Incorporating attitudinal factors and multi-agent decision making within the context of discrete choice experiments

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For my husband Chris.

Abstract

Whilst there has been much progress in the development of discrete choice models, which expand upon the basic random utility model, some limitations still exist. One such limitation, which has gained widespread recognition in recent years, is that many real life decisions are not made by a single person, but in consultation with other *actors*. This recognition, has led to the assessment that the traditionally used unitary household model, which assumes that a household has a single utility function, does not sufficiently reflect the reality of household decision making. In this case it is more likely that the members of the household engage in a process of joint deliberation in order to maximise both their individual and joint utility functions.

In addition, it is well recognised that *attitudes* towards different attributes of the alternatives are also, *inter alia*, an important determinant of an individual's choices and underlying preferences. What is less well understood is the consideration that individuals give to the attitudes held by other actors/agents. Therefore, inclusion of the individual's and their respective partner's attitudinal data may contribute to richer discrete choice models. In this context, integrated choice and latent variable models may be advantageous.

The aim of the thesis is to explore these issues. The thesis is based on the discrete choice experiment methodology and attempts to explain preferences within different decision making structures. The research explores the role that the different opinions, attitudes and preferences play when actors/agents make a *joint* decision. The thesis also incorporates additional factors that may have a bearing on the choices made by an individual, such as socio-demographics. The thesis aims to bridge the gap between models which specialise in modelling multi-agent choices and hybrid choice models, which integrate many of the components that have been identified as important when defining the choice process.

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The Ph.D. road is definitely a rocky one, but I hear that even the Himalayas are climbable if you have the right team with you.

Declaration

I hereby declare that, unless otherwise indicated in the text, the research presented in this thesis is original work undertaken by myself, Vikki O'Neill, between October 2009 and March 2012. The thesis comprises of a collection of papers which have been submitted to journals and/or presented at international conferences. In all cases, the major contributions were made by myself with input from my co-authors.

During the period of study for the Ph.D., I developed a questionnaire centered around a discrete choice experiment, aimed at gaining an improved understanding of intra-household trade-offs between different meal options. The results from this questionnaire are analysed in Chapter 3, Chapter 5 and Chapter 6.

A separate dataset was analysed in Chapter 2. The data used for Chapter 2 come from a survey conducted in the Stockholm region of Sweden in 2005. The specific interest of the survey was a study of the trade-offs between salary and commuting time. For more detailed information on the data the reader is directed to Swärdh and Algers (2009).

Finally, I declare that the thesis is not one for which a degree has been or will be conferred by any other university or institution, nor is the thesis one for which a degree has already been conferred by this University.

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Chapter 1

Introduction

1.1 Introduction

This thesis is concerned with the enhancement of discrete choice models, which are methods used to model a decision-maker's choice among a finite set of mutually exclusive and collectively exhaustive alternatives. The research explores the role that different opinions, attitudes and preferences play within different decision making structures. The motive for this research, is to bridge the gap between models which specialise in modelling multi-agent choices and hybrid choice models, which integrate many of the components that have been identified as important when defining the choice process. Such enhancements will allow for a more realistic representation of the behaviour which takes place during the choice process, consequently not only providing a better understanding of behaviour but also improving the specification and explanatory power of discrete choice models.

1.1.1 Background

Discrete choice models belonging to the family of Random Utility Models (RUM) (Ben-Akiva and Lerman, 1985; Manski, 1977; McFadden, 1974; Thurstone, 1927) have been used extensively in many areas of behavioural research, for over thirty years (c.f. Hensher and Rose, 2011, for a comprehensive history on the development of the choice modelling field). Traditionally they have been used to elicit the economic value of non-market goods and services. The development of random utility maximization theory, or RUM theory, became the benchmark for the use of choice techniques in the economic literature as it provided the necessary link between observed consumer behaviour and economic theory (Kjær, 2005). Discrete choice experiments are theoretically grounded in Lancaster's theory of value (Lancaster, 1966), which states that a good can be described by the different characteristics, or attributes, that it possesses and by the levels that these attributes can take. Furthermore, Lancaster (1966) states that it is these attributes (and associated attribute levels) from which an individual will derive utility rather than the *good* itself and as a result, utility can be expressed as a function of the attributes of a good. Accordingly, a change in one of the attributes (such as price) can cause a discrete switch from one alternative to another if it will provide a higher level of utility given the new adjusted attribute (Alpizar et al., 2003).

