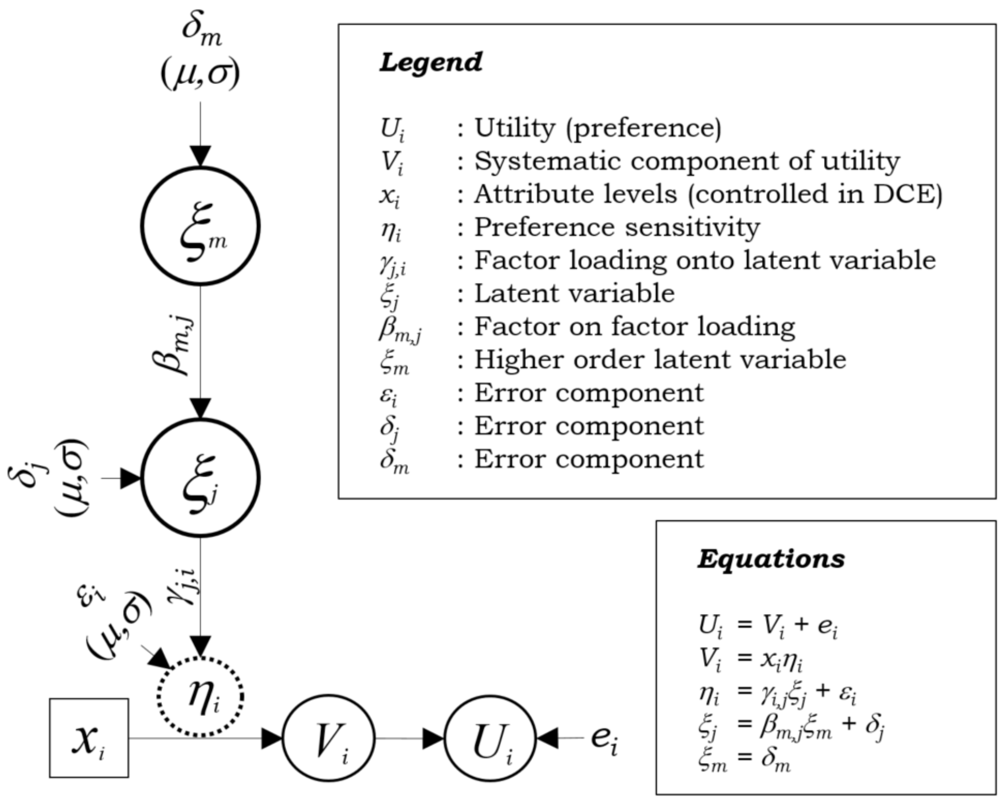

FIGURE 1.3: Structural choice model diagram

The model is built on structural equations to link different components of interest in the variance-covariance matrix to answer theoretically relevant questions about the sources of taste sensitivity for different attributes in one or more choice scenarios. An error components specification of mixed logit estimates the entire variance-covariance matrix, and if particular elements of this matrix of interest they may be reported. By contrast, the structural choice model is much more parsimonious, as only the elements of theoretical interest in the variance-covariance matrix are estimated enabling models much less dimensionality than fully parameterised correlated error components specifications of mixed logit to be estimated.

In a structural choice model the taste sensitivities are the dependent variables in these equations and are specified as a function of latent explanatory variables. We model structure within the random (error) components of these latent variables. That is, the sensitivity η in a decision makers systematic component of utility V_i to different levels of an attribute x_i is determined by some unobserved source of variation ξ which has an error distribution. Structure found among the latent dimensions to decision makers' preference via specification of this effect using higher order sensitivity parameters γ and β.

Estimation

The estimation of a structural choice model uses simulated maximum likelihood to locate the set of model parameters which maximise a log-likelihood function (Rungie et al., 2012). The algorithm used for structural choice models in the DisCoS package run in MatLab is Nelder-Mead which is a slow but highly stable and reliable estimator (Nelder & Mead, 1965; Rungie, 2011). At this time, this is the only available software in which to estimate structural choice models.

The model converges when changes in the log-likelihood reach a point of concavity located by the Nelder-Mead algorithm (Rungie et al., 2012). Indeed, we do not know for sure that the model has reached the global maxima or if this point is a local maxima. To check, the model is run again with different initial values and if it converges to the same point, we can be more confident it is likely to be the global maxima for the model. The log-likelihood value for a given model can be used as a measure of model fit relative to competing models with the same number of parameters, and for models with different numbers of parameters (or models not nested) the Bayesian and Akaike information criterion (BIC and AIC) may also be used (Rungie et al., 2011; Hensher, 1994; Louviere, Hensher & Swait, 2000; Hensher & Greene, 2003). The rules for structural choice model identification are the same as those for structural equation models (Joreskog & Sorbom, 1979; Bollen, 1989; Bollen & Lennox, 1991). Given this the general notation used in the equations for structural choice models are written using a similar convention to those used in structural equations modelling (Rungie et al., 2011, 2012). Rungie et al. (2014) provides a detailed overview of the estimation and identification of structural choice models. Sampson (2017) further outlines the identification conditions of the structural choice model in addition to assessing the accuracy and predictive validity of structural choice models under different sampling and experimental design conditions for discrete choice experiments.

Experimental design considerations

There are several important assumptions about the data and design of experiments important when using structural choice models. First, for a structural choice model it is assumed the data are in the form of discrete choices. In terms of estimation, the structural choice model assumes the error components of decision makers' utility functions are independent and identically distributed.

The independent variables of a choice model are the attributes and levels of the alternatives available to choose by respondents, as well as other characteristics of the decision scenario (*e.g.* choice complexity). The structure of this data allows for analysis of how these variables impact on decision making. Comparing differences between manipulated decision scenarios permit causal inferences and descriptive interpretations of theories that explain decision behaviour.

There is no immediate apparent standard for theory testing using discrete choice experiments, let alone structural choice models specifically. The literature on the design of choice experiments tends to focus on statistical issues such as how to most efficiently combine attributes and levels when constructing choice experiments. Some prominent exceptions include Adamowicz, Boxall, Williams and Louviere (1998); de Bekker-Grob, Ryan and Gerard (2012); Breidert, Hahsler and Reutterer (2006); Louviere and Timmermans (1990); Ryan and Gerard (2003). These papers tend to provide overviews of the use of discrete choice experiments within various disciplines and provide advice for practitioners about how best to use information from choice models to inform policy development. With respect to structural choice models, Sampson et al. (2015) provides the most practical and immediate advice on issues related to design. These include favouring larger designs which collect more information per respondent over smaller designs with larger respondent sample sizes.

Structural choice models are best suited to testing research questions using experiments in which treatment conditions are applied within-subjects. Within-subjects designs present all participants in an experiment with all treatment conditions (Greenwald, 1976). This is an attractive property as it allows stronger causal inferences about the effects of some treatment on an outcome variable at a respondent level rather than a sample level, which contributes to strong evidence in support of theory development (Sutton & Staw, 1995). In contrast, between-subjects designs do not present all treatment conditions to all participants, which by necessity require control groups to support cause inferences about effects of experimental manipulations (Erlebacher, 1977).

Within-subjects experiments require larger overall designs which increases chances of respondent fatigue and other response biases (Greenwald, 1976; Sawyer, 1975). However, given the greater amount of information gathered using a larger design smaller sample sizes are required to fill each experimental cell which reduces measurement error attributable to between group differences (Greenwald, 1976).

Choice models, including the structural choice model, are specifically developed to analyse data generated using the kinds of repeated measures designs typical of discrete choice experiments (Hensher, 1994; Louviere, Carson, Burgess, Street & Marley, 2013; Rungie et al., 2011, 2012). Discrete choice experiments generate many observations from each respondent using repeated measures such the statistical power of the data permits preferences for each attribute to be reliably estimated using smaller respondent sample sizes relative to those required when using rating scales (Hensher, 1994). Further, participants in choice experiments known to be less susceptible to the effects of cognitive burden common with repeated measures observed when using rating scales as the task at hand mimics choices consumers readily engage with in the real world (Louviere et al., 2013). In transport and other fields, there is a tendency to minimise sample size as gathering data is very expensive which motivates the use of efficient designs. Furthermore, with respect to structural choice models, evidence also indicates it is preferable to maximise on information efficiency using larger repeated measures designs rather than it is to maximise on sample size using smaller designs to reduce burden on respondents (Sampson et al., 2015).

Within-subjects design choice experiments are commonly used in applications to theory testing in marketing. For example Gilbride and Allenby (2006) consider how elimination by aspects modes of decision making rules vary depending on whether data from full versus incomplete profiles is modelled. Otter, Allenby and van Zandt (2008) fit factor analytic latent variable choice models to within-subjects data to test theory about different modes of deliberation that survey respondents may use in web based surveys vs in-house computer aided personal interviews (CAPI). Rouwendal, de Blaeij, Rietveld and Verhoef (2010) collect data from two choice experiments that test for context dependent preferences between short term and long term decision making scenarios. Swait (2001) test a tipping point theory by showing that decision makers can have different utility functions for an alike attribute in different contexts. Zhu and Timmermans (2010) compare the information simplification strategies consumers use in one product category when price information is available versus not available. Positioned against these studies, our contribution is new with respect to the evidence we present about the interrelationship between the latent sources of decision makers preferences in different scenarios. We demonstrate that across different decision making contexts the stability in decision makers preferences depends in part on the strength of their context independent inherent preferences relative to context specific constructed preferences.

In choice modelling contexts between-subjects designs are more suited to applications considering theory on differences between consumer segments or different styles of decision making that are unrelated to manipulation within a particular decision scenario. For example, Goettler and Clay (2006) use a dynamic choice model incorporating consumer learning effects to investigate different modes of consumer learning between different types of consumers. Draganska and Klapper (2010) explore how different segments of a market respond to different advertising strategies. Lewis (2004) test theory on how different loyalty program structures effect the preferences of different loyalty reward program members. Note the hallmark of these examples are multiple experiments presented to different samples. While they present valid tests of theory, they relate more to market effects and less to behavioural change within individuals.

Both design types, within- vs. between-, have merit for theory testing in different contexts. For behavioural decision theory research, between-subjects designs do not control for changes in individual cognitive processes as a result of context dependent factors related to the type of choice tasks (Louviere et al., 2000). The structural choice model is specifically designed to link data collected from multiple choice experiments, which is estimated most efficiently using data collected from a single sample, thus a within-subjects type of experiment is most suitable. The types of behavioural decision theory we test have their most relevant interpretations at a within-subjects level rather to describe differences between groups.

Software

The experimental designs of studies 1 and 2 are generated using a combination of orthogonal designs (Street et al., 2005) generated in SPSS. Study 2 uses a unique design to contrive the alternatives of an OMEP algorithmically in Microsoft Excel to construct compromising alternatives. Study 3 uses D-efficient designs generated in Ngene (Choice Metrics, 2014) and Youden designs located in design catalogues using *crossdes* in R using (Sailer, 2015). Data restructuring and arithmetic analysis is completed in Microsoft Excel, conditional logit and mixed logit models are run in Stata (StataCorp, 2015) to produce starting values for structural choice models, all of which are run in DisCoS (Rungie, 2011) in the MatLab programming environment (The MathWorks, 2012).

Ethical Clearance

All studies included in this thesis have received ethical clearance from the university's ethics committee. None of the research methods used as part of this thesis pose significant risks to participants beyond the minor inconvenience incurred to complete a questionnaire. The tasks used to collect data from respondents do not contain questions targeting any particular vulnerable groups, minorities or children. All data collected as part of this research thesis stored securely under strict password protection.

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2

Paper 1 - A structural choice model of the compromise effect

2.1 Introduction

An alternative within a choice set gains a greater share of choice when it is a middling option as opposed to an extreme option. "Middling" and "extreme" refer to the levels of the attributes of each alternative. Simonson (1989) called this phenomena the compromise effect. For example, the most expensive/cheapest alternatives from a set would be considered to be extreme with respect to price, while an alternative that is in between is a compromise alternative (with respect to price). Such decision/buyer behaviour is a violation of the assumption about the utility maximising notion of independent of irrelevant alternatives. Neoclassical economic theory suggests the relative choice share of one alternative relative to another will not be impacted by the addition of alternatives with objectively worse and/or irrelevant attributes (Arrow, 1951; Luce, 1959; Radner & Marschak, 1952).

The compromise effect is well studied, but what is not yet understood is how the effect manifests on a latent variable level in terms of how it might affect the structure of decision makers' utility functions. Further, it is not clear to what extent the compromise effect is a key determinant of the stability in taste sensitivities. We construct a choice experiment comprised of two tasks, one in which a compromise alternative is available and one in which it is not. We use a specification that estimates the indirect utilities for the attributes of international flights dependent on a latent variable linked the alternative specific constant of the compromise alternative. The model provides information about the structural relations that manifest as a result of the compromise effect and the generality of the compromise effect at an attribute and latent taste sensitivity level. Understanding the compromise effect at these two levels allows marketers and policy makers to predict which attributes decision makers' preferences for are robust against threats to rational decision making. The specification can also be used as template for the investigation of other similar behavioural effects.

Research questions Do different latent sources of preference heterogeneity account for decision makers' behaviour in scenarios where a compromise effect is manipulated versus when it is not? To what extent does the compromise effect account for variation in between task stability in taste sensitivity?

2.2 Conceptual framework

The compromise effect The compromise effect posits middling options will be preferred to extreme options (Simonson, 1989). This is a classic violation of random utility theory, as the position of an option within a choice set relative to other alternatives does not objectively affect the absolute value of each option. However, evidence does seem to suggest relative (as opposed to absolute) attribute levels are important to decision makers, hence compromising behaviour is commonly observed in both experimental and real world scenarios (Dhar, Menon

& Maach, 2004; Kivetz, Netzer & Srivastava, 2004b).

The compromise effect has been recently popularised in publications such as Kahneman's (2011) New York Times best-seller "Thinking, Fast and Slow" and Simonson and Rosen's (2014) "Absolute Value: What Really Influences Customers in the Age of (Nearly) Perfect Information" (winner of the 2016 Berry-AMA prize for the best book in marketing). Despite widespread acceptance among theorists and practitioners, the methods used to measure and model such behavioural effects are often criticised for being overly stylistic (Frederick, Lee & Baskin, 2014). Such effects are purported to rarely manifest in predictable or reproducible ways in real world scenarios (Yang & Lynn, 2014), despite the evidence the phenomenon does occur both in and out of the behavioural lab (Dhar et al., 2004; Kivetz et al., 2004b). To this end, this study investigates the compromise effect using methods of analysis that stem from the more rigorous econometric sciences.

Measuring the compromise effect The compromise effect is typically measured by counting the relative frequency that an option is chosen in situations when it is a middling option versus when it is not (Simonson, 1989). Simonson and Tversky's (1992) classic demonstration of the compromise effect involved counting the relative number of times cameras are chosen in differently constructed choice sets. The choice shares of three different cameras are compared in absolute terms without the estimation of statistically sophisticated models. The cheapest of the cameras is chosen most often in a paired comparison context but less often when more expensive camera is added to choice set. When decision makers face a trinary choice set, the middling priced camera receives the largest share of the experiment participants' choices; a compelling demonstration of the effect.

There are several advantages and disadvantages associated with the standard measurement approach outlined above. First, it has the advantage of being very easy to implement and is readily interpreted by general audiences. The standard measurement approach enables a convincing story to be told about how the relative number of times an option is selected depends on its position in a choice. However, a more complex model is required to generate insights over and above those permissible using this standard measurement, specifically to answer questions about the generality of the effect in terms of how it manifests on attribute specific levels and how it may have effects on more abstract levels (specifically within the error components of decision makers' utility functions). Understanding these additional dimensions of the compromise effect permits a discussion about which components of decision makers' preferences are more/less susceptible to influence using techniques designed to encourage such behaviours.

We adopt the above approach in this study to serve as a benchmark to establish that the phenomenon occurs within our data in a manner consistent with Simonson's (1989) definition. That is, we first count the relative difference in the frequency that particular options are chosen in our data between two choice scenarios. We then build a structural choice model to explore how the compromise effect manifests in ways that the frequency analysis does not permit.

Others have explored alternative approaches to investigating the compromise effect, each of which with their own advantages and disadvantages in terms of their suitability for exploring different outcomes of the compromise effect. For example, Kivetz, Netzer and Srivastava (2004a) measure concavity within localised choice sets and use theory of loss aversion behaviour as a way to account for compromise effects in a choice model. They do this by introducing a concavity parameter into the estimation of a standard choice model, and observe diminishing returns in terms of gains across the utility function for alternatives beyond the middling alternatives within localised choice sets.

Dhar et al. (2004); Kivetz et al. (2004b) contribute to establishing further evidence of the generality of compromise effects in complex buying scenarios such as business-to-business negotiations by specifying similar concavity models. They consider various attribute specific effects with a discussion of how the magnitude of extremeness aversion differs between attributes. Our modelling approach offers similar benefits at this level, although differs in application in the sense we map attribute specific preferences onto different sources of random taste variation to test whether compromising behavioural tendencies share a common theoretical driver. While Kivetz et al. (2004a); Dhar et al. (2004); Kivetz et al. (2004b) fit utility estimates to concave utility function, our model estimates a standard linear in parameters model, and captures the attribute specific effects within the latent dimensions of a structural choice model equation. Rather than focusing on localised effects for specific choice sets within individuals, our approach captures attribute specific variation as exogenous on a latent compromise alternative specific constant that is general across the sample.

It is often assumed decision makers' preferences are constructed based on the absolute value of attributes in each choice set (Payne & Johnson, 1992). Compromise effects under this assumption are a by-product or artefact of decision makers' changes in preferences that are differently constructed in different decision scenarios. An opposing view of preference formation suggests preferences for certain attributes are inherent or are formed via a process of antecedent volition (Simonson, 2008; Swait, 2013). Under this view, contextual factors are thought to be less likely given decision makers' are assumed to be more stable. These assumptions in part determine which measurement and modelling approach to use in investigating behavioural phenomena such as the compromise effect.

Non-choice based measurement methods are available for measuring compromise effects which have further advantages/disadvantages. For example, in one study Drolet, Simonson and Tversky (2000) measure respondents intentions to compromise using a 4 point rating scale for alternatives in choice sets that present only relative values, and compare them to their preferences in comparative choice sets using absolute values. Drolet et al. (2000) further demonstrate the effect is robust over a range of attribute values, with no changes the patterns of substitution observed when decision makers' are given absolute versus relative attribute information. The advantage in these studies is in studying decision makers' conscious decision/tendencies to make compromising choices, suggesting decision makers' are inherently aware of the approximate shape of their preference indifference curve.

A commonality among extant research into compromise effects is the use of stylised experiments that often lack repeated measures within-subjects (e.g. (Drolet et al., 2000)). Our approach uses systematically designed choice experiments in which respondents make repeated choices from among choice sets that follow a strict experimental design plan. The approach is not stylised in anyway, and attribute levels for each alternative are presented in a balanced way that ensures representativeness of attribute level combinations. Our design approach includes a targeted compromise alternatives within trinary choice sets that are constructed by algorithmically inserting alternatives into a baseline binary choice set that systematically ensures a "middling" alternative is always available based on attributes known to be most important in the product context considered (air travel).

The modelling approach used in this paper tests the strength and stability of the latent drivers of decision makers' preferences for alike attributes common to different choice scenarios. We identify how the compromise effect manifests at both an abstract level as well as at the choice set level using conventional simple arithmetic approaches to analysis. Specifically, we consider whether a common latent variable accounts for a taste sensitivity that is general to a choice task in which compromise behaviour occurs and to what extent the strength of compromise effects affect the between task stability in decision makers taste sensitivities.

In terms of measuring and modelling the effect, we are able to use both the conventional approach of comparing choice frequencies between tasks in which the compromise alternative is present versus absent, and using a structural choice modelling approach. The former approach provides a useful descriptive analysis of the data, and indeed shows that on average across all choice tasks completed "middling" alternatives are chosen more often. The latter structural choice modelling approach provides additional insights into commonalities among decision makers' preferences across each of the choices they make. Further, it allows tests of the stability in the drivers of decision makers preferences between scenarios with and without compromise alternatives present.

In terms of specification our model combines an attribute and alternative specific constant specification to test how the presence of a compromise alternative within choice sets effects the between scenario stability in the taste sensitivities of each of the attributes. We clarify the econometric specification in more detail in a later section.

Structural choice modelling The structural choice model was developed by Rungie, Coote and Louviere (2011, 2012) specifically with applications such as testing behavioural theory about the differences in decision makers' preferences between difference choice scenarios in mind. The model is general in that it subsumes conventional choice models including the fixed and random coefficients specifications of mixed logit.

Before elucidating further on the specifics of the econometrics of the model, this section will provide a brief overview of where the model has been applied in testing behavioural phenomena similar to that under considering in this study. Our study of compromise effects essentially questions to what extent the sources of decision makers' preference heterogeneity vary under different information conditions. Similarly Coote, Islam, Louviere and Magor (2015) test the generality and stability of preferences for using four wave panel data. Specifically, their structural choice model tracks whether a common latent variable accounts for variation in decision makers preferences over time in a fast moving consumer goods market or if there are time dependent sources of preference heterogeneity. Their findings indicate a stability across time in the source of decision makers preferences, while noting some local/time dependent variation in strength of preferences for particular attributes. The theoretical suggestion brought forward in Coote, Islam, Louviere and Magor (2015) is decision makers apply a consistent decision rule across time, yet this need not necessarily result in the same preferences expressed in each period.

Wallin and Coote (2015) consider decision makers' preferences under two different information conditions in a similar way to the current study. In the first decision makers have only information about one product and are given a buy/not buy option. In the second comparison information about competing products is available, which is characterised by information being either available or missing for particular attributes. The modelling approach tests behavioural theory about how structures in the unobserved components of decision makers' preference vary under the two information conditions, which is similar to our scenarios with/without a compromise alternative available.

Rungie, Scarpa and Thiene (2014) use a multi-factor structural choice model to test theory on influence within group decision making contexts. In this application, a model is set up that estimates the strength of association between the drivers of preferences for different decision makers. The model enables a test of how strong particular decision makers' preferences are expressed (a test of influence) when those two decision makers complete a choice experiment together.

2.3 Research context

A hypothetical website for booking international flights is used as the context for a discrete choice experiment. Choice sets are constructed to mimic the style of a popular price aggregator which consumers use to compare options among several airlines. Alternatives are constructed using an unlabelled design. Brand is not an attribute and generic alternatives are presented. Respondents are instructed to imagine they are booking a one-way flight to a long-haul overseas destination of their choice. Respondents are asked to select a departure time that is within the next 6 months, a departure city from a drop down list of Australian capital cities and an arrival city from a list of European cities (see Figure 2.1). While a two-way (return) flight is a more common booking scenario, a one-way flight was chosen to simplify the experimental design.

To improve incentive alignment (Ding, Grewal & Liechty, 2005) respondents are told the flights shown to them correspond to the flights they had searched for, although respondents were all shown the same choice sets. Our sampling frame is representative of the general Australian population. Between 2005 and 2014, the numbers of Australians embarking on overseas trips (including both holiday and business trips) increased from 4.3 to 8.2 million trips between 2005 and 2014 (approximately one-third of the total Australian population), while the numbers of Australians travelling domestically for holiday purposes over the same period remained stable (ATR, 2015).

During the years 2010 to 2011, the Australian dollar peaked in value at USD$1.09 per AUD$1.00 and the annual number of Australians embarking on outbound trips grew by 20% to its highest rate in 30 years (ABS, 2014). More generally, Australians embark on overseas

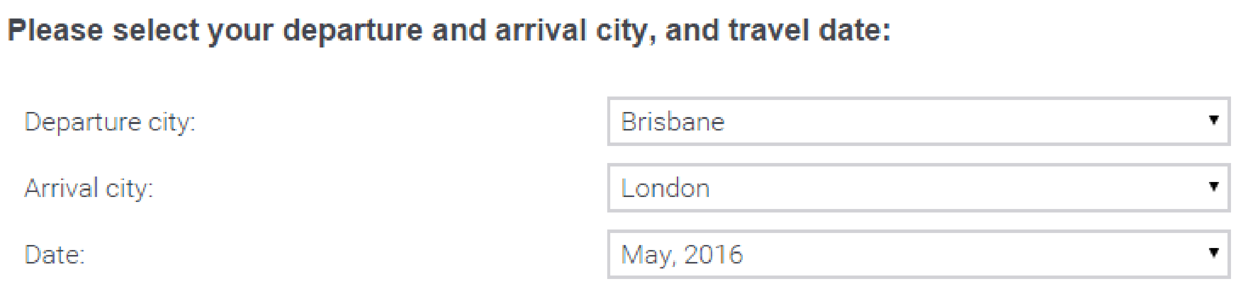

Figure 2.1: Flight configuration screen

travel at a similar rate to European countries (0.5 outbound trips per person per year), which translates into many more kilometres travelled due to Australias geography as the majority of these trips are to long-haul destinations (Timetric, 2014). By comparison, the top ranking countries in terms of outbound passengers are dominated by Scandinavian countries, with the majority of overseas trips taken to nearby short-haul destinations (Timetric, 2014). The United States which is similar in geographic size to Australia but geographically much closer to popular long-haul destinations saw only 0.2 outbound trips per person per year in 2013, yet had double the rate of short-haul domestic trips over the same period (Timetric, 2014). Hence, we are confident that our sample consists of a demographic who are familiar with the cost and experience long-haul overseas travel.

Experimental designs The experimental design consists of two discrete choice experiments; the first is a binary choice task and the second is a trinary choice task. The first task is constructed using SPSS following orthogonal main effects plan (OMEP) and its folder-over per Street, Burgess and Louviere (2005). The design matrix for the trinary choice task is a repeat of the first task, but contains a contrived compromise alternative generated algorithmically in Microsoft Excel.

This contrived alternative sits at a less attractive level on attributes known to be important to consumers in this context. The added alternative need not be less attractive on all attributes, as decision makers do not necessarily compromise based on all attributes (Kivetz et al., 2004b), nor do they strictly speaking only use absolute values (Drolet et al., 2000; Drolet, 2002). We assume price is always going to be important, hence the contrived alternative is always proportionally more expensive. Further, specific to our transport context we assume trip length related attributes are critical to most consumers as is seen from previous studies in all areas of transport including air travel (Bliemer & Rose, 2011), trip-chaining/transfers in public transport (Hensher & Reyes, 2000), waiting (Li & Hensher, 2011) as well as more general disutility for factors of inconvenience in travel being more salient than comfort (Cantillo, Heydecker & de Dios Ortúzar, 2006; Obeng & Sakano, 2012). Hence, the contrived alternative has either an equal number of (or proportionally more) stop-overs and is equally as long (or proportionally longer) that the most expensive option in each of the binary tasks.

The design strategy ensures that in each choice set there is an identifiable compromise alternative that pertains to one of the original two alternatives from the binary task such that it becomes a middling alternative in the trinary task in terms of those most salient attributes mentioned above. There is the potential for some decision makers to subjectively think of their decision making process as not compromising, especially if some decision makers do not horizontally differentiate. Some decision makers may prefer flights at a particular time of day, or derive disutility from long-haul flights and thus prefer some optimal number of stops (as opposed to always less). Our design allows us to track the relative change in choice share for each alternative across the two tasks, and thus test the basic components of the theory as per Simonson (1989).

We provide manipulation checks in our initial arithmetic analysis of the data to determine that the contrived alternative is indeed considered less attractive. We do this at an individual level counting how many of the respondents who do select not contrived inferior option in the experiment. This is in addition to the choice models which also provide aggregate estimates of the relative strength of the compromise effect using an alternative specific constant.

Table 2.1: Attribute and level definitions

Stops:	The number of stopovers (1; 2; 3; 4)
Duration:	The total number of hours in transit (20; 24; 28; 32; 36)
Inclusions:	Entertainment, baggage and meals (None; Entertainment; Entertainment and Meals; Entertainment, Meals and Checked Baggage)
Price:	The cost of the one-way flight in Australian dollars ($1009; $1261; $1513; $1765; $2521)
Departure Time:	The time of departure from the airport (Morning; Midday; Afternoon; Evening)

Stops, duration and price were chosen for this contrived manipulation due to their known importance to consumers (Bliemer & Rose, 2011) and based on feedback from attendees at the 2015 UQ Business School Research Colloquium where an earlier research proposal for this study was presented.

The ordering of choice sets is randomised for each respondent, such that no two respondents saw the same choice sets in the same order. Further, the two tasks were presented simultaneously. That is, respondents were randomly served choice sets from the design matrix of both experiments using a randomisation algorithm built into the online survey software to control for ordering effects both across and within choice sets.

The binary/trinary choice sets are also randomly served, such that the sequence of binary/trinary is not the same for any two cases. This in part controls for some amount of habit persistence (such as preferring a particular attribute level in either of the scenarios). The vertical positions of each alternative are also randomised within each choice set.

The complete set of attributes and levels include number of stops (1; 2; 3; 4), total duration in hours (20; 24; 28; 32; 36), inclusions (None; Entertainment; Entertainment and Meals; Entertainment, Meals and Checked Baggage), price ($1009; $1261; $1513; $1765; $2521) and departure time (Morning; Midday; Afternoon; Evening). Example choice sets from the two discrete choice experiments are shown in Figure 2.2.

Note the second task features a third alternative which is proportionally more expensive than the most expensive option in the first task, has an additional stopover and longer duration. Departure time and inclusions are generated randomly, and are balanced across the design. This randomising for departure time and inclusions results in some alternatives not being objectively inferior on only those attributes we have specifically targeted. For example, in the choice set shown above in Figure 2.2, the contrived alternative happens to have more included extras than the middling alternative. This has the effect that the relative difference between alternatives is not necessarily linear across all attributes in each choice set. In some choice sets the middling alternative may in fact be closer/further away from one of two extremes in terms of attractiveness on those attributes known to be overall less important, but in all cases will be middling on those attributes known to be most important.

The flight priced at $1513 in DCE 2 shown in Figure 2.2 represents the compromise alternative. Note that the $1513 appears in both tasks and it is the middling alternative in the second. Theory on compromise effects suggests the $1513 option receive an increased market share relative to the $1261 option in the trinary choice tasks.

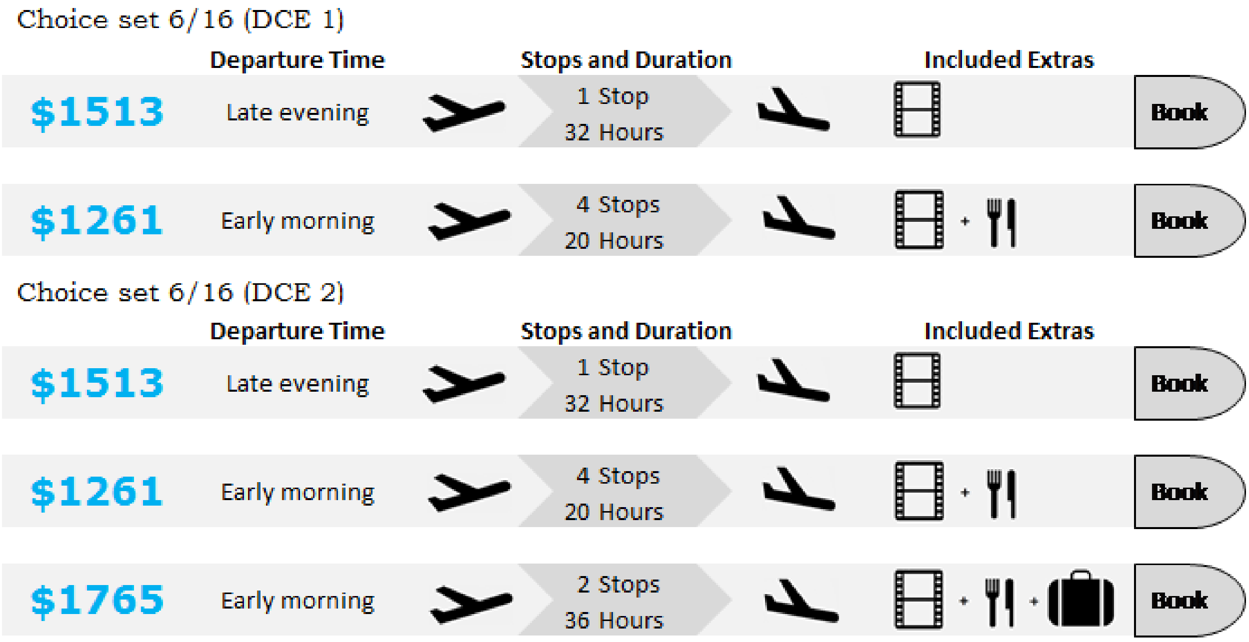

Figure 2.2: Example choice sets

2.4 Model specification

The structure of latent variables associated with decision makers' taste sensitivities between the two tasks in this experiment are expected to characterise the impact the compromise effect has on decision makers' choices. Specifically, the regression coefficients of one and two factor structural choice models are expected to reveal a different source of variation to decision makers preferences that are task specific.

The taste sensitivities for the alike attributes common to both tasks are expected to have unique sources of heterogeneity specific to each task. In the trinary choice situation decision makers are expected to engage in compromising behaviour, as such the latent drivers of their sensitivities in this situation are expected to be different to those in the binary condition.

Further, the alternative specific constant specification we use is expected to show the compromise effect differentially affects the level of between task preference stability for some attributes more strongly than others. This is similar to the polarising effect of compromise behaviour (Kivetz et al., 2004b), whereby some attributes exhibit significant extremeness aversion and some do not. Our model captures this effect indirectly. Our model specifies a latent variable which represents a source of taste sensitivity specifically associated with a compromise effect alternative specific constant. As a theoretically driven specification, the effect this variable has on between-task stability in taste sensitivities informs us to what extent the compromise effect accounts for the stability in the taste sensitivities for attributes between the two tasks.

Model equations The general equation is $U_i = V_i + e_i$, where the systematic component of utility V_i comprises the summation of indirect utilities for each attribute of each alternative, hence, $U_i = v_1^{ST1} + v_2^{DU1} + v_3^{IN1} + v_3^{PR1} + v_5^{DE1} + v_6^{ST2} + v_7^{DU2} + v_8^{IN2} + v_9^{PR2} + v_{10}^{DE2} + v_{11}^{CE2} + e_i$ for the models included in the current study. The systematic component of utility is a function of a taste sensitivity multiplied by the levels of the attributes as they appear in each discrete choice experiment, $v_i = \eta_i x_i + \epsilon_i$. The taste sensitivity is a function of the mean and/or standard deviations of latent variables in the case of a mixed logit model to capture individual differences (or just the mean in the case of the conditional logit), $\Sigma(\mu_i + \sigma_i \xi_i)x_i$. In structural choice models the ξ is not a single random entity general to all attributes, rather it is specified using structural factor analytic regression equations to give structure to the individual differences of the mixed logit model $\Sigma(\mu_i + \gamma_{i,m}\xi_i)x_i$ (Thiene, Rungie & Scarpa, 2013). The ξ's in these equations may also have higher order dimensions such that $\xi_i = (\beta_{i,m}\xi_m + \delta_i)$ where ξ_m are higher order latent variables.

In the case of the conditional logit model, v_i is only function of the mean μ_ϵ of the random component of utility multiplied by the attribute levels x_i from the design matrix of the discrete choice experiment. For a random parameters specification of mixed logit, in addition to μ_ϵ we estimate a dispersion parameter σ_ϵ which captures the level of preference heterogeneity in taste sensitivities for each attribute. For structural choice models, we again estimate μ_ϵ but instead of a dispersion parameter, factor loadings onto latent variables give structure to the random sources of variation to the taste sensitivities. This structure can be extended to link sources of variation between different attributes, as well as between different latent variables common to attributes in multiple experiments (including those associated with alternative specific constants). It is the latter of these specifications which permit insights into how the presence of a compromise alternative effects the stability in taste sensitivities between tasks. This allows for a model that links binary and trinary decision task scenarios to estimate both between task stability, as well as sources of this stability.

In the equations that follow, the indirect utilities are written out for the systematic component of the utility equation for some decision maker i. Each equations show the specification of each attribute taste sensitivity in each model. The items in parentheses show the specification of η which in each case is multiplied by the attribute levels x_i taken from the design matrices of both experiments (binary and trinary) as per $v_i = \eta_i x_i + \epsilon_i$. The taste sensitivities for attributes from both experiments are estimated simultaneously in one equation. Note the name of each attribute is referred to in abbreviated form in superscript above each taste sensitivity as a descriptor (not as an exponent), e.g. $(\mu_1)x_1^{ST1}$ refers to the taste sensitivity for the attribute "STOPS" in DCE 1 and $(\mu_6)x_6^{ST2}$ for "STOPS" in DCE 2. The attribute CE2 is an alternative specific constant associated with the middling alternative uniquely identified in each choice set from DCE 2.

Conditional and mixed logit models In these first two models aggregate preferences for each attribute are estimated. Their indirect utilities are a function of only the mean of the random component μ_ϵ in the utility equation. The random coefficient specification of mixed logit nests the fixed coefficient model, and in addition estimates a dispersion parameter σ_ϵ which provides information about the level of preference heterogeneity around each attribute including the compromise alternative specific constant.

Conditional logit model,

$$
\begin{aligned}
v_i = (\mu_1)x_1^{ST1} + (\mu_2)x_2^{DU1} + (\mu_3)x_3^{IN1} + (\mu_4)x_4^{PR1} + (\mu_5)x_5^{DE1} \\
+ (\mu_6)x_6^{ST2} + (\mu_7)x_7^{DU2} + (\mu_8)x_8^{IN2} + (\mu_9)x_9^{PR2} + (\mu_{10})x_{10}^{DE2} \\
+ (\mu_{11})x_{11}^{CE2}
\end{aligned}
\tag{2.1}
$$

Random coefficients (mixed logit) model,

$$
\begin{aligned}
v_i = (\mu_1 + \sigma_1)x_1^{ST1} + (\mu_2 + \sigma_2)x_2^{DU1} + (\mu_3 + \sigma_3)x_3^{IN1} + (\mu_4 + \sigma_4)x_4^{PR1} \\
+ (\mu_5 + \sigma_5)x_5^{DE1} + (\mu_6 + \sigma_6)x_6^{ST2} + (\mu_7 + \sigma_7)x_7^{DU2} + (\mu_8 + \sigma_8)x_8^{IN3} \\
+ (\mu_9 + \sigma_9)x_9^{PR4} + (\mu_{10} + \sigma_{10})x_{10}^{DE5} + (\mu_{11} + \sigma_{11})x_{11}^{CE2}
\end{aligned}
\tag{2.2}
$$

Structural Choice Models (SCM) The compromise effect is expected to have effects on the latent source of variation in decision makers taste sensitivities η. More generally we expect the compromise effect to affect the commonalities in decision makers' latent sources of preference heterogeneity between the two tasks. To test this conjecture we specify a catalogue of structural choice models and test various assumptions about the structure of the latent sources of preference heterogeneity.