Stated preference techniques

In addition to discrete choice experiments, there are three other main choice techniques that together form a class of preference elicitation methods called 'stated preference' (SP) (Boxall et al., 1996). These are contingent ranking, contingent rating and paired comparisons. The underlying idea for most stated preference techniques is that any good can be described in terms of its attributes (or characteristics) and the levels that these attributes can take. Respondents are presented with various alternative descriptions of a good, differentiated by their attributes and associated attribute levels, and are asked to either rank the various alternatives; rate them or choose their most preferred (Hanley et al., 2001).

Hanley et al. (2001) show that each of the stated preference techniques listed above differ in the quality of information they generate, in their degree of complexity and also in their ability to produce willingness to pay (WTP) estimates that can be shown to be consistent with the usual measures of welfare change. These differences reflect differences with respect to theoretical assumptions, methods of analysis and experimental procedures (Bateman et al., 2002; Louviere et al., 2000).

For example, in a discrete choice experiment, a respondent is asked to choose one alternative (usually the one that will provide him or her with the most utility) out of a given number of alternatives. Whereas, in a contingent ranking exercise, respondents are asked to rank all of the alternatives that are presented to them, usually in increasing preference order. In a contingent rating exercise respondents are presented with a single alternative, and are then asked to rate this alternative on a semantic or numeric scale. Respondents will usually face a series of alternatives, for which they are required to 'rank' each separately. Finally, paired comparison exercises use a combination of contingent ranking and contingent rating techniques, where respondents first choose their preferred alternative out of a set of two and then subsequently, indicate the strength of their preference on a semantic or numeric scale. For a comprehensive review of the contingent ranking, contingent rating and paired comparisons techniques, see Hanley et al. (2001).

McFadden (1974) introduced the fundamental concept that individual choice behaviour is intrinsically probabilistic rather than deterministic. Hence, according to this theory, each individual has a utility function associated with each of the alternatives. This utility function can then be divided into two parts; a systematic part, which considers the effect of the explanatory variables on the utility function; and a random part that takes into account all the effects which have not been included in the systematic part (Bolduc and Alvarez-Daziano, 2010).

Since its first application in environmental management by Adamowicz et al. (1994) there has been an increasing interest in use of discrete choice methodology by both practitioners and academics alike. This recent surge has been the result of mounting evidence showing the advantages that discrete choice experiments possess over the previously dominant contingent valuation methods (both the advantages and disadvantages of discrete choice experiments are considered in Adamowicz et al., 1998, Alpizar et al., 2003 and Hanley et al., 1998, to name just a few). Given the evidence in the literature demonstrating that discrete experiments have the ability to produce a much richer description of respondents' preferences, it is possible to use many different advanced techniques to model preference data. Hence the stated preference technique used throughout this thesis is discrete choice experiments.

Discrete choice

The concept of random utility theory was originally conceived by Thurstone (1927); this was later developed into the Logit formula by Luce (1959). Later, Marschak (1960) showed that the model is consistent with utility maximisation. This is a key concept for discrete choice models. McFadden (1974) also showed that the form of the Logit formula necessarily implies the use of the type I extreme value (Gumbel) distribution for the unobserved part of the utility.

Depending on the assumptions made about the distribution of the random error term(s) in the utility function, there are many different choice models, which can be exercised (Ben-Akiva and Lerman, 1985; Bolduc and Alvarez-Daziano, 2010). Initially, the Multinomial Logit (MNL) model (McFadden, 1974) and the nested logit model (Ben-Akiva, 1973) were the 'workhorses' for most discrete choice applications (Bolduc and Alvarez-Daziano, 2010). However, significant gains in computer power and improvements in the efficiency of simulation and estimation techniques have led to the increased use of advanced nesting structures and models based on mixture distributions, such as the Mixed Logit (MMNL) model (Bhat, 2003; Bolduc and Ben-Akiva, 1991; Brownstone and Train, 1999; Hess, 2005; Train, 2009). The MMNL model, is considered a powerful modelling alternative (Bolduc and Alvarez-Daziano, 2010), as it can approximate any RUM model (McFadden and Train, 2000). See Train (2009) for an extensive guide to the different choice models. Compared to the Multinomial Logit model, the MMNL model is generally shown to have a significant improvement in model fit (Hensher and Greene, 2003) in addition to providing greater insights into individuals' choice behaviour (McFadden and Train, 2000) and welfare estimation (Hynes et al., 2008; Sillano and Ortúzar, 2004). Some of the most popular specifications for the MMNL model include random parameters logit (RPL) models (see, for example Batley et al., 2004, Bhat and Gossen, 2004, Greene et al., 2006 and Hensher and Greene, 2003), latent class (LC) models (see, for example Boxall and Adamowicz, 2002, Greene and Hensher, 2003, Hess and Rose, 2007 and Hess et al., 2009), or more recently, a combination of both, namely the 'latent class mixed multinomial logit model' (see, for example Beharry-Borg and Scarpa, 2010 and Greene and Hensher, 2013).