The specifications follow a logical sequence beginning with a one factor model similar to an exploratory factor analysis (EFA) model common to the structural equations modelling literature. A confirmatory specification with two separate factors unique to each task is specified to test the assumption that taste sensitivities in the different tasks have separate sources of heterogeneity. After this, we specify two further models to test for the between task stability in the latent sources of preference heterogeneity. The first regresses the taste sensitivities from the second task onto the first, without any direct links to the compromise alternative specific constant. The second introduces the compromise alternative specific constant as a predictor of the between task stability of preferences. Ultimately, this final specification is shown to be the best fitting model to the data.

One and two factor structural choice models The first two structural choice models test for differences between the two tasks in terms of their structural heterogeneity by first regressing all attributes onto a single common factor in the first model, and then onto two unique factors in the second. These models test the differences in the latent structure to decision makers preferences between the two tasks as a result of our experimental manipulation.

The models serve a purpose similar to that of an exploratory factor analysis in the case of the one factor model, and confirmatory factor analysis in case of the two factor model. Per theory on the compromise effect, under the confirmatory specification it is expected the taste sensitivities between the two tasks will load onto separate unique factors due to compromise effects eliciting different decision making processes between the tasks.

The econometric specification for the first two structural choice models consist of undefined higher order latent preferences (HoP). In the first model, ξ_1^{HoP1} is a normally distributed (Gaussian) latent variable and we also estimate the standard deviation of its random component σ_δ. The taste sensitivities for all attributes are specified as a function of this higher order preference, linked by a regression coefficients (factor loadings) γ's. The two factor model follows a similar specification, but with two higher order preferences specific to each task.

One factor (congeneric) structural choice model (SCM1),

$$\begin{aligned} v_i = {} & (\mu_1 + \gamma_{1,1}\xi_1)x_1^{ST1} + (\mu_2 + \gamma_{2,1}\xi_1)x_2^{DU1} + (\mu_3 + \gamma_{3,1}\xi_1)x_3^{IN1} + (\mu_4 + \gamma_{4,1}\xi_1)x_4^{PR1} \\ & + (\mu_5 + \gamma_{5,1}\xi_1)x_5^{DE1} + (\mu_6 + \gamma_{6,1}\xi_1)x_6^{ST2} + (\mu_7 + \gamma_{7,1}\xi_1)x_7^{DU2} + (\mu_8 + \gamma_{8,1}\xi_1)x_8^{IN2} \\ & + (\mu_9 + \gamma_{9,1}\xi_1)x_9^{PR2} + (\mu_{10} + \gamma_{10,1}\xi_1)x_{10}^{DE2} + (\mu_{11} + \gamma_{11,1}\xi_1)x_{11}^{CE2} \end{aligned} \tag{2.3}$$

Two factor (confirmatory) structural choice model (SCM2),

$$\begin{aligned} v_i = {} & (\mu_1 + \gamma_{1,1}\xi_1)x_1^{ST1} + (\mu_2 + \gamma_{2,1}\xi_1)x_2^{DU1} + (\mu_3 + \gamma_{3,1}\xi_1)x_3^{IN1} + (\mu_4 + \gamma_{4,1}\xi_1)x_4^{PR1} \\ & + (\mu_5 + \gamma_{5,1}\xi_1)x_5^{DE1} + (\mu_6 + \gamma_{6,2}\xi_2)x_6^{ST2} + (\mu_7 + \gamma_{7,2}\xi_2)x_7^{DU2} + (\mu_8 + \gamma_{8,2}\xi_2)x_8^{IN2} \\ & + (\mu_9 + \gamma_{9,2}\xi_2)x_9^{PR2} + (\mu_{10} + \gamma_{10,2}\xi_2)x_{10}^{DE2} + (\mu_{11} + \gamma_{11,2}\xi_2)x_{11}^{CE2} \end{aligned} \tag{2.4}$$

Compromise effect stability models The two models (SCM3 and SCM4) test for generality in decision makers' taste sensitivities between the two tasks. First, without specifically modelling any direct influence of the compromise effect and second by introducing the effect on between-task stability attributable to an alternative specific constant associated with the compromise alternative.

The two models both test the extent to which taste sensitivities in the first task predict those in the second task for the alike attributes. Attributes unique to each attribute in both tasks are regressed onto each other with an implied directionality from DCE 1 to DCE 2. This specification differs substantially from the two earlier exploratory and confirmatory models. In earlier models, all attributes are regressed onto a common factor which only allows for a test of a general kind of decision rule or behaviour that decision makers engage in with respect to the task(s) overall. Attribute specific information is obtained via the specification of attributes that allow between task linkages, and in the case of SCM4 how these linkages are affected by the compromise effect.

These models together test whether the compromise effect is a determinant of between-task stability in decision makers' preferences. The specification links a latent variable uniquely associated with the compromise alternative specific constant to attributes that are common to the pairs of alike attributes between the two tasks. As the latent variables are common to pairs of attributes, there is an explicitly implied commonality in their source(s) of taste sensitivity achieved via the model specification. By regressing the compromise alternative specific constant onto these attributes, we obtain a regression parameter β that represents the effect the compromise alternative specific constant has on the commonality in sensitivities towards each pair of attributes. In other words, this specification enables a test of the extent to which the compromise alternative specific constant determines stability in preferences between each pair of attributes.

The compromise effect may strengthen (or weaken) the extent to which preferences in the first experiment might predict those in the second. This is partially analogous to a moderation test, although strictly speaking we do not test for moderation in the conventional sense per Baron and Kenny (1986). The compromise alternative specific constant is not an interaction effect variable, nor does SCM4 contain the direct effect in same way it is represented in the previous model. In SCM3, the between-task stability model, the direct effect of how sensitivity towards attributes in the first task predict those in the second are estimated. This provides stability parameters for each attribute while not explicitly accounting for the compromise effect.

In SCM4 the between-task stability in decision makers' preferences are contained within the attribute specification as described above. The attributes (ξ_1 through ξ_5) are common in their specification of each η in both DCE 1 and DCE 2 whereas in SCM3 there are 10 ξ's specific (not common) to each of the DCEs. The ξ's in SCM4 subsume/contain the correlations in preferences that exist between the two tasks as revealed by the β coefficients of SCM3. Under the SCM4 specification, each of the ξ variables are regressed onto a compromise alternative specific constant, which allows us to infer to what extent the compromise effect is a determinant of the strength of the between-task correlations.

SCM4 contains fewer variance components compared to the stability model as the latent variables are specified as a common sources of heterogeneity for the pairs of alike attributes between tasks as opposed to being unique to the attributes in each. This specification accounts for variation between tasks through the latent variable, and permits interpretations of how the compromise effect attenuates the strength in decision makers' preferences between the two scenarios. This allows policy makers to better predict which attributes are more/less robust to the influence of the presences/absences of a compromise alternative.

Between-task stability model (SCM3),

$$\begin{aligned} v_i = &(\mu_1 + \beta_{1,1}\xi_1)x_1^{ST1} + (\mu_2 + \beta_{2,2}\xi_2)x_2^{DU1} + (\mu_3 + \beta_{3,3}\xi_3)x_3^{IN1} \\ &+ (\mu_4 + \beta_{4,4}\xi_4)x_4^{PR1} + (\mu_5 + \beta_{5,5}\xi_5)x_5^{DE1} + (\mu_6 + \beta_{6,1}\xi_1)x_6^{ST2} \\ &+ (\mu_7 + \beta_{7,2}\xi_2)x_7^{DU2} + (\mu_8 + \beta_{8,3}\xi_3)x_8^{IN2} + (\mu_9 + \beta_{9,4}\xi_4)x_9^{PR2} \\ &+ (\mu_{10} + \beta_{10,5}\xi_5)x_{10}^{DE2} + (\mu_6 + \xi_6)x_6^{CE2} \end{aligned} \tag{2.5}$$

Compromise effect structural choice model (SCM4),

$$\begin{aligned} v_i = &(\mu_1 + \beta_{1,6}\xi_6)x_1^{ST1} + (\mu_2 + \beta_{2,6}\xi_6)x_2^{DU1} + (\mu_3 + \beta_{3,6}\xi_6)x_3^{IN1} + (\mu_4 + \beta_{4,6}\xi_6)x_4^{PR1} \\ &+ (\mu_5 + \beta_{5,6}\xi_6)x_5^{DE1} + (\mu_6 + \beta_{6,6}\xi_6)x_6^{ST2} + (\mu_7 + \beta_{7,6}\xi_6)x_7^{DU2} + (\mu_8 + \beta_{8,6}\xi_6)x_8^{IN2} \\ &+ (\mu_9 + \beta_{9,6}\xi_6)x_9^{PR2} + (\mu_{10} + \beta_{10,6}\xi_6)x_{10}^{DE2} + (\mu_{11} + \xi_6)x_{11}^{CE2} \end{aligned} \tag{2.6}$$

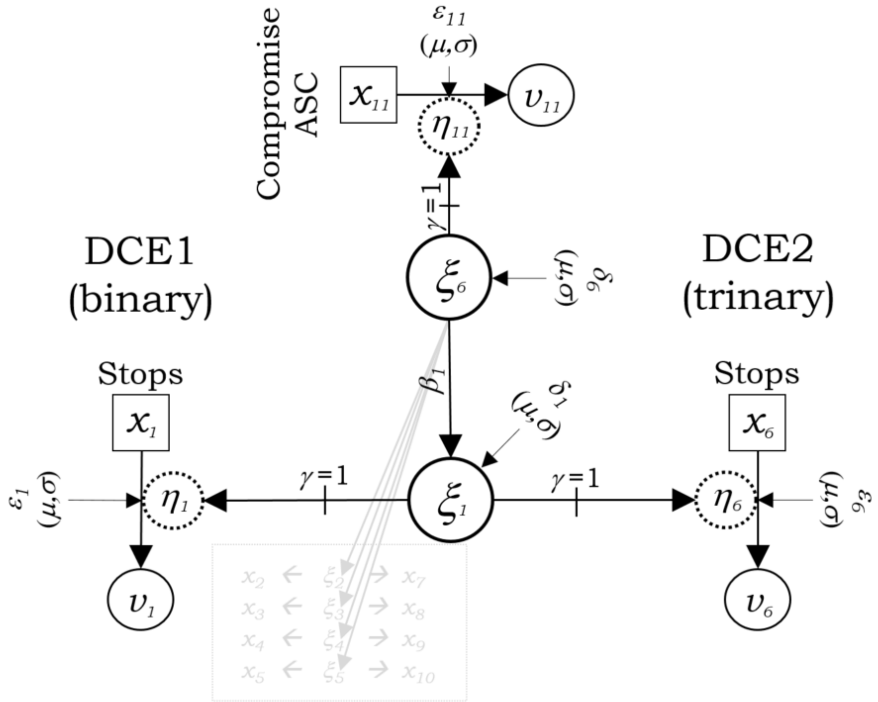

Figure 2.3: Compromise effect model structural choice model

2.5 Results

Sample size and characteristics A panel of 547 consumers were contacted in October, 2015 using an online survey. Of these 137 opened the survey, and 93 successfully completed the survey. The panel was contacted again in November, 2015 resulting in a further 23 complete responses bringing the total sample size to 116. The demographic profile is 68% female with an average age of 45 years and income between \$60,000 to \$80,000. This is representative of Australian consumers who have made long-haul flights in their lifetime (ATR, 2015). A majority of respondents (94%) chose to search for a flight departing from Brisbane, Australia. 37% of respondents searched for flights to London, U.K. and 24% to Paris, France. There was an even distribution travel date preferences. As the majority of respondents searched for flights to and from similar geographic locations, we assume that for the most part respondents completed the task with similar considerations in mind. 32 choice sets were presented (16 per DCE) from which 80 choice observations are made per respondent (two and three observations are made per each two and three alternatives choice set). Given a sample size of n = 116, 9280 observations are made from the data.

Relative choice share analysis The compromise effect manifests when the choice shares for a particular product are enhanced when it is a middling alternative (Simonson, 1989). A simple count of the relative changes in choice shares between the two experiments shows the compromise effect is manifest in our data. DCE 1 contains alternatives *A* and *B*, and DCE 2 contains alternatives *A, B* and *C*. In the case of DCE 2, alternative B is always the compromise alternative, and alternative C is the contrived alternative. Note that in the experiment, the order within an each choice set is randomised but for analysis purposes the data fields are arranged such that they can be compared easily in terms of A, B, and C. A frequency analysis of the relative choice shares shows that for at least 11 out of 16 choice sets the share of the alternative *B* increases in the trinary task relative to the binary choice task (see: Table 2.2).

As a manipulation check we count how many individuals choose the contrived inferior alternative. The contrived inferior alternative is in all choice sets the least preferred alternative. The highest share of choice it received is 13.4%, and in many choice sets it less than 0%, with many (but not all) respondents never selecting it in any choice set. For 77.6% of cases the contrived inferior option is chosen 0% of the time (i.e. is never chosen in any choice set). Of those cases who did select the inferior option, those who did so more than once do not comprise more than 5% of the sample. For some choice sets as many as 25% of respondents switch their preference to the compromise alternative from the more superior alternative. A tendency towards the compromise alternative is prevalent in the majority choice sets.

The strength of the effect varies across the different choice sets. Choice set 6 (shown earlier as the example in Figure 2.2) shows the strongest compromise effect, with an increase of 17.9% in the choice share of the middling alternative *B* when the contrived alternative *C* is added to the set. Choice set 5 is also typical, in which the contrived alternative captured 0% of choices while the middling alternative *B* gains substantially. For this choice set the $1765 flight was chosen 9.8% more times when a $2521 flight is available. In only three out of the 16 choice sets, the choice share of the middling alternative declined, the largest decline being 1.8% in choice set 11 which we see as practically insignificant.

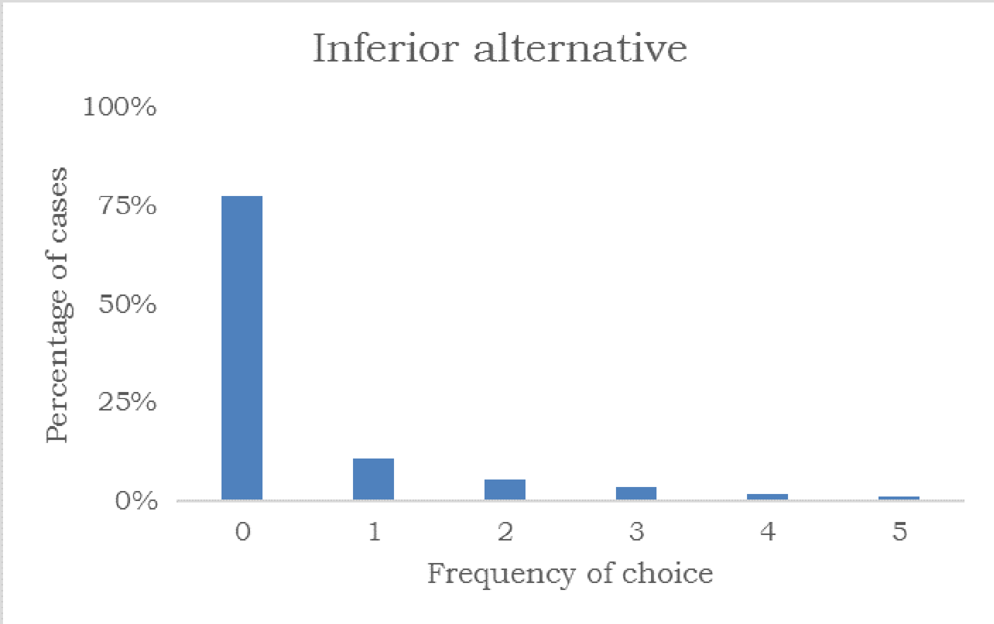

Figure 2.4: Manipulation check, inferior alternative choice share

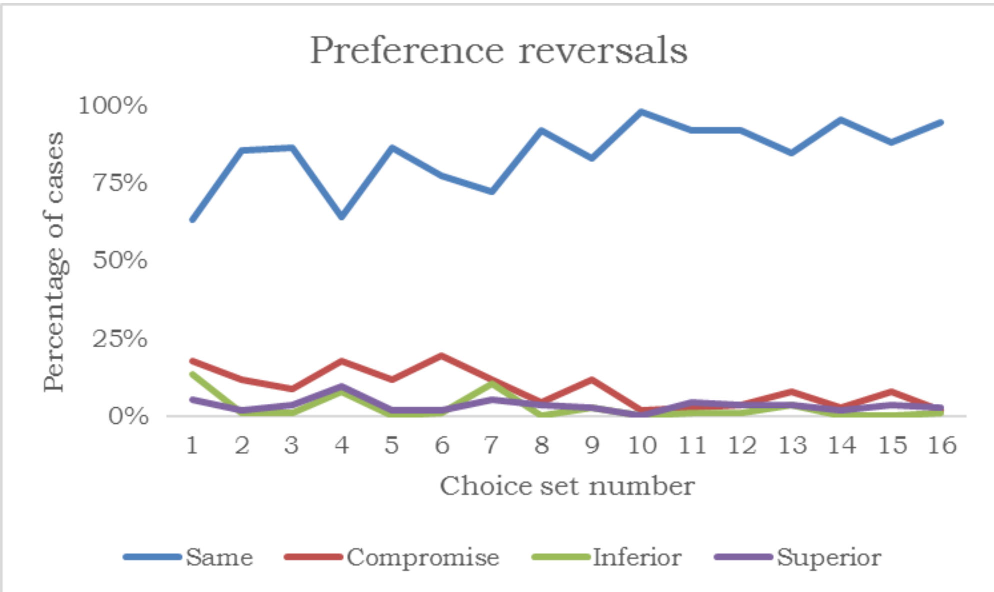

Figure 2.5: Preference reversals

In choice sets 1 and 4 there is an increase in the choice share for the middling alternative relative to alternative A, however alternative C in both sets gain 13.4% and 7.1% of choice share respectively. This is more than the gain netted by the middling alternative, as such we are reluctant to include these two choice sets in our count of compromise effects. Looking at the x-matrix pertaining to these two choice sets, the C alternative is objectively a worse option given it is more expensive in both and feature more stopovers and longer total duration. Given this effect is not prevalent throughout the choice sets it is not expected to reflect any particular alternative theoretical phenomena that occurs generally.

These descriptive results indicate compromising behaviour occurs as expected per Simonson (1989). Alternative B as the middling alternative gains market share in the majority of choice sets which indicates substantial welfare changes for consumers arising due to the way the tasks are designed.

Based on our data an air travel retailer could substantially increase the sales of, for example, a \$1513 flight by positioning it between otherwise objectively equivalent flights priced at \$1261 and \$1765, instead of two flights at \$1261 and \$1513. Using the numbers from choice set 6, 103 out of the 112 people sampled chose for the \$1261 flight when it was positioned (advertised) next to a \$1513 flight, generating \$143,489 in gross revenue. When positioned (advertised) in the trinary set containing a \$1261, \$1513 and a \$1765 flight (the latter of which is also features a longer travel time and more stop overs), the choice share of the \$1513 option increases by 17.9% which represents an additional \$21,319 in gross revenue. A behavioural explanation for this non-utility maximising compromising behaviour is decision makers see the middling alternative in each set as a bargain relative to the objective worse contrived alternative (Simonson & Tversky, 1992), although objectively speaking it is not.

Choice models We estimate several choice models to test how the compromise effect manifests at an attribute and latent variable level. A summary of our results is that a structural choice model that accounts for the compromise effect yields significant improvements to the overall model fit compared to other candidate models. Further, these models present new insights into the compromise effect showing how it has differential or polarising

Table 2.2: Compromise Effect

Choice Set	Alternative	DCE 1	DCE 2	Compromise Effect	ΔChoice Share
	A	75.0%	59.8%		
1	B	25.0%	26.8%	Maybe	1.8%
	C	–	13.4%		
	A	71.4%	60.7%		
2	B	28.6%	38.4%	Yes	9.8%
	C	–	0.9%		
	A	54.5%	49.1%		
3	B	45.5%	50.0%	Yes	4.5%
	C	–	0.9%		
	A	69.6%	59.8%		
4	B	30.4%	32.1%	Maybe	1.8%
	C	–	8.0%		
	A	86.6%	76.8%		
5	B	13.4%	23.2%	Yes	9.8%
	C	–	0.0%		
	A	92.9%	74.1%		
6	B	7.1%	25.0%	Yes	17.9%
	C	–	0.9%		
	A	70.5%	56.3%		
7	B	29.5%	33.0%	Yes	3.6%
	C	–	10.7%		
	A	92.9%	92.0%		
8	B	7.1%	8.0%	Yes	0.9%
	C	–	0.0%		
	A	55.4%	45.5%		
9	B	44.6%	51.8%	Yes	7.1%
	C	–	2.7%		
	A	97.3%	95.5%		
10	B	2.7%	4.5%	Yes	1.8%
	C	–	0.0%		
	A	12.5%	13.4%		
11	B	87.5%	85.7%	No	-1.8%
	C	–	0.9%		
	A	13.4%	12.5%		
12	B	86.6%	86.6%	No	0.0%
	C	–	0.9%		
	A	90.2%	83.9%		
13	B	9.8%	12.5%	Yes	2.7%
	C	–	3.6%		
	A	95.5%	94.6%		
14	B	4.5%	5.4%	Yes	0.9%
	C	–	0.0%		
	A	84.8%	80.4%		
15	B	15.2%	19.6%	Yes	4.5%
	C	–	0.0%		
	A	92.0%	92.0%		
16	B	8.0%	7.1%	No	-0.9%
	C	–	0.9%		

effects on specific attributes between the tasks such that for some attributes the effect is stronger/weaker.

The general pattern of results mirrors those found in the frequency analysis of the relative choice shares between the two tasks. The choice models add value by being able to partition variance in the observed changes in decision makers' taste sensitivities into components explained by the presence of a compromise alternative and components explained by a stable source preference heterogeneity common across the two scenarios. More generally, these models provide a more nuanced set of interpretations relative to the frequency analysis to support theory on how the compromise effect manifests at various levels of abstraction within the structure of decision makers preferences.

The catalogue of models include fixed and random coefficients models, and 4 structural choice models. Model fit indices are reported in Table 2.3 including, the log-likelihood and Akaike Information Criterion (AIC). The AIC takes into account the number of parameters (k) estimated so allows for direct comparison between models. The number of varied attributes is 5 in DCE1 and 6 in DCE2, giving 11 variances along the diagonal of the variance-covariance matrix and 55 covariances on the off diagonal.

Each of the models are in the catalogue satisfy one of the fundamental identifications conditions used in structural equations modelling (SEM), the t-rule. Alternatively, the number of identifiable parameters is given by $\frac{k(k-1)}{2}$ (Bollen, 1989; Bollen & Lennox, 1991)), and where $k = 11$, then the identifiable parameters are 55. Following the t-rule (Bollen, 1989; Bollen & Lennox, 1991), the known values equal or exceed the maximum number of free parameters estimated in the catalogue which is 22 for the mixed logit and first two structural choice models. Hence, there are sufficient degrees of freedom to estimate an identified model.

MNL - Fixed parameters The fixed parameters conditional multinomial logit model parameters consists of the means associated with the systematic component of utility, *i.e.* the η from equation (1.3) for each attribute. These means indicate which attributes of the alternatives are most influential when it comes to predicting which alternative will be chosen. The MNL model estimates 21 means and fits to the data with a log-likelihood of

TABLE 2.3: Model fit

		k	LL	AIC	BIC
MNL	Conditional logit (fixed parameters)	11	−1878.46	3778.92	3818.86
MXL	Mixed logit (random parameters)	22	−1475.35	2994.71	3074.59
SCM1	One factor exploratory	22	−1537.88	3119.76	3199.65
SCM2	Two factor confirmatory	22	−1642.93	3329.85	3409.75
SCM3	Between tasks stability	16	−1577.13	3186.26	3244.36
SCM4	Between tasks compromise effects	16	−888.77	1809.54	1867.64

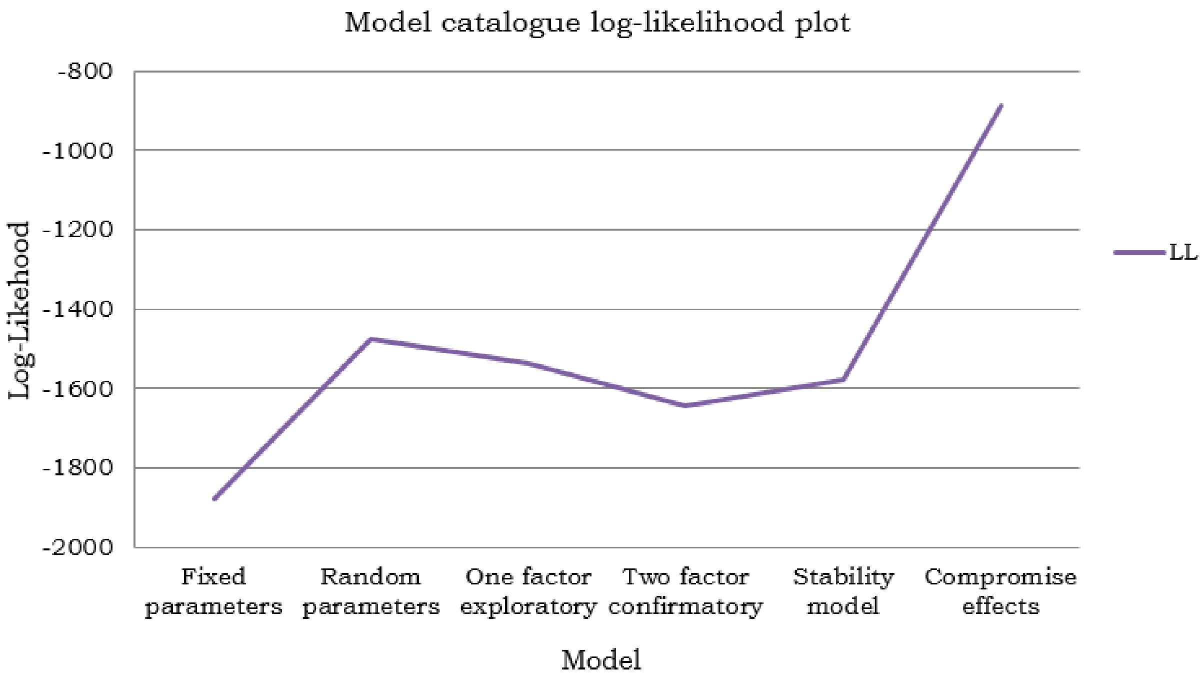

FIGURE 2.6: Log-likelihood plot

$LL = -1878.46$.

This model provides a good indication of which attributes are important to consumers. Unsurprisingly, *price* is the most important attribute in both datasets, and somewhat strengthens in importance in the presence of the compromise alternative (DCE 1 $\mu_{\epsilon}{}^{price} = -.57$, $DCE2 \quad \mu_{\epsilon}{}^{price} = -.73$). The relative order of the importance of attributes remains the same irrespective of the inclusion of a compromise alternative. The compromise alternative specific constant is statistically significant. At this stage, we may conclude decision makers tend to choose the compromise alternative more often than not, and most likely with a polarisation on price.

MXL - Random parameters The random parameters mixed logit model parameters consist of both the means and standard deviations associated with the systematic component of utility. The standard deviation in this case refers to the distribution of primary preferences within the population. Respondents preferences for each attribute are assumed to sit somewhere within this estimated distribution. For attributes showing a large/wide distribution, this indicates differences between people when it comes to either the relative importance of this attribute or direction (positive/negative) of influence of this attribute. This model also estimates a random coefficient for an alternative specific constant associated with the compromise alternative.

The MXL model estimates 21 means and 21 standard deviations and fits to the data with a log-likelihood of $LL = -1475.5$, a significant improvement vis-á-vis the conditional logit model. The patterns of significance through the primary preferences remains unchanged. There are some changes in the relative order in which attributes are important to consumers. Price remains the most important attribute irrespective of the presence of a compromise alternative. In the absence of the compromise alternative, price and trip duration are equally important (DCE 1 $\mu_\epsilon{}^{duration} = -1.15$, $\mu_\epsilon{}^{price} = -1.15$) and inclusions ranks as the third most important attribute (DCE 1 $\mu_\epsilon{}^{inclusions} = -.98$), whereas in the presence of the compromise alternative inclusions becomes more important than trip duration (DCE 2 $\mu_\epsilon{}^{duration} = -.62$, $\mu_\epsilon{}^{price} = -1.59$, $\mu_\epsilon{}^{inclusions} = 1.09$). The standard deviation for decision makers preferences for the compromise alternative is not significant suggesting the compromise effect is unlikely to be a basis for behavioural segmentation in our data. In other words it would seem the effect is likely to be consistent across people.

As in the MNL model, the strength of the importance of price in this model increases from DCE 1 to 2 and the compromise alternative specific constant is statistically significant. Despite the significant improve in model fit, the story is more or less the same with the addition that inclusions may also play a significant role in driving consumers choice of the compromise alternative. In terms of attribute heterogeneity, there is a significant distribution in preferences among decision makers in this sample for all attributes except departure time in both tasks. Primary preferences for departure time is also not significant in either of the two models considered so far. There is also no significant heterogeneity around preferences for the compromise alternative specific constant suggesting it is similarly attractive to all respondents. This is encouraging, or is at least convenient in terms of our discussion of theory as it further suggests the compromise effect manifests in a similar way for most (if not all) people.

The MNL and MXL are naïve in that no assumptions are made about the behavioural decision makers' latent sources of taste sensitivity which our choice experiments are specifically designed to capture. In the subsequent structural choice models we present, the specifications test particular behavioural assumptions about the way in which the compromise effect is predicted to manifest in the data.

SCM1 - Exploratory one factor model The first structural choice model considered is the one factor model, which estimates 21 means and 21 regression coefficients and fits to the data with log-likelihood of $LL = -1537.88$, a significant improvement vis-á-vis the conditional logit model, but is a decrement in fit vis-á-vis the mixed logit model. The pattern of significance and attribute importance through this model is the same as the mixed logit model. The importance for trip duration is present, although is not as marked as in the mixed logit. This specification assumes nothing about any behavioural differences between the two tasks so in this sense it is an exploratory model.

The pattern of factor loadings through the regression coefficients shows the most significance for attributes in the compromise effect task, which suggests more commonality among the drivers of decision makers taste sensitivities in this task. There is less significance through these parameters in the absence of the compromise alternative. Consumers tend to trade off more between attributes when a compromise alternative is available, most notably between favourable levels of price and duration which load onto the polar ends of the same factor (DCE 2 $\gamma^{duration} = -.21$, $\gamma^{price} = .79$). In the absence of the compromise alternative, decision makers' taste sensitivities have less shared sources of variation, suggesting the attributes are more likely to be evaluated in a manner that is in more accordance with neoclassical assumptions about rational decision making.

SCM2 - Confirmatory two factor model The second structural choice model features two factors. The specification of a factor over each task forms a confirmatory test for behavioural differences in the way in which decision makers approach their choices in the two tasks. The model estimates 21 means and 21 regression coefficients and fits to the data with log-likelihood of $LL = -1642.93$.

In this model, the primary preferences from the two tasks are loaded onto to separate factors which are unique to each task. The model fit is like before, with an improvement upon the conditional logit model but not the mixed logit model, or the previous one factor specification. The pattern of results through the primary preferences in this model is closer to that of the conditional logit model. The effect of inclusions becoming more important in the presence of the compromise alternative is not present in this model. The pattern of factor loadings is similar to that of the one factor model, with the majority of significant factor loadings coming through only in the presence of the compromise alternative.

As the model does not fit to the data better than the one factor model, the interpretation is similar showing there is more shared preference heterogeneity among attributes in the task featuring compromise alternative. The two factor model does not best summarise the data, as the taste sensitivities in the first task do not clearly share a common factor while the taste sensitivities in the second task do. Further, there are cross-loadings for the *price* attribute onto two factors, which does not support the theory that the compromise effect uniquely affects sensitivity to price. Overall, there does appear to be differences in the sources of preference heterogeneity to the two tasks, although there is not enough information to be able to claim they are entirely unique.

SCM3 - Between tasks stability model The between tasks stability model tests to what extent the taste sensitivities from the first task predict the taste sensitivities in the second. The model estimates 11 means and 5 higher order regression coefficients, and fits to the data with a log-likelihood of $LL = -1577.13$ which is similar to the one-factor exploratory model. The pattern of means for the primary preferences follow very similarly to the previously estimated models, with the exception that the attribute *departure* is significant for the first time in this model.

Interpreting the μ parameters in isolation may lead to a conclusion that decision makers preferred cheaper options, with fewer stops and overall duration. The model implies a decrease in utility (increase in sensitivity) for *price* (DCE 1 $\mu_{\epsilon}{}^{price} = -1.57$, DCE 2 $\mu_{\epsilon}{}^{price} = -2.80$). We know this not to be true given our analysis of the choice shares which shows the middling alternative in each set is chosen more often in the second task. The middling option is never the cheapest, and is balanced with respect to stops and duration per the (Street et al., 2005) OMEP design.

The specification of the stability model uses an attribute specific specification. Under this type of specification, the taste sensitivities toward each attribute are loaded onto separate latent variables (*i.e.* 11 in total) that have a constant variance (γ coefficients are fixed 1). This structure allows for the taste sensitivities (η) to be indirectly regressed onto other taste sensitivities in any direction both within and between tasks, and allow stability in the sensitivities of decision makers preferences for each attribute to be considered separately.

The between task stability in decision makers taste sensitivities is given by the β coefficients, which are estimated in the direction from the task without the compromise alternative towards task with the compromise alternative. The rationale for this directionality is driven by the theory decision makers are "more rational" in the first task as there is no chance to compromise, or at least make decisions following a schema closer to neoclassical assumptions about rational decision making. The model is set up such that we test how strongly these taste sensitivities predict those which we know share a common source of variation likely attributable to the compromise effect. In effect, this forms a test of how robust the preferences are from one task to the next. The higher the β the stronger that taste sensitivity is expressed or carried through to the compromise alternative task.

The β coefficients for every attribute are significant, particularly those targeted by our strategy to induce compromising behaviour (*stops, duration* and *price*). In all choice sets the level of price is higher (but not the highest) for the middling alternative, and in some cases so are the levels for other attributes. This supports the conjecture that preferences for objects are driven by their position within the choice set rather than their absolute values (Drolet et al., 2000; Drolet, 2002; Simonson, 1989).

Recall the way in which the compromise effect was contrived in our experimental design through the addition of a third *alternative* C to the choice sets of the original two alternative design that is proportionally more expensive, includes an additional stop over and is of a longer duration, such that *alternative* B becomes the middling alternative. Table 2.2 shows that all for at least 13 out 16 choice sets there is an increase in the relative choice share of *alternative* B when a compromise alternative is added to the choice set, suggesting an increase in the strength of consumers' taste sensitivities towards attribute levels that are contrived to be systematically higher in this choice set.

The strongest effects are for *stops* ($\beta_1^{stops} = 1.94$), *price* ($\beta_4^{price} = 1.74$), and *duration* ($\beta_2^{duration} = 1.13$) which corresponds exactly with the attributes we manipulated in the experimental design. Note we are careful to interpret these values as *effects* rather than changes in *sensitivity* as these parameters represent the extent to which sensitivities in the first task predict those in the second.

The means (μ_ϵ) of this model show that when we account for the link between the two tasks in terms of consumers taste sensitivities, the increase in the strength of consumers preferences across all attributes in the compromise effect task is much more marked, particularly for those attributes manipulated in the experimental design. We next consider whether these effects are predicted by the compromise alternative specific constant.

SCM4 - Compromise effects model This model tests to what extent taste sensitivity in the compromise alternative specific constant accounts for the between task stability in decision makers taste sensitivities. The specification is achieved by specifying a latent variable common to the pairs of alike attributes across the two tasks as a variable dependent on decision makers taste sensitivity for the compromise effect alternative specific constant. This specification provides a much more nuanced interpretation of how the compromise effect affects the structure of consumers preferences' by assessing the degree to which it indirectly affects stability in consumers taste sensitivities. Further, the estimates for the primary preferences for each of the attributes through the μ_ϵ parameters are now estimated controlling for what influence the compromise alternative may have on stability of decision makers' preferences.

The model has the same number of parameters as the stability model, but is more parsimonious in terms of variance components. The model estimates 11 means and 5 higher order regression coefficients. Whereas the stability model has 11 variance components, this model has 6. The model fits to the data with a log-likelihood of $LL = -888.77$ which is the best fitting model in our catalogue, and is the only model to fit to the data better than the random parameters mixed logit model.

The same type of specification is used in this model, however in this specification the attributes common in both DCEs are regressed onto a general attribute, rather than a task specific attribute. The correlations among the sources of preference heterogeneity which the stability model captures are contained within this attribute for each pair of attributes between tasks. Thus, regressing these attributes onto the compromise alternative specific constant results in a test of the extent to which the compromise effect determines the magnitude of the β's in the stability model.

The pattern of means for primary preferences for the second task appears to be much more attenuated compared to the stability model, or any of the previous models, when accounting for the compromise effect. The interpretation of these parameters is more in line with our expectations of how the compromise effect would manifest. Specifically, decision makers are less sensitive to *stops, duration* and *price* in the second task under this specification. Recall the levels of these attributes are systematically less favourable in the third alternative of the second task, which standard neoclassical assumptions about rationality would suggest lead to decision makers displaying more price and time sensitive preferences in this task. This apparent violation is much more clearly represented in this model.

The β parameters of this model tell an interesting story. These parameters indicate the strength of association between decision makers taste sensitivity towards the compromise alternative and the level of stability in the between task sensitivities. Recall from the stability model that for all of the attributes studied, taste sensitivities in the first task significantly predict sensitivities in the second. Also recall from the results of our one and two factor structural choice model specifications that it is not entirely clear that the two tasks elicit entirely different global decision rules. Our analysis of the choice shares supports the conjecture that the middling alternatives are preferred in the second task, but it is unclear if this is driven by our manipulations of the key attributes *stops, duration* and *price*.

When controlling for the compromise alternative, there appears to be no effect on the between task stability in decision makers sensitivity towards *price* (β_4^{price} = n.s., p < .05). This is interesting if not unexpected, as it suggests decision makers taste sensitivity towards price is robust against compromise effects, despite decision makers selecting an alternative with a higher price in the second task more often than in the first. Stability in the sensitivity towards *inclusions* appears to be most strongly impacted ($\beta_3^{inclusions}$ = 1.18), followed by *duration* and *stops* which both have significant coefficients but the effect is not quite as strong compared to *inclusions*.

Table 2.4: Choice model results

	MNL	MXL		SCM1		SCM2		SCM3		SCM4	
DCE 1	μ	μ	σ	μ	$\gamma_{i,1}$	μ	$\gamma_{i,1}$	μ		μ	
Stops	−0.15	−0.39	0.20	−0.23	n.s.	−0.23	n.s.	0.34		0.61	
Duration	−0.46	−1.15	0.55	−0.57	n.s.	−0.56	n.s.	−0.93		−0.65	
Inclusions	0.50	0.98	0.60	0.57	0.19	0.59	n.s.	0.55		1.33	
Price	−0.57	−1.15	0.82	−0.79	0.80	−0.69	0.73	−1.57		−1.25	
Departure	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	−0.19		−0.31	
DCE 2	μ	μ	σ	μ	$\gamma_{i,1}$	μ	$\gamma_{i,2}$	μ	β	μ	β
Stops	−0.19	−0.32	0.17	−0.24	−0.22	−0.30	−0.13	1.31	1.94	0.45	0.60
Duration	−0.46	−0.62	0.81	−0.55	−0.21	−0.60	n.s.	−1.34	1.13	−0.62	0.68
Inclusions	0.55	1.09	0.64	0.70	0.15	0.57	0.35	1.02	0.61	1.42	1.18
Price	−0.73	−1.59	1.00	−0.91	0.79	−0.90	0.62	−2.80	1.74	−1.23	n.s.
Departure	n.s.	n.s.	n.s.	n.s.	0.11	n.s.	0.11	0.30	0.46	−0.19	0.16
Compromise (ASC)	0.59	0.98	n.s.	0.77	0.28	0.73	0.26	1.10		1.06	

n.s. *Not statistically significant ($p > .05$)*

2.6 Discussion

The compromise effect manifests in a more nuanced way than previously expected. Specifically, decision makers more often than not select the more expensive alternative when it was a middling alternative, but decision makers' sensitivity to price remains constant when we consider latent drivers of taste sensitivity. The compromising behaviour observed in our data appears to be driven more by ancillary attributes like *inclusions*, and to a lesser extent *stops* and *duration*. As attribute specific effects such as this are not as easily predictable *a priori*, analysis of this type becomes crucial to understand how such behavioural effects manifest on a case by case (context by context) basis. In our case, we did not have *a priori* theory relating specifically to decision makers sensitivity towards *inclusions* as something that the compromise would affect the stability of more strongly than others. To the contrary, if anything a more naïve assumption might be that a polarisation effect (Kivetz et al., 2004b) would be more likely with price as decision makers tend to exhibit extremeness aversion for this (and only this) attribute. This was not the case.

The compromise effect yields significant differences in the latent structures in the source decision makers taste sensitivities. Specifically, models SCM1 and SCM2 show that when decision makers engage in compromising behaviour their preferences for the attributes of a choice are more likely to share a common source of preference heterogeneity. On the one hand, trading off between more attributes seems like it would lead to higher levels of consumer welfare, however our analysis of absolute choice shares shows this is not the case with more respondents selecting less favourable options when compromising. In contrast, decision makers preferences in a binary task are not driven a common source of variation. Instead, in the preferences for the attributes in non-compromising situations are evaluated separately and more in line with what might categorised as rational behaviour. In this situation, decision makers choose more favourable options more often (i.e. cheaper, faster and more convenient flights). The reality of consumers' decision making scenarios is rarely as simple as a binary choice task, and in some cases these scenarios are specifically designed in the marketplace to induce such behavioural biases.

Contribution to theory Our contribution to theory is decision makers are more likely to use specific trade off rules when compromising, and our structural choice model provides evidence what these rules may be. It holds true that decision makers tend to select the middling alternative more often than not, but the assertion this is based entirely on its relative position in the choice set is simplistic. The standard choice models (e.g. our conditional logit model) generate a naïve interpretation decision makers' follow a simple combination of rules (e.g. "go for the one that's not too expensive, not too cheap"). Our results show however that decision makers are drawn to the middling alternative after a more deliberative search of the attribute space than in the trinary task. The significant degree of commonality among taste sensitivities that is present in the trinary task, but absent in the binary tasks supports this contribution to theory.

The compromise effect is a key determinant of the between-task stability at attribute specific levels. Decision makers' taste sensitivities from the first (non-compromising) task not only predict those in the second (compromising) task, but are strengthened. This supports the earlier findings that decision makers trade off more between attributes under the compromise effect scenario. That is, decision makers' choices are more predictable in the trinary task when we account for the compromise effect.

We see a re-ordering of the attributes thought to be most important to decision makers when we control for the compromise effect. Specific to our air travel context, the marked increase in importance of the attribute *inclusions* is most strongly driven by the compromise effect compared to other attributes. Price elasticity is increased by only a small margin with preference for lower levels for *price* increasing by .02 on a utility scale. Further, preferences for *price* are robust against influence from the compromise effect as the change in price sensitivity is not significantly affected by the compromise effect and there is little evidence of an attribute polarisation effect (Kivetz et al., 2004b) in this data.

A more general finding is the way in which the compromise effect manifests is seemingly uniform across the population, but it is not uniform across all attributes. We have demonstrated these effects in one context, although we suspect the type of compromise effects at the latent level may be context dependent even though the compromise effect itself is known to be robust across contexts (Simonson, 2014).

Practical implications This research has implications beyond the most immediate that pertain to the potential benefits firms may derive from eliciting compromise behaviour from their consumers. The insights afforded from our structural choice models allow for insights into which attributes of a product/service decision makers may be more (less) likely to be sensitive to when compromising. For policy makers wishing to boost the choice share of a particular product by positioning it as a middling (e.g. on price) alternative, our evidence suggests key to such a strategy working is to pair it with ancillary extras (such low cost inclusions in the air travel example). Pairings of this nature help consumers to justify viewing the middling alternative as a bargain relative to more expensive options, yet more valuable relative to cheaper options (Simonson & Tversky, 1992).

In our application to consumers booking tickets for international flights, price sensitivity was unaffected by a compromise effect (their regression parameter for price remained stable controlling for compromise effect). However, consumers' sensitivity to non-price attributes are significantly affected by the compromise effect. Based on our results a travel booking agent stands to increase their revenues by making available a range of options, rather than promoting only one or two options. Specifically, a mid-tier option which bundles inclusions such as meals, entertainment and checked baggage as "free added extras" into an airline ticket is likely to attract the largest percentage of consumer choices. Our data shows close to a fifth of consumers will pay an additional $252 for a flight with entertainment, meals and baggage included but with more stopovers with no savings in overall transit time when it is a middling priced alternative. When it is not a middling alternative, these consumers were much more likely to choose a cheaper and faster flight (presumably more expensive to operate), which includes entertainment and meals but no baggage (presumably cheap to add-on).

Air travel consumers, on average, are less impressed by inclusions for more expensive offers at the highest price as these are expected or assumed as default (Holland, Jacobs & Klein, 2016). Budget tickets where the inclusions are not expected may not appear as such good deals when they appear next to a middling compromise alternative that does include them (despite the additional cost of adding meals, entertainment and baggage rarely costing as much as $252!). We suspect travel agents and airlines are already savvy to such product configurations, as are their consumers as evidenced by the anecdotal rise in popularity of direct booking and use of comparison sites (Holland et al., 2016). Our choice experiment was designed to mimic the layout of a popular flight comparison site, although we do not find any evidence to suggest such choice formats lead to better decisions from a consumer welfare point of view.

Lastly, our modelling also suggests consumers are less sensitive to longer and less convenient flights (compared to available alternatives). From a travel agent's or airline's perspective, positioning offers as compromise alternatives may assist with disposing of hard-to-sell inventory (Obeng & Sakano, 2012). More generally our results suggests marketers have much scope to compete on the non-price attributes in industries where demand is traditionally seen as driven by price sensitive consumers (Wensveen & Leick, 2009). Careful consideration of the results we describe may also be useful in the design of campaigns to increase consumer welfare such as strategically positioning choices that maximise health outcomes.

Conclusion The compromise effect leads to an increase in attribute trade off behaviour that can be linked to a common source of preference heterogeneity in tasks in which compromising behaviour occurs. While there are still declines to consumer welfare, our models suggest decision makers' behaviour is more predictable when not conforming to perfectly compensatory decision rules. The modelling approach we have presented is unique with respect to extant literature on compromise effects and provides new insights which are useful for strategic marketing practise and policy development.

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3

Paper 2 - Latent variables as a proxy for inherent preferences

3.1 Introduction

The literature on context effects is well established and has significantly influenced thinking about utility maximization. Classic papers by Simonson and Tversky (1992) and (Tversky & Simonson, 1993) introduced the theory of context dependent preferences, offered applied examples, and provided a foundation for decades of experimental work consistent with their thinking and theorizing. Their work and related work collectively forms the basis of behavioural decision theory (BDT). The basic premise of BDT is the value of a choice alternative is determined by context effects. They specifically outline the effects of the broader context (they call this the background context) and the immediate set of choice alternatives under comparison (the local context) on choice. For example, the relative value of a choice alternative relative to another one (local context) may depend in part on the presence or absence of a third alternative (background context). Central concepts in their formulation of choice are trade-off contrast and extremeness aversion: an alternative may appear more attractive against the background of a less attractive one and losses loom larger than gains. BDT further implies preferences are constructed and attempts to establish conditions under which the standard model of economic choice breaks down. However, a more subtle viewpoint is needed.

More recently, the ubiquitous nature of context effects has been questioned and is giving way to theorizing on antecedent volition (Simonson, 2008; Swait, 2013). Indeed, the emerging view is decision makers have stable and inherent preferences. These stable and inherent preferences may be more strongly manifest under some conditions than others (e.g., more strongly evident for search goods than experience goods and/or attributes). Moreover, the notion of decision makers holding stable and inherent preferences is consistent with literature and theory on antecedent volition. The basic premise of antecedent volition is decision makers, despite the decision scenario they confront, will behave in ways broadly consistent with their "true" underlying preferences for the choice alternatives under evaluation. That is, antecedent volition offers one conceptualization of how stable and inherent preferences are manifest. To give a few examples, the choices decision makers make may be separated by time, be recorded pre- and post-purchase, or be complicated by varying degrees of task complexity. The basic premise of antecedent volition is a general behavioural process common to the tasks should be evident in the pattern of choices of decision makers even in the presence of context effects.

Moving the literature on decision making forward requires some mechanism for accommodating the competing views outlined above. On one hand, context effects are anticipated. For example, decision scenarios that differ by level of complexity should yield differences in aggregate preferences for the attributes defining the choice alternatives of the varying decision scenarios. On the other hand, evidence of stable and inherent preferences should be evident per the notion of antecedent volition. Latent variables are a useful proxy for stable and inherent preferences common to the attributes of choice alternatives under different conditions of complexity. More specifically, the effects of the latent variables on the taste sensitivities for the attributes of a choice alternative should be consistent across choice contexts. These effects should be evident even if the aggregate preferences for the attributes of the choice alternatives vary across contexts. The basic premise of the current study is this: aggregate preferences may be specific to choice contexts but a common antecedent volition process defined by latent variables and structures can be established. Testing this premise requires flexible model forms that incorporate latent variables. Hence, we specify and estimate factor-analytic structural choice models (SCMs) (Rungie, Coote & Louviere, 2011, 2012) as a test of antecedent volition.

Our study aims to make two contributions. Firstly, we attempt a contribution to the emerging literature and theory on antecedent volition. Our views of antecedent volition are strongly motivated by the now classic literature on context effects per BDT. Plus, we are strongly influenced by the critique of this literature and recent emphasis on the presumption of decision makers holding stable and inherent preferences. To be sure, the notion of antecedent volition built on stable and inherent preferences is much more consistent with utility maximization and thus should be of some conceptual comfort to choice modellers working in this paradigm. Second, we attempt a modelling contribution. We specify and fit factor-analytic SCMs consistent with a conceptualization of antecedent volition. More specifically, our model catalogue specifies five models: a fixed coefficient specification of conditional logit, a random coefficient specification of mixed logit, a single-factor model, and two multi-factor models. All five models are fit to data recording the choices of decision makers under three conditions of task complexity. A comparison of the model specifications highlights the relative advantages of the multi-factor models: a better representation of antecedent volition, better model fit, and better interpretations.

3.2 Conceptual framework

Theories of decision making Competing views of decision makers are evident in the literature. The standard view is decision makers behave according to random utility theory

(Luce, 1959; Thurstone, 1927); that is, rational utility maximizers pursuing known and stable preferences. These assumptions are generally sound when using the multinomial logit model to understand the primary drivers of decision makers preferences (McFadden, 1973). However, as Simon (1956) posits, the choice environment constrains the extent to which decision makers are able to process the full set of information available at the time of decision making. Quantifying bounded rationality has proven challenging using conventional model forms. More generally, the counter view formalised under the rubric of BDT posits that rather than evaluating the full set of alternatives available, decision makers consider an edited problem using simplifying heuristics in line with some decision rule (Kahneman & Tversky, 1979; Tversky & Kahneman, 1973). While this account seems more plausible than the perfectly rational decision maker, Simonson (2008) suggests that regardless of the choice environment, decision makers will behave in ways consistent with their underlying preferences. That is to say, decision makers should behave per some common antecedent volition, i.e. their underlying true preferences/motivations are not context dependent. Only in exceptional circumstances such as when subject to coercion, manipulation, or severe cognitive burden, should the stability in the way decision makers make choices break down.

Past research focuses on providing tractable accounts of the decision processes involved in the formation of constructed preferences (Ross & Nisbett, 1991; Schwarz, 2007). This is useful in the development of marketing strategy, particularly advertising, as this concerns the process of decision making at points in time close to the point of purchase. This information, however, provides limited insights into understanding how more enduring consumer preferences are formed. Simonson (2008) contends it is unclear if the context effects observed in past studies have an enduring effect on consumers stable and inherent preferences. For example, the number of alternatives in a task is known to affect the importance of particular attributes that influence choice (Caussade, Ortúzar, Rizzi & Hensher, 2005; Gilovich, Griffin & Kahneman, 2002; Swait, 2001), but it is not clear whether this has a permanent effect on the preferences consumers hold for attributes of the alternatives. There is no theoretical justification for such a proposition. In situations where contextual reference points are less salient, consumers' more enduring preferences are more likely to emerge and to determine decision making behaviour (Simonson, 2008).

A multitude of decision rules have been explored in attempts to reconcile these views. For example, the individual characteristics of decision makers are known to be important (Ben-Akiva, McFadden & Gärling, 1999) and decision makers can be classified according to the types of decision rules they use (Swait, 2001). For instance, some decision makers differ in their regulatory focus, such that they choose to focus on attributes which minimize losses while others attend mostly to attributes which promote gains (Higgins, 1997; Lee, Aaker & Gardner, 2000; Wang & Lee, 2006). Motivational orientations drive inherent preferences for those particular attributes which may satisfy decision makers promotional goals, which are known to be subject to environmental influence (Emmons, 1989; Lisjak, Molden & Lee, 2012). While the use of non-compensatory decision rules in decision making is widely accepted in the behavioural economics and psychology literatures, there lacks consensus with regards to how complexity affects the consistency with which decision makers choose a decision rule.

Inherent and stable preferences: Antecedent volition More recently, literature and theory on antecedent volition has come to the fore. Antecedent volition refers to the higher-level processes that direct evaluative behaviour (Swait, 2013). The notion of stable and inherent preferences has important implications for this literature: aggregate preferences may be subject to context effects but underlying and stable preferences for the attributes of choice alternatives should be evident. The view that consumers have stable and inherent preferences for particular objects is an emerging perspective that is in marked contrast to the classic literature on BDT (Simonson & Tversky, 1992; Tversky & Simonson, 1993). Stable and inherent preferences represent consumers receptiveness or tendency to prefer objects exhibiting particular attributes and are often unknown to decision makers and hence are difficult to capture using standard quantitative and/or qualitative research methods (Simonson, 2008). Consumers also have inherent preferences that exist for not yet experienced objects, such as new products. These form an important determinant of consumer decision making behaviour which is both enduring and not easily affected by contextual factors. By contrast, context effects on decision makers constructed preferences are readily observed.

The recent literature on stable and inherent preferences provides a rich source of theory for conceptualizing the choice process, but leaves open challenges for analysts. Formalizing this theory and thinking into tractable model specifications is a prerequisite to test for a stable antecedent volition (i.e., representing behavioural processes consistent with this theorizing). Standard model forms do not sufficiently capture the behavioural processes of antecedent volition. For example, the conditional logit specification places emphasis on the estimation of aggregate preferences for the attributes and/or levels that define the choice alternatives of interest to the analyst and/or policy maker. The literature reports context effects, but typically past studies use conditional logit specifications thus placing emphasis on aggregate preferences. Literature and our theorization on antecedent volition, by contrast, imply a latent behavioural process of stable preferences. A factor-analytic structure can represent this process whereby a latent variable(s) is specified antecedent to the formation of aggregate preferences. Our study builds on and tests the theorizing of (Simonson, 2008) that decision makers have inherent and stable preferences which influence their decision making. This influence is representative of the latent antecedent behavioural process that decision makers go through prior to engaging in a decision scenario, which should be evident as a stable latent source of preference heterogeneity regardless of the choice context environment.

In our study, we identify the presence of latent structures in discrete choice data that are indicative of an antecedent volition which drives preferences in multiple decision scenarios. The decision rules that this antecedent volition gives rise to can be described by the choice set they consider (Swait, 2001) or by the attributes they attend or do not attend to (Hensher, Rose & Greene, 2011; Hess & Hensher, 2010; Hess, Stathopoulos, Campbell, ONeill & Caussade, 2012). Building on this literature and theory, we propose and implement a choice study in which we vary the design of the decision scenarios faced by decision makers; specifically, we record the choices of decision makers under three different conditions of varying complexity as defined by the number of alternatives available in each scenario. We analyse these data simultaneously using a flexible factor-analytic choice model. The factors or latent variables we specify represent latent preferences for the attributes of the choice alternatives we study (i.e., the latent variables represent deep preferences or meta-attributes). We further link the taste sensitivities from each of the choice tasks to latent variables specific to each attribute. Thus, we specify a latent structure that reflects a structure of antecedent volition for the choice task(s). The model form allows for context effects (i.e., differences in aggregate preferences for attributes common to multiple decision scenarios) and specifies a process of antecedent volition (i.e., a latent structure running across decision scenarios linking common attributes). Before describing the econometric specifications in more detail we briefly introduce the research context and design.

3.3 Research context

In 2013, the operator of the public bus network in Brisbane, Australia delivered recommendations for a major network overhaul centred on reducing service duplication and increasing service frequency. The public bus network in this city operates a very large number of services covering a wide geographic area. In the year 2013, 230 bus routes operated within the Brisbane city area and of these 19 routes account for 44 percent of all journeys taken within the greater South East Queensland region out of a total of 361 routes (Department of Transport and Main Roads, 2013). Capacity utilisation across the network is low, with over 80 percent of all routes operating with less than 14 passengers and over 50 percent with less than 7 passengers (Department of Transport and Main Roads, 2013). Service duplication occurs throughout the network, whereby several lower frequency routes share main corridors to access remote spurs of outer urban areas. Electronic ticketing data reveal high frequency routes are more patronised than low frequency routes, and most importantly that access to these routes is not made via transfers from lower frequency spur routes (TransLink, 2013). This implies that commuters are willing to walk further from their homes to access transport hubs or make use of "park-and-ride" facilities (TransLink, 2013). In some instances, commuters have a choice from among many alternative services which departing from and travelling to the same location(s). The bus network review suggests a reduction in the number of alternatives available through a merger of duplicate routes along main trunk lines. An increase in efficiency was expected to be realised through shorter overall total trip and in-vehicle times. The network changes would have implied significant changes to the way some passengers travel; for instance, some may have been required to make more transfers to complete their journeys, or some may have been required to endure longer walking distances. The recommendations of the review were never put into action for a range of reasons, including (potentially) the lack of evidence around how commuters may have responded to the changes. The research presented here concludes with policy implications that will be of interest to transport planners.

The modelling conducted as part of the network review was unable to make evaluations regarding the potential change in commuters sensitivity toward some of the attributes mentioned above as a result of what is effectively a change in the number of alternatives available. Understanding the stability of decision makers taste sensitivities for transport related attributes given changes to the number of alternatives available may help policy makers to better understand the structure of preference heterogeneity. The theory examined in this study suggests the tendency of commuters to prefer high frequency routes, for example, is an inherent preference which should remain stable regardless of how many alternatives are available. Choice complexity is known to constrain decision makers utility maximizing ability (Simon, 1956), yet choice complexity ought not to affect a decision makers true utility function (i.e. their "true" or inherent preferences). Thus, the antecedent volition some decision maker holds ought not to depend on things such as the complexity or otherwise of a decision scenario. That is, the latent decision rules formed well prior to arriving at a choice scenario are expected to be accessed (or at least attempted) regardless of the complexity of the choice scenario.

To test these notions, structural choice models were fitted to a dataset originally collected for the purpose of assessing the impact of choice experiment design on choice behaviour in a bus travel context described above. The data were interdependently collected at the same time the bus network review was being undertaken, although at that time the types of models advanced in this study were not known. The original study (Magor, 2012) using this dataset reports primarily on the results of a single factor model which does not allow for the generality of sensitivities towards particular attributes across the different levels of complexity to be appropriately evaluated. In brief, the use of a single factor model assumes a global decision rule that is general and generic to all attributes across all choice scenarios, which is theoretically implausible. Policy implications cannot reliably be made from such a model. The theory and models developed for this study offer policy makers an alternative understanding of how such transport network changes may affect commuter behaviour with greater detail (tractability) at the attribute level.

The data are collected from a discrete choice experiment with choice sets containing the attributes listed in Table 3.1. The experimental design consists of an orthogonal array which forms a baseline pair of alternatives. To this pair, additional alternatives are added to form choices sets of three, five and seven alternatives using a fold over and column shifting procedure. The data used in this study were collected as part of a previous study (Magor, 2012), in which an extended discussion of this design procedure can be found. The data structure allows within-subjects effects to be considered as respondents completed tasks corresponding to all three complexity conditions. The dataset contains 279 usable responses from which 33,480 observations are made (8 choice sets per complexity condition per respondent).

Table 3.1: Attribute levels of the choice alternatives

	Covariates	Levels	Label
1	Service Type	2	Regular; Express
2	Service Availability	2	Available; Anticipated
3	Comfort	2	Sitting; Standing
4	Number of Transfers	4	None; 1; 2; 3
5	Anticipated Wait Time	4	2mins; 4mins; 6mins; 8mins
6	In Vehicle Time	4	10mins; 20mins; 30mins; 40mins
7	Walking Time	4	1min; 5mins; 10mins; 15mins
8	Price	4	$2.50; $5.00; $7.50; $10.00
9	Total Travel Time Variation	4	+/- 1min; +/- 6mins; +/- 12mins; +/- 18mins

3.4 Model specification

To represent antecedent volition the latent variables of a structural choice model are used to give structure to the taste sensitivities of attributes across several contexts by representing them with a common antecedent source of randomness. The latent variable in this case is not exogenously defined, although we have theory to guide us such that any significant loading onto a common latent factor across different decision scenarios is reflective of some common antecedent guiding evaluative behaviour. We may speculate about the nature of the antecedent volition, for example, relating to higher-order preferences or meta-attributes independent of context such as convenience or safety in the bus transport context considered here. For example, we expect the taste sensitivities for comfort in a bus journey to load onto a common meta-attribute representing a stable and inherent preference for this attribute (reflecting a context independent inherent preference/decision rule for the attribute). Linking the taste sensitivities for an attribute common to decision scenarios in this way has several advantages. Firstly, assigning meaning to the latent variable(s) is relatively straightforward. In the example above, the latent variable represents a meta-attribute easily labelled as comfort. Second, the regression coefficients, γ's, are interpretable as factor loadings per confirmatory factor analysis. The expectation is factor loadings onto latent variables representing an attribute common to multiple decision scenarios will have the same sign. This model specification allows an initial test of the commonality (or otherwise) of the theory of antecedent volition and has good interpretations. In summary, theory guides the expected pattern matrix of regression coefficients per a specification of structural choice models described subsequently.

Five choice models per the catalogue of Table 3.2 are specified and estimated. Model 1 (M1) is a fixed coefficient specification of conditional logit (McFadden, 1973). This model provides a useful baseline for evaluating models M2 and M3. These models introduce preference heterogeneity, but in different forms. They impose different latent structures with different and competing explanations of the data structure. They represent rival models and/or explanations of the antecedent volition process for each attribute. M2 is a traditional random coefficient or random parameter specification (McFadden & Train, 2000). Thus, M2 introduces unobserved sources of preference heterogeneity or taste variation. The unobserved sources of taste variation or variance components are uncorrelated in this model. M3 and M4 are factor-analytic structural choice models. M3 is defined by the introduction of a single latent variable. The latent variable represents a single unobserved source of preference heterogeneity. Under M3, the taste sensitivities are specified as a function of this latent variable and their respective random components. M4 is a multi-factor model. The defining characteristic of the specification of M4 is multiple ξ's. Each ξ represents a latent preference for a specific attribute common to the multiple DCEs. The taste sensitivities under the specification of M4 are functions of latent variables and their respective random components. Note in the specification of M3 and M4, the random components have means only. The latent variable(s) is the source of "randomness" in the taste sensitivities. M5 is an addendum to the version of this study that appears in the thesis. It is a two factor higher order structural choice model which is used to produce a two dimensional choice map of consumers' preferences controlling for any context effects across the three decision scenarios. This model allows an evaluation of attributes with shared sources of antecedent volition (attributes which are closer together have correlated sources of antecedent volition). Recall the design of the survey and data structure. The choice sets in each decision scenario have three alternatives, five alternatives, and seven alternatives. These decision scenarios are separate DCEs, which are subsequently combined for purposes of analysis. That is, the dataset records the choices of all respondents from all choice sets of all three decision scenarios. This data structure allows for the specification of latent variables, common to the taste sensitivities of the attributes common to the separate DCEs. All models are estimated using the DisCoS software (Rungie, 2011). Model parameters are estimated using maximum simulated likelihood with 1000 Halton draws. The full model specifications are listed below.

The conditional logit model,

$$\begin{aligned}
v_i &= (\mu_1)x_1^{ser.t_1} + (\mu_2)x_2^{ser.a_1} + (\mu_3)x_3^{comf_1} + (\mu_4)x_4^{n.tran_1} + (\mu_5)x_5^{wait.t_1} \\
&+ (\mu_6)x_6^{ivt_1} + (\mu_7)x_7^{walk.t_1} + (\mu_8)x_8^{price_1} + (\mu_9)x_9^{time.v_1} + (\mu_{10})x_{10}^{taxi_1} \\
&+ (\mu_{11})x_{11}^{ser.t_{12}} + (\mu_{12})x_{12}^{ser.a_2} + (\mu_{13})x_{13}^{comf_2} + (\mu_{14})x_{14}^{n.tran_2} + (\mu_{15})x_{15}^{wait.t_2} \\
&+ (\mu_{16})x_{16}^{ivt_2} + (\mu_{17})x_{17}^{walk.t_2} + (\mu_{18})x_{18}^{price_2} + (\mu_{19})x_{19}^{time.v_2} + (\mu_{20})x_{20}^{taxi_2} \\
&+ (\mu_{21})x_{21}^{ser.t_3} + (\mu_{22})x_{22}^{ser.a_3} + (\mu_{23})x_{23}^{comf_3} + (\mu_{24})x_{24}^{n.tran_3} + (\mu_{25})x_{25}^{wait.t_3} \\
&+ (\mu_{26})x_{26}^{ivt_3} + (\mu_{27})x_{27}^{walk.t_3} + (\mu_{28})x_{28}^{price_3} + (\mu_{29})x_{29}^{time.v_3} + (\mu_{30})x_{30}^{taxi_3}
\end{aligned} \tag{3.1}$$

The mixed logit model,

$$\begin{aligned}
v_i &= (\mu_1+\sigma_1)x_1^{ser.t_1} + (\mu_2+\sigma_2)x_2^{ser.a_1} + (\mu_3+\sigma_3)x_3^{comf_1} + (\mu_4+\sigma_4)x_4^{n.tran_1} \\
&+ (\mu_5+\sigma_5)x_5^{wait.t_1} + (\mu_6+\sigma_6)x_6^{ivt_1} + (\mu_7+\sigma_7)x_7^{walk.t_1} + (\mu_8+\sigma_8)x_8^{price_1} \\
&+ (\mu_9+\sigma_9)x_9^{time.v_1} + (\mu_{10}+\sigma_{10})x_{10}^{taxi_1} + (\mu_{11}+\sigma_{11})x_{11}^{ser.t_2} + (\mu_{12}+\sigma_{12})x_{12}^{ser.a_2} \\
&+ (\mu_{13}+\sigma_{13})x_{13}^{comf_2} + (\mu_{14}+\sigma_{14})x_{14}^{n.tran_2} + (\mu_{15}+\sigma_{15})x_{15}^{wait.t_2} + (\mu_{16}+\sigma_{16})x_{16}^{ivt_2} \\
&+ (\mu_{17}+\sigma_{17})x_{17}^{walk.t_2} + (\mu_{18}+\sigma_{18})x_{18}^{price_2} + (\mu_{19}+\sigma_{19})x_{19}^{time.v_2} + (\mu_{20}+\sigma_{20})x_{20}^{taxi_2} \\
&+ (\mu_{21}+\sigma_{21})x_{21}^{ser.t_3} + (\mu_{22}+\sigma_{22})x_{22}^{ser.a_3} + (\mu_{23}+\sigma_{23})x_{23}^{comf_3} + (\mu_{24}+\sigma_{24})x_{24}^{n.tran_3} \\
&+ (\mu_{25}+\sigma_{25})x_{25}^{wait.t_3} + (\mu_{26}+\sigma_{26})x_{26}^{ivt_3} + (\mu_{27}+\sigma_{27})x_{27}^{walk.t_3} + (\mu_{28}+\sigma_{28})x_{28}^{price_3} \\
&+ (\mu_{29}\sigma_{29})x_{29}^{time.v_3} + (\mu_{30}+\sigma_{30})x_{30}^{taxi_3}
\end{aligned} \tag{3.2}$$

The one factor model,

$$\begin{aligned}
v_i &= (\mu_1+\gamma_{1,1}\xi_1)x_1^{ser.t_1} + (\mu_2+\gamma_{2,1}\xi_1)x_2^{ser.a_1} + (\mu_3+\gamma_{3,1}\xi_1)x_3^{comf_1} \\
&+ (\mu_4+\gamma_{4,1}\xi_1)x_4^{n.tran_1} + (\mu_5+\gamma_{5,1}\xi_1)x_5^{wait.t_1} + (\mu_6+\gamma_{6,1}\xi_1)x_6^{ivt_1} \\
&+ (\mu_7+\gamma_{7,1}\xi_1)x_7^{walk.t_1} + (\mu_8+\gamma_{8,1}\xi_1)x_8^{price_1} + (\mu_9+\gamma_{9,1}\xi_1)x_9^{time.v_1} \\
&+ (\mu_{10}+\gamma_{10,1}\xi_1)x_{10}^{taxi_1} + (\mu_{11}+\gamma_{11,1}\xi_1)x_{11}^{ser.t_2} + (\mu_{12}+\gamma_{12,1}\xi_1)x_{12}^{ser.a_2} \\
&+ (\mu_{13}+\gamma_{13,1}\xi_1)x_{13}^{comf_2} + (\mu_{14}+\gamma_{14,1}\xi_1)x_{14}^{n.tran_2} + (\mu_{15}+\gamma_{15,1}\xi_1)x_{15}^{wait.t_2} \\
&+ (\mu_{16}+\gamma_{16,1}\xi_1)x_{16}^{ivt_2} + (\mu_{17}+\gamma_{17,1}\xi_1)x_{17}^{walk.t_2} + (\mu_{18}+\gamma_{18,1}\xi_1)x_{18}^{price_2} \\
&+ (\mu_{19}+\gamma_{19,1}\xi_1)x_{19}^{time.v_2} + (\mu_{20}+\gamma_{20,1}\xi_1)x_{20}^{taxi_2} + (\mu_{21}+\gamma_{21,1}\xi_1)x_{21}^{ser.t_3} \\
&+ (\mu_{22}+\gamma_{22,1}\xi_1)x_{22}^{ser.a_3} + (\mu_{23}+\gamma_{23,1}\xi_1)x_{23}^{comf_3} + (\mu_{24}+\gamma_{24,1})x_{24}^{n.tran_3} \\
&+ (\mu_{25}+\gamma_{25,1}\xi_1)x_{25}^{wait.t_3} + (\mu_{26}+\gamma_{26,1}\xi_1)x_{26}^{ivt_3} + (\mu_{27}+\gamma_{27,1}\xi_1)x_{27}^{walk.t_3} \\
&+ (\mu_{28}+\gamma_{28,1}\xi_1)x_{28}^{price_3} + (\mu_{29}+\gamma_{29,1}\xi_1)x_{29}^{time.v_3} + (\mu_{30}+\gamma_{30,1}\xi_1)x_{30}^{taxi_3}
\end{aligned} \tag{3.3}$$

The ten meta-attribute model,

$$\begin{aligned}
v_i = {} & (\mu_1 + \gamma_{1,1}\xi_1)x_1^{ser.t_1} + (\mu_2 + \gamma_{2,2}\xi_2)x_2^{ser.a_1} + (\mu_3 + \gamma_{3,3}\xi_3)x_3^{comf_1} \\
& + (\mu_4 + \gamma_{4,4}\xi_4)x_4^{n.tran_1} + (\mu_5 + \gamma_{5,5}\xi_5)x_5^{wait.t_1} + (\mu_6 + \gamma_{6,6}\xi_6)x_6^{ivt_1} \\
& + (\mu_7 + \gamma_{7,7}\xi_7)x_7^{walk.t_1} + (\mu_8 + \gamma_{8,8}\xi_8)x_8^{price_1} + (\mu_9 + \gamma_{9,9}\xi_9)x_9^{time.v_1} \\
& + (\mu_{10} + \gamma_{10,10}\xi_{10})x_{10}^{taxi_1} + (\mu_{11} + \gamma_{11,1}\xi_1)x_{11}^{ser.t_2} + (\mu_{12} + \gamma_{12,2}\xi_2)x_{12}^{ser.a_2} \\
& + (\mu_{13} + \gamma_{13,3}\xi_3)x_{13}^{comf_2} + (\mu_{14} + \gamma_{14,4}\xi_4)x_{14}^{n.tran_2} + (\mu_{15} + \gamma_{15,5}\xi_5)x_{15}^{wait.t_2} \\
& + (\mu_{16} + \gamma_{16,6})\xi_6)x_{16}^{ivt_2} + (\mu_{17} + \gamma_{17,7}\xi_7)x_{17}^{walk.t_2} + (\mu_{18} + \gamma_{18,8}\xi_8)x_{18}^{price_2} \\
& + (\mu_{19} + \gamma_{19,9}\xi_9)x_{19}^{time.v_2} + (\mu_{20} + \gamma_{20,10}\xi_{10})x_{20}^{taxi_2} + (\mu_{21} + \gamma_{21,1}\xi_1)x_{21}^{ser.t_3} \\
& + (\mu_{22} + \gamma_{22,2}\xi_2)x_{22}^{ser.a_3} + (\mu_{23} + \gamma_{23,3}\xi_3)x_{23}^{comf_3} + (\mu_{24} + \gamma_{24,4}\xi_4)x_{24}^{n.tran_3} \\
& + (\mu_{25} + \gamma_{25,5}\xi_5)x_{25}^{wait.t_3} + (\mu_{26} + \gamma_{26,6}\xi_6)x_{26}^{ivt_3} + (\mu_{27} + \gamma_{27,7}\xi_7)x_{27}^{walk.t_3} \\
& + (\mu_{28} + \gamma_{28,8}\xi_8)x_{28}^{price_3} + (\mu_{29} + \gamma_{29,9}\xi_9)x_{29}^{time.v_3} + (\mu_{30} + \gamma_{30,10}\xi_{10})x_{30}^{taxi_3}
\end{aligned} \tag{3.4}$$