There has been much interest in developing models, which provide an accurate representation of random taste heterogeneity across individuals. However, whilst it is generally accepted that these models give researchers greater ability to reveal the *true* underlying preferences across respondents, there still remains much debate about the most appropriate functional form to use. These models allow for increased flexibility with regard to specification, but the consequence of this, is that they also increase the risk of misspecification by the researcher. For example, choosing inappropriate distributions to explain the random taste heterogeneity will have a direct influence on the model results, consequently leading to spurious conclusions and potentially misguided policy-decisions (Hess et al., 2005, 2007). Therefore, with the gains in model flexibility, comes an increased risk of misspecification and misinterpretation (Hess et al., 2005). Subsequently there remains much ongoing debate about the most appropriate form to use (see discussions in Hensher and Greene, 2003, Munizaga and Alvarez-Daziano, 2002 and Walker, 2002 of the risks involved). Based on the accumulated empirical evidence, the general consensus seems to suggest that the most appropriate form will depend on the specific data, as well as the specific objectives of the research.

1.2 Aims

Quoting Bolduc and Alvarez-Daziano (2010):

> "According to 2002 Nobel Laureate Daniel Kahneman, there still remains a significant difference between economist modellers who develop practical models of decision making and behavioural scientists

> who focus on in-depth understanding of agent behaviour. Both have fundamental interests in behaviour, but each work with different assumptions and tools. McFadden (1986) points out the need to bridge these worlds by incorporating attitudes in choice models. In his 2000 Nobel lecture, McFadden emphasized the need to incorporate attitudinal constructs in conventional economics models of decision making."

It is with this intention; 'to bridge the worlds' between the economic modellers and behavioural scientists, that many enhancements have been made, enriching the RUM specification (Ben-Akiva et al., 2002a; Walker and Ben-Akiva, 2002). Recently, there has been an increase in interest in the way that individuals evaluate and make choices (Hensher, 2010). Hensher (2010) provides a list of research which has considered examples of attribute processing, heuristics and preference construction: Cameron and DeShazo (2011), Cantillo and Ortúzar (2005), Cantillo et al. (2006), Caussade et al. (2005), Greene and Hensher (2010), Hensher (2006, 2008), Hensher and Layton (2010); Hensher and Rose (2009), Hensher et al. (2005), Hess and Hensher (2010), Layton and Hensher (2010), Puckett and Hensher (2008), Scarpa et al. (2009), Scarpa et al. (2010) and Swait (2001). Within this wealth of empirical evidence, we find a number of strategies which have been used by individuals to arrive at a choice outcome. Hensher (2010) lists a few of these strategies: cancellation or attribute exclusion, degrees of attention paid to attributes in a package of attributes, referencing of new or hypothetical attribute packages around a recent or past experience, and attribute aggregation where attributes are in common units.

1.2.1 Intra-household choices

Whilst there has been much progress in the development of discrete choice models, which expand upon the basic random utility model, some limitations still exist. One such limitation, which has gained widespread recognition in recent years, is that many real life decisions are not made by a single person, but in consultation with other *actors*. This recognition, has led to the assessment that the traditionally used unitary household model, which assumes that a household has a single utility function, does not sufficiently reflect the reality of household decision making. In this case it is more likely that the members of the household engage in a process of joint deliberation in order to maximise both their individual and joint utility functions.