Two higher order factors,

$$\begin{aligned}
v_i = {} & (\mu_1 + \gamma_{1,1}\xi_1 + \beta_{1,11}\xi_{11} + \beta_{1,12}\xi_{12})x_1^{ser.t_1} + (\mu_2 + \gamma_{2,2}\xi_2 + \beta_{2,11}\xi_{11} + \beta_{2,12}\xi_{12})x_2^{ser.a_1} \\
& + (\mu_3 + \gamma_{3,3}\xi_3 + \beta_{3,11}\xi_{11} + \beta_{3,12}\xi_{12})x_3^{comf_1} + (\mu_4 + \gamma_{4,4}\xi_4 + \beta_{4,11}\xi_{11} + \beta_{4,12}\xi_{12})x_4^{n.tran_1} \\
& + (\mu_5 + \gamma_{5,5}\xi_5 + \beta_{5,11}\xi_{11} + \beta_{5,12}\xi_{12})x_5^{wait.t_1} + (\mu_6 + \gamma_{6,6}\xi_6 + \beta_{6,11}\xi_{11} + \beta_{6,12}\xi_{12})x_6^{ivt_1} \\
& + (\mu_7 + \gamma_{7,7}\xi_7 + \beta_{7,11}\xi_{11} + \beta_{7,12}\xi_{12})x_7^{walk.t_1} + (\mu_8 + \gamma_{8,8}\xi_8 + \beta_{8,11}\xi_{11} + \beta_{8,12}\xi_{12})x_8^{price_1} \\
& + (\mu_9 + \gamma_{9,9}\xi_9 + \beta_{9,11}\xi_{11} + \beta_{9,12}\xi_{12})x_9^{time.v_1} + (\mu_{10} + \gamma_{10,10}\xi_{10} + \beta_{10,11}\xi_{11} + \beta_{10,12}\xi_{12})x_{10}^{taxi_1} \\
& + (\mu_{11} + \gamma_{11,1}\xi_1 + \beta_{1,11}\xi_{11} + \beta_{1,12}\xi_{12})x_{11}^{ser.t_2} + (\mu_{12} + \gamma_{12,2}\xi_2 + \beta_{2,11}\xi_{11} + \beta_{2,12}\xi_{12})x_{12}^{ser.a_2} \\
& + (\mu_{13} + \gamma_{13,3}\xi_3 + \beta_{3,11}\xi_{11} + \beta_{3,12}\xi_{12})x_{13}^{comf_2} + (\mu_{14} + \gamma_{14,4}\xi_4 + \beta_{4,11}\xi_{11} + \beta_{4,12}\xi_{12})x_{14}^{n.tran_2} \\
& + (\mu_{15} + \gamma_{15,5}\xi_5 + \beta_{5,11}\xi_{11} + \beta_{5,12}\xi_{12})x_{15}^{wait.t_2} + (\mu_{16} + \gamma_{16,6}\xi_6 + \beta_{6,11}\xi_{11} + \beta_{6,12}\xi_{12})x_{16}^{ivt_2} \\
& + (\mu_{17} + \gamma_{17,7}\xi_7 + \beta_{7,11}\xi_{11} + \beta_{7,12}\xi_{12})x_{17}^{walk.t_2} + (\mu_{18} + \gamma_{18,8}\xi_8 + \beta_{8,11}\xi_{11} + \beta_{8,12}\xi_{12})x_{18}^{price_2} \\
& + (\mu_{19} + \gamma_{19,9}\xi_9 + \beta_{9,11}\xi_{11} + \beta_{9,12}\xi_{12})x_{19}^{time.v_2} + (\mu_{20} + \gamma_{20,10}\xi_{10} + \beta_{10,11}\xi_{11} + \beta_{10,12}\xi_{12})x_{20}^{taxi_2} \\
& + (\mu_{21} + \gamma_{21,1}\xi_1 + \beta_{1,11}\xi_{11} + \beta_{1,12}\xi_{12})x_{21}^{ser.t_3} + (\mu_{22} + \gamma_{22,2}\xi_2 + \beta_{2,11}\xi_{11} + \beta_{2,12}\xi_{12})x_{22}^{ser.a_3} \\
& + (\mu_{23} + \gamma_{23,3}\xi_3 + \beta_{3,11}\xi_{11} + \beta_{3,12}\xi_{12})x_{23}^{comf_3} + (\mu_{24} + \gamma_{24,4}\xi_4 + \beta_{4,11}\xi_{11} + \beta_{4,12}\xi_{12})x_{24}^{n.tran_3} \\
& + (\mu_{25} + \gamma_{25,5}\xi_5 + \beta_{5,11}\xi_{11} + \beta_{5,12}\xi_{12})x_{25}^{wait.t_3} + (\mu_{26} + \gamma_{26,6}\xi_6 + \beta_{6,11}\xi_{11} + \beta_{6,12}\xi_{12})x_{26}^{ivt_3} \\
& + (\mu_{27} + \gamma_{27,7}\xi_7 + \beta_{7,11}\xi_{11} + \beta_{7,12}\xi_{12})x_{27}^{walk.t_3} + (\mu_{28} + \gamma_{28,8}\xi_8 + \beta_{8,11}\xi_{11} + \beta_{8,12}\xi_{12})x_{28}^{price_3} \\
& + (\mu_{29} + \gamma_{29,9}\xi_9 + \beta_{9,11}\xi_{11} + \beta_{9,12}\xi_{12})x_{29}^{time.v_3} + (\mu_{30} + \gamma_{30,10}\xi_{10} + \beta_{10,11}\xi_{11} + \beta_{10,12}\xi_{12})x_{30}^{taxi_3}
\end{aligned} \tag{3.5}$$

3.5 Results

TABLE 3.2: Model catalogue

Model	*k*	*C*	*LL*	*AIC*	*BIC*
M1 Fixed coefficient	30 μ_ϵ's	n.a.	-8,081.52	16223.04	16331.98
M2 Random coefficient	30 μ_ϵ's, 30 σ_ϵ's	30	-7,068.27	14256.54	14474.41
M3 Single factor	30 μ_ϵ's, 30 γ's	1	-6,895.01	13910.02	14127.89
M4 Multi factor	30 μ_ϵ's, 30 γ's	10	-6,413.33	12946.66	13164.53
M5 Higher order multi factor	30 μ_ϵ's, 30 γ's, 20 β's	12	-6,343.12	12846.42	13136.92

[k] Estimated parameters

[C] Variance components

[LL] Log-likelihood

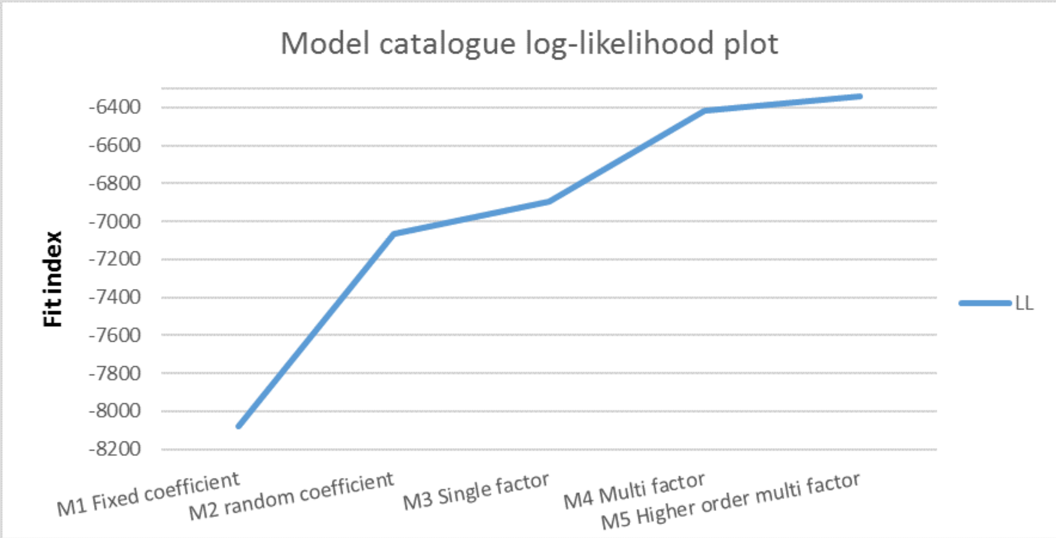

Figure 3.1: Model Fit

Each of the models in the catalogue satisfy one of the fundamental identifications conditions used in structural equations modelling (SEM), the t-rule. The number of identifiable parameters is given by $\frac{k(k-1)}{2}$ (Bollen, 1989; Bollen & Lennox, 1991)). Here, $k = 30$, so the identifiable parameters is 435. Following the t-rule (Bollen, 1989; Bollen & Lennox, 1991), the known values equal or exceed the maximum number of free parameters estimated in the catalogue which is 80 at the most for M5 the higher order multi-factor model. Hence, there are sufficient degrees of freedom to estimate an identified model.

M1 - Fixed coefficient model

Estimating M1 yields a maximum log-likelihood of -8,081.52. Similarities are evident in the pattern of μ_ϵ's across the conditions studied. Price, for example, is consistently important (μ_{ϵ_8} = -.15, t = -14.86; $\mu_{\epsilon_{18}}$ = -.21, t = -19.57; $\mu_{\epsilon_{28}}$ = -.21, t = -20.22) but is not consistently the most significant attribute. The number of transfers is consistently important and especially so in the five and seven alternatives conditions (μ_{ϵ_4} = -.17, t = -7.31; $\mu_{\epsilon_{14}}$ = -.59, t = -21.09; $\mu_{\epsilon_{24}}$ = -.47, t = -18.82). This pattern of results implies decision makers in aggregate prefer lower prices and fewer transfers. A pattern of qualitative differences in aggregate preferences is evident. When selecting from three alternatives, service availability is important but not so in the conditions with five and seven alternatives. The number of transfers is important in all three decision scenarios, but markedly more so in the decision scenarios with five and seven alternatives. Decision makers do not favour the option to take a taxi in the conditions with three and five alternatives, but do in the decision scenario with seven alternatives. This pattern of results implies decision makers prefer to opt out of using public transport if the complexity of finding a suitable route becomes too difficult.

For a quantitative test of differences in μ_ϵ's, simple equality constraints are imposed on the model parameters of M1. Specifically, μ_ϵ's for common attributes are constrained to be equal ($\mu_{\epsilon_1} = \mu_{\epsilon_{11}} = \mu_{\epsilon_{21}}$, $\mu_{\epsilon_2} = \mu_{\epsilon_{12}} = \mu_{\epsilon_{22}}$, ...). Thus, the effective total number of parameters of the constrained model is 10. Estimating the constrained model yields a log-likelihood of -8,221.51. This represents a significant decrement in fit vis-á-vis the free specification of M1 (χ^2 = 279.99, $d.f.$ = 20, $p < .01$). Based on this initial evidence we conclude that there are statistically significant differences in the parameters pertaining to aggregate preferences across the three scenarios. For further specificity, subsidiary models were estimated which highlight the magnitude of the differences for attribute by attribute showing significant parameter differences across conditions. These subsidiary models are not reported in detail here as no attributes in particular differ in a theoretically interesting or perplexing way. Overall, the results from the above test(s) are consistent with prior research into context-dependent preferences but offer little insight into antecedent volition. Other models forms warrant investigation.

M2 - Random coefficient model

M2 is the random coefficient specification. M2 specifies 60 parameters in total: 30 μ_ϵ's and 30 σ_ϵ's. The μ_ϵ's retrieve decision makers' aggregate preferences for the attributes. The σ_ϵ's represent unobserved sources of taste variation.

M2 has an estimated log-likelihood of -7,068.27. This represents a significant improvement in fit vis-á-vis the fixed coefficient specification (χ^2 = 2,026.50, $d.f.$ = 30, $p < .05$). The pattern of aggregate preferences is similar to that for M1; however, there is significant heterogeneity around the preferences for most attributes (see Table 3.3). The heterogeneity captures variation between decision makers in relation to their preferences for the attributes of the choice alternatives. Decision makers differ most significantly in their preferences for the number of transfers required to complete a trip and trip comfort. These results are consistent with past research in the transportation literature (Hensher & Reyes, 2000; Hensher & Rose, 2007). There are significant differences between decision makers with regards to preferences for trip prices, although the coefficient for this attribute is small. Other attributes which show significant preference heterogeneity are service type, service availability, in-vehicle time, and total time variation. There was no significant preference heterogeneity for anticipated wait-time, walking time, or the taxi alternative.

The importance of the random coefficient specification is the introduction of unobserved sources of preference heterogeneity. Although the random coefficient specification introduces taste variation, the sources of preference heterogeneity are independent (i.e., no common antecedent is specified that accounts for the variation in decision makers taste sensitivities). The significant improvement in fit compared to the fixed coefficient model warrants consideration of other model forms. Contrasting the random coefficient specification of M2 with the factor-analytic specification of M3 is a natural next step. M3 is defined by the specification of a single factor, thus giving structure to the covariance matrix of the taste sensitivities. Further, M3 is our first candidate model for a test of latent variables as proxies for stable and inherent preferences consistent with notion of antecedent volition.

From a behavioural perspective it is interesting to note that in the mixed logit model the standard deviation of the in-vehicle time is higher than the mean, which hints to a high proportion of the sample with positive marginal utility for travel time. This motivates us to proceed with latent factor specification of the structural choice model to determine which if preferences for changes in other attributes correlate with preferences (or more at least more tolerance of) for increases in in-vehicle time.

M3 - Single factor model

The single-factor model is introduces an unexogenously defined latent variable. The single-factor model has 60 parameters in total: 30 μ_ϵ's and 30 γ's. Note this is the same number of parameters as the random coefficient specification. The single-factor model introduces an antecedent latent variable common to all attributes across all three scenarios. Under the single-factor specification, the taste sensitivities for the attributes are a function of the latent variable, ξ, and the mean of their random components, μ_ϵ's. Thus, the ξ is a common source of preference heterogeneity in this model. The η's are therefore random coefficients but the randomness has a common source. Further, the latent variable accounts for covariation in all attribute preferences across all decision scenarios (thus, allowing correlation among the taste sensitivities). Note however, that this specification lacks a strong theoretical justification beyond that of the random coefficients model. This model is parametrically more parsimonious (it has fewer variance components), and as a consequence does not make specific assumptions/predictions about structural relations between the random components of particular attributes.

The comparison between this model and the standard random coefficients model (M2) warrants some further explanation. The parallel between the single-factor model and an error component specification of mixed logit lies in the correlations among random components in the model. For our data, in addition to the vector of means, the full error component specification of the random coefficients model would necessitate the estimation of 435 correlations. However, only a subset of those 435 correlations is likely to be of interest to the analyst as indicated by theory. By contrast, the single-factor model gives structure to the covariance matrix of taste sensitivities in a more parsimonious way. The factor model is subject to fewer identification constraints than an error components specification and has better interpretations. More generally, the single-factor model can be described as an exploratory specification in the sense that we do not rely on theory to guide specification of the Γ matrix. All of the elements of the Γ matrix in this single-factor specification; that is, the taste sensitivities for all of the attributes of each decision scenario are regressed on a single common factor.

Estimating the single-factor model yields a maximum log-likelihood of -6,895.01. This represents a significant improvement in fit vis-á-vis the fixed coefficient specification ($\chi^2 =$ 2,373.02, $d.f. = 30$, $p < .05$). Moreover, the single-factor model has a smaller absolute log-likelihood than the random coefficient specification. Keep in mind these models (the random coefficient specification of M2 and the single-factor specification of M3) have the same number of parameters. The single-factor model has a single variance component whereas the random coefficient specification has 30 variance components. A model with a single and common source of preference heterogeneity allowing for correlation in the taste sensitivities fits the sampled data better than a model with 30 independent sources of preference heterogeneity.

The pattern of aggregate preferences revealed by M3 is similar to M1 and M2 (see Table 3.3), though some notable differences are evident. Across the decision scenarios the pattern of regression coefficients or factor loadings suggests some commonalities common to the taste sensitivities across the different choice scenarios. There is much significance in the pattern matrix of regression coefficients. For example, the factor loadings associated with price ($\gamma_{8,1}$ = .17, $t = 8.52$; $\gamma_{18,1} = .26$, $t = 10.04$; $\gamma_{28,1} = .25$, $t = 10.29$) and on the taste sensitivities for in-vehicle time ($\gamma_{6,1} = .01$, $t = 2.90$; $\gamma_{16,1} = .01$, $t = 2.69$; $\gamma_{26,1} = .01$, $t = 4.01$) are consistently supported. The taste sensitivities load onto a common factor implying a common source of taste sensitivity toward these attributes that is correlated.

These results and behavioural decision theory motivate the specification of a confirmatory model that tests a more specific structure of the antecedent volition toward the attributes in this data. The single-factor model is not easily labelled and potentially confounds two sources of correlation: correlation among attributes within a scenario with correlation among attributes across the decision scenarios. The specific focus in the multi-factor specification of M4 is correlation among attributes common to the difference decision scenarios. The latent variables of the multi-factor model map directly onto the attributes of the choice alternatives. This aids greatly in assigning meaning to the latent variables (we may now conceive of "meta-attributes") and provides a more direct test of the stability of antecedent volition at the attribute level across the decision scenarios that a single-factor model is not capable of.

M4 - Multi factor model

The multi-factor model has 60 parameters in total: 30 μ_ϵ's and 30 γ's. The defining characteristic of the multi-factor model is the specification of ten latent variables corresponding to the ten attributes of each choice alternatives. That is, each latent variable represents a common source of preference heterogeneity as a meta-attribute related for each of the attributes in the choice alternatives. Thus, the taste sensitivities for common attributes are regressed on latent variables common across each of the scenarios. To be clear, the taste sensitivities for service type (η_1, η_{11}, and η_{21}) are regressed onto $\xi_1^{serv.type}$ (via $\gamma_{1,1}$, $\gamma_{11,1}$, and $\gamma_{21,1}$) and the taste sensitivities for service availability (η_2, η_{12}, and η_{22}) are regressed on $\xi_2^{serv.avail}$ (via $\gamma_{2,2}$, $\gamma_{12,2}$, and $\gamma_{22,2}$), and so on. Each of these parameters retrieve the context dependent taste sensitivities, thus represent the source of decision makers constructed preferences in each task. Note the multi-factor model has the same number of parameters as the random coefficient specification and the single-factor model. The multi-factor model has fewer variance components (10) than the random coefficient specification, but more than the single-factor model. The multi-factor model introduces multiple sources of preference heterogeneity and a specific structure to the pattern of the taste sensitivities. The structure given to the taste sensitivities is driven by theory and is designed to test the notion of a stable antecedent volition for the attributes of the choice alternatives.

Estimating the multi-factor model yields a maximum log-likelihood of -6,413.33. This represents a significant improvement in fit vis-á-vis the fixed coefficient specification (χ^2 = 3,336.39, $d.f.$ = 30, $p < .05$). This supports the conjecture that taste sensitivities for the attributes across the decision scenarios are subject to common sources of preference heterogeneity in each scenario. In other words, a behavioural process consistent with the notion of a stable antecedent volition is evident. Contextual differences are evident in the means of the multi-factor model, most notably for walking time. This result is consistent with models M1 through M3. The multi-factor specification of M4, however, extends these findings by using latent variables to specify the structure of the covariation in the taste sensitivities. For example, the effects of $\xi_3^{comfort}$ on the individual taste sensitivities for comfort across each scenario are consistently positive and significant ($\gamma_{3,3} = 1.08$, $t = 7.23$; $\gamma_{13,3} = 1.57$, $t = 9.53$; $\gamma_{23,3} = 1.40$, $t = 9.46$) and the effects of ξ_8^{price} on the taste sensitivities for price are consistently positive and significant ($\gamma_{8,8} = .84$, $t = 13.23$; ($\gamma_{18,8} = 1.16$, $t =$ 13.60; ($\gamma_{28,8} = 1.08$, $t = 14.57$). The taste sensitivities for comfort have a common source and the taste sensitivities for price have a common source. This pattern of significant factor loadings is general to the attributes but not universal. For example, the factor loadings on

$\xi_8^{time.v}$ for total time variation are significant in the decision scenarios with five and seven choice alternatives but not in the scenario with three alternatives ($\gamma_{9,9}$ = -.02, t = -.71 (n.s.); $\gamma_{19,9}$ = -.09, t = -2.91; $\gamma_{29,9}$ = -.08, t = -2.94). Finally, two attributes showed a pattern of non-significance in the factor loadings. These attributes are service availability and wait-time. Aggregate preferences for these attributes are neither strong nor consistent (i.e., they have non-significant μ_ϵ's and γ's).

Theory motivates a factor unique to each attribute accounting for the covariation in the posited taste sensitivities for the attribute. In general, the results are consistent with this expectation. Evidence of a common antecedent volition is strongest for service type, comfort, number of transfers, in-vehicle time, walking time, price, and the taxi alternative. Note statistical testing of differences in γ's is possible by imposing simple equality constraints on M4 such that $\gamma_{1,1} = \gamma_{11,1} = \gamma_{21,1}$, $\gamma_{2,2} = \gamma_{12,2} = \gamma_{22,2}$, ... Imposing these constraints for a global test of differences yields a model with a log-likelihood of -6,548.63. This represents a significant decrement in fit vis-á-vis M4 (χ^2 = 270.60, $d.f.$ = 20, p < .01). Subsidiary models to separately test the equality of regression coefficients one attribute at a time show equality in the γ's for some attributes (e.g., in-vehicle time) and not others (e.g., number of transfers). That is, differences in regression coefficients for a number of attributes are evident.

Note our theorizing does not inform an expectation about the equality of the γ's. Instead, our focus is the structure of the pattern matrix of regression coefficients for the effects of the latent variables. The patterns of significance and signs of the regression coefficients are supportive of the hypothesized structure (i.e., latent variables common to the decision scenarios representing meta-attributes). Stated differently, we cannot reject the hypothesis the taste sensitivities have a common source(s) of antecedent volition. Further, this antecedent volition is very stable for some attributes (achieving an empirical equality).

Chorus and Kroesen (2014) present the case that latent variable models (LVMs) and hybrid choice models (HCMs) more specifically, are limited in their ability to derive useful policy implications (for transportation planners in particular). The specification of M5 addresses some of the concerns raised by Chorus and Kroesen (2014). Specifically, the structural choice model does not include a measurement component per the more common

HCM (Ben-Akiva, Walker et al., 2002; Ben-Akiva, McFadden, Train & Walker, 2002; Walker, 2001). The specification adds two higher order latent variables antecedent to the 10 common meta-attribute variables.

M5 - Higher order multi factor model

The higher order multi-factor model has 80 parameters in total: 30 μ_ϵ's, 30 γ's and 20 β's. The defining characteristic of the higher order multi-factor model is the specification of the 2 context independent higher order factors. As these factors are context independent we interpret them to reflect inherent preferences for the attributes studied. Comparing the strength of the β and γ coefficients allows us to consider to what extent decision makers rely on inherent versus constructed preferences.

Each of the meta-attributes are regressed onto both of the two higher factors, thus summarising the sources of taste sensitivity to the attributes across decision scenarios into two dimensions. The factor loadings are plotted (Figure: 3.2), which provides a 2D map of the attributes controlling for context/decision scenario effects. The map is readily interpretable; attributes which are spatially co-located on the map have a similar intensity of effect on consumers preferences and are also similarly traded off against each other (in all complexity conditions). Attributes occupying their own isolated space ("Taxi", "Price" and "Walk" are most noteworthy) have no real substitute attributes. To explain further, if the attribute "Wait" is important to someone, then the nearby attributes of "Trans" and "Serv Type" are also important. If someone is sensitive to walking distances, "Walk", then the levels of this attribute will trump all others, irrespective of the decision scenario complexity. Attributes with weak coefficients in these dimensions are said to be attributes decision makers' do not have strong inherent preferences for.

An interesting observation is the similarity in structure through the μ values of M5. Across all five models, we see the significance in the no-choice (take a taxi) alternative vary in terms of the aggregate preferences. The behavioural explanation is quite apparent as we consider differences between the three tasks. In the main, as task complexity increases so too does the tendency to not engage in decision making, *i.e.* the option to take a taxi instead of deliberating between the bus alternatives becomes more favourable. Interestingly, however, is that this pattern does not appear so strongly between models M2 through M4. In fact, in these models the model parameters suggest that the no choice (take a taxi) option has a positive marginal utility in all three scenarios (albeit with varying degrees of magnitude). M5 introduces a more likely structure to the preference heterogeneity as evidenced by its significantly improved fit, and further the behavioural interpretation of both its higher and lower order parameters are more theoretically appealing. The option to take a taxi and opt out of choosing a bus in a more complex decision making scenario is strongest in M5. Further, there is a strong association with a higher order latent variable general to this option running across all three experiments suggesting decisions makers may be segmented along this dimension between those more or less likely to engage depending on task complexity.

Not all attributes are significant on both dimensions. Comparatively, there is more significance through the γ's in this model, and not as many of the β's are significant. This suggests there is some structure on the higher order level with commonalities in what the sources of heterogeneity are for some attributes but differences for others. Some attributes are only significant on one dimension, others are significant on both and some on none. The fact that some attributes have common sources of heterogeneity and others do not is behaviourally important as this suggests the effects of cognitive burden or choice overload do not equally apply to all facets of consumers preferences for bus transport services. In other words, there is stability in the places where we find significance and susceptibility to behavioural effects in places where there is not. The dimensions are unlabelled, but the analyst may theorize about their possible labels based upon what may be understood about the attributes which co-locate. For example, the attributes *price*, *comfort*, *time.v* and *walk* all sit at a similar level on the horizontal axis, but are quite disparate on the vertical axis. A sense of perceived value could be a possible descriptor for this dimension, which is theoretically derived from the value one would enjoy from a combination of favourable levels of price and walking distance. One may guess at the theoretical nature of the horizontal axis by considering similarities the attributes which significantly load onto this dimension, which include *walk*, *price*, *wait time* and *number of transfers*. Each of these attributes, except price, have some time dimension to them so one may guess at this dimension to be related to overall trip duration. Behaviourally, this makes sense as we assume consumers preferences for these types of attributes are not easily affects meanwhile for attributes like *service type* and *service availability* consumers preferences are more likely to be hold constructed preferences depending on the scenarios they face.

Given the subjectivity related to what the dimensions are, future research should attempt to replicate a higher order factor model of this type, supplementing it with some amount of perceptual data collected from the respondents to assist in the process of labelling the factors. Given the significantly improved fit to the data these models provide, these models are likely to outperform less informed models in areas of policy development, and thus warrant the extra information needed to more accurately label these dimensions so as to be much more useful.

Estimating the multi-factor model yields a maximum log-likelihood of -6,343.12. This represents a significant improvement in fit vis-á-vis the fixed coefficient specification ($\chi^2 = 3476.86413.1$, $d.f. = 50$, $p < .05$), and is the best fitting model of full catalogue.

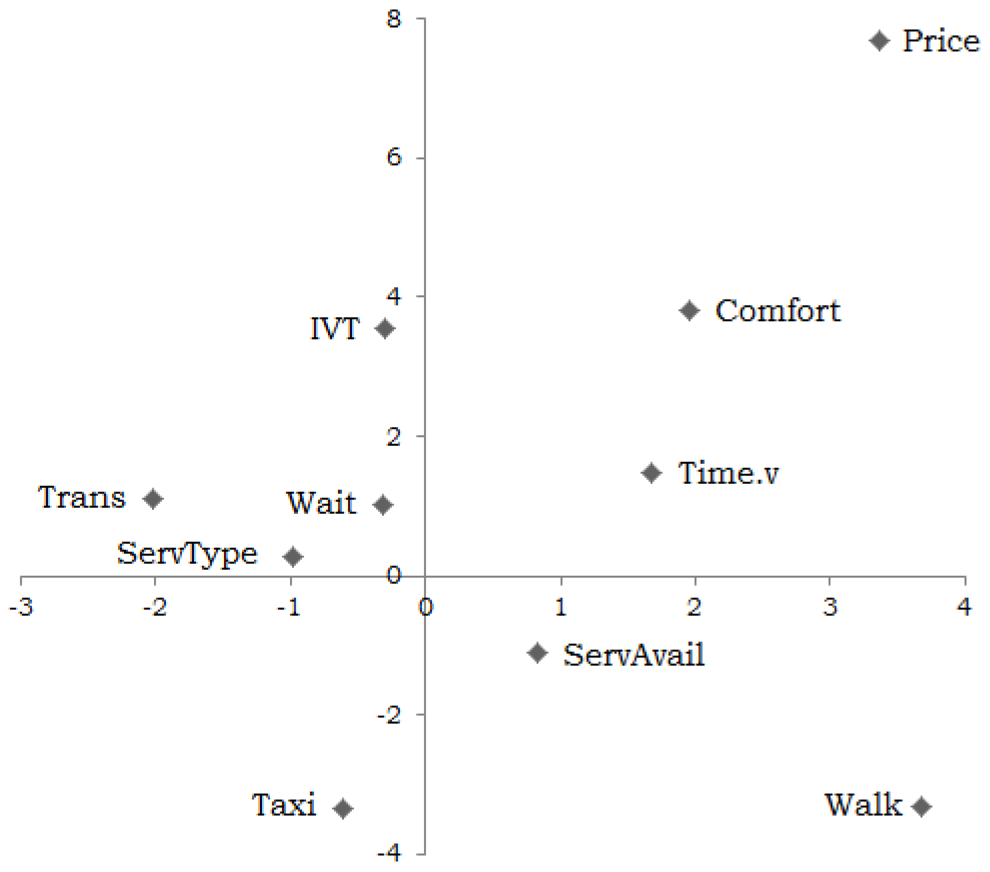

Figure 3.2: Choice map

TABLE 3.3: Results

	MNL (M1) fixed	MXL (M2) random		SCM (M3) one factor		SCM (M4) multi factor		SCM (M5) higher order factors		
3 Alternatives (DS1)	μ_ϵ	μ_ϵ	σ_ϵ	μ_ϵ	γ	μ_ϵ	γ	μ_ϵ	γ	$\beta\ (\xi_1)$
Service Type (η_1)	0.10	0.13	n.s.	0.10	n.s.	0.14	0.20	0.15	0.11	n.s.
Service Availability (η_2)	−0.11	−0.12	0.25	−0.09	n.s.	n.s.	n.s.	n.s.	−0.46	n.s.
Comfort (η_3)	−0.19	−0.27	0.28	−0.21	n.s.	−0.85	1.08	−1.19	1.02	0.29
Number of Transfers (η_4)	−0.17	−0.24	0.35	−0.22	n.s.	−1.02	1.32	−1.05	1.39	−0.18
Anticipated Wait Time (η_5)	n.s.	n.s.	n.s.	n.s.	0.05	n.s.	n.s.	n.s.	n.s.	n.s.
In Vehicle Time (η_6)	−0.02	−0.03	0.04	−0.03	0.01	−0.11	0.13	−0.12	0.06	n.s.
Walking Time (η_7)	−0.03	−0.05	0.05	−0.04	n.s.	n.s.	−0.15	n.s.	−0.09	1.15
Price (η_8)	−0.15	−0.21	0.22	−0.15	0.17	−0.65	0.84	−0.86	0.72	0.24
Travel Time Variation (η_9)	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Take Taxi (η_{10})	−0.58	−2.65	0.95	−6.71	6.13	2.32	−12.45	n.s.	−15.14	n.s.
5 Alternatives (DS2)										$\beta\ (\xi_2)$
Service Type (η_{11})	0.07	0.12	n.s.	0.09	n.s.	0.09	0.14	n.s.	0.15	n.s.
Service Availability (η_{12})	n.s.	−0.08	n.s.	−0.07	n.s.	n.s.	n.s.	n.s.	−0.37	n.s.
Comfort (η_{13})	−0.32	−0.44	0.31	−0.34	n.s.	−1.27	1.57	−1.66	1.40	0.48
Number of Transfers (η_{14})	−0.59	−0.73	0.50	−0.62	−0.14	−2.10	2.29	−2.18	2.45	n.s.
Anticipated Wait Time (η_{15})	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
In Vehicle Time (η_{16})	−0.04	−0.05	0.02	−0.04	0.01	−0.12	0.13	−0.14	0.07	1.66
Walking Time (η_{17})	−0.03	−0.05	0.06	−0.04	n.s.	0.07	−0.25	0.07	−0.17	−0.65
Price (η_{18})	−0.21	−0.32	0.33	−0.24	0.26	−0.92	1.16	−1.24	1.03	0.45
Travel Time Variation (η_{19})	−0.01	−0.02	0.03	−0.02	n.s.	n.s.	−0.09	0.06	−0.08	n.s.
Take Taxi (η_{20})	n.s.	−4.45	3.85	−5.94	3.66	3.86	−19.41	2.32	−23.67	−0.15
7 Alternatives (DS3)										
Service Type (η_{21})	0.11	0.15	n.s.	0.13	n.s.	0.17	0.26	n.s.	0.32	
Service Availability (η_{22})	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	−0.41	0.29	−0.68	
Comfort (η_{23})	−0.44	−0.54	0.27	−0.46	n.s.	−1.29	1.40	−1.77	1.36	
Number of Transfers (η_{24})	−0.47	−0.66	0.49	−0.50	−0.12	−1.80	2.05	−1.82	2.13	
Anticipated Wait Time (η_{25})	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	
In Vehicle Time (η_{26})	−0.03	−0.03	0.02	−0.03	0.01	−0.10	0.12	−0.12	0.06	
Walking Time (η_{27})	−0.04	−0.05	0.04	−0.04	n.s.	n.s.	−0.19	0.05	−0.14	
Price (η_{28})	−0.21	−0.27	0.37	−0.24	0.25	−0.87	1.08	−1.19	0.98	
Travel Time Variation (η_{29})	−0.02	−0.03	0.02	−0.02	−0.02	0.01	−0.08	0.08	−0.11	
Take Taxi (η_{30})	0.42	−2.39	1.19	−4.08	2.78	4.70	−19.30	3.35	−23.31	

n.s. *Not statistically significant ($p > .05$)*

3.6 Discussion

Consumers have both inherent and constructed preferences. Inherent preferences remain stable over time and relate to enduring tendencies. Constructed preferences are more wavering and are subject to contextual factors. The use of heuristics to inform choice provides a well-established foundation that explains why decision makers choose alternatives differently when faced with increasing levels of choice complexity (Swait & Adamowicz, 2001; Swait, 2013; Tversky & Kahneman, 1973). One of the major determinants of information usage in choice is the number of alternatives faced when making a decision. Past empirical work reports differences in the preferences of decision makers under different contexts of choice complexity. Studies which use models retrieving aggregate preferences only (e.g., conditional logit and probit models) present results which imply the use of different decision rules as complexity varies. A more subtle view of the decision making process is needed using models that specify the structure of the preference heterogeneity to better understand whether or not the observed differences in aggregate preference models are the result of a changing antecedent volition. Our results indicate stability in the way in which decision makers approach decision scenarios of varying complexity suggesting a process of antecedent volition common across the decision scenarios.

The literature on stable and inherent preferences implies a latent structure consistent with a theory of antecedent volition. We investigate the effects of complexity on antecedent volition by varying the number of alternatives available in decision scenarios. We present results suggesting that choice complexity does not significantly affect decision makers antecedent volition for the attributes under evaluation. We observe differences in aggregate preferences per prior empirical research, but also find evidence of latent variables and structures consistent with a behavioural process of antecedent volition. Our results are produced using a flexible factor-analytic SCM (Rungie et al., 2011, 2012), which has the advantage of linking preferences associated with attributes that are common to multiple decision scenarios through the specification of latent variable(s). We specify a separate latent variable for each attribute. The latent variables specifically represent meta-attributes and are common to the taste sensitivities of the decision scenarios we construct and study. More generally, the latent variables represent sources of preference heterogeneity common to the decision scenarios. The insights available from this latent variable specification allow us to investigate the stability with which preferences for attributes in multiple decision scenarios are determined by a common antecedent volition.

Implications for theory Antecedent volition relates to the cognitive processes which precede behaviour (Swait, 2013). They are unobserved by the analyst, yet are an important part of the process of how decision makers determine how-to-decide. One of the earliest known uses of the term antecedent volition is found in Edwards (1757). Referring to the reasons driving human decision making, he posits "every free volition arises from another *antecedent volition* [which] is determined by another going before that; and so on, until we come to the first in the series (emphasis added)." (pg.47). Our specification(s) of factor-analytic choice models capture antecedent volition in this way through a specification of the systematic component of utility V which sets it to be linearly dependent on a set of random variables which are dependent on latent variables. The latent variables represent the impact of the decision makers antecedent volition as predetermined by some decision rule. Where the taste sensitivity for an attribute common to decision scenarios does not load onto a common latent variable, then this attribute lacks a stable antecedent volition. In this instance, preferences for the attribute may be constructed under different scenarios and subject to stronger context effects. Our data and analysis generally support the conclusion that attributes have stable antecedent volition despite context effects being evident at the aggregate preference level.

To be sure, a latent structure for common attributes was not always evident. One line of speculation is context effects are more likely for these attributes, but our results show decision makers preferences for these attributes were not strong in aggregate. Contextual factors may affect decision makers ability to consistently express a stable and inherent preference and defer to the use of a simplifying decision rule which is not consistently applied across all scenarios. Such heuristics can result in decision making behaviour that does not truly reflect underlying inherent preferences (Gilovich et al., 2002), hence we find no consistency in the pattern of factor loadings for attributes for which decision makers do not have strong preferences. In these cases, the antecedent volition a decision maker might arrive at the task with (e.g., I will avoid options that make me wait longer) is not applied when the task becomes more difficult, which may result in a poorer outcome for the decision maker. In other instances, a decision makers antecedent volition remains stable (e.g., I will avoid options that make me walk further) regardless of the number alternatives available. This reflects an efficient and effective allocation of cognitive resources consistent with a latent process of antecedent volition.

Our model demonstrates that for some attributes decision makers will mix between states of inherent versus constructed preferences. For example, consumers consistently tend to have a context dependent preferences (therefore constructed) for *service type*, while have much stronger context independent preferences (therefore inherent) for *walking time*. Conceptually, this appears to have face validity if we consider the travel context used. *Service type* appears to be more important in the most complex decision scenario, with a positive parameter indicating rapid/express bus routes are preferred there are many buses to choose from. Conversely, *walking time* is only marginally significant as a constructed preference, but is much stronger an inherent preference in at least two dimensions.

Implications for policy and practice The specification of our latent variable model provides insights into the stability of the antecedent drivers of decision makers preferences. Following random utility theory, the decision maker is assumed able to evaluate all alternatives and that the choices we observe in a choice scenario are perfectly reflective of a compensatory process. Previous research has arguably been quick to claim decision makers violate the axioms of economic rationality when they are not consistent in the way they reveal their preferences and appear to use non-compensatory processes (Simonson, 2008). Our results are consistent with the notion that decision makers are consistent in how they approach decisions concerning common attributes under varying levels of complexity. Communicating all the possible alternatives to a decision maker is likely to have a mixed effect on how people consider a product offering. Our data suggest that when faced with a changing number of alternatives, there is consistency in the way decision makers determine their preferences for public transport service types (regular vs. express trips), the availability of a seat, the time and effort required to complete a journey, and price. Though the latent structure antecedent to the taste sensitivities for these attributes is generally stable, the aggregate preferences we observe in the decision scenarios are subject to context effects (due to varying complexity). Evidence in relation variation in total trip time was mixed (i.e., for this attribute a common latent variable was evident in two of the three decision scenarios). Finally, the drivers of preferences for services that are available for immediate departure were not subject to a common antecedent.

For policy makers, our results provide a more complete and subtle basis for policy formulation. Understanding which attributes decision makers will consistently cue to in a consistent manner allows for the development of communication strategies which make use of this information. From our example, the advertising of public transport might seek to emphasize the more salient experienced attributes of public transport, such as comfort and the availability of direct routes. Less emphasis should be placed on attributes for which consumers may be experience-poor such as shorter lead times and measures of on-time efficiency. Consistent with Simonson (2008), decision makers are likely to have stronger preferences for search attributes (rather than experience attributes). If the number of alternatives were to change, our results do not indicate that commuters would significantly change the way in which they decide to consider their available transport alternatives.

The choice map generated from model M5 allows planners to visualize the shared relationships between attributes. From our model, attributes such as the number of transfers, service type and wait times are co-located in a latent preference space. Understanding this gives transport planners greater insight into how targeted campaigns may affect preferences for related attributes in the market. Similarly, these mapping techniques allow transport planners to better develop strategy with regards to what features of a service sit on opposing dimensions with the minds of the travelling public. Our model suggests that the price attribute sits on the opposite end of some latent preference scale to the attribute of walking distance, but sits on the same end of a different scale. Planners may theorize about what the labels of these dimensions are which allows for a better understanding of how these attributes interact.

Future research We studied a single transport context, but applications of the modelling approach we put forward are many and varied. Researchers may seek to test the boundary conditions of antecedent volition under complexity. We investigate the effects of complexity defined at three levels by the number of alternatives available. Scope exists for exploring higher levels of complexity or complexities defined differently (e.g., differing numbers of attributes and/or levels). An even more subtle agenda is to explore attributes which are more or less subject to context effects versus attributes subject to stable and inherent preferences. The literature highlights the notion of search versus experience goods; that is, some attributes are known to decision makers through experience and others are less well known. A latent structure of antecedent volition may be stronger for those attributes most easily evaluated through search (i.e., prior to purchase). Another consideration concerns whether consumers mix between relying on inherent and constructed preferences. Which is more/less prominent may be attribute or context dependent (or both). Finally, the drivers of preferences for attributes common to multiple product categories is likely to have a common source of antecedent volition that reflects stable and inherent preferences for those attributes (e.g., meta-attributes common to multiple categories but manifest in different attributes). The model forms we put forward have application to tests of this conjecture and related hypotheses and we offer these to researchers for this purpose.

Conclusion The results of our study reconcile competing views on context effects versus stable and inherent preferences. Decision makers are adaptive problem solvers. On one hand, context effects due to choice complexity impact on decision makers choices. On the other hand, a latent process of antecedent volition is evident independent of context effects. The analyst observes decision makers choices from which context effects may be easily inferred, whereas inherent and stable preferences of decision makers are latent. The latent variables of SCMs provide a proxy for these preferences and provide a valid test of antecedent volition.

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4

Paper 3 - Priority alignment: linking priorities to preferences

4.1 Introduction

A key assumption in undertaking market research activities is that what consumers tell us are most/least important to them are indicative of the priorities they adhere to when making choices in a market. In this study we set up a structural choice model which links decision makers' priorities as measured using a best-worst task to their preferences as elicited using a discrete choice experiment. The model is set up such that sources of taste sensitivity for the attributes of alternatives in the discrete choice experiment is exogenously and theoretically defined using information about consumers priorities.

The naïve assumption is the attributes decision makers' select as key priorities will align with corresponding attributes in the discrete choice experiment. As we will see, this is not necessarily the case, which highlights some concerns policy makers should be aware of when using market research tools to inform product/service management decisions. We return to a bus public transport context for the experiment, and use an experimental design which mimics a common type of customer satisfaction survey.

The extent to which priorities and preferences align can be aptly referred to as *priority alignment*. We use this term to describe situations in which in the aggregate there are statistically significant and strong positive associations between the priorities people indicate they hold and the taste sensitivity of related attributes in a market. Where priority alignment is weak or diminished, policy makers may consider theoretical reasons why this may be. In some cases weak priority alignment may be indicative of a divide between ideally sought after attributes which can be attained freely without compromise. We discuss policy options that leverage a range of different alignment scenarios which derive from the structural choice model results we derive.

4.2 Research context

Public transport providers regularly collect and report on customer engagement surveys. As part of this effort it is not uncommon to see metrics such as customer satisfaction with various aspect of services reported. To some extent the collection and reporting of these metrics relates to obligations to demonstrate the performance effectiveness of ongoing efforts to improve services, but is also assumed to be used for identifying service areas needing improvement.

The quarterly *TransLink Tracker* released by the Department of Main Roads and Transport in Queensland, Australia reports public transport patronage levels and customer satisfaction metrics. The report includes measures of satisfaction towards 10 broad areas ("safety and security", "reliability and frequency", "comfort", "ease of use", "proximity", "efficiency", "information", "accessibility", "staff" and "affordability"). Tracking satisfaction with attributes of public transport is useful as satisfaction is known to correlate strongly with important business outcome variables, namely purchase intention, profitability, market share etc. (Fornell, 1992; Anderson, Fornell & Lehmann, 1994; Oliver, 1980, 1997). However, it is not immediately apparent from such data the extent to which such attributes are priority issues for decision makers. Compare the attributes of "efficiency" (how fast a public transport journey is relative to other transport modes) and "comfort" (usually a proxy by the availability of uncrowded seating). Consumers' may have a low/high level of satisfaction with these attributes, however the attribute will clearly differ within decision makers' with respect to their relative importance. There exists the potential to over/under-inflate the relative importance of what drives firm performance when considering customer satisfaction information. Decision makers' may rate comfort as a high priority item, and also be highly satisfied with their experience of comfort using public transport, yet may not be sensitive to variations in comfort when making choices about using public transport. Our model presents a way forward, reconciling these competing views by providing specificity with regards to how decision makers' think about the attributes of alternatives and the way they behave in markets.

In this study, we consider the same service areas measured in the South East Queensland *TransLink Tracker*, but instead of measuring satisfaction we capture the preferences of decision makers using two elicitation tasks. The first asks decision makers to reflect on their priorities, and indicate which attributes of a bus service are of highest/lowest priority when they think about using a public bus transportation service. The second measures which attributes are most important in predicting consumers' bus route preferences. Our structural choice model provides insights on the link between what attributes are of priority to decision makers' and those attributes which actually drive their choices. The benefit of this approach is in providing information for policy makers such that they may prioritise which service areas which are most critical to ensure consumers are satisfied with.

4.3 Conceptual framework

Priorities vs. attitudes Priorities are a form of explicit attitude. Explicit attitudes are those which people tend to have a degree of conscious control over and awareness of (Paladino, Nagpal & Posadas, 2015). In this study, we use a measurement of priorities as a proxy for explicit attitudes. Contrast this with implicit attitudes which manifest as automatic responses which people are not consciously aware of (Paladino et al., 2015). More generally, an attitude is an *evaluation* of an object, ranging from positive to negative (Wood, 2000) while a priority is something which takes precedence over others, and are different to attitudes in the way they do not comprise evaluations (hence our choice based best-worst measurement approach is most suitable here).

A distinct concept of consumers' priorities is not something we find clearly articulated in marketing or related literatures. Some notable exceptions include Brandstätter, Gigerenzer and Hertwig (2006), who develop a priorities heuristic model that is able to account for an extensive range of non-compensatory behaviours by considering the ranked order in which decision makers screen reasons for selecting one alternative over another. Inglehart (1971) argues a ranking of decision makers priorities will better predict choices than ratings of the relative importance of attributes, which Moors and Vermunt (2007) test using data from a ranking task in which decision makers' list those items as being priority policy areas to estimate latent class choice models. Burgess and Steenkamp (1999) present a model of value priorities in a marketing context using a rating scales approach which produces relative importance measures rather than strictly ranked priorities. Their study is one of few to use a similar terminology relating to priorities, however in application the study is more closely aligned with studies of values.

Values are those guiding principles that determine what is important to someone (Kahle, 1983) which unlike attitudes, can be ranked in terms of importance with respect to the degree to which they dictate behaviour (Schwartz, 1994, 1992; Rokeach, 1973). Values are also either be implicit or explicit or are typically measured as an evaluation along a positive-negative continuum (Schwartz & Bilsky, 1990). In the marketing literature, much of the discussion around values centre around the role of marketing and advertising actors in using methods of persuasion to encourage consumers' to act in ways which are misaligned with their priorities considered as personal values (Borgmann, 2000; Heath & Heath, 2008; Pollay & Mittal, 1993).

In our study we conceive of priorities as distinct from both attitudes and values, as they relate to an evaluation about the importance of an attribute in a decision making' task.

Priorities are inherently less subjective than values or attitudes as they are not considered along a continuum, but rather as discrete rank ordered items that compliment one's decision making goals. The objects/issues people prioritise are thought to represent the outcome of a process of antecedent volition, such that priorities are a reflection of enduring values and explicit/implicit attitudes. Their translation into product preferences is not perfect, as the ample amount of evidence suggesting decision makers' are not perfect utility maximisers suggests. The development a model of priority alignment parameterises the link between preferences elicited for product attributes in a discrete choice task and the consumption priorities we assume decision makers to be attempting to maximise on.

The structural choice model depicted in Figure 4.1 summarises the conceptual model. It is set up to reflect the theory that preferences on the right hand side are exogenous on those priorities measured on the left. A specification with the direction of this effect going from preference to priorities is also possible, and also holds theoretical merit, however has poorer fit to this data so we do not report on the results of such a specification.

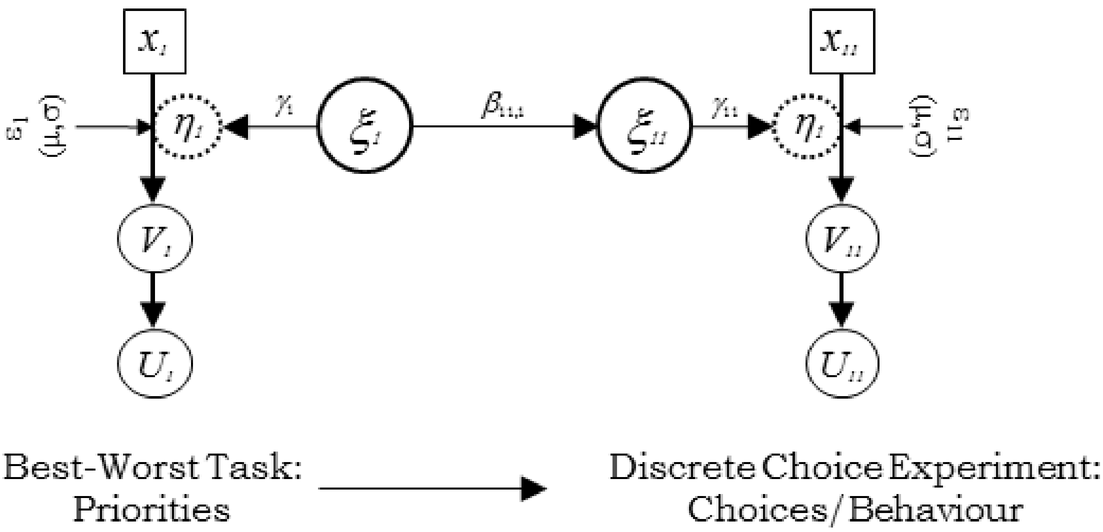


Figure 4.1: Model of priority alignment (regressed meta-attributes)

Measuring priorities

A best-worst task is used to measure consumers' priorities when using public transport. A best-worst task requires respondents to consider their preferences for objects relative to others, thus forcing discrimination among items (Finn & Louviere, 1992). Compared to using rating scales used for evaluating objects along some continuous scale, best-worst tasks reduce the level of between-subjects ambiguity due the removal of between-subjects scale biases. Best-worst tasks are typically used as a method of preference elicitation, although they are increasingly being used as a method of attitudinal measurement in which respondents indicate which attitudinal statements they most/least agree with (Lee, Soutar & Louviere, 2008, 2007; Flynn, 2010; Beck & Rose, 2016), including measuring values (Lee et al., 2007). Further, best-worst tasks are the best fitting measurement model for our conceptualisation of priorities as a ranking of precedence items.

When using a rating scales, individual characteristics may dictate how they interpret the points on the scale. For example, two respondents who both indicate "strongly agree" with some statement may represent two different things between two different people. Consider a respondent completing a rating scale task. One who "strongly agrees" that issues of *comfort* are important may also "strongly agree" that *affordability* is important to them. In a best-worst measurement model, the respondent must discriminant between the two and select which one is more important (of higher priority). In addition, compared to a simpler ranking task where all items are presented in one set, a best-worst experiment typically requires respondents to make repeated choices from among several sets. This property provides a much larger dataset from which more reliable estimates about the respondents true rankings can be made, as well as enables the analyst to position of experimental subjects on an identical utility scale (Finn & Louviere, 1992).

Methods developed to deal with scale differences (or at least identify them) in rating scale data are costly and inefficient (Louviere, 1988). For example, Steenkamp and Baumgartner (1998) propose a 13 step procedure for assessing measurement invariance between groups. Such remedies unnecessarily deal with the symptoms of scale differences rather than attempt to develop better performing measurement instruments. These remedies necessitate steps to purify attitudinal measures by either removing nonconforming respondents or to collect more data using a redesigned ratings scale measurement instrument. Given the high monetary costs of such steps, these issues in ratings data are rarely corrected. As a consequence, much of the evidence provided by studies which employ rating scales may be ambiguous or erroneous. As such, our best-worst measurement approach to capture decision makers' priorities is seen as appropriate choice.

Experimental design

Best-worst priorities task The same 10 attributes contained in the *TransLink Tracker* with some minor variations to attribute labels and definitions are used to populate our best-worst task experimental design plan. In terms of these variations, "safety and security", "reliability and frequency" are renamed "safety" and "reliability" and our definition of "comfort" does not include on-board temperature and relates only to the availability of seats/crowding for the sake of brevity. "Proximity" is renamed to "Convenience" as this label was deemed to be semantically closer to the actual meaning of the attribute. The attributes original definitions and their definitions as operationalised in this study are compared in Table 4.1.

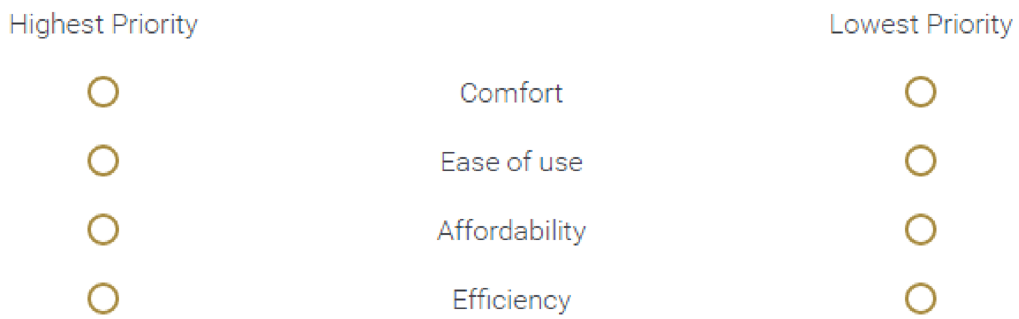


Figure 4.2: Example best-worst task

Respondents are a given instructions on how to complete the best-worst task, including the operational definitions of each attribute. A hyperlink is available on each page of the survey linking to a pop-up containing attribute definitions to help guide participants throughout the task (see figure 4.3).

TABLE 4.1: Best-worst attribute operational definitions

TransLink Tracker definition		Current study operational definition
Safety and Security Safety at stops, stations and on board vehicles.	→	**Safety** Safety at stops, stations and on board vehicles.
Reliability and frequency Ability to meet departure times, frequency of services and reliability of go card readers.	→	**Reliability** Ability to meet scheduled arrival/departure times.
Comfort of ride Cleanliness, availability of seats, temperature on board and facilities at stops and stations.	→	**Comfort** Availability of seats and level of crowding at stops and on vehicles.
Ease of use Using and understanding ticketing including transferring between modes, purchasing, topping up and using go card, ease of finding stops.	→	**Ease of use** Simplicity of ticketing system, including how to transfer between routes and purchase/top up travel cards.
Proximity Convenience of available routes, distances from stops and stations and proximity of go card outlets.	→	**Convenience** Walking distances between stops and your home/work, convenience of available routes and locations of ticket sellers.
Efficiency Door-to-door travel time, connections with other services and avoidance of congestion.	→	**Efficiency** Door-to-door travel time, connections with other routes and avoidance of congestion (e.g. using dedicated "busways").
Information Ability to understand on board and at-station information, timetables, maps and journey planning information.	→	**Information** Accuracy of electronic signs displayed at stops. Legibility of timetables, maps and other journey planning information.
Accessibility Ease of getting on and off the platform, and on and off the vehicles, reliability of escalators and elevators.	→	**Accessibility** Ease of access to stops, vehicles, and reliability of escalators/elevators.
Helpfulness of staff Knowledge, conduct, presentation and helpfulness of staff.	→	**Staff helpfulness** Knowledge, conduct, presentation and helpfulness of staff.
Affordability Cost of tickets and benefit of not having to pay for parking.	→	**Affordability** Transport fares/costs relative to other modes of transport (including parking costs and tolls).

Feature	Definition
Safety	Safety at stops and on board vehicles.
Reliability	Ability to meet scheduled arrival/departure times.
Comfort	Availability of seats and level of crowding at stops and on vehicles.
Ease of use	Simplicity of ticketing system, including how to transfer between routes and purchase/top up travel cards.
Convenience	Walking distances between stops and your home/work, convenience of available routes and locations of ticket sellers.
Efficiency	Door-to-door travel time, connections with other routes and avoidance of congestion (e.g. using dedicated "busways").
Information	Accuracy of electronic signs displayed at stops. Legibility of timetables, maps and other journey planning information.
Accessibility	Ease of access to stops, vehicles, and reliability of escalators/elevators.
Staff helpfulness	Knowledge, conduct, presentation and helpfulness of staff.
Affordability	Transport fares/costs relative to other modes of transport (including parking costs and tolls).
How to answer:	Thinking about what is important to you when taking public transport, indicate which of the above features are of highest/lowest priority to you in each set. You must select two options in each set. The task is repetitive, requiring you to compare each of the features together multiple times. This allows us to paint a very accurate picture of what features are of highest priority to people in a way which is much more reliable than traditional survey methods.

Figure 4.3: Pop-up best-worst attribute definitions available to respondents

A generalised Youden design (GYD) is generated using *crossdes* in *R* to generate the design matrix used to create the best-worst tasks. The parameters of the design include a balanced incomplete block design (BIBD) with $trt = 10$ treatment conditions (attributes), $b = 5$ rows (choice sets) and $k = 4$ columns (alternatives) which is run for $inter = 100$ iterations. This design is then combined with a Williams design to get a carryover balanced generalised Youden design per the methods outlined in Patterson (1951). A Williams design is a row-column designs used such that each of the attributes are shown in each position of the best-worst task equally across the whole design (Patterson, 1951).

10 treatment conditions are used in the best-worst section of the survey, whereas the discrete choice experiment contains 9 attributes for identification. The n^{th}+1 treatment condition allows for all effects between each attribute between the best-worst task and discrete choice experiment. The parameters of the best-worst task choice model are interpreted with respect to the omitted baseline treatment condition. The Youden combined with the Williams design contains 20 rows across 4 columns. The design consists of two Latin squares which are checked and confirmed to be a balanced block design with respect to columns (Sailer, 2015). Before converting the design into choice sets, the design is re-arranged such that in each subsequent choice set a different range of attributes are shown to respondents (the order of choice sets in this study are not randomised). This procedure has no effect on the column balance of the overall design. The final matrix of re-arranged rows are used to

generate the best-worst tasks as they appear in the online survey.

Table 4.2: Discrete choice experiment attribute levels

Safety	**Reliability**	**Comfort**
Often unsafe	Always late	Standing (crowded)
Sometimes unsafe	Usually late	Standing alone (not crowded)
Usually safe	Usually on-time	Sitting (crowded)
Always safe	Always on-time	Sitting alone (not crowded)
Ease of use	**Convenience**	**Efficiency**
Often difficult	Lots of walking	Slower than driving
Sometimes difficult	Some walking	Same as driving (must transfer)
Usually easy	Not much walking	Same as driving (direct route)
Always easy	No walking	Faster than driving
Information	**Staff helpfulness**	**Affordability**
Print only (hard to read)	Never helpful	More expensive than driving
Print only (easy to read)	Sometimes helpful	Same as driving (with tolls/parking)
Digital real-time (inaccurate)	Usually helpful	Same cost driving (without tolls/parking)
Digital real-time (accurate)	Always helpful	Cheaper than driving

Discrete choice experiment The same attributes adopted from the *TransLink Tracker* (Department of Transport and Main Roads, 2015) are used in the generation of the discrete choice experiment. Each attribute is coded with 4 possible levels as shown in Table 4.2, and furthered detailed definitions accompanied by graphics are made available to respondents available throughout the survey as a floating pop-up. The respondents' task in this discrete choice experiment is to choose the alternative which best aligns with their preferences.

The decision making scenario possesses some important conceptual differences to the best-worst task. Most importantly, in each scenario all attributes are present but with varying levels. For instance, two bus services might be available that are both described as being comfortable rides but one might be more efficient than the other, or higher/lower in price. This necessitates that decision makers' trade off these attributes. Standard neoclassical economic assumptions would dictate that decision makers perform this trade off in such a way that perfectly maximises their utility to best align with their priorities. In the absence of any other information we assume the results of analysis of discrete choice data reflects decision makers' priorities. The proposition is that someone who selects, for example, *comfort* as a priority concern when using public transport should also be sensitive to levels of *comfort* when choosing a public transport in the discrete choice experiment.

The attributes and their levels are combined together using a D-efficient experimental design plan. The design is generated using N*gene* (Choice Metrics, 2014). By way of process, we first selected a design for a multinomial logit model with 12 rows (choice sets), 9 attributes (each with 4 levels, using dummy continuous coding). This design was modified for a mixed logit specification as this closely resembles the structural choice model (Rungie, Coote & Louviere, 2011, 2012). The signs for each of the priors in the specification of design were set according to the average satisfaction levels reported in the *TransLink tracker* (Department of Transport and Main Roads, 2015) and using the signs for similar attributes used earlier in Study 2 (Magor & Coote, 2014). The final design has a D-error = 0.50, A-error = 0.52, B-estimate = 54.74 and S-estimate = 8.59. The choice probabilities expected from this design are balanced across each of the alternatives such that there no clearly dominating alternative across the design columns.

Table 4.3: Discrete choice experiment attribute level definitions

Safety

Always safe: Never encounter nuisance behaviour on your journey, no security risks at all.

Usually safe: Rarely encounter nuisance behaviour on your journey, but some risk is possible.

Sometimes unsafe: Sometimes encounter nuisance behaviour on your journey, such as witnessing abusive language or threats of violence directed at you or others.

Often unsafe: Regularly encounter nuisance behaviour such as abusive language or threats of physical violence directed at you or others.

Comfort

Sitting alone (not crowded): Seated by yourself, not in close physical contact with other people. There are many available completely empty seats on the bus.

Sitting (crowded): Seated next to someone because there are no available completely empty seats, but many seats available next to other people so you must sit in close physical contact with other people.

Standing alone (not crowded): Standing alone in the aisle because there are no seats available, but not in close contact with other people.

Standing (crowded): Standing in the aisle of a very crowded bus in close physical contact with other people who are also standing in the aisle.

Reliability

Always on-time: The bus runs perfectly on time to the nearest minute, always arriving/departing strictly according to the schedule.

Usually on-time: The bus runs mostly on time but can be up to 5 minutes late sometimes.

Usually late: The bus runs at least 10 minutes late most of the time, rarely arriving/departing according to the schedule.

Always late: The bus runs late all of the time, never arriving/departing according to the schedule. Buses seem to turn up randomly, making it impossible to tell if the bus is late or early.

Ease of use

Always easy: Ticket machines always work and there are many ways to pay (travel cards, paper tickets, mobile phone, wearable device, etc.). Online account top up available.

Usually easy: Ticket machines usually work and there are some alternative ways to pay (travel cards and paper tickets). Online account top up available.

Sometimes difficult: Ticket machines are often broken so sometimes have to locate a retailer. Payment only by travel card, paper tickets not available. Cannot top up online.

Often difficult: Ticket machines nearly always broken and there no alternative ways to pay/top up your account (must locate a retailer). Payment only by travel card, paper tickets not available. Cannot top up online.

Efficiency

Faster than driving: Catching the bus is reliably quicker door-to-door than driving or any other transport method.

Same as driving (direct route): Catching the bus is reliably about the same time door-to-door as driving or any other transport method and you never have to make transfers, so there is not the risk of added wait time.

Same as driving (must transfer): Catching the bus is usually about the same time door-to-door as driving or any other transport method, but the bus route requires transfers, so there is always the risk of added wait time if a connection runs late.

Slower than driving: Catching the bus is always the slowest option door-to-door. Driving or other transport methods are always faster.

Convenience

No walking: Bus stops are very conveniently located (i.e. right in front of your home/work).

Not much walking: Bus stops are conveniently located but a little bit of walking to/from your home/work (less than 200m).

Some walking: Bus stops are not very conveniently located require some walking to/from your home/work (200 to 500m).

Lots of walking: Bus stops are inconveniently located and require lots of walking to/from your home/work (at least 500m or more).

Staff

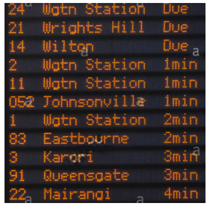
Always helpful: Staff are knowledgeable and always willing to answer questions when approached. Staff are never rude or impolite.

Usually helpful: Staff are knowledgeable and willing to answer questions most of the time, but occasionally give incorrect information.

Sometimes helpful: Staff are knowledgeable but not always willing to answer questions. Staff often give incorrect information due to incompetence.

Never helpful: Staff are not knowledgeable and are regularly rude or impolite when approached.

Information



Digital real-time (accurate): Electronic signs at stops and live feeds online are perfectly accurate showing actual arrival/departure times to the nearest 10 seconds. Maps and other information at stops is up-to-date.

Digital real-time (inaccurate): Electronic signs at stops and live feeds online sometimes do not match the actual arrival/departure times experienced, but they are generally more useful than printed schedules/signs. Maps and other information at stops is up-to-date.

Print only (easy to read): There are no digital real-time signs, but the printed information at stops/on-board is generally easy enough to read that you can find information about the next arrivals/departures at a glance. Printed information can never be as accurate as digital real-time information.

Print only (hard to read): There are no digital real-time signs, and the printed information at stops/on-board cannot be understood at a glance. The signs cannot be relied upon to easily find information about the next arrivals/departures. The maps are confusing and timetables too complex to be useful.

Affordability

More expensive than driving: Catching the bus is always cheaper than driving your own car.

Same as driving (with tolls/parking): Catching the bus is about the same as the running costs of driving a car, not including the costs of tolls or parking (with tolls and parking, driving is more expensive).

Same as driving (no tolls/parking): Catching the bus is about the same as the running costs of driving a car, including the costs of tolls or parking (without tolls and parking, driving is cheaper).

Cheaper than driving: Catching the bus is always more expensive than driving your own car, including running costs, tolls and parking.

4.4 Model specification

The structural choice model links priorities captured in the best-worst task to taste sensitivities measured in the discrete choice experiment. Where $U_i = v_i + e_i$ and $v_i = \eta_1 x_i$, the effect of priorities is treated as an antecedent to preferences in the specification of the η pertaining to the discrete choice experiment. The specification has some conceptual similarities with how a hybrid choice model exogenously defines latent variables that are linked directly to consumers' utility function as an x variable Walker (2001). The difference in our specification compared to a typical hybrid choice model is important to note. The hybrid choice model is more analogous to the approach of using structural equations modelling within a choice modelling framework to establish cause and effect relationships between attitudes and choice (Joreskog & Sorbom, 1979), while our model seeks to identify commonalities between priorities and preferences to determine whether or not they are conceptually analogous.

The best-worst task data is readily incorporated into the structural choice model as exogenous inputs to the latent variables associated with taste sensitivities in the discrete choice experiment. The modelling approach is unique to the behavioural choice literature and offers a way forward to investigate the relationship between consumers priorities and their choice behaviour.

The specification of the structural choice models used in the present student achieve a similar outcome to that of a hybrid choice model, by linking a proxy measure of attitudes to a latent choice variable. The key difference is in the specification of the model using a best-worst ranking measure of priorities as opposed to a continuous scale measure of attitudes, and the latent choice variable is exogenous to consumers taste sensitivities, rather than the choice itself. The conceptual model is summarised in the structural choice model diagram seen in 4.1, which also depicts an econometric specification. In this model, a utility function is estimated for U_i for each attribute in both tasks. The two experiments are linked via the β parameter, for which 10 are estimated (1 for each attribute). The model equations are as follows.

The conditional logit model,

$$\begin{aligned}
v_i = {} & (\mu_1)x_1^{safe_{BW}} + (\mu_2)x_2^{reli_{BW}} + (\mu_3)x_3^{comf_{BW}} + (\mu_4)x_4^{ease_{BW}} + (\mu_5)x_5^{conv_{BW}} \\
& + (\mu_6)x_6^{effi_{BW}} + (\mu_7)x_7^{info_{BW}} + (\mu_8)x_8^{acce_{BW}} + (\mu_9)x_9^{help_{BW}} + (\mu_{10})x_{10}^{affo_{BW}} \\
& + (\mu_{11})x_{11}^{safe_{DCE}} + (\mu_{12})x_{12}^{reli_{DCE}} + (\mu_{13})x_{13}^{comf_{DCE}} + (\mu_{14})x_{14}^{ease_{DCE}} + (\mu_{15})x_{15}^{conv_{DCE}} \\
& + (\mu_{16})x_{16}^{effi_{DCE}} + (\mu_{17})x_{17}^{info_{DCE}} + (\mu_{18})x_{18}^{help_{DCE}} + (\mu_{19})x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.1}$$

The mixed logit model,

$$\begin{aligned}
v_i = {} & (\mu_1 + \sigma_1)x_1^{safe_{BW}} + (\mu_2 + \sigma_2)x_2^{reli_{BW}} + (\mu_3 + \sigma_3)x_3^{comf_{BW}} + (\mu_4 + \sigma_4)x_4^{ease_{BW}} \\
& + (\mu_5 + \sigma_5)x_5^{conv_{BW}} + (\mu_6 + \sigma_6)x_6^{effi_{BW}} + (\mu_7 + \sigma_7)x_7^{info_{BW}} + (\mu_8 + \sigma_8)x_8^{acce_{BW}} \\
& + (\mu_9 + \sigma_9)x_9^{help_{BW}} + (\mu_{10} + \sigma_{10})x_{10}^{affo_{BW}} + (\mu_{11} + \sigma_{11})x_{11}^{safe_{DCE}} + (\mu_{12} + \sigma_{12})x_{12}^{reli_{DCE}} \\
& + (\mu_{13} + \sigma_{13})x_{13}^{comf_{DCE}} + (\mu_{14} + \sigma_{14})x_{14}^{ease_{DCE}} + (\mu_{15} + \sigma_{15})x_{15}^{conv_{DCE}} + (\mu_{16} + \sigma_{16})x_{16}^{effi_{DCE}} \\
& + (\mu_{17} + \sigma_{17})x_{17}^{info_{DCE}} + (\mu_{18} + \sigma_{18})x_{18}^{help_{DCE}} + (\mu_{19} + \sigma_{19})x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.2}$$

The one factor (congeneric) model,

$$\begin{aligned}
v_i = {} & (\mu_1 + \gamma_{1,1}\xi_1)x_1^{safe_{BW}} + (\mu_2 + \gamma_{2,1}\xi_1)x_2^{reli_{BW}} + (\mu_3 + \gamma_{3,1}\xi_1)x_3^{comf_{BW}} \\
& + (\mu_4 + \gamma_{4,1}\xi_1)x_4^{ease_{BW}} + (\mu_5 + \gamma_{5,1}\xi_1)x_5^{conv_{BW}} + (\mu_6 + \gamma_{6,1}\xi_1)x_6^{effi_{BW}} \\
& + (\mu_7 + \gamma_{7,1}\xi_1)x_7^{info_{BW}} + (\mu_8 + \gamma_{8,1}\xi_1)x_8^{acce_{BW}} + (\mu_9 + \gamma_{9,1}\xi_1)x_9^{help_{BW}} \\
& + (\mu_{10} + \gamma_{10,1}\xi_1)x_{10}^{affo_{BW}} + (\mu_{11} + \gamma_{11,1}\xi_1)x_{11}^{safe_{DCE}} + (\mu_{12} + \gamma_{12,1}\xi_1)x_{12}^{reli_{DCE}} \\
& + (\mu_{13} + \gamma_{13,1}\xi_1)x_{13}^{comf_{DCE}} + (\mu_{14} + \gamma_{14,1}\xi_1)x_{14}^{ease_{DCE}} + (\mu_{15} + \gamma_{15,1}\xi_1)x_{15}^{conv_{DCE}} \\
& + (\mu_{16} + \gamma_{16,1}\xi_1)x_{16}^{effi_{DCE}} + (\mu_{17} + \gamma_{17,1}\xi_1)x_{17}^{info_{DCE}} + (\mu_{18} + \gamma_{18,1}\xi_1)x_{18}^{help_{DCE}} \\
& + (\mu_{19} + \gamma_{19,1}\xi_1)x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.3}$$

The two factor (task specific) model,

$$\begin{aligned}
v_i = {} & (\mu_1 + \gamma_{1,1}\xi_1)x_1^{safe_{BW}} + (\mu_2 + \gamma_{2,1}\xi_1)x_2^{reli_{BW}} + (\mu_3 + \gamma_{3,1}\xi_1)x_3^{comf_{BW}} \\
& + (\mu_4 + \gamma_{4,1}\xi_1)x_4^{ease_{BW}} + (\mu_5 + \gamma_{5,1}\xi_1)x_5^{conv_{BW}} + (\mu_6 + \gamma_{6,1}\xi_1)x_6^{effi_{BW}} \\
& + (\mu_7 + \gamma_{7,1}\xi_1)x_7^{info_{BW}} + (\mu_8 + \gamma_{8,1}\xi_1)x_8^{acce_{BW}} + (\mu_9 + \gamma_{9,1}\xi_1)x_9^{help_{BW}} \\
& + (\mu_{10} + \gamma_{10,1}\xi_1)x_{10}^{affo_{BW}} + (\mu_{11} + \gamma_{11,2}\xi_2)x_{11}^{safe_{DCE}} + (\mu_{12} + \gamma_{12,2}\xi_2)x_{12}^{reli_{DCE}} \\
& + (\mu_{13} + \gamma_{13,2}\xi_2)x_{13}^{comf_{DCE}} + (\mu_{14} + \gamma_{14,2}\xi_2)x_{14}^{ease_{DCE}} + (\mu_{15} + \gamma_{15,2}\xi_2)x_{15}^{conv_{DCE}} \\
& + (\mu_{16} + \gamma_{16,2}\xi_2)x_{16}^{effi_{DCE}} + (\mu_{17} + \gamma_{17,2}\xi_2)x_{17}^{info_{DCE}} + (\mu_{18} + \gamma_{18,2}\xi_2)x_{18}^{help_{DCE}} \\
& + (\mu_{19} + \gamma_{19,2}\xi_2)x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.4}$$

The two factor (exploratory) model,

$$\begin{aligned}
v_i = {} & (\mu_1 + \gamma_{1,1}\xi_1 + \gamma_{1,2}\xi_2)x_1^{safe_{BW}} + (\mu_2 + \gamma_{2,1}\xi_1 + \gamma_{2,2}\xi_2)x_2^{reli_{BW}} \\
& + (\mu_3 + \gamma_{3,1}\xi_1 + \gamma_{3,2}\xi_2)x_3^{comf_{BW}} + (\mu_4 + \gamma_{4,1}\xi_1 + \gamma_{4,2}\xi_2)x_4^{ease_{BW}} \\
& + (\mu_5 + \gamma_{5,1}\xi_1 + \gamma_{5,2}\xi_2)x_5^{conv_{BW}} + (\mu_6 + \gamma_{6,1}\xi_1 + \gamma_{6,2}\xi_2)x_6^{effi_{BW}} \\
& + (\mu_7 + \gamma_{7,1}\xi_1 + \gamma_{7,2}\xi_2)x_7^{info_{BW}} + (\mu_8 + \gamma_{8,1}\xi_1 + \gamma_{8,2}\xi_2)x_8^{acce_{BW}} \\
& + (\mu_9 + \gamma_{9,1}\xi_1 + \gamma_{9,2}\xi_2)x_9^{help_{BW}} + (\mu_{10} + \gamma_{10,1}\xi_1 + \gamma_{10,2}\xi_2)x_{10}^{affo_{BW}} \\
& + (\mu_{11} + \gamma_{11,1}\xi_1 + \gamma_{10,1}\xi_2)x_{11}^{safe_{DCE}} + (\mu_{12} + \gamma_{12,1}\xi_1 + \gamma_{12,1}\xi_2)x_{12}^{reli_{DCE}} \\
& + (\mu_{13} + \gamma_{13,1}\xi_1 + \gamma_{13,1}\xi_2)x_{13}^{comf_{DCE}} + (\mu_{14} + \gamma_{14,1}\xi_1 + \gamma_{14,1}\xi_2)x_{14}^{ease_{DCE}} \\
& + (\mu_{15} + \gamma_{15,1}\xi_1 + \gamma_{15,1}\xi_2)x_{15}^{conv_{DCE}} + (\mu_{16} + \gamma_{16,1}\xi_1 + \gamma_{16,1}\xi_2)x_{16}^{effi_{DCE}} \\
& + (\mu_{17} + \gamma_{17,1}\xi_1 + \gamma_{17,1}\xi_2)x_{17}^{info_{DCE}} + (\mu_{18} + \gamma_{18,1}\xi_1 + \gamma_{18,1}\xi_2)x_{18}^{help_{DCE}} \\
& + (\mu_{19} + \gamma_{19,1}\xi_1 + \gamma_{19,1}\xi_2)x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.5}$$

Unique meta attributes,

$$
\begin{aligned}
v_i = {} & (\mu_1 + \gamma_{1,1}\xi_1)x_1^{safe_{BW}} + (\mu_2 + \gamma_{2,2}\xi_2)x_2^{reli_{BW}} + (\mu_3 + \gamma_{3,3}\xi_3)x_3^{comf_{BW}} \\
& + (\mu_4 + \gamma_{4,4}\xi_4)x_4^{ease_{BW}} + (\mu_5 + \gamma_{5,5}\xi_5)x_5^{conv_{BW}} + (\mu_6 + \gamma_{6,6}\xi_6)x_6^{effi_{BW}} \\
& + (\mu_7 + \gamma_{7,7}\xi_7)x_7^{info_{BW}} + (\mu_8 + \gamma_{8,8}\xi_8)x_8^{acce_{BW}} + (\mu_9 + \gamma_{9,9}\xi_9)x_9^{help_{BW}} \\
& + (\mu_{10} + \gamma_{10,10}\xi_{10})x_{10}^{affo_{BW}} + (\mu_{11} + \gamma_{11,11}\xi_{11})x_{11}^{safe_{DCE}} + (\mu_{12} + \gamma_{12,12}\xi_{12})x_{12}^{reli_{DCE}} \\
& + (\mu_{13} + \gamma_{13,13}\xi_{13})x_{13}^{comf_{DCE}} + (\mu_{14} + \gamma_{14,14}\xi_{14})x_{14}^{ease_{DCE}} + (\mu_{15} + \gamma_{15,15}\xi_{15})x_{15}^{conv_{DCE}} \\
& + (\mu_{16} + \gamma_{16,16}\xi_{16})x_{16}^{effi_{DCE}} + (\mu_{17} + \gamma_{17,17}\xi_{17})x_{17}^{info_{DCE}} + (\mu_{18} + \gamma_{18,18}\xi_{18})x_{18}^{help_{DCE}} \\
& + (\mu_{19} + \gamma_{19,19}\xi_{19})x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.6}
$$

Common meta attributes,

$$
\begin{aligned}
v_i = {} & (\mu_1 + \gamma_{1,1}\xi_1)x_1^{safe_{BW}} + (\mu_2 + \gamma_{2,2}\xi_2)x_2^{reli_{BW}} + (\mu_3 + \gamma_{3,3}\xi_3)x_3^{comf_{BW}} \\
& + (\mu_4 + \gamma_{4,4}\xi_4)x_4^{ease_{BW}} + (\mu_5 + \gamma_{5,5}\xi_5)x_5^{conv_{BW}} + (\mu_6 + \gamma_{6,6}\xi_6)x_6^{effi_{BW}} \\
& + (\mu_7 + \gamma_{7,7}\xi_7)x_7^{info_{BW}} + (\mu_8 + \gamma_{8,8}\xi_8)x_8^{acce_{BW}} + (\mu_9 + \gamma_{9,9}\xi_9)x_9^{help_{BW}} \\
& + (\mu_{10} + \gamma_{10,10}\xi_{10})x_{10}^{affo_{BW}} + (\mu_{11} + \gamma_{11,1}\xi_1)x_{11}^{safe_{DCE}} + (\mu_{12} + \gamma_{12,2}\xi_2)x_{12}^{reli_{DCE}} \\
& + (\mu_{13} + \gamma_{13,3}\xi_3)x_{13}^{comf_{DCE}} + (\mu_{14} + \gamma_{14,4}\xi_4)x_{14}^{ease_{DCE}} + (\mu_{15} + \gamma_{15,5}\xi_5)x_{15}^{conv_{DCE}} \\
& + (\mu_{16} + \gamma_{16,6}\xi_6)x_{16}^{effi_{DCE}} + (\mu_{17} + \gamma_{17,7}\xi_7)x_{17}^{info_{DCE}} + (\mu_{18} + \gamma_{18,8}\xi_9)x_{18}^{help_{DCE}} \\
& + (\mu_{19} + \gamma_{19,9}\xi_{10})x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.7}
$$

Regressed meta attributes,

$$
\begin{aligned}
v_i = {} & (\mu_1 + \gamma_{1,1}\xi_1)x_1^{safe_{BW}} + (\mu_2 + \gamma_{2,2}\xi_2)x_2^{reli_{BW}} + (\mu_3 + \gamma_{3,3}\xi_3)x_3^{comf_{BW}} + (\mu_4 + \gamma_{4,4}\xi_4)x_4^{ease_{BW}} \\
& + (\mu_5 + \gamma_{5,5}\xi_5)x_5^{conv_{BW}} + (\mu_6 + \gamma_{6,6}\xi_6)x_6^{effi_{BW}} + (\mu_7 + \gamma_{7,7}\xi_7)x_7^{info_{BW}} + (\mu_8 + \gamma_{8,8}\xi_8)x_8^{acce_{BW}} \\
& + (\mu_9 + \gamma_{9,9}\xi_9)x_9^{help_{BW}} + (\mu_{10} + \gamma_{10,10}\xi_{10})x_{10}^{affo_{BW}} + (\mu_{11} + \gamma_{11,11}\xi_{11} + \beta_{11,1}\xi_1^{safe_{BW}})x_{11}^{safe_{DCE}} \\
& + (\mu_{12} + \gamma_{12,12}\xi_{12} + \beta_{12,2}\xi_2^{reli_{BW}})x_{12}^{reli_{DCE}} + (\mu_{13} + \gamma_{13,13}\xi_{13} + \beta_{13,3}\xi_3^{comf_{BW}})x_{13}^{comf_{DCE}} \\
& + (\mu_{14} + \gamma_{14,14}\xi_{14} + \beta_{14,4}\xi_4^{ease_{BW}})x_{14}^{ease_{DCE}} + (\mu_{15} + \gamma_{15,15}\xi_{15} + \beta_{15,5}\xi_5^{conv_{BW}})x_{15}^{conv_{DCE}} \\
& + (\mu_{16} + \gamma_{16,16}\xi_{16} + \beta_{16,6}\xi_6^{effi_{BW}})x_{16}^{effi_{DCE}} + (\mu_{17} + \gamma_{17,17}\xi_{17} + \beta_{17,7}\xi_7^{info_{BW}})x_{17}^{info_{DCE}} \\
& + (\mu_{18} + \gamma_{18,18}\xi_{18} + \beta_{18,9}\xi_9^{help_{BW}})x_{18}^{help_{DCE}} + (\mu_{19} + \gamma_{19,19}\xi_{19} + \beta_{19,10}\xi_{10}^{affo_{BW}})x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.8}
$$

4.5 Results

Data were collected over a two week period in September 2016 with respondent contact attempts made at various times of the day on various days of the week to ensure an evenly distributed time and location of respondents (i.e. at home/work). Respondents were specifically asked to reflect upon their "usual trip", whether it be for work or leisure reasons to improve the generalisability of the model results of public transport use in general. Trip purpose is a known important factor in determining preference for the different attributes of public transport (Hensher, 1994), however we do not seek to model this interaction in this application.

Respondents who indicated they did not reside in the Brisbane metropolitan area of South East Queensland, Australia or who did not use public transport at least once per month were excluded from the final sample. Respondents who took less than one third of the median time (approximately 9 minutes) to complete the online tasks were also excluded from the final sample.

In total, complete responses were obtained from 308 consumers representative of users of public transport in the metropolitan area of south east Queensland, Australia. The demographic characteristics of the sample are 62% female, 39% with an income of AUD$37-80,000, 54% with an undergraduate or other tertiary qualification and 65% in full-time employment. In terms of public transport usage, 39% indicated they use public transport at least once a month, and 17% indicated using public transport at least once everyday (including weekends).

The sample were present within the south east region of Queensland, Australia serviced by the local public transport operator TransLink. GPS data indicates over 92% of respondents were located in this region at the time of survey completion (see: Figure 4.4). Those not located in this region at the time of survey completion were all located in other Australian metropolitan areas and are assumed to have been travelling interstate temporarily.

Design fit The results from the discrete choice experiment largely match the expected choice shares as predicted by the efficient design generated in *N*gene. The majority (greater

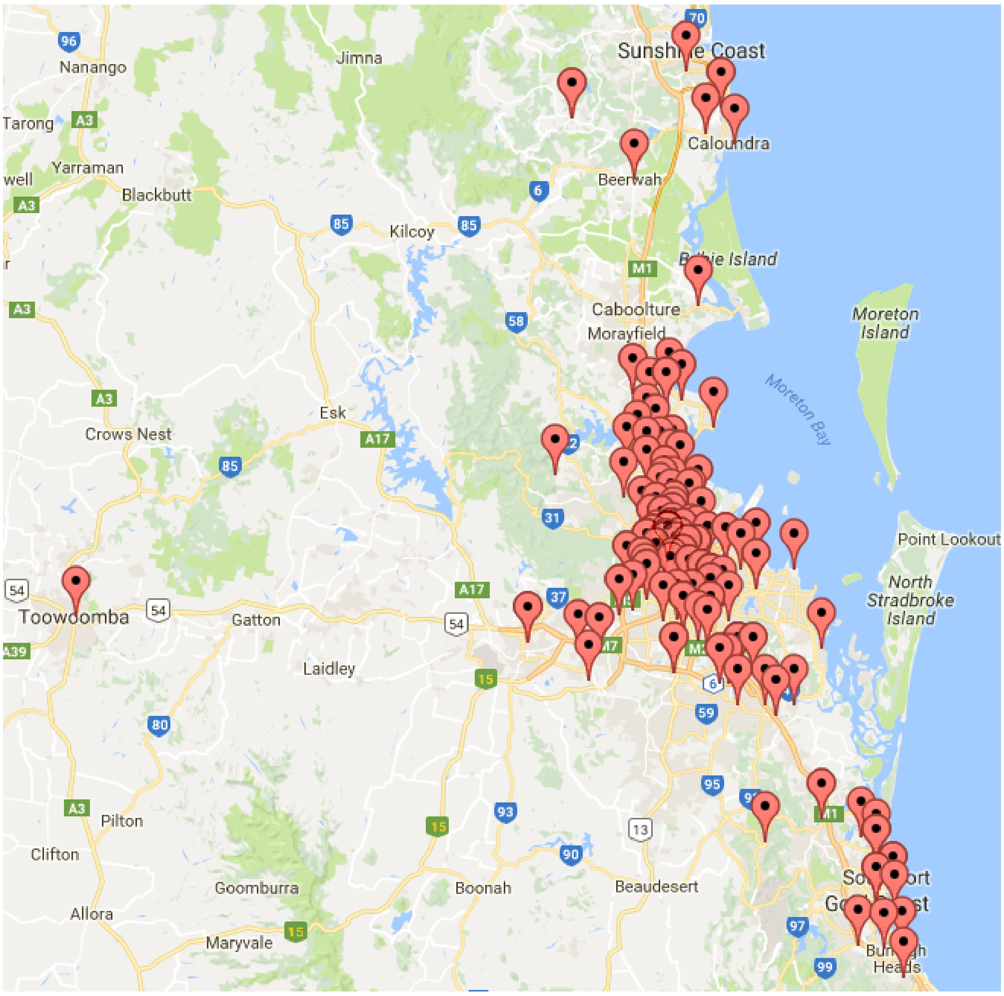


Figure 4.4: Respondent distribution

than 60%) of choice shares for any given alternative in a choice set are within 10 percentage points of those predicted by the model design. Table 4.4 compares the expected and observed choice shares.

Of those choice sets where the observed choice shares differ substantially from the design predictions, the most likely alternative to be chosen usually remains the same. For example, the predicted choice shares for choice set 10 are 16%, 16%, 44% and 24% for alternatives 1, 2, 3 and 4 respectively. The probabilities observed are 6%, 13%, 78% and 3%. Alternative 3 is 34% more likely to be chosen than what the model design predicts and retains its position as the preferred alternative. In some choice sets there is a change in which alternative is the most likely within the set, such as choice set 6. It is only in choice set 8 that we observe two alternatives vying for an equal share of choice with alternatives 3 and 4 representing 40% and 46% of choice respectively. Overall, the design is appropriate given the observed data, which has resulted in a clearly preferred alternative in each choice set and no particular alternative dominating across the experiment.

TABLE 4.4: Choice Shares (expected → observed)

Choice set	Alternative 1	Alternative 2	Alternative 3	Alternative 4
1	11% → 8%	53% → 63%	20% → 19%	16% → 10%
2	51% → 53%	19% → 6%	15% → 28%	15% → 13%
3	52% → 64%	16% → 20%	13% → 3%	19% → 13%
4	12% → 12%	27% → 51%	40% → 6%	22% → 30%
5	12% → 31%	12% → 6%	18% → 8%	59% → 54%
6	57% → 31%	17% → 48%	14% → 18%	12% → 3%
7	11% → 10%	47% → 27%	21% → 58%	21% → 5%
8	15% → 6%	15% → 7%	22% → 40%	49% → 46%
9	52% → 77%	13% → 10%	16% → 9%	19% → 4%
10	16% → 6%	16% → 13%	44% → 78%	24% → 3%
11	21% → 22%	14% → 14%	47% → 54%	17% → 10%
12	13% → 5%	54% → 25%	16% → 13%	16% → 57%

Descriptive analysis The results from the best-worst task are plotted in a means-variance vector space per the approach of Mueller and Rungie (2009) in Figure 4.5 as a way to visually interpret the strength and consistency of consumers' priorities for the different attributes of a public transport service. The plot shows the attributes *affordability*, *safety reliability* are those which consumers consider to be of highest priority. Interestingly, these three attributes were also selected as most important with the highest level of variance, suggesting respondents actively traded between these attributes more than others. *Efficiency* (door-to-door travel time) consistently rates as a low priority item, which is a surprising result. *Accessibility*, *Convenience* and *Ease of use* are all of middling level importance in terms of decision makers priorities, although there is more consistency in how often *accessibility* is chosen given this middling level of priority.

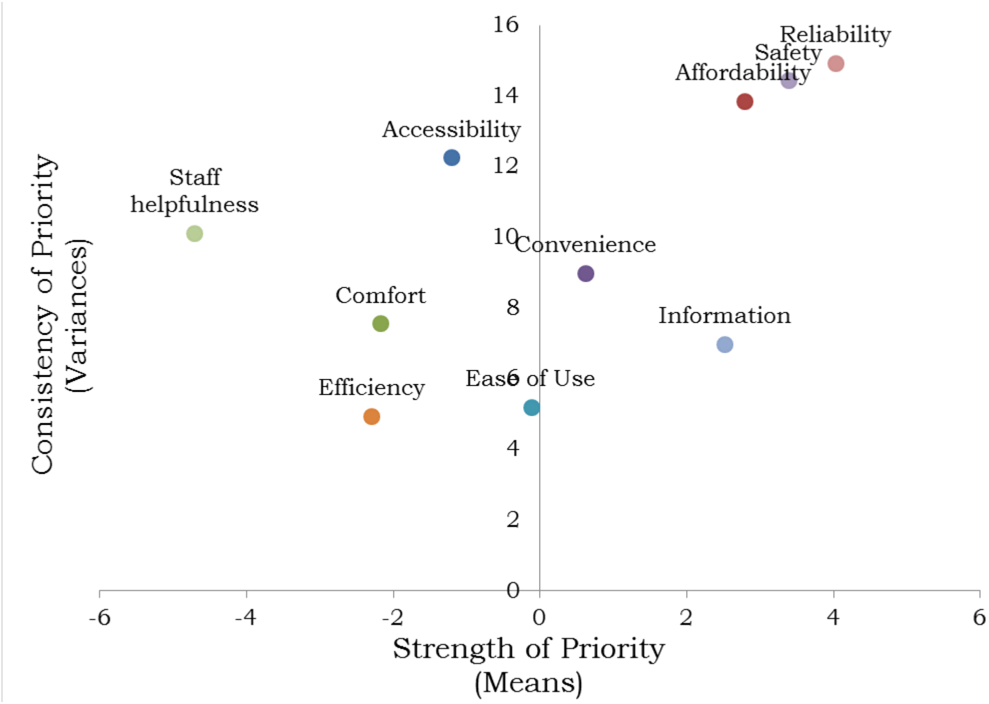


FIGURE 4.5: Priorities map

The priorities map provides a useful descriptive analysis of decision makers priorities. This information is immediately useful in terms of information policy makers about which attributes are important, including their variances. Compared to more common extant methods of collecting and reporting customer satisfaction information, a priorities plot seems to provide more immediately useful information. By way of comparison, the satisfaction data reported by the TransLink Tracker plots satisfaction scores on a 0 - 100 scale over time. The ratings scale data does not permit strict ordinal ranking of the attributes, and the lack of repeated measures per respondent does not permit calculation of consistency scores.

Choice models A model catalogue is fitted to the data, which includes a conditional fixed effects multinomial logit model (MNL), an error components specification of mixed logit, an exploratory one factor structural choice model, a meta-attributes structural choice model and a regressed latent factors model (structural choice model with meta-attribute on meta-attribute regressions).

Each of the models satisfy one of the fundamental identifications conditions used in structural equations modelling (SEM), the t-rule (Bollen, 1989; Bollen & Lennox, 1991). The number of identifiable parameters is given by $\frac{k(k-1)}{2} > \alpha$ (Bollen, 1989; Bollen & Lennox, 1991)). Here, $k = 18$ from the best-worst task and discrete choice experiment combined, so the identifiable parameters is 153. Following the t-rule (Bollen, 1989; Bollen & Lennox, 1991), the known values equal or exceed the maximum number of free parameters estimated in the catalogue which is 54 at the most for the exploratory two factor model the higher order multi-factor model. Hence, there are sufficient degrees of freedom to estimate an identified model. The model catalogue is summarised in Table 4.5.

Table 4.5: Model catalogue

Model	k	LL	AIC	BIC
Conditional logit	18	-14660.88	29285.75	29236.19
Mixed logit	36	-12680.23	25288.47	25189.34
Exploratory one factor	36	-13842.13	27612.25	27513.12
Task specific two factor	36	-13749.90	27427.80	27355.80
Exploratory two factor	54	-13099.84	26307.68	26456.38
Unique meta-attributes	36	-12738.35	25404.69	25305.56
Common meta-attribute	36	-12540.68	25009.36	24910.23
Regressed meta-attributes	45	-12273.22	24456.44	24332.53

Model 1: Conditional logit The conditional logit model is the first model fitted to the data. The model estimates the primary preferences for attributes in both tasks simultaneously, but does not link the two tasks together in any way. In terms of importance, the attributes *safety*, *reliability*, and *affordability* are strongest in both tasks which matches the results obtained from the earlier arithmetic analysis of the best-worst data. There are some notable differences between the tasks, for instance with the attribute *information*, which respondents rated on average as the 4$^{\text{th}}$ most important priority but in the discrete choice experiment appears to be one of the least important attributes driving choice. Respondents rated *staff helpfulness* as important priority, however this attribute does not appear to be

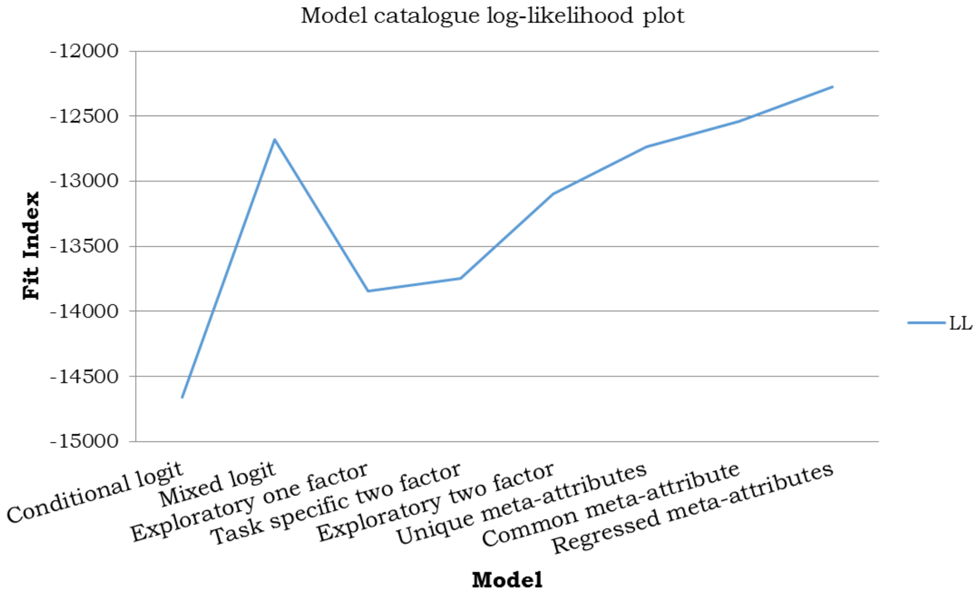


FIGURE 4.6: Fit indicies plot

an important factor in determining respondents choices in the discrete choice experiment. The log-likelihood of this model with $k = 18$ parameters (18 μ_ϵ) is -14660.88.

Model 2: Mixed logit The mixed logit specification relaxes the assumption of homogeneous preferences between respondents. This specification achieves a significant improvement in fit vis-á-vis the conditional logit model, and is overall the third best fitting model in the catalogue.

The log-likelihood of this model with $k = 36$ parameters (18 μ_ϵ and 18 σ_ϵ) is -12680.23. The pattern of primary preferences mirrors the conditional logit model closely, and the pattern of standard deviation coefficients (σ_ϵ) provide insight into the level of heterogeneity around each attribute. Most notably, there is much more diversity in consumers' stated attribute priorities than there are in their preferences for bus routes with only 2 insignificant heterogeneity parameters in the best-worst task versus 7 insignificant out of the 9 attributes in the discrete choice experiment.

While the model fits to the data better than the conditional logit, most of the standard deviations are in fact insignificant suggesting there is only heterogeneity for a small number of attributes. Preferences for the attribute *safety* are the most heterogeneous, and is significant in both tasks, indicating there is a significant distribution within the sample population of people for whom this attribute is important and those who it is not. There is a small distribution in preferences in both tasks for *affordability*.

Recall the definition of this attribute in both tasks as being the cost of transport fares relative to other modes of transport (including parking costs and tolls), with the possible levels in the discrete choice experiment stated in relative terms compared to driving. Given this definition, the distribution in preferences is not all that surprising as some respondents may be more or less sensitive to the relative affordability of driving a private vehicle.

The somewhat differing implications between the best-worst (priorities) data and the discrete choice experiment (preference) data motivates the exploration of model specifications which link these two. Taken at face value, these results suggest that there are differences in what respondents rate as priority attributes and what attributes actually influence their decision making.

Model 3: Exploratory one factor (SCM 1) The first structural choice model is an exploratory factor analytic model. All attributes from both tasks are regressed onto one common latent variable which can be described as a source of all preference heterogeneity in the combined tasks model.

The log-likelihood of this model with $k = 36$ parameters (18 μ_ϵ and 18 γ) is -13842.13. The model fit improves upon the initial conditional logit model, although does not fit as well as the mixed logit model. The main insight from this model is that there appears to be differences between the priorities in the best-worst task and discrete choice experiment, the pattern of results mirrors and emphasises those of the mixed logit. The majority of factor loadings pertaining to the best-worst task achieve significance, while the majority of parameters pertaining to the discrete choice experiment do not. The two attributes which appear to have a common source of preference heterogeneity in both tasks are *safety* and *affordability*. This invites the specification of a 2 factor model.

Model 4: Task specific two factor (SCM 2) Two specifications of a two factor model are estimated, the first specifies the attributes of the best-worst task loading onto one factor and the attributes of the discrete choice task onto a second. This model improves upon the fit of the one factor model by a small margin, and further sees more significance with regards to the factor loadings of taste sensitivities within the discrete choice experiment task.

The log-likelihood of this model with $k = 36$ parameters (18 μ_ϵ and 18 γ) is -13749.90. This provides further indication that there may be different sources of preference heterogeneity to the two tasks at a global level (*i.e.* not an attribute specific level). The factors of this model, and the previous one factor model, produce a model structure wherein the attribute common to one task are assumed to have a share source of context dependent variation. This specification ascertains that there is at least some context dependent differences between the tasks on some higher order level, showing how consumers' apparent taste sensitivities for each attribute differs between the tasks.

Model 3: Exploratory two factor (SCM 3) This model is simple extension of SCM 3, and is theoretically motivated by the results of SCM 2. The specification sees the attributes of both tasks loaded onto two higher factors which are common to both tasks.

The log-likelihood of this model with $k = 54$ parameters (18 μ_ϵ and 36 γ) is -13099.90. Given the results of the previous model, we expected to see some discrimination between the factor loadings under γ_{F1} and γ_{F2}, although this result is not clearly seen. *F2* has 5 significant parameters under the best-worst task, compared to 2 under the discrete choice task, while *F1* has 7 significant parameters under the discrete choice task and 7 (although not the same) under the best-worst task.

The pattern which seems to emerge is that *F1* has significance through both tasks, while *F2* has varying significance (on different attributes) through both tasks, suggesting an attribute specific specification will be more appropriate. Such a specification will provide the greater granularity that is needed to be better explain the relationship between the preferences within and between each task on an attribute level.

Model 4: Unique meta-attributes (SCM 4) The remaining set of meta-attribute models assume different structures in the data. Given the differences between the two tasks implied by the global one and two factor models, a unique factor structural choice model follows as the logical next candidate model. This model tests the assumption that the sources of preference heterogeneity for each attribute is unique in each task, *i.e.* not shared with any other attribute, nor are there any context dependent factors.

The log-likelihood of this model with $k = 36$ parameters (18 μ_ϵ and 18 γ) is -12738.30, which improves upon the one and two global factor models but does improve in fit vis-á-vis the mixed logit model. The pattern of results to an extent mirrors the mixed logit and global factor models, however based on the global factor models it was expected the attributes of the discrete choice task would load onto unique factors. Two attributes of the discrete choice task (*safety* and *affordability*) have significant unique factor loadings, which is to an extent consistent with the implications of the global two factor and mixed logit models. Taken at face value, this model is able to provide some account for the observed differences in between the tasks, which can be put down to differences in the drivers of heterogeneity for two of the most important attributes to consumers, *safety* and *affordability*, however there are further possible preference structures to explore which are yet to be ruled out.

Model 5: Common meta-attributes (SCM 5) The next specification is a common meta-attributes model which tests the assumption each attribute has a source of preference heterogeneity that is common to both tasks, yet unique to that attribute. This specification is different to the 1 factor specification, in which the attributes within a task had a common source of heterogeneity to both tasks, but was shared with all other attributes. This distinction becomes important as we interpret these parameters.

The log-likelihood of this model with $k = 36$ parameters (18 μ_ϵ and 18 γ) is -12540.70, which is the second best fitting model in the catalogue. This is a curious result given that the previous models suggest differences in the source of heterogeneity between the priorities task and discrete choice experiment on a global level in the 1 and 2 factor models. This model is suggestive of a different type commonality between the tasks that previous models were unable to consider.

All but only three attributes (*comfort*, *efficiency* and *information*) share a common source of preference heterogeneity. This suggests there are commonalities between the tasks at the attribute level, which is an inviting interpretation as the parameters of this meta-attribute specification provide much more granularity to the phenomenon observed in the data than do the global one and two factor models. To be clear, the global factor models provide estimates of commonalities *within* a task or decision scenario, whereas the meta-attribute specification provide context independent estimates.

The meta-attribute specification parses out any context dependent effects at the attribute level to provide a more reliable estimate of the attribute specific preference stability between the two tasks. The unique factor model considered previously also does this, however the lack of significance of parameters within the discrete choice experiment and poorer fit of that specification suggests this structure is more a likely representation of the structure of consumers' preferences.

Model 6: Regressed meta-attributes (SCM 6) Given the apparent commonality in the sources of preference heterogeneity between the tasks as suggested by the common meta-attributes model, the next step is to consider any possible directionality between the two tasks. This is achieved using a specification that alters unique factor specification to include structural coefficients linking the meta-attributes from the best-worst priorities task with the corresponding attribute in the discrete choice experiment. The unique meta-attributes model was a promising candidate model given the apparent differences between tasks implied by the global factor models, although it did not outperform the common factor model. This specification gives structure to that observed commonality by introducing the assumption that the attributes do not only share common source of heterogeneity, but that these preferences have a structure which includes a theoretically justifiable implied directionality them. In other words, an implied causality between consumers priorities and their behaviour in the discrete choice experiment.

The log-likelihood of this model with $k = 45$ parameters (18 μ_ϵ, 18 γ and 9 β) is -12273.20, which is the best fitting model of the catalogue. There is much more significance throughout the unique meta-attribute factor loadings in this specification, but more importantly all structural regression coefficients (β) are significant. Among the strongest links those between the attributes shown to be important on an aggregate preference level in the earlier arithmetic analysis of the means and variances of the best-worst count data (see: Figure 4.5).

These coefficients can be interpreted following the classic regression model rule that "1 unit Δ in x leads to a β Δ in y", where in this case x is the meta-attribute (ξ_1), a source of heterogeneity specific to an attribute in one task, and y is another meta-attribute (ξ_2) specific to an attribute in the second task. The effect is not universal however, with the links much more marked between specific attributes. *Reliability* and *affordability* show the strongest links with β coefficients of 6.02 and 11.56 respectively that are statistically significant. The results of this model imply a change to these priorities will lead to the strongest change in consumers choice behaviour.

Table 4.7: Results (MNL, MXL and SCM1)

Model	MNL		MXL				SCM 1			
Task	BW	DCE	BW		DCE		BW		DCE	
Attribute	μ	μ	μ	σ	μ	σ	μ	γ_{F1}	μ	γ_{F1}
Safety	1.21	1.82	1.37	1.94	1.94	0.97	1.45	0.67	1.90	0.30
Reliability	1.34	0.96	1.90	0.98	0.98	n.s.	1.58	0.74	0.98	n.s.
Comfort	−0.47	0.33	−0.84	0.33	0.33	n.s.	−0.53	n.s.	0.33	n.s.
Ease of Use	n.s.	n.s.	n.s.	n.s.	n.s.	0.09	n.s.	−0.17	n.s.	n.s.
Convenience	0.67	0.37	0.82	0.37	0.37	n.s.	0.92	0.34	0.38	n.s.
Efficiency	0.43	0.25	0.38	0.23	0.23	n.s.	0.60	0.35	0.25	n.s.
Information	−0.70	0.11	−0.81	n.s.	n.s.	n.s.	−0.85	−0.25	0.11	n.s.
Staff helpfulness	−0.98	n.s.	−1.87	n.s.	n.s.	n.s.	−1.27	−0.67	n.s.	n.s.
Affordability	1.15	−0.80	0.75	−0.82	−0.82	0.65	1.92	1.95	−0.87	−0.59
LL	-14660.88		-12680.23				-13842.13			
ΔLL			-1980.64				-818.75			
Resample	100		100				100			

n.s. *Not statistically significant ($p > .05$)*

Table 4.9: Results (SCM2 and SCM3

Model	SCM 2				SCM 3					
Task	BW		DCE		BW			DCE		
Attribute	μ	γ_{F1}	μ	γ_{F2}	μ	γ_{F1}	γ_{F2}	μ	γ_{F1}	γ_{F2}
Safety	1.64	0.71	1.99	0.40	1.78	2.40	1.16	2.01	0.66	0.22
Reliability	1.76	0.69	0.90	−0.38	1.82	0.45	0.16	0.98	0.84	n.s.
Comfort	−0.53	n.s.	0.34	n.s.	−0.61	0.67	0.13	0.35	n.s.	n.s.
Ease of Use	−0.13	−0.15	0.13	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Convenience	0.98	0.30	0.45	n.s.	0.93	n.s.	n.s.	0.39	0.28	n.s.
Efficiency	0.69	0.35	0.35	0.40	0.65	0.54	n.s.	0.21	0.36	n.s.
Information	−0.88	−0.17	n.s.	n.s.	−0.88	n.s.	n.s.	n.s.	−0.25	n.s.
Staff helpfulness	−1.38	−0.54	n.s.	n.s.	−1.39	0.45	0.16	n.s.	−0.73	n.s.
Affordability	2.14	1.54	−1.02	−1.14	2.10	n.s.	0.41	−0.89	2.14	−0.65
LL	-13749.89827				-13099.84					
ΔLL	-92.23				-650.06					
Resample	100				100					

n.s. *Not statistically significant ($p > .05$)*

Table 4.11: Results (SCM4, SCM5 and SCM6)

Model	SCM 4				SCM 5				SCM 6				
Task	BW		DCE		BW		DCE		BW		DCE		BW $\rightarrow$ DCE
Attribute	μ	γ	μ	γ	μ	γ	μ	γ	μ	γ	μ	γ	$\beta_{BW \rightarrow DCE}$
Safety	1.53	2.32	1.84	0.63	1.59	2.38	1.9	1.16	2.16	1.4	2.03	1.01	1.47
Reliability	1.73	1.22	0.95	n.s.	1.87	1.4	0.95	0.38	2.04	0.22	1.00	0.35	6.02
Comfort	−0.68	1.54	0.33	n.s.	−0.62	1.56	0.33	n.s.	−0.65	1.7	0.36	−0.22	−0.11
Ease of Use	n.s.	0.74	n.s.	n.s.	0.12	0.83	0.08	0.1	0.14	0.34	n.s.	−0.15	−2.32
Convenience	0.87	0.89	0.37	n.s.	0.91	0.93	0.37	−0.1	0.92	0.7	0.36	n.s.	1.38
Efficiency	0.48	0.42	0.24	n.s.	0.5	0.58	0.23	n.s.	0.39	0.44	0.2	n.s.	1.91
Information	−1.02	−1.00	0.09	n.s.	−1.01	−1.00	0.08	n.s.	−0.92	−0.36	0.1	n.s.	−1.86
Staff helpfulness	−1.55	1.33	n.s.	n.s.	−1.45	1.28	n.s.	0.12	−1.65	1.18	n.s.	n.s.	0.95
Affordability	2.53	2.02	−0.77	0.55	2.51	2.12	−0.99	−0.62	2.16	0.21	−0.85	−0.69	11.56
LL	-12738.30				-12540.68				-12273.20				
ΔLL	197.68				-1301.45				-465.12				
Resample	100				100				100				

n.s. *Not statistically significant ($p > .05$)*

4.6 Discussion

Implications for policy development Information on consumers' priorities and consumers' preferences do not necessarily match up perfectly–the importance of consumers' priorities for some attributes carries through more strongly than others. Most importantly, the way in which consumers' think about priorities is not necessarily driven by the same latent source of heterogeneity that drives sensitivity towards identically labelled attributes in choice. Conceptually, this suggests the two (priorities and preferences) are distinct and thus we urge caution in treating either as a proxy for the other. There are however links between the two, the pattern of association between priorities and preferences reveals exactly which priorities are salient in decision making scenarios. To this end, there exists value in collecting data on both priorities and preferences, as it allows the analyst to calibrate a structural choice model with information that is important to consumers.

Relying on only one source of preference information may lead to a theoretical misspecification of what is actually important to consumers at different stages of the decision making process. Combining information on priorities and preferences allows policy makers to better understand the relationships between consumers' priorities and their behaviour. The challenge for policy makers is to locate the product attributes for which consumers' stated intentions and actual behaviour are reliably aligned. The model presented here is a good tool for such a purpose.

We present a model which describes a situation of "priority alignment" between those attributes decision makers' indicate are important to them, and there being a strong predictive link between this priority and the parameters associated with an identically described attribute in a choice experiment. In the case of high priority alignment, the policy recommendations in terms of a communication strategy are relatively straight forward. This would entail the promotion attributes which are of high priority to consumers.

In the case of a low priority alignment, the policy recommendation is to consider that consumers sensitivity towards those attributes with a low priority alignment may be driven by a completely different source of heterogeneity. For all intents and purposes, that attribute may even be considered a *different attribute* in the choice task. The theoretical explanations for differences in the sources of heterogeneity between priorities and preferences will always be context dependent. For example, this may reflect differences between what consumers' prefer in ideal settings vs. what is available to them in a real market (where they are subject to constraints, e.g. budgets). Policy response options may include attempting to promote these attributes to heighten their priority, if it is thought priority alignment will be beneficial to the firm. In many cases, the level of priority is not expected to be a driving factor behind metrics such as profitability or market share, but rather simply a reflection of what drives (or does not drive) the structure of consumers' preferences.

In our application we find that priority alignment is not equal across all attributes. In the public transport context we explored the most salient alignment is between consumers priority rating of *affordability* and preferences for desirable levels of this attribute in their choice behaviour. This result is not particularly surprising, as customer satisfaction data indicate the most variability with this attribute. The attributes *safety* and *reliability* show an interesting pattern. *Safety* rates being of equal priority to consumers, however the link to consumers' preference for this attribute in the choice task is not nearly as strong, while the link between priority measures for *reliability* carry through much more strongly. This does not mean safety is not important to consumers but the implication for practice is that the extent to which consumers' preferences in real life decision scenarios are sensitive to change is much more likely to be seen with the attributes with the strongest levels of priority alignment. That is, to increase public transport patronage, emphasising *safety* in marketing communications is less likely to affect behavioural change.

Implications for choice modelling practice The measurement of consumers' attitudes are in practice typically measured using variants of rating scale approaches (especially the Likert scale). This approach performs well in exploratory work for the identification of potentially important salient attitudes. Such information may be sufficient if the only goal of measuring this information is to receive some feedback from customers about how they perceive a firm to be performing in terms of satisfaction on the measured metrics. Such information may also be useful if one wishes to specify hybrid choice models, in which exogenously defined latent variables comprise inputs into the utility equation. The purpose of such models differs to our application, in that hybrid choice models typically seek to generate insights to inform marketing strategies that target attitudinal change (Vij & Walker, 2016).

Ratings scale data of the type used in traditional surveys or for hybrid choice models cannot be easily parsed using a structural choice model. While technically possible, the model is not designed for this purpose. The structural choice model, as used in this application, serves the purpose of data reduction tool to reduce the dimensions of the sources of heterogeneity in a choice model. In our case, we test whether a model can be suitably reduced to a set of common latent variables representing sources of heterogeneity common to both a priorities elicitation and preference elicitation task. In our example, which will not be general to all, it is the case that a specification assuming unique latent variables is more likely. Building on that specification, the model permits linking priorities to preferences to test which priorities predict preferences, and which that do not.

Conclusions The study demonstrates how the items contained in a regular reporting tracker (the *TransLink Tracker*) can be integrated into a behavioural decision theory driven model of choice. The results of the model are more immediately useful from a policy development perspective, maintain the ease of use of the ratings scale approach with only minimal cost in terms of difficulty to design, analyse and report.

From a planning perspective, the purpose of gathering information is most useful when it informs engineering decisions around which aspects of the service need improving in order to encourage more efficient use of the network (such as increasing patronage, promoting transport mode switching, shifting on/off peak demand). For policy development purposes rating scale approaches suffer well known scale issues (Finn & Louviere, 1992) and do not encourage discrimination between the objects measured as part of the survey. Further, consumers' self-reported ratings of their satisfaction with the various features of a product/service do not reliably relate to the features of a product/service that actually drives decision making in the real market. For these reasons, tracking consumers' self-reported satisfaction with various aspect of a transport service only reliably serves the purpose of providing a rough metric of performance success if only done in isolation. The attributes of a public transport service which consumers are most/least satisfied with may not necessarily be the attributes that most significantly affect their decisions to use or not use public transport, as such we recommend complimenting satisfaction surveys with data on priorities as well as preferences.

4.7 Appendix: Alternative notation

In this section we provide an alternative notation following that used by Rungie, Scarpa and Thiene (2014). Subscripts are omitted for individuals as in all applications in this thesis all individuals complete all tasks. The specifications do not vary between any subgroups in the data (individuals or tasks). In this alternative notation we use β in the place of μ for regression coefficients, $\widetilde{\beta}$ in place of ξ for random (latent) variables and α in place of γ for latent variable on latent variable regression coefficients. This notation should be of more familiarity to those used to working with mixed logit models.

The general form of the mixed logit can be written thus: $v_i = \Sigma_k(\beta_k + \widetilde{\beta}_{k,n})x_k$. The utility of an alternative is a function of a set of explanatory variables (x's); each x is multiplied by the sum of a location parameter, β_kk, and a variance component, $\widetilde{\beta}_{k,n}$; the $\widetilde{\beta}_{k,n}$ is a random variable drawn from some distribution for the nth decision maker (typically, a standard normal distribution) with standard deviation, σ_k, to be estimated. The general form of the structural choice model is $\widetilde{\beta}_k = \alpha_{k,1}\widetilde{\beta}_1 + ... + \alpha_{k,m}\widetilde{\beta}_m + \delta_k$. This generalises the random coefficient model to allow each $\widetilde{\beta}_{k,n}$ to be expressed using structural equations.

The specification of each of the models from this study follow. Note the subscripts for the individual are omitted but reintroduced for model estimation. This alternative notation may be used as a way to translate other model specifications later in this thesis as required by the reader.

The conditional logit model,

$$
\begin{aligned}
v_i &= (\beta_1)x_1^{safe_{BW}} + (\beta_2)x_2^{reli_{BW}} + (\beta_3)x_3^{comf_{BW}} + (\beta_4)x_4^{ease_{BW}} + (\beta_5)x_5^{conv_{BW}} \\
&+ (\beta_6)x_6^{effi_{BW}} + (\beta_7)x_7^{info_{BW}} + (\beta_8)x_8^{acce_{BW}} + (\beta_9)x_9^{help_{BW}} + (\beta_{10})x_{10}^{affo_{BW}} \\
&+ (\beta_{11})x_{11}^{safe_{DCE}} + (\beta_{12})x_{12}^{reli_{DCE}} + (\beta_{13})x_{13}^{comf_{DCE}} + (\beta_{14})x_{14}^{ease_{DCE}} + (\beta_{15})x_{15}^{conv_{DCE}} \\
&+ (\beta_{16})x_{16}^{effi_{DCE}} + (\beta_{17})x_{17}^{info_{DCE}} + (\beta_{18})x_{18}^{help_{DCE}} + (\beta_{19})x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.9}
$$

The mixed logit model,

$$
\begin{aligned}
v_i &= (\beta_1 + \widetilde{\beta}_1)x_1^{safe_{BW}} + (\beta_2 + \widetilde{\beta}_2)x_2^{reli_{BW}} + (\beta_3 + \widetilde{\beta}_3)x_3^{comf_{BW}} + (\beta_4 + \widetilde{\beta}_4)x_4^{ease_{BW}} \\
&+ (\beta_5 + \widetilde{\beta}_5)x_5^{conv_{BW}} + (\beta_6 + \widetilde{\beta}_6)x_6^{effi_{BW}} + (\beta_7 + \widetilde{\beta}_7)x_7^{info_{BW}} + (\beta_8 + \widetilde{\beta}_8)x_8^{acce_{BW}} \\
&+ (\beta_9 + \widetilde{\beta}_9)x_9^{help_{BW}} + (\beta_{10} + \widetilde{\beta}_{10})x_{10}^{affo_{BW}} + (\beta_{11} + \widetilde{\beta}_{11})x_{11}^{safe_{DCE}} + (\beta_{12} + \widetilde{\beta}_{12})x_{12}^{reli_{DCE}} \\
&+ (\beta_{13} + \widetilde{\beta}_{13})x_{13}^{comf_{DCE}} + (\beta_{14} + \widetilde{\beta}_{14})x_{14}^{ease_{DCE}} + (\beta_{15} + \widetilde{\beta}_{15})x_{15}^{conv_{DCE}} + (\beta_{16} + \widetilde{\beta}_{16})x_{16}^{effi_{DCE}} \\
&+ (\beta_{17} + \widetilde{\beta}_{17})x_{17}^{info_{DCE}} + (\beta_{18} + \widetilde{\beta}_{18})x_{18}^{help_{DCE}} + (\beta_{19} + \widetilde{\beta}_{19})x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.10}
$$

The one factor (congeneric) model,

$$
\begin{aligned}
v_i &= (\beta_1 + \alpha_{1,1}\widetilde{\beta}_1)x_1^{safe_{BW}} + (\beta_2 + \alpha_{2,1}\widetilde{\beta}_1)x_2^{reli_{BW}} + (\beta_3 + \alpha_{3,1}\widetilde{\beta}_1)x_3^{comf_{BW}} \\
&+ (\beta_4 + \alpha_{4,1}\widetilde{\beta}_1)x_4^{ease_{BW}} + (\beta_5 + \alpha_{5,1}\widetilde{\beta}_1)x_5^{conv_{BW}} + (\beta_6 + \alpha_{6,1}\widetilde{\beta}_1)x_6^{effi_{BW}} \\
&+ (\beta_7 + \alpha_{7,1}\widetilde{\beta}_1)x_7^{info_{BW}} + (\beta_8 + \alpha_{8,1}\widetilde{\beta}_1)x_8^{acce_{BW}} + (\beta_9 + \alpha_{9,1}\widetilde{\beta}_1)x_9^{help_{BW}} \\
&+ (\beta_{10} + \alpha_{10,1}\widetilde{\beta}_1)x_{10}^{affo_{BW}} + (\beta_{11} + \alpha_{11,1}\widetilde{\beta}_1)x_{11}^{safe_{DCE}} + (\beta_{12} + \alpha_{12,1}\widetilde{\beta}_1)x_{12}^{reli_{DCE}} \\
&+ (\beta_{13} + \alpha_{13,1}\widetilde{\beta}_1)x_{13}^{comf_{DCE}} + (\beta_{14} + \alpha_{14,1}\widetilde{\beta}_1)x_{14}^{ease_{DCE}} + (\beta_{15} + \alpha_{15,1}\widetilde{\beta}_1)x_{15}^{conv_{DCE}} \\
&+ (\beta_{16} + \alpha_{16,1}\widetilde{\beta}_1)x_{16}^{effi_{DCE}} + (\beta_{17} + \alpha_{17,1}\widetilde{\beta}_1)x_{17}^{info_{DCE}} + (\beta_{18} + \alpha_{18,1}\widetilde{\beta}_1)x_{18}^{help_{DCE}} \\
&+ (\beta_{19} + \alpha_{19,1}\widetilde{\beta}_1)x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.11}
$$

The two factor (task specific) model,

$$\begin{aligned}
v_i = &(\beta_1 + \alpha_{1,1}\widetilde{\beta}_1)x_1^{safe_{BW}} + (\beta_2 + \alpha_{2,1}\widetilde{\beta}_1)x_2^{reli_{BW}} + (\beta_3 + \alpha_{3,1}\widetilde{\beta}_1)x_3^{comf_{BW}} \\
&+ (\beta_4 + \alpha_{4,1}\widetilde{\beta}_1)x_4^{ease_{BW}} + (\beta_5 + \alpha_{5,1}\widetilde{\beta}_1)x_5^{conv_{BW}} + (\beta_6 + \alpha_{6,1}\widetilde{\beta}_1)x_6^{effi_{BW}} \\
&+ (\beta_7 + \alpha_{7,1}\widetilde{\beta}_1)x_7^{info_{BW}} + (\beta_8 + \alpha_{8,1}\widetilde{\beta}_1)x_8^{acce_{BW}} + (\beta_9 + \alpha_{9,1}\widetilde{\beta}_1)x_9^{help_{BW}} \\
&+ (\beta_{10} + \alpha_{10,1}\widetilde{\beta}_1)x_{10}^{affo_{BW}} + (\beta_{11} + \alpha_{11,2}\widetilde{\beta}_2)x_{11}^{safe_{DCE}} + (\beta_{12} + \alpha_{12,2}\widetilde{\beta}_2)x_{12}^{reli_{DCE}} \\
&+ (\beta_{13} + \alpha_{13,2}\widetilde{\beta}_2)x_{13}^{comf_{DCE}} + (\beta_{14} + \alpha_{14,2}\widetilde{\beta}_2)x_{14}^{ease_{DCE}} + (\beta_{15} + \alpha_{15,2}\widetilde{\beta}_2)x_{15}^{conv_{DCE}} \\
&+ (\beta_{16} + \alpha_{16,2}\widetilde{\beta}_2)x_{16}^{effi_{DCE}} + (\beta_{17} + \alpha_{17,2}\widetilde{\beta}_2)x_{17}^{info_{DCE}} + (\beta_{18} + \alpha_{18,2}\widetilde{\beta}_2)x_{18}^{help_{DCE}} \\
&+ (\beta_{19} + \alpha_{19,2}\widetilde{\beta}_2)x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.12}$$

The two factor (exploratory) model,

$$\begin{aligned}
v_i = &(\beta_1 + \alpha_{1,1}\widetilde{\beta}_1 + \alpha_{1,2}\widetilde{\beta}_2)x_1^{safe_{BW}} + (\beta_2 + \alpha_{2,1}\widetilde{\beta}_1 + \alpha_{2,2}\widetilde{\beta}_2)x_2^{reli_{BW}} \\
&+ (\beta_3 + \alpha_{3,1}\widetilde{\beta}_1 + \alpha_{3,2}\widetilde{\beta}_2)x_3^{comf_{BW}} + (\beta_4 + \alpha_{4,1}\widetilde{\beta}_1 + \alpha_{4,2}\widetilde{\beta}_2)x_4^{ease_{BW}} \\
&+ (\beta_5 + \alpha_{5,1}\widetilde{\beta}_1 + \alpha_{5,2}\widetilde{\beta}_2)x_5^{conv_{BW}} + (\beta_6 + \alpha_{6,1}\widetilde{\beta}_1 + \alpha_{6,2}\widetilde{\beta}_2)x_6^{effi_{BW}} \\
&+ (\beta_7 + \alpha_{7,1}\widetilde{\beta}_1 + \alpha_{7,2}\widetilde{\beta}_2)x_7^{info_{BW}} + (\beta_8 + \alpha_{8,1}\widetilde{\beta}_1 + \alpha_{8,2}\widetilde{\beta}_2)x_8^{acce_{BW}} \\
&+ (\beta_9 + \alpha_{9,1}\widetilde{\beta}_1 + \alpha_{9,2}\widetilde{\beta}_2)x_9^{help_{BW}} + (\beta_{10} + \alpha_{10,1}\widetilde{\beta}_1 + \alpha_{10,2}\widetilde{\beta}_2)x_{10}^{affo_{BW}} \\
&+ (\beta_{11} + \alpha_{11,1}\widetilde{\beta}_1 + \alpha_{10,1}\widetilde{\beta}_2)x_{11}^{safe_{DCE}} + (\beta_{12} + \alpha_{12,1}\widetilde{\beta}_1 + \alpha_{12,1}\widetilde{\beta}_2)x_{12}^{reli_{DCE}} \\
&+ (\beta_{13} + \alpha_{13,1}\widetilde{\beta}_1 + \alpha_{13,1}\widetilde{\beta}_2)x_{13}^{comf_{DCE}} + (\beta_{14} + \alpha_{14,1}\widetilde{\beta}_1 + \alpha_{14,1}\widetilde{\beta}_2)x_{14}^{ease_{DCE}} \\
&+ (\beta_{15} + \alpha_{15,1}\widetilde{\beta}_1 + \alpha_{15,1}\widetilde{\beta}_2)x_{15}^{conv_{DCE}} + (\beta_{16} + \alpha_{16,1}\widetilde{\beta}_1 + \alpha_{16,1}\widetilde{\beta}_2)x_{16}^{effi_{DCE}} \\
&+ (\beta_{17} + \alpha_{17,1}\widetilde{\beta}_1 + \alpha_{17,1}\widetilde{\beta}_2)x_{17}^{info_{DCE}} + (\beta_{18} + \alpha_{18,1}\widetilde{\beta}_1 + \alpha_{18,1}\widetilde{\beta}_2)x_{18}^{help_{DCE}} \\
&+ (\beta_{19} + \alpha_{19,1}\widetilde{\beta}_1 + \alpha_{19,1}\widetilde{\beta}_2)x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.13}$$

Unique meta attributes,

$$\begin{aligned}
v_i = &(\beta_1 + \alpha_{1,1}\widetilde{\beta}_1)x_1^{safe_{BW}} + (\beta_2 + \alpha_{2,2}\widetilde{\beta}_2)x_2^{reli_{BW}} + (\beta_3 + \alpha_{3,3}\widetilde{\beta}_3)x_3^{comf_{BW}} \\
&+ (\beta_4 + \alpha_{4,4}\widetilde{\beta}_4)x_4^{ease_{BW}} + (\beta_5 + \alpha_{5,5}\widetilde{\beta}_5)x_5^{conv_{BW}} + (\beta_6 + \alpha_{6,6}\widetilde{\beta}_6)x_6^{effi_{BW}} \\
&+ (\beta_7 + \alpha_{7,7}\widetilde{\beta}_7)x_7^{info_{BW}} + (\beta_8 + \alpha_{8,8}\widetilde{\beta}_8)x_8^{acce_{BW}} + (\beta_9 + \alpha_{9,9}\widetilde{\beta}_9)x_9^{help_{BW}} \\
&+ (\beta_{10} + \alpha_{10,10}\widetilde{\beta}_{10})x_{10}^{affo_{BW}} + (\beta_{11} + \alpha_{11,11}\widetilde{\beta}_{11})x_{11}^{safe_{DCE}} + (\beta_{12} + \alpha_{12,12}\widetilde{\beta}_{12})x_{12}^{reli_{DCE}} \\
&+ (\beta_{13} + \alpha_{13,13}\widetilde{\beta}_{13})x_{13}^{comf_{DCE}} + (\beta_{14} + \alpha_{14,14}\widetilde{\beta}_{14})x_{14}^{ease_{DCE}} + (\beta_{15} + \alpha_{15,15}\widetilde{\beta}_{15})x_{15}^{conv_{DCE}} \\
&+ (\beta_{16} + \alpha_{16,16}\widetilde{\beta}_{16})x_{16}^{effi_{DCE}} + (\beta_{17} + \alpha_{17,17}\widetilde{\beta}_{17})x_{17}^{info_{DCE}} + (\beta_{18} + \alpha_{18,18}\widetilde{\beta}_{18})x_{18}^{help_{DCE}} \\
&+ (\beta_{19} + \alpha_{19,19}\widetilde{\beta}_{19})x_{19}^{affo_{DCE}}
\end{aligned} \tag{4.14}$$

Common meta attributes,

$$\begin{aligned} v_i = {} & (\beta_1 + \alpha_{1,1}\widetilde{\beta}_1)x_1^{safe_{BW}} + (\beta_2 + \alpha_{2,2}\widetilde{\beta}_2)x_2^{reli_{BW}} + (\beta_3 + \alpha_{3,3}\widetilde{\beta}_3)x_3^{comf_{BW}} \\ & + (\beta_4 + \alpha_{4,4}\widetilde{\beta}_4)x_4^{ease_{BW}} + (\beta_5 + \alpha_{5,5}\widetilde{\beta}_5)x_5^{conv_{BW}} + (\beta_6 + \alpha_{6,6}\widetilde{\beta}_6)x_6^{effi_{BW}} \\ & + (\beta_7 + \alpha_{7,7}\widetilde{\beta}_7)x_7^{info_{BW}} + (\beta_8 + \alpha_{8,8}\widetilde{\beta}_8)x_8^{acce_{BW}} + (\beta_9 + \alpha_{9,9}\widetilde{\beta}_9)x_9^{help_{BW}} \\ & + (\beta_{10} + \alpha_{10,10}\widetilde{\beta}_{10})x_{10}^{affo_{BW}} + (\beta_{11} + \alpha_{11,1}\widetilde{\beta}_1)x_{11}^{safe_{DCE}} + (\beta_{12} + \alpha_{12,2}\widetilde{\beta}_2)x_{12}^{reli_{DCE}} \\ & + (\beta_{13} + \alpha_{13,3}\widetilde{\beta}_3)x_{13}^{comf_{DCE}} + (\beta_{14} + \alpha_{14,4}\widetilde{\beta}_4)x_{14}^{ease_{DCE}} + (\beta_{15} + \alpha_{15,5}\widetilde{\beta}_5)x_{15}^{conv_{DCE}} \\ & + (\beta_{16} + \alpha_{16,6}\widetilde{\beta}_6)x_{16}^{effi_{DCE}} + (\beta_{17} + \alpha_{17,7}\widetilde{\beta}_7)x_{17}^{info_{DCE}} + (\beta_{18} + \alpha_{18,8}\widetilde{\beta}_9)x_{18}^{help_{DCE}} \\ & + (\beta_{19} + \alpha_{19,9}\widetilde{\beta}_{10})x_{19}^{affo_{DCE}} \end{aligned} \tag{4.15}$$

Regressed meta attributes,

$$\begin{aligned} v_i = {} & (\beta_1 + \alpha_{1,1}\widetilde{\beta}_1)x_1^{safe_{BW}} + (\beta_2 + \alpha_{2,2}\widetilde{\beta}_2)x_2^{reli_{BW}} + (\beta_3 + \alpha_{3,3}\widetilde{\beta}_3)x_3^{comf_{BW}} + (\beta_4 + \alpha_{4,4}\widetilde{\beta}_4)x_4^{ease_{BW}} \\ & + (\beta_5 + \alpha_{5,5}\widetilde{\beta}_5)x_5^{conv_{BW}} + (\beta_6 + \alpha_{6,6}\widetilde{\beta}_6)x_6^{effi_{BW}} + (\beta_7 + \alpha_{7,7}\widetilde{\beta}_7)x_7^{info_{BW}} + (\beta_8 + \alpha_{8,8}\widetilde{\beta}_8)x_8^{acce_{BW}} \\ & + (\beta_9 + \alpha_{9,9}\widetilde{\beta}_9)x_9^{help_{BW}} + (\beta_{10} + \alpha_{10,10}\widetilde{\beta}_{10})x_{10}^{affo_{BW}} + (\beta_{11} + \alpha_{11,11}\widetilde{\beta}_{11} + \beta_{11,1}\widetilde{\beta}_1^{safe_{BW}})x_{11}^{safe_{DCE}} \\ & + (\beta_{12} + \alpha_{12,12}\widetilde{\beta}_{12} + \beta_{12,2}\widetilde{\beta}_2^{reli_{BW}})x_{12}^{reli_{DCE}} + (\beta_{13} + \alpha_{13,13}\widetilde{\beta}_{13} + \beta_{13,3}\widetilde{\beta}_3^{comf_{BW}})x_{13}^{comf_{DCE}} \\ & + (\beta_{14} + \alpha_{14,14}\widetilde{\beta}_{14} + \beta_{14,4}\widetilde{\beta}_4^{ease_{BW}})x_{14}^{ease_{DCE}} + (\beta_{15} + \alpha_{15,15}\widetilde{\beta}_{15} + \beta_{15,5}\widetilde{\beta}_5^{conv_{BW}})x_{15}^{conv_{DCE}} \\ & + (\beta_{16} + \alpha_{16,16}\widetilde{\beta}_{16} + \beta_{16,6}\widetilde{\beta}_6^{effi_{BW}})x_{16}^{effi_{DCE}} + (\beta_{17} + \alpha_{17,17}\widetilde{\beta}_{17} + \beta_{17,7}\widetilde{\beta}_7^{info_{BW}})x_{17}^{info_{DCE}} \\ & + (\beta_{18} + \alpha_{18,18}\widetilde{\beta}_{18} + \beta_{18,9}\widetilde{\beta}_9^{help_{BW}})x_{18}^{help_{DCE}} + (\beta_{19} + \alpha_{19,19}\widetilde{\beta}_{19} + \beta_{19,10}\widetilde{\beta}_{10}^{affo_{BW}})x_{19}^{affo_{DCE}} \end{aligned} \tag{4.16}$$

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5
Conclusion

This thesis provides new perspectives on the ways in which choice modelling and behavioural economics can be combined to generate insights into how decision makers' make choices. For a long time, the field of choice modelling has progressed using a fairly strict framework of models that make normative assumptions about decision makers' behaviour in line with the standard neoclassical economic view of the consumer as a rational agent. Meanwhile, the divergent field of behavioural economics has come to the fore both in the popular press and academic literature. Numerous popular science books are published in this field, and two Nobel prizes have been awarded to researchers in behavioural economics in recent years. The two fields continue to grow however with little integration between them. Choice modelling is now commonplace in both commercial and academic market research, widely used in areas related to policy development in transportation, health and environment. Meanwhile, business leaders are increasingly turning to behavioural decision theory looking for ways to better run their businesses while at the same time searching for data driven approaches to addressing their management objectives. This thesis brings together a data driven approach to conceptualising behavioural decision theory.

We have explored the use of structural choice modelling (Rungie, Coote & Louviere, 2011, 2012) as a way to better represent preference heterogeneity in choice experiments. The model is very general in form and works of the level of locating structure within the error components of a mixed logit model. Such specifications allow for a partitioning of variance between dimensions that may be considered representative of "constructed preferences" versus those that constitute "inherent preferences" (Simonson, 2008). We achieve this using specifications that allow for the components of decision makers' preferences attributable to variations in decision context (method) to be partitioned off from the variance attributable to variation in the levels of the attributes that describe choice alternatives. Such specifications considered as multi-trait-multi-method models, partitioning the sources of variance in decision makers' taste sensitivities into those which are separate trait driven and method driven. The model forms we have developed permit insights into the components of preferences which are context dependent (i.e. constructed) versus those which are context independent (i.e. inherent). These specifications of a structural choice model join the family of more general latent variable models which have been gaining traction in the literature in recent years, most notably hybrid choice models (Walker, 2001) and other applications of factor analytic choice models (Elrod & Keane, 1995).

The estimation of structural choice models, like most choice models, involves the maximisation of a likelihood function. This thesis demonstrates how meta-attribute specifications of this model that allow for multi-trait-multi-method models achieve the best fit to sampled data, and offer the most theoretically meaningful insights into decision makers' behaviour. The exploration of these model forms and the theories they are able to test was the focus of this thesis, and represents a unique integration of behavioural decision theory into a standard economic framework that has not been achieved in the same way elsewhere. A challenge remains however, with respect to improving the speed and efficiency in estimating structural choice models. A technical appendix follows this conclusion chapter of the thesis which outlines some of the challenges faced in estimating the models contained in this thesis, as well presenting some initial background research which may be useful to future researchers who may seek to write new estimation software for structural choice models. With this, it is hoped a more widespread of adoption of the structural choice modelling can be achieved and to allow for further integration of rich behavioural theory into choice models.

The bringing together of fields

Choice modelling and behavioural decision theory are generally thought of as separate fields. On the one hand, choice modelling is heavily embedded with a rich history in empiricism. Perhaps most notable of these is McFadden's (1973) Nobel Prize winning work leading to the conditional logit model, which to this day remains the workhorse choice model of econometricians and market researchers alike. On the other hand, behavioural decision theory uses a more descriptive rather than empirical approach to describing the drivers of choice behaviour and has had similar impact on the scientific community with Kahneman's (2002) work similarly recognised with a Nobel Prize.

Both fields share the common goal of seeking to explain and predict decision makers' behaviour however it seems their fundamentally different approaches to data collection, analysis and interpretation has not permitted them to be considered as complimentary. We have shown in this thesis that there exists both a theoretical and empirical rationale for the bringing together of these two otherwise disparate fields to permit more behaviourally informed choice models. The structural choice models estimated as part of this thesis are specified in ways designed to test some of the classic effects predicted by behavioural decision theory using a modelling framework that is familiar to strictly econometric audience. Such models provide a more probable representation of the structure of consumers' preferences using established fit measures commonly used in choice modelling and provide more theoretically plausible accounts of decision making. The interpretations that are permitted through more behaviourally informed specifications also allow for more nuanced policy responses that take into account the modelled aspects of behavioural decision theory.

From the perspective of the choice modellers, research in behavioural decision theory could be considered to be lacking in statistical rigour and that the results of research in this area are upon stylised experiments that are not representative of real world phenomena. From the perspective of behavioural decision theorists, the research using choice modelling based upon random utility theory could be considered to lack a realistic descriptive basis upon which to accurately describe the nuances of consumer decision making. The reliance on pure empiricism as opposed to a critical assessment of the anomalies of non-utility maximising behaviour may further detract from the potential realism of such research.

Choice modellers heavily rely upon assumptions of rationality in decision making. The standard economic view regarding decision makers' rationality is one that assumes consumers are perfectly indefatigable whose preferences are both well-known and stable in face of sources of influence that attempt to affect them in one way or another (Simon, 1956). Such assumptions are built in the economic specification of mainstream choice models, most notably the standard conditional logit model (McFadden, 1973) which must account for the large majority of research using choice modelling in both academic and commercial settings. Such models do well in recovering the aggregate preferences of a sample of consumers and when specified with random coefficients do well in describing what the spread of preferences might be in a sample. The specification of two-way and even three-way interactions among attributes in a choice model allows for insights into what kinds of particular bundling of attributes and levels decision makers prefer, however such models fall short of considering interactions among latent sources of variation. Higher order sources of variation include the influence of the decision making environment such as cognitive burden, decision rules that people may follow in order to optimise on unseen factors and (but not limited to) other sources of variation latent to the decision scenario. The examples explored in each of the studies in this thesis comprise the specification of a variant of the standard choice model (i.e. the structural choice model) in ways which attempt and do capture the effects of such latent sources of variation within the standard economic framework.

In contrast to choice modelling, behavioural decision theorists tent to focus on understand and describing the cognitive illusions which affect or impede decision makers' ability to make fully rational decisions. Indeed, Kahneman's (2002) Nobel Prize winning work is most well-known for describing prospect theory, whereby decision makers are said to differentially derive utility from losses and gains. Other well-known illusions include phenomena such as the way decision makers might anchor their preferences upon some baseline attribute level available in the decision scenario rather than considering attribute values in absolute terms (Tversky & Kahneman, 1973). Similarly, decision makers are known to prefer alternatives that represent a compromise between two extremes which is very much at odds with the concept of utility maximisation (Simonson, 1989).

Resolving of tensions

The integration of rich theories about the way choices are made into the standard economic framework has for a long time been an issue of incompatibility between disparate fields of study. The structural choice modelling framework that is exemplified through three example applications in this thesis demonstrates how the two otherwise disparate fields of choice modelling and behavioural decision theory can be integrated. Specifically, the tools made available from the strictly empiricist approach to understanding decision making from within the standard economic framework can be specified with latent dimensions that reflect the descriptive theory of behavioural economics within a random utility equation. Structural choice modelling provides a way to parameterise the effects of cognitive illusions by way of describing how latent variables indirectly affect the taste sensitivity for the attributes of alternatives in choice.

The resolving of tensions between otherwise disparate fields recognises that both behavioural decision theory and choice modelling offer insights into decision making. Neither should supersede the other given they approach the question of what drives decision making from two different starting points. Given their differing strengths, they should be seen as naturally complimentary rather than in opposition. The normative assumptions of choice modelling about how decision makers ought to behave can be put into balance by assessing the extent to which decision makers stray from idealistic behaviour as a measure of decision quality. The descriptive accounts provided by behavioural decision theory provide a guide for the specification of flexible structure choice models which may parameterise the effects of behavioural phenomena into formal choice models, and in doing so provide more parsimonious and better fitting models.

The integrations of fields does not necessarily lead to a new field, rather it simply acknowledges that the tools, techniques and theories of decision making from each permit an enhanced understanding of decision making within both frameworks. From a policy perspective, the configuration of products and services, or the way in which information about products and services is communicated to consumers, requires an understanding about the ways in which consumers think about the attributes of alternatives in those markets. The status quo approach has been to consider the taste sensitivities for individual attributes of products and services as being independent which for the most part permits strategies focusing on the most important drivers of primary preferences. The new approach that is suggested from this thesis is to consider the ways in which preferences for the attributes of alternatives may in fact be partially dependent on latent factors which go beyond simple interactions among attributes. These should include the range of rich descriptive accounts of how cognitive illusions have effects on decision making, to the point structural models can be specified in ways that reflect theory about how such behavioural phenomena manifest as structures within the error components of a rational utility equation.

As choice based methods and models have come to the fore in recent decades, there is much value to be gained by embedding them with the ability to derive richer and more theoretically tractably insights. Choice modelling approaches like metric conjoint analysis are particularly popular due to its similarity to simple linear regression with respect to interpretation and easy implementation. More advanced logistic regression models such as the fixed and random parameters specifications of mixed logit further offer value by offering more nuanced insights into the distribution of preferences in a market.

For researchers in marketing, especially those with backgrounds in psychometric theory and modelling using structural equations, the extant models have lacked the ability to theorise about structures of commonality across and between the attributes of alternatives in choice models. The integration achieved in this thesis demonstrates a way forward in order to overcome such limitations. This does not, however, represent the end of the road or completion of this effort more so than it represents only the beginning of what should be a further concerted effort to integrate behavioural decision theory into the standard economic framework of choice modelling.

Summary of thesis contributions

This thesis documents three studies which approach research questions about how behavioural decision theory may manifest within the latent dimensions of decision makers' utility for transport services. More generally, we present models which allow for testing components of decision makers' preferences which are inherent and those which are constructed or context dependent. The research contexts considered throughout the thesis are positioned as marketing problems, insofar as investigating how the ways in which marketers design decision scenarios (such as servicescapes) within which consumers' make choices. Specifically, we consider how these affect the trade-off structures between the attributes of alternatives and to what extent consumers' reliance on inherent versus constructed preferences is determined by the decision making environment.

The type of theorising using behavioural decision theory is approached in a way that should be familiar to marketing scholars, in that the theories and models estimated are embedded with the assumption that preferences for the attributes of alternatives are not independent but in fact correlated. This is in direct contrast with the standard assumptions of mainstream choice models that the sources of variation in decision makers' attribute preferences are independent. Behavioural decision theory has relevance in this domain in terms of providing a theoretical justification for correlations among latent sources of variation in preferences. These are empirically testable using specialised specifications of structural choice models that allow for interpretations relating to the structure of latent sources of preference variation that are common to groupings of particular attributes. This modelling framework which combines econometric rigour with behavioural theory offers unique insights for the development of policy and strategy that not possible using conventional methods. A summary of the contributions from each paper presented in the thesis now follows.

Firstly, we develop a parsimonious representation of the latent effects the compromise effect (Simonson, 1989) has on the structure of the random components of decision makers utility. The model developed further provides strong quantitative empirical evidence that the compromise effect manifests at both the decision level (in terms of absolute shifts in observed choice shares), as well as at higher order levels in terms of correlations among latent sources of preference heterogeneity. The components of decision makers' preferences which specified within the utility equation as not context dependent (i.e. inherent preferences) are less affected by the compromise effect, and those which are context dependent (i.e. constructed) are tractably affected by the compromise effect. Specifically, the links between these dimensions within the utility function are strong and significant and in alignment with theory on compromise effects. The value of these contributions is in the new kinds of insights into the compromise effect that the unique model form provides which previous research was unable to provide. The more nuanced insights the model forms provide should enable a more considered approach by marketers in responding to how they develop strategy to either compensate or benefit from this behavioural tendency in consumers. We demonstrate that for some attributes the compromise effect is stronger than others, and that overall the compromise effect is not as strong as previously thought, but nevertheless is evident in the majority of choice scenarios studied. Further, we show there are significant effects on the latent structure of decision makers' both directly and indirectly attributed to the presence of a compromise alternative. The experimental design used is not stylised to elicit the hypothesised effect, but follows the strict approaches to experimental design used in choice models, while also incorporating an alternatives which are systematically within the design plan to sit within certain attribute levels so as to represent a compromise alternative.

Second, the thesis contributes to an emerging literature of research which considers a process oriented view of antecedent volition (Swait, 2013) combined with the idea that preferences contain components which are both inherent and constructed (Simonson, 2008). It is within this theoretical framework that we consider decision makers' taste sensitivities for the attributes of alternatives in choice to be determined. We demonstrate an example of a structural choice model of that generates insights into which of the latent dimensions of decision makers are stable and which are dynamic across contexts of varying decision complexity. The theoretical lens of antecedent volition provides a useful framework within which to consider what might be meaningful explanatory reasons for the presence or absence of correlations among the latent dimensions within decision makers utility. Further, the model forms developed in our study of antecedent volition lend themselves well to permitting insights about the extent to which decision makers' mix between states of reliance on inherent versus constructed preferences. We compared competing model forms which test different assumptions about the structure of the drivers of taste sensitivities as either context dependent (constructed preference model) versus those which are attribute unique across contexts (inherent preference model).

Thirdly, we contribute to theory development regarding the extent to which decision makers stated priorities align with (and predict) their behaviour in choice tasks. In doing so, a new application of structural choice modelling is presented which is new to the literature in the way data from two different types of preference elicitation tasks are combined into a simultaneously estimated model. The findings and insights generated provide marketers with more detailed and tractable information about whether the links between those attributes consumers say are important to them are indeed important when predicting their choices. Specifically, the model form used estimates which attributes share common latent variables as their source of heterogeneity between a priorities measurement task and a choice task. Where such commonalities are found to occur a condition of priority alignment is said to exist, in which case marketers may proceed to have confidence in such attributes being important predictors of behaviour. This model form allows a direct empirical linkage between priorities and preferences. This model presents a direct test of the impact of inherent preferences on choice by individually measuring priorities before a choice task and determining the extent to which priorities share common sources of variation as with their aligned attributes in a discrete choice task. Similar to the first study, we find variation between attributes which again suggests the extent to which decision makers' rely on inherent versus constructed preferences is attribute dependent. For some attributes, there is a strong consistency between decision makers' priorities (inherent preferences) while for others there are no commonalities found (hence preferences are constructed).

A finding consistent throughout the three studies is the systematic component of utility can be partitioned at higher order levels of abstraction in behaviourally and theoretically meaningful ways. Decision makers have unobserved sources of taste sensitivity and structural choice models are able to capture and map their shapes to provide evidence about the ways in which certain behavioural phenomena manifest at these latent variable levels. This partitioning of the systematic component of utility is achieved using different specification of the structural choice model in each of the presented studies.

In terms of the compromise effect, the systematic component of utility when partitioned to include latent dimensions specifically associated with the availability of a compromise alternative, shows that the extent to which decision makers trade-off between attributes to increases under such a specification. When controlling for the compromise effect we see decision makers apparent change in sensitivity towards important attributes like price significantly polarised.

The partitioning of the systematic components of utility to account for the effects of task complexity reveals a consistency in the drivers of taste sensitivities for some attributes across different levels of complexity. Theory of antecedent volition supports a conjecture decision makers pursue a consistent decision rule which relates to the interplay between decision makers' preferences which are context independent inherent versus those which are context dependent constructed. With this explanation, the practical outcome remains the same although the theoretical explanation describes the effect of cognitive burden as being having a more subtle nuanced effect than what previous research suggests.

The systematic component of utility can be specified to be partly driven by a decision makers' priorities, and partly driven by their preferences. Understanding which has the strongest influence on behaviour or if the two are correlated permits marketers to develop more informed strategies that relate to the true drivers of behaviour. Decision makers' priorities are not the same as their preferences, which we take as a general reflection of the difference between ideals and reality. There are commonalities between latent variables specified for alike attributes in a priorities elicitation and preference elicitation task, however there are important behavioural interpretations about the strength and significance of these links. The priorities decision makers indicate in a best-worst task about the attributes most important to them do significantly predict preferences for those attributes in a choice experiment. The importance of some priorities are either over or under estimated when considered in isolation from the choice task. The drivers of decision makers' sensitivities towards attributes in choice tasks does tend to match decision makers' priorities but this is not general for all attributes. For this reason, it is important marketers and policy makers understand the interplay between both.

The thesis introduces to the literature a variety of new ways in which to both consider theory on consumer behaviour as well as develop new models to better predict behavioural responses to the various ways in which the decision environment is strategically designed. For example, two attributes may share a common source of taste sensitivity in low complexity scenarios, suggesting marketing activities targeting preferences for offerings based on these attributes might benefit from treating these attributes as compliments in low complexity settings. If such attributes are shown to have unique sources of taste sensitivity in other contexts, then context dependent marketing activity may be warranted, such as using more clearly delineated communication strategies in high complexity settings. Modelling the sources of taste sensitivity for attributes can assist strategy and policy makers to build a more nuanced picture of the way consumers' preferences change between different settings. Attributes for which consumers' aggregate preferences change between contexts, but share a common source of taste sensitivity across contexts, suggest the use of consistent decision rules such as reliance on heuristics or being susceptible to cognitive illusions. In such cases, decision making environments should be designed in ways to suit the decision rules most conducive to maximising decision makers utilities in those contexts.

Deriving policy directions using structural choice models

Structural choice models offer policy analysts a way to understand the structure of heterogeneity in decision makers' preferences. Specifically, compared to a fully parametrised correlated error components specification of the mixed logit, structural choice models allow for a much more parsimonious representation of the taste sensitivities towards the attributes of alternatives in choice. Correlations among taste sensitivities can be specified under this framework to present theorised commonalities in the drivers of heterogeneity for different attributes, both within and across different decision making tasks. Before continuing this discussion on using structural choice models for policy setting, it is worth briefly commenting on the use of alternative latent variable models in this context.

Chorus and Kroesen (2014) present a critique on the use of integrating latent variables into choice models for deriving transport policy. Their critique focuses on the types of models including latent variables as characteristics of decision makers (e.g. attitudes and perceptions), commonly known as hybrid choice models. These models are argued to be limited with respect to their usefulness in policy setting as such attitudes may be endogenous to choice, and because of the cross sectional nature of attitudinal data entering these types of models Chorus and Kroesen (2014). These criticisms, however, are not unique to latent variable models and particularly so in transport contexts (Vij & Walker, 2016). Observable variables such as destination choice are likely to be endogenous on the availability and frequency of services to that destination, however the latent characteristics of a decision maker such as their core values are unlikely to be endogenous in choice (Vij & Walker, 2016). Further, longitudinal data offers more reliable information in all contexts.

By contrast, structural choice models do not include the latent characteristics of decision makers' as inputs to the utility equation. Rather, the way structural choice models incorporate latent variables is via dimension reduction with respect to the random parameters describing heterogeneity in the sensitivity of preferences for each of the attributes in a choice model. The model further is able to specify structural equations to reflect how sources of heterogeneity specific to particular attributes they may influence or be related each other based on theory.

The benefits of including latent characteristics of decision makers' as inputs into the utility equation per the approach of hybrid choice models is perhaps more obvious. Under that framework, policy can be developed with respect to developing strategy to affect attitudes or address social norms in ways tractably shown to affect choice in a hybrid choice model (Vij & Walker, 2016). The output from a structural choice model provides a different kind of benefit. By understanding and locating where commonalities existing among the sources of heterogeneity for the particular attributes of alternatives in choice, the analyst may effectively assume decision makers' consider these attributes as interchangeable.

To be useful in policy making settings, it is critical we understand how stable or dynamic the structures of these commonalities are under different conditions. This has been the focus of this thesis. Consider the results from the first study in this thesis whereby under the specification of the structural choice model used in that study, all of the attributes unique to each particular task are specified to have the same common source of variation. Our result here shows that when a compromise alternative is made available, decision makers' sensitivities towards all attributes in that task share a single context dependent source of heterogeneity. When the compromise alternative is not available, decision makers' taste sensitivities are stable (or as we theorise to be based on inherent preferences). For the policy maker, this supports the predictions of behavioural decision theory regarding compromise effects (Simonson, 1989), and thus allows a policy response which may take this into account. With respect to the specific results in that study, this may entail a configuring of services that presents one particular offering as a compromise relative to take advantage of the induced commonality among attribute preferences with the aim to reduce decision makers' reliance on attribute specific preferences.

The policy implications from the second study show that despite differences in aggregate preferences for attributes between tasks of varying complexity, for the most part the taste sensitivities for these attributes share a common source of heterogeneity. By using a multi-trait-multi-method type of model specification, we are able to generate insights based on the effects of common and unique factors across multiple scenarios. The results from the second study suggests that policy makers need not consider that decision makers' might think about these attributes differently in contexts of varying complexity as our model suggests there is a latent source of variation that is common to all complexity scenarios that represent decision makers' stable and inherent preferences. This is useful because in developing marketing strategies to target behaviour towards particular attributes or features of a product, the results of this study suggest that in this context managers need not differentially elevate particular attributes in scenarios which may be more or less complex.

The specification of common and unique factor specifications permits interpretations that suggest the way in which decision makers' approach their choices in each scenario is in fact consistent, despite aggregate preferences differing marginally in each. In the transportation context of we studied we suggest there is evidence of inherent preferences among consumers for attributes like service reliability that is unaffected by task complexity. Conventional choice models which rely only aggregate preferences would indicate context effects are significant for this attribute. When we partition variance into the stable and dynamic components, we see the taste sensitivities towards attributes in fact share a common source of variation that is stable across contexts while dynamic components are all found to be within context. To be sure, inherent preferences appear to trump constructed preferences most of the time. Therefore, marketing communications in the context we studied need not differ in message between complexity scenarios. In other words, these results suggest a consistent integrated marketing communications strategy is most appropriate in this particular context.

From the third study, we consider whether the method of preference elicitation affects the sensitivity in decision makers' preferences for attributes common to both tasks. A specification which treats the source of heterogeneity towards alike attributes as different fits to the data better than one that treats them as having a shared source. Understanding that decision makers approach expressing their priorities for a bus service in a different way to the way they actually choose bus services has important policy implications. For example, based on measures of priorities alone a transport service provider may receive a biased estimate of the importance of certain attributes. By combining both data sets on decision makers priorities with their choice data, the choice model can be calibrated to take both into account. In our model, we find certain priorities have stronger (weaker) effects on the sensitivity towards attributes in the task which do not line up in the same order as the priorities model alone would suggest.

Future research directions

We have demonstrated the efficacy of using the structural choice model for investigating effects on consumer decision making that are in line with the thoughts addressed by behavioural theorists. Future research in behavioural decision theory appears to be generally on a path characterised by an increased level of integration of its classic theories of behaviour into formal econometric specifications (Simonson, 2014). This thesis is positioned on this same path. Beyond quantifying behavioural effects into models, future research in behavioural decision theory is expected to evolve on a trajectory that specifically responds to structural changes in the way in which decision makers' receive information and further considering how to partition inherent and constructed preferences (Simonson & Rosen, 2014).

Accessibility of information The accessibility of readily available attribute level quality diagnostics is of substantive interest in behavioural decision theory research. The research methods used in this thesis are readily applicable to research into the effects of information accessibility on choice. The justification for increased attention in this area relates to the now widespread proliferation of hybridised information-rich socially-intensive environments that has changed the accessibility and diagnosticity of information, particularly with the digitisation of consumer decision making environments (Feldman & Lynch, 1988). Information accessibility is a topic of interest across multiple disciplines although it is of particular relevance to those in the business of communicating information about the attributes and levels of alternatives in decision making contexts.

We might consider the ways in which the diagnosticity of information affects behaviours such as variety seeking or maintenance of habitual choice patterns. Such questions are relevant in the debate on consumer rationality, as consumers who are habitual in their purchases might be foregoing higher levels of utility that would be attainable from untried alternatives about which they do not have quality diagnostic information (e.g. alternative transport routes, best practice medical options, etc.). A structural choice model could be specified which assesses whether the availability of more reliable diagnostic information about absolute and real-time attribute levels promotes variety seeking, or at least considerations of larger choice sets that represent a more complete range of possible alternatives such that their behaviour is more consistent with that of a fully or at least more rational decision maker.

A further justification for considering the diagnosticity of attribute information concerns what effects it may potentially have on consumer welfare in the day and age of so called "fake news". As an example, in online settings consumers are known to restrict themselves to a narrow band of information channels within which misinformation is known to spread and echo, which in certain contexts can lead to deleterious outcomes (consider, for example, healthcare practices) (Pariser, 2011). To investigate the strength of the effect misinformation may have on consumer welfare, a structural choice model could be fitted to data collected from a choice experiment in which attributes with contain levels akin to "alternative facts" are linked to decision makers' sensitivities for the levels of attributes that best represent optimal outcomes (for example, best practice healthcare options). This would allow for a test of how strongly (or otherwise) the presence of misinformation may affect the diagnosticity of both real-time and static attribute level information. Our expectation should be consumers hold inherent preferences for objectively optimal outcomes, while misinformation injected into an information environment presents itself to appeal to the components of decision makers preferences that are constructed.

Re-thinking (ir)rationality Modern information environments are evolving and changing the way information is presented to consumers to the point whereby the nature of decision making environments is both simultaneously saturated with an overburdening amount of choice and information, as well as tools which permit a highly structured filtering and searching of the information needed to maximise one's personal utility. The research method used in this thesis lends itself well to applications which may consider, for example, the effects of reliable and up-to-date real-time information on consumer's (ir)rationality. To the extent decision makers do or do not conform to normative assumptions about decision making, there is still value in the continued and extended efforts of behavioural decision theorists to either debunk or integrate their views into the standard economic frameworks. Further considerations into how cognitive illusions affect choice within the standard economic framework are needed using new tools such as structural choice modelling as the way to bring these fields together.

Simonson (2014) specifically outlines a need to better understand the factors that moderate the stability of decision makers' preferences in decision scenarios characterised by increased availability of real-time objective quality cues. Research into the drivers (or attenuators of) consumer rationality have been the mainstay of behavioural decision theory research (Iyengar & Lepper, 2000; Schwartz, 2004; Scheibehenne, Greifeneder & Todd, 2010), and will most likely continue to be as there are potentially an unlimited number of ways that consumer irrationality may manifest given the constantly evolving information environment.

The now widespread availability of real-time information about the current attribute levels of for particular products/services characterises many decision making contexts in modern consumption contexts. For example, real-time timetabling/service information (when accurate) increases the diagnosticity of information about public transport, crowding in restaurants, one's own health, or the availability of stock in retail settings. Such technology allows a decision maker to better maximise their utility for time or effect spent search for alternatives. The benefits of these technology are well understood in transport applications (Brakewood, Macfarlane & Watkins, 2015), however as mentioned are now utilised in a wide range of applications. In marketing contexts to date, research on real-time information has been limited to turbulent contexts, such as stock markets (Glazer & Weiss, 1993). More generally, there has been an anticipation of changes in how marketers ought to respond to the increased availability of real-time information (including product reviews) about products (McKenna, 1997), nevertheless this is an area still only scantily understood in the literature (King, Racherla & Bush, 2014).

Embedded experiments to test framing effects

The three studies in this thesis provide insights into the effects of decision contexts and the effects of task characteristics, however we have not considered framing effects (Kahneman & Tversky, 1984). Framing is known to be an important determinant of when decision makers' preferences will be constructed versus inherent (Simonson, 2008). As an extension of the studies in this thesis we would use the same modelling approach on data generated from experimental designs that included embedded experiments. An embedded experiment which include different frames could comprise two or more common or alike discrete choice experiments that participants complete under different frames such as a primed level of risk aversion or an emotional state. We could further extend this to a consideration of the effects of varying information diagnosticity in terms of how stable the structure of common and unique factors are under a multi-trait-multi-method specification of the structural choice model that links decision makers' preferences collected in different frames.

The ways in which information is presented to consumers is known to affect latent taste sensitivities towards the attributes of alternatives in choice. The effectiveness of modern marketing and advertising that appeals to emotion rather than reason seem to demonstrate our intuitive appreciation and understanding of consumers as heterogeneous in preferences and who do not systematically behave as rational decision makers unaffected by the way information is communicated. Marketing strategies designed to promote phenomena of behavioural decision theory in consumers decision making produce commonalities among attributes that reveal unique (and perhaps unexpected) trade off patterns. For example a comparative study of the different latent preference structure of decision makers following receiving information from a variety of media channels would allow more theory driven development of strategies related to the positioning of messages within particular channels.

Exploring possible interaction effects between contexts in which real-time information is available may further reveal how these information-rich socially-intensive sources of information affect decision making in a variety of areas. In many contexts (transport, hospitality, retail, etc.) certain attributes have either not featured in marketing communications in the past, or arguably have not been immediately apparent to consumers that this information was important, such as real-time travel congestion, on-shelf availability and current restaurant crowding (Xu, Frankwick & Ramirez, 2016). Thus, it will be important for marketers to better understand how the presence of these new kinds of attributes which digital technologies are able to deliver have on consumers preferences. In the same way that the compromise effect has general and attribute level interactions with consumer preferences, we should expect that different information environments will give rise to different general and attribute specific interactions that have both stable and dynamic components as revealed by structural choice models.

Concluding remarks

This thesis has integrated theory of behavioural decision theory into the specification of a series of structural choice models that have extended our understanding about the way in which decision makers preferences manifest as either inherent or constructed preferences. We have specifically focussed on the various ways in which the drivers of decision makers sensitivities for the attributes of alternatives in the choices they face have commonalities among them in theoretically meaningful ways. The commonalities studied relate to factors which are either common or unique to decision scenarios, thus representing sources of variation in decision tasks that relate to inherent or constructed preferences. The specific model forms developed represent multi-trait-multi-method specifications of the structural choice model that allow partitioning of the decision makers preferences into components affected by factors within the local context and factors general across contexts.

Our research has shown that commonalities arise as the result of particular manipulations to the way in which alternatives are presented to decision makers. In our first study, decision makers are shown to have a greater degree of commonality in the way they express their preferences when a compromise alternative is available in the form of a trinary choice task. Such commonalities between the drivers of decision makers taste sensitivities are not present in a binary choice task. In the second study, we show that there are stable commonalities among latent sources of variation in decisions makers' preferences for buses which are not entirely effected by choice complexity, *i.e.* decision makers have an antecedent volition based on stable inherent preferences while local context constructed preferences can be modelled using a unique factor structure specification. Finally, we link two different preference elicitation tasks (a best-worst and discrete choice task) together to test how decision makers' priorities align with their choices. The priorities decision makers' have for attributes of a more functional nature predict choice more strongly than do priorities for more ancillary/hedonic types of attributes.

Theories about inter-relationships between latent attitudes account for commonalities among responses given on attitudinal rating scales. Similarly, we have shown that behavioural decision theory accounts for commonalities we can observe in the error components of choice models of consumers preferences. The use of structural choice models has allowed for nuanced interpretations about the nature of inherent and constructed preferences in choice models which until now alternative model forms could not permit. In doing so, we have combined choice modelling with behavioural theory in a way that improves the usefulness of both as tools for understanding consumer behaviour.

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Appendices

Structural choice model estimation issues

A limitation of the structural choice model is its onerous estimation times. For final specifications of models with large resample sizes, several days of computer time can be needed for models to reach convergence and to calculate standard errors via inversion of complex Hessian matrices. If structural choice models are to be more broadly adopted addressing the issue of estimation time is seen as critical. In this section, documentation of the process of estimating an exploratory catalogue candidate structural choice models with small resample sizes is provided.

To specify a well-fitting structural choice model requires one to think and theorise about a research problem in a particular way. The most immediate and naïve approach is to think in terms of the types of structural equations models (SEM) used to test theory in marketing. That is, an outcome variable that choice may be a proxy for that is driven by latent variables representative of attitudes (*e.g.* perceived risk, environmental concerns, etc.). The model is better suited to testing claims about the commonality in decision makers latent source(s) of preference heterogeneity for the attributes of alternatives in choice. Usually, the theory is about shared or common sources variance in decision makers preferences. It is possible these sources of variation do represent attitudes, although we do not have a specific framework or paradigm to accurately deduce what those attitudes might be conceptually in the same way researchers using semantically meaningful indicator items can. A notable exception is Atto (2013)'s work testing identifying latent variables within a structural choice model that can be tractably linked to values schemes (Lee, Soutar & Louviere, 2007, 2008) using a best-worst measurement approach. In all other published demonstrations of the model, the application is to retrieve correlations among latent sources of variation between attributes in one or more choice tasks (Bowe, Rungie, Lee & Lockshin, 2016).

A process of trial and error can be typical when investigating a catalogue of candidate models. A benchmark model, usually fixed or random effects models such as conditional and mixed logit are compared against models with structural parameters along various fit criteria to determine which best represent some data. The conditional logit model is estimated as per McFadden (1973) by maximising the likelihood function, probabilities for each alternative are summed over all respondents to arrive at a log-likelihood value,

$$LL = \sum \log P_n \tag{5.1}$$

To maximise the function in equation 5.1 an optimising algorithm is used to locate the set of parameters that maximise the likelihood function. This can be readily achieved in Microsoft Excel using Solver with the Generalised Reduced Gradients (GRG2) algorithm. The standard errors for the model parameters are calculated from the diagonals of the inverse Hessian matrix using the function =MINVERSE(.) after model estimation. Using Excel is not efficient compared to purpose written choice modelling packages in more dedicated statistics software although there is pedagogical value in fitting a model this way.

Table 5.1 summarises the conditional logit models fitted in four software packages to the same smart phones data. Each of the packages reproduces near identical estimates to the 4^{th} decimal place. Packages in Stata and R converge on the same model near instantaneously, Stata does so with 3 iterations of the Newton-Raphson algorithm while R finds the same result with 7 iterations of the Iteratively Reweighted Least Squares (IRLS) algorithm. Excel converges in 9 iterations using the GRG2 algorithm, while DisCoS converges with 10 iterations of the Nelder-Mead algorithm; plus about another 1 minute to derive and inverse the Hessian matrix.

As for the estimation of structural choice models, it is not possible to obtain close initial

Table 5.1: Comparison of estimation times

	Stata		**R**		**Excel**		**MatLab**	
	.clogit		***mclogit()***		***Solver***		***DisCoS***	
	μ_ϵ	SE	μ_ϵ	SE	μ_ϵ	SE	μ_ϵ	SE
Apple	1.47	0.09	1.47	0.09	1.47	0.08	1.47	0.09
HTC	0.64	0.08	0.64	0.08	0.64	0.08	0.64	0.08
Motorola	0.34	0.08	0.34	0.08	0.34	0.08	0.34	0.08
Blackberry	0.46	0.08	0.46	0.08	0.46	0.08	0.46	0.08
Samsung	1.58	0.09	1.58	0.09	1.58	0.08	1.58	0.09
LG	0.65	0.08	0.65	0.08	0.65	0.08	0.65	0.08
HP/Palm	–							
LL	-1754.1		-1754.1		-1754.1		1754.1	
Iterations	4		7		9		10	
Method	Newton-Raphson		IRLS		GRG2		Nelder-Mead	
Speed	< 1 second		< 1 Second		12 seconds		36 seconds	

values from other software packages. In such cases, the analyst must rely on their intuitive judgement as to what might be appropriate initial values based on theory. For some problems, the researcher may have a relatively good idea about the expected sign of the parameter, but this is not always the case so typically some arbitrarily chosen value is used. Initial values of 0.3 for γ and 0.5 for β parameters are typical but somewhat uninformed.

Table 5.2 shows the time for convergence for an incomplete catalogue of candidate models considered for Study 2 in the thesis. The times shown are those recorded by MatLab (The MathWorks, 2012) for models with resample sizes of 100 each. Note that the times shown measures only account for the time taken for the Nelder-Mead algorithm used by DisCoS and not the additional time to calculate standard errors via Hessian inversion. For complex models, this additional step can take longer than the initial estimation. All models listed in Table 5.1 were estimated on PC running dual Intel Xeon X5690 3.47GHz processors with 48GB of RAM. The PC was dedicated for this purpose and ran no other resource intensive processes at the time of estimation. Models were left running overnight and on weekends for much of the 2013/2014 summer period.

TABLE 5.2: Extended model catalogue estimation times

Model type	**Parameters**	ξ	$\boldsymbol{k}$	$\boldsymbol{LL}$	**hh:mm:ss**
Conditional logit	$10 \times \mu_\epsilon$	0	10	1799.72	00:01:38
Conditional logit	$10 \times \mu_\epsilon$	0	10	2739.35	00:01:16
Conditional logit	$10 \times \mu_\epsilon$	0	10	3542.46	00:01:31
Mixed logit	$10 \times \mu_\epsilon$ $10 \times \sigma_\epsilon$	20	20	1573.35	00:23:57
Mixed logit	$10 \times \mu_\epsilon$ $10 \times \sigma_\epsilon$	20	20	2518.07	00:22:43
Mixed logit	$10 \times \mu_\epsilon$ $10 \times \sigma_\epsilon$	20	20	3229.5	00:32:10
1 factor SCM	$10 \times \mu_\epsilon$ $10 \times \gamma$	1	20	1490.3	00:24:49
1 factor SCM	$10 \times \mu_\epsilon$ $10 \times \gamma$	1	20	2455.94	00:26:21
1 factor SCM	$10 \times \mu_\epsilon$ $10 \times \gamma$	1	20	3277.8	00:28:09
Conditional Logit	$\mathbf{30} \times \boldsymbol{\mu_\epsilon}$	**0**	**30**	**8081.52**	**00:12:57**
Mixed Logit	$\mathbf{30} \times \boldsymbol{\mu_\epsilon}$ $\mathbf{30} \times \boldsymbol{\sigma_\epsilon}$	**60**	**60**	**7068.27**	**131:37:35**
1 factor SCM	$\mathbf{30} \times \boldsymbol{\mu_\epsilon}$ $\mathbf{30} \times \boldsymbol{\gamma}$	**1**	**60**	**6895.02**	**22:51:55**
2 factor SCM	$30 \times \mu_\epsilon$ $60 \times \gamma$	2	90	6976.66	26:17:13
3 factor SCM	$30 \times \mu_\epsilon$ $90 \times \gamma$	3	120	6862.71	27:51:40
3 factor SCM	$30 \times \mu_\epsilon$ $30 \times \gamma$	3	60	7226.03	20:27:27
4 factor SCM	$30 \times \mu_\epsilon$ $90 \times \gamma \times 2\beta$	4	122	6843.08	204:55:45
4 factor SCM	$30 \times \mu_\epsilon$ $90 \times \gamma \times 2\beta$	4	122	6867.77	63:07:40
4 factor SCM	$30 \times \mu_\epsilon$ $90 \times \gamma \times 2\beta$	4	122	6845.22	64:08:18
4 factor SCM	$30 \times \mu_\epsilon$ $90 \times \gamma \times \beta = 1$	4	120	6858.37	88:36:08
Correlated factors	$30 \times \mu_\epsilon$ $30 \times \gamma$ $3 \times \phi$	3	63	6985.67	21:33:43
Factor-factor regression	$30 \times \mu_\epsilon$ $30 \times \gamma$ $4 \times \beta$	4	64	7000.45	14:37:32
Factor-factor regression	$30 \times \mu_\epsilon$ $30 \times \gamma$ $2 \times \beta$	4	62	7000.45	12:07:31
Factor-factor regression	$30 \times \mu_\epsilon$ $30 \times \gamma$ $\beta = 1$	4	60	7226.03	18:38:31
Factor-factor regression	$30 \times \mu_\epsilon$ $30 \times \gamma$ $6 \times \beta$	6	66	6998.85	780:35:30
Meta-factor SCM	$10 \times \mu_\delta$	10	10	8359.94	00:08:42
Meta-factor SCM	$10 \times \mu_\epsilon$ $10 \times \sigma_\epsilon$	10	20	7109.24	01:25:50
Meta-factor SCM	$10 \times \mu_\epsilon$ $10 \times \beta$	11	20	8359.94	00:10:46
Meta-factor SCM	$30 \times \mu_\epsilon$ $10 \times \beta$	11	40	7018.23	02:46:38
Meta-factor SCM	$\mathbf{30} \times \boldsymbol{\mu_\epsilon}$ $\mathbf{30} \times \boldsymbol{\gamma}$	**10**	**60**	**6413.33**	**42:16:55**
Meta-factor SCM	$\mathbf{30} \times \boldsymbol{\mu_\epsilon}$ $\mathbf{30} \times \boldsymbol{\gamma}$ $\mathbf{20} \times \boldsymbol{\beta}$	**12**	**80**	**6343.12**	**90:11:08**
Mixed logit equal-variance 1	$3 \times \mu_\epsilon$ $10 \times \mu_\delta$	10	13	8220.48	00:09:27
Mixed logit equal-variance 2	$3 \times \mu_\epsilon$ $10 \times \mu_\delta$	10	13	8218.08	00:14:26
Mixed logit equal-variance 3	$3 \times \mu_\epsilon$ $10 \times \mu_\delta$	10	13	8206.05	00:21:07
Mixed logit equal-variance 4	$3 \times \mu_\epsilon$ $10 \times \mu_\delta$	10	13	8143.88	00:23:23
Mixed logit equal-variance 5	$3 \times \mu_\epsilon$ $10 \times \mu_\delta$	10	13	8207.85	00:23:23
Mixed logit equal-variance 6	$3 \times \mu_\epsilon$ $10 \times \mu_\delta$	10	13	8211.47	00:21:07
Mixed logit equal-variance 7	$3 \times \mu_\epsilon$ $10 \times \mu_\delta$	10	13	8215.86	00:15:54
Mixed logit equal-variance 8	$3 \times \mu_\epsilon$ $10 \times \mu_\delta$	10	13	8207.76	00:28:12
Mixed logit equal-variance 9	$3 \times \mu_\epsilon$ $10 \times \mu_\delta$	10	13	8209.93	00:17:43
Mixed logit equal-variance 10	$3 \times \mu_\epsilon$ $10 \times \mu_\delta$	10	13	8194.97	00:12:19
Multi-factor equal-variance 1	$30 \times \mu_\epsilon$ $3 \times \gamma$ $9 \times \beta$	12	42	7007.97	03:05:25
Multi-factor equal-variance 2	$30 \times \mu_\epsilon$ $3 \times \gamma$ $9 \times \beta$	12	42	7012.14	05:25:51
Multi-factor equal-variance 3	$30 \times \mu_\epsilon$ $3 \times \gamma$ $9 \times \beta$	12	42	6960.15	18:07:18
Multi-factor equal-variance 4	$30 \times \mu_\epsilon$ $3 \times \gamma$ $9 \times \beta$	12	42	6927.52	18:34:58
Multi-factor equal-variance 5	$30 \times \mu_\epsilon$ $3 \times \gamma$ $9 \times \beta$	12	42	7019.06	18:40:32
Multi-factor equal-variance 6	$30 \times \mu_\epsilon$ $3 \times \gamma$ $9 \times \beta$	12	42	6954.65	17:05:09
Multi-factor equal-variance 7	$30 \times \mu_\epsilon$ $3 \times \gamma$ $9 \times \beta$	12	42	6999.91	14:11:11
Multi-factor equal-variance 8	$30 \times \mu_\epsilon$ $3 \times \gamma$ $9 \times \beta$	12	42	7018.8	20:10:28
Multi-factor equal-variance 9	$30 \times \mu_\epsilon$ $3 \times \gamma$ $9 \times \beta$	12	42	6963.25	17:25:27
Multi-factor equal-variance 10	$30 \times \mu_\epsilon$ $3 \times \gamma$ $9 \times \beta$	12	42	6773.31	18:17:33

The bold faced models are those reported in the final paper which are re-estimated on a re-sample size of $R = 1000$ using starting values from previous models with a smaller re-sample of $R = 100$. As such, the table does not contain the completely exhaustive list of all models run, nor does it include models which were terminated before convergence as the model could not be identified. The estimation times of structural choice models improve as the analysis becomes become more adept in identifying more appropriate and elegant ways to structure data and to address their substantive research questions, although in applications requiring exploratory analysis this may not be possible.

If the correct model is estimated the estimation times of a structural choice model are reasonable for academic purposes. None of the final models reported in each of the three studies in the thesis took longer than 1 or 2 days for models of resample sizes $R = 100$, and no more than 1 week for models of $R = 1000$. Running a model over the course of a week or two does not impede the completion of a multi-year doctoral project. For the theoretical approach to underpinning the specification of structural choice models to be more widely accepted, however, it is expected the challenges presented by such onerous estimation times will be discouraging for many scholars. As such, an exploration of alternative approaches to estimation is warranted as part of an ongoing effort to promote structural choice modelling.

Estimation Algorithms

The process of maximising a log-likelihood function involves both derivation and exponentiation to compute the gradient of the likelihood curve (Train, 2009). By working with natural logarithms, this can be done using the sum of items rather than the product of items, which is computationally much easier to perform. There are several approaches to the process of finding a unique solution to maximum likelihood problems. The process is generally iterative, and thus relies on an optimisation algorithm to solve for the unknown parameters.

Microsoft Excel's Solver uses the Generalised Reduced Gradient (GRG2) algorithm to maximise or minimise an objective cell based on a function of other specified cells in the spreadsheet (Fylstra, Lasdon, Watson & Waren, 1998). Stata's *.clogit* uses an estimator based on a modified Newton-Raphson algorithm (Gould, Pitblado & Sribney, 2006). Most base packages of R use an Iteratively Reweighted Least Squares (IRLS) algorithm. For example, *mclogit()* uses a two-step method combining an IRLS and Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm, the latter is used if convergence cannot be achieved using the former. This two-step method is highly favourable as some optimisers can be particularly quick at finding the general region where the local optima are located, however can be slow to finally converge. DisCoS (Rungie, 2011) uses a direct search Nelder-Mead algorithm (Nelder & Mead, 1965), which while very accurate and stable is very slow.

Given the current estimation times upwards of several days, it will take several technological generations before a hardware solution overcomes computational issues to the point of these models taking fractions of a second to estimate (Moore, 1965). Train (2009) provides an extensive overview of some of the more popular estimation approaches and algorithms available which is summarised here with respect to their relevance to the estimation of structural choice models. The different approaches have important implications for how slowly or quickly the maximum of the function can be found, and hence which are likely to present as candidates for improving estimation of the structural choice model.

Simulated Maximum Likelihood Structural choice models use simulated maximum likelihood, which for all practical purposes is the same as maximum likelihood except that simulated probabilities are used in estimation rather than exact probabilities. This method of estimation modifies the regular likelihood function $LL = \sum \log P_n$ by replacing P_n with S_n which are simulated probabilities rather than observed probabilities, hence,

$$LL = \sum \log S_n \tag{5.2}$$

The point at which this function is maximised remains the same as in normal likelihood maximisation, that is, where the sum of simulated probabilities gives a gradient of the function that is equal to zero,

$$\sum_n S_n = 0 \tag{5.3}$$

A problem with simulated maximum likelihood is that the simulated probabilities are not unbiased, since the log transformation is non-linear, i.e. $\log S_n$ is biased for $\log P_n$, even though S_n is unbiased for P_n. This bias is diminished by using larger resamples of simulated probabilities, however this has the downside of significantly increasing the computational effort required. The advised procedure for estimating a structural choice model is to first estimate models using a small resample size of $R = 100$, and once the researcher has decided on the model specifications they are satisfied with, re-estimate the models using larger resamples of $R = 1000$ or $R = 10,000$ (Rungie, 2011). This process assumes a fixed resample size R although it would be advantageous to allow the resample R to rise automatically at a rate faster than $\sqrt{n}$. In doing so, the maximum simulated likelihood estimates are more consistent across resamples and would improve the time efficiency of the model (Train, 2009).

Nelder-Mead This method searches the parameter space around the set of initial values provided by the researcher, looking for those values which the objective function is lower than the value at the current point (Nelder & Mead, 1965). The closer the initial values are to the final solution, the better this algorithm performs. This results in reliable parameters, however for significantly more than two dimensions, the method is slow (Lagarias, Reeds, Wright & Wright, 1998). For a structural choice model with many higher order dimensions, estimation is slow because it must compare the current point on the function with all n other points simultaneously. Where one is uninformed about the possible neighbourhood of values the final solution might take, the user might specify initial values close to zero. In many cases, the researcher will not be able to obtain reliably informed starting values, and it is indeed possible that bad (those very far from the final solution) starting values may slow the model down even more by effectively starting it further away from the solution than is necessary. For the lower order parameters of a structural choice model, these are readily obtained from other software but for higher order parameters pertaining to correlations or regressions between latent variables, there is no reliable method for obtaining accurate initial values.

Other methods of improving estimation efficiency are to specify more constrained and parsimonious models to reduce this dimensionality. For example, if correlations between latent variables are dropped, run times are noticeably faster, however this has the drawback of limiting the generality of the model to test behavioural theory.

Newton-Raphson This numeric approach to equation solving based on methods used to approximate square-roots taken developed by Isaac Newtown and later refined by Joseph Raphson for more complex sequences. These methods are perhaps the most widely used hill climbing algorithms for solving maximum likelihood problems (Train, 2009). The logic behind this algorithm is intuitively easy to understand, following the formula

$$\beta_{t+1} = \beta_t + \lambda(-H_t^{-1})g_t \tag{5.4}$$

where g_t is the gradient of the log likelihood function LL, H_t is the Hessian and λ the step size. If the log likelihood function is a perfect quadratic, the maximum is found in one step, although in practice the function is not perfectly quadratic so some iterations of the algorithm are required. To prevent stepping past the maximum of the function, Newton-Raphson multiplies the Hessian and gradient by a scalar λ which updates at each iteration to provide the algorithm with information about the slope of the likelihood function without needing to recalculate the Hessian at each step. The main drawback of this method is that the Newton-Raphson is prone to stalling in local minima (valleys) where the likelihood function is non-concave. In these instances, the sign of the Hessian can be inverse.

BHHH The Berndt-Hall-Hall-Hausman (Berndt, Hall, Hall & Hausman, 1974) algorithm takes into consideration the likelihood function being maximised is the sum of the log probabilities of discrete choices from a sample of observations. Each observation is given a score which is the derivative of that observations log likelihood with respect to the unknown parameters. The gradient of the likelihood function is then the average of these scores, and the likelihood function is maximised when the average scores equal zero. The variance of these scores provides the BHHH with information about the slope of the likelihood function.

A good fitting choice model is one which captures the meaningful differences between people. In situations where people display similar preferences, *i.e.* the variance in their scores is low then the likelihood function will be flat and many values of β will maximise the likelihood function. In situations where there is a large degree of preference heterogeneity, the likelihood function is markedly steep, thus deviation away from β maximise the log likelihood function lead to a large loss of model fit. The BHHH uses an almost identical algorithm to the Newton-Raphson,

$$\beta_{t+1} = \beta_t + \lambda(-B_t^{-1})g_t \tag{5.5}$$

where g_t is the gradient of the log likelihood function, B_t is average outer product of the observation specific gradients and λ is the step size. B_t is much easier to calculate than the second derivatives of the log likelihood function because it works on average variances rather than complex derivation and inversion of matrices

$$\beta_{t+1} = \beta_t + \lambda(-H_t^{-1})g_t \tag{5.6}$$

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DFP and BFGS The Davidon-Fletcher-Powell, and Broyden-Fletcher-Goldfarb-Shanno algorithms (Davidon, 1991; Fletcher, 2013; Powell, 1981) are both approximate Hessian algorithms. DFP and BFGS take information from several points along the log likelihood function to infer information about the curvature of the function. This provides more information about the shape of the function than do individual points on the curve, which greatly assists the estimation procedure in identifying local minima. By calculating arcs this method also captures changes in gradient which is used to update the scalar parameter.

Expectation-Maximisation (EM) The EM algorithm was originally developed by Dempster, Laird and Rubin (1977) to estimate parameters using incomplete or missing data, where the analyst has some informed expectation about the missing data. The idea is an intuitive answer to a complex problem, that is to treat the too hard to find parameters as missing data, as opposed to unknown parameters.

The general procedure of EM is to assume a distribution about the missing parameters, based on expectations derived from the observed information available. The log likelihood estimation approach takes into account the expectations about the log likelihood of both the missing and observed data. The EM procedure iterates to maximise these joint expectations based on initial values which are updated with each iteration of the algorithm.

EM has been used to estimate structural models using rating scale data (Breffle & Morey, 2000). In the context of a mixed logit, Train (2009) shows that the EM algorithm is efficient for estimating models with many latent classes. Bhat (1997) uses a combined EM and DFP approach whereby EM is used to locate accurate initial values which bring the model close to convergence, and efficient DFP method is used to find the final parameters. This method shown to improve both model fit as well as estimation time when compared to using alternative methods in isolation, as it obviates the need for the computationally intense inversion of the Hessian.

Cherchi and Guevara (2012) provide some guidelines regarding the use of EM with mixed logit models. Specifically, they found that the efficiency and efficacy of the EM method is comparatively unaffected as the number of parameters being estimated increases. Further, the EM method is reported to be faster than maximum simulated likelihood when the number of parameters estimated is greater than eight (Cherchi & Guevara, 2012). However, Cherchi and Guevara (2012) recommend that maximum simulated likelihood be used for demand forecasting applications as their EM methods did not recover the true scale of the parameters.

Bayesian Approaches Models too complicated to estimate may become more tractable if a Bayesian approach is adopted. Bayesian procedures concern conditional probabilities per Bayes theorem,

$$P(A|B) = \frac{P(B|A).P(A)}{P(B)} \tag{5.7}$$

The probability of each parameter in the model is informed by the distribution of conditional probabilities. The probabilities ascribed to parameters in the model as priors are multiplied by those ascribed after estimation, the posteriors. In this way, the model automatically updates its expectations. In the above equation, $P(B)$ is a normalising constant which in practice is set to 1 for convenience (Train, 2009).

Markov Chain Monte Carlo (MCMC) The MCMC approach iterates two steps: first, find the probability of x conditional on y, $P(x|y)$ and second, find the probability of y conditional on x, $P(y|x)$. Sampling from the joint distribution of probabilities for x and y, we find both $P(x)$ and $P(y)$.

Bayesian procedures do not involve the maximisation of any function, however the result is one which converges on the parameters which do maximise the classical likelihood function (Train, 2009). As Bayesian approaches do not maximise a specific function, initial values are not needed, it is not necessary to calculate the Hessian and the parameters of the model can be estimated without needing to calculate individual choice probabilities.

The accuracy of these estimates increases as the number of samples taken increases. If the probabilities of each parameter are assumed to be conditional on the probabilities of other parameters in the model, then increasingly complex models can be divided into smaller, yet interrelated, models. The MCMC principal further states that the joint density functions of higher order parameters can be perfectly described by the joint density functions of lower order parameters (Jackman, 2009). Finding the solution to a likelihood maximisation problem for a model of high dimensionality becomes intuitively easy. Imai, Jain and Ching (2009) present a compelling argument in favour of the use of this Bayesian approach in choice modelling in showing that the computational burden required for estimating a dynamic choice model reduces to that of a static choice model when using an MCMC procedure.

The future for structural choice modelling

The overview of estimation methods given here is by no means an exhaustive overview of available estimation methods. The approach used by Bhat (1997) whereby EM is used to obtain reliable initial values and then DFP is used for the remainder of estimation appears promising as it obviates the need for computationally intense processes to obtain standard errors for structural choice model estimates. Bayesian approaches also present an intuitive appeal, although considering the goal of improving estimation efficiency these approaches still present considerable challenges due to the required computational power.

Selecting a new estimation method should be take the speed and accuracy into consideration. Estimation times less than several hours should be considered ideal for models with many higher order factor correlations. In terms of accuracy, minimising the standard errors of the estimates provided by models should form the primary criterion. The method of calculating standard errors differs between each of the estimation procedures. The Hessian matrix is used in the estimation process of many of the discussed optimisation algorithms, and in many cases is the main limiting factor in terms of computational difficulty.

The future of structural choice modelling will rely upon improving estimation times. Despite the valuable theoretical insights the model can provide using slow albeit very reliable methods, onerous estimation procedures are significant barrier to its adoption. Therefore, it is an earnest recommendation that this issue be addressed with the aim to promote the benefits of structural choice modelling to a broader audience.

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Ethical approval for studies

This appendix includes the details of the approvals as they relate to the collection of data for each of the studies included in the thesis. As the research involved human subjects by way of their completion of discrete choice experiments, ethical approval is required. Copies of the ethics approval letters are included in this appendix. The approval notices are presented in the order they were received.

UQ BUSINESS SCHOOL
THE UNIVERSITY OF QUEENSLAND AUSTRALIA

25 July 2012

Mr Thomas Magor
UQ Business School

Student ID Number: 41389780

Dear Thomas

Application for Ethical Clearance

Thank you for your ethical clearance application for a project entitled “Which bus to take? A study into the effects of choice set size in public transport using discrete choice modelling", which forms part of a Bachelor of Business Management (Honours) program.

The Ethical Review Committee has reviewed the application, and ethical clearance is approved, subject to the following conditions:

1. A copy of the data collection instrument should be submitted to the committee before the data collection.

2. The area code and time taken to complete the survey should be included in Form E2. The area code should be included in Form E3.

Yours sincerely

Dr Ravi Pappu
Chair, Ethical Review Committee
UQ Business School

THE UNIVERSITY OF QUEENSLAND
AUSTRALIA

UQ BUSINESS SCHOOL

Date: 15/10/2015

To: **Thomas Magor**
From: Dr. Tyler G. Okimoto, Chair UQBS Ethical Review Committee

RE: Your application for ethical clearance:
"Measuring Compromise Effects Using Latent Variables" (#116205)

Dear Thomas:

The UQBS Ethical Review Committee has processed your expedited application for ethical clearance. You fulfil the requirements for expedited review, and I have closely examined your documentation. I am writing to inform you that the committee has determined that your application is **approved**.

Approval is subject to the conditions listed on the additional notes document (attached) – please retain both of these documents for your records. Although not yet a formal requirement of the UQBS ethics process, we strongly encourage you to review your data management plan with your supervisor (see attached checklist). If changes to the approved study protocol are required for any reason, please submit a written letter of ethical clearance amendment to the committee detailing all required changes and any implied ethical considerations (submit to Vivienne Balson, v.balson@business.uq.edu.au).

Regards,

Dr. Tyler G. Okimoto
Chair, UQBS Ethical Review Committee

Dr. Tyler G. Okimoto (BA, MA, PhD)
Chair, UQBS Ethical Review Committee
UQ Business School
The University of Queensland
Brisbane, QLD, 4072, Australia

Phone: (+61 7) 3346 8043
Email: t.okimoto@business.uq.edu.au

THE UNIVERSITY OF QUEENSLAND AUSTRALIA

UQ BUSINESS SCHOOL

Date: 05/09/2016

To: **Thomas Magor**
From: Dr. Tyler G. Okimoto, Chair UQBS Ethical Review Committee

RE: Your application for ethical clearance:
"A process of attitudinal priority alignment: Linking attitudes to behaviour in public transport using in a structural choice model" (#157181)

Dear Thomas:

The UQBS Ethical Review Committee has processed your expedited application for ethical clearance. You fulfil the requirements for expedited review, and I have closely examined your documentation. I am writing to inform you that the committee has determined that your application is **approved**.

Approval is subject to the conditions listed on the additional notes document (attached) – please retain both of these documents for your records. Although not yet a formal requirement of the UQBS ethics process, we strongly encourage you to review your data management plan with your supervisor (see attached checklist). If changes to the approved study protocol are required for any reason, please submit a written letter of ethical clearance amendment to the committee detailing all required changes and any implied ethical considerations (submit to Vivienne Balson, v.balson@business.uq.edu.au).

Regards,

Dr. Tyler G. Okimoto
Chair, UQBS Ethical Review Committee

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