The *household* is one of the smallest and most common units within society and therefore, it has become a frequent starting point for studying the phenomenon of decisions that require negotiations (Beharry-Borg et al., 2009). A comprehensive introduction of how multi-agent decisions are incorporated into discrete choices is provided in Chapter 2. Here, we reproduce a review provided by Marcucci et al. (2011) of the different sampling strategies, which have been undertaken in the attempt to represent a household's choice accurately. Marcucci et al. (2011) list the following procedures:

1. Randomly interview a single member and assume that their choice is analogous to the households.
2. Target the specific member of the household who is most likely to be the decision-maker, to interview (e.g. household bill payer).
3. Whilst interviewing a single member ask him or her to represent the preferences of the whole household, when making their choice.
4. Interview the whole household collectively and assume that their joint choice will be representative.
5. Interview and compare both the single and collective choices from the household and choose the most adequate approach.

Empirically, results for intra-household models within the stated preference literature are usually obtained from studies in which each member of the household (or usually couple) is first asked to carry out the choice experiment individually, and then the choice experiment is repeated, but in this second experiment, the couple answer jointly. Examples of this include Arora and Allenby (1999) and Beharry-Borg et al. (2009).

Dosman and Adamowicz (2006) provided a novel contribution to the study of intra-household bargaining. They examined household behaviour in a bargaining framework by combining stated preference information from individual members of the household with revealed preference information on the household's actual choices. Dosman and Adamowicz (2006) looked at how susceptible the joint decisions were to the influences of the individual decision makers involved.

When modelling households specifically (using the typical dyadic interaction approach), most studies would take the preferences of each member of the couple and weight these, using some 'bargaining coefficient' (also known as a *'power coefficient' or 'power indicator'*). The 'bargaining coefficient' is determined by comparing the *ex ante* single preferences and the *ex post* joint choice outcomes. Corfman and Lehmann (1987) define this 'power' as the ability of one individual to change another person's attitudes, beliefs or behaviour in an intended direction. They also point out that a person may exercise their power either deliberately or unintentionally. Hence, studies for joint decision making have typically been based on studies where individual and joint choices are modelled at the same time, with the joint choices being driven by a weighted average of the sensitivities of the individual decision makers.

The hypothesis put forward in this thesis is that just as with individual choice processes, joint decisions are similarly driven in part by unobserved heterogeneity. The theoretical part of the thesis thus presents a framework for modelling the joint decision processes within the context of a multi-agent decision environment. Results suggest that significant improvements in model fit can be obtained through accounting for the unobserved bargaining heterogeneity. Finally, this modelling approach also reveals some of the interesting dynamics which can arise during the joint decision-making process of a couple.

1.2.2 Integrated choice and latent variable models

In addition, it is well recognised that *attitudes* towards different attributes of the alternatives are also, *inter alia*, an important determinant of an individual's choices and underlying preferences. What is less well understood is the consideration that individuals give to the attitudes held by other actors/agents. Therefore, inclusion of the individual's and their respective partner's attitudinal data may contribute to richer discrete choice models. In this context, integrated choice and latent variable models may be advantageous. A more comprehensive introduction of integrated choice and latent variable models is provided in Chapter 4 and empirical applications are shown in Chapter 5 and Chapter 6.

The aim of this thesis is to explore the issues outlined above. The thesis is based on the discrete choice experiment methodology and attempts to explain preferences within different decision making structures. The research explores the role that the different opinions, attitudes and preferences play when actors/agents make a *joint* decision. The thesis also incorporates additional factors that may have a bearing on the choices made by an individual, such as socio-demographics. The thesis aims to bridge the gap between models which specialise in modelling multi-agent choices and hybrid choice models (outlined in Ben-Akiva et al., 2002a), which integrate many of the components that have been identified as important when defining the choice process. This will be achieved through the following main objectives:

- Examine and test the current hybrid models considering any improvements to be made
- Extend the existing integrated choice and latent variable (ICLV) models

(Ben-Akiva et al., 2002a,b) to accommodate multi-agent choices and attitudes

- Build upon and add to the existing literature, which will link these models, thereby creating a much more general and accessible way of modelling household choices.

1.3 Outline of the thesis and contributions

The thesis is based on 4 standalone, but related, papers. The thesis has been split into two parts, with the first focussing on the development of intra-household models; containing a literature review and analysis of existing decision-making structures. The second part of the thesis extends the existing integrated choice and latent variable (ICLV) models.

Subsequently, the thesis concludes with a general discussion, summarising the key findings and contributions. The importance of accounting for both the different opinions and attitudes of other agents/actors within the decision making process and the need to properly accommodate for their combined preferences in order to avoid misleading results is highlighted. This discussion acknowledges potential limitations and provides recommendations for researchers engaged in discrete choice analysis when the need is to consider preferences at a household level. Additionally, avenues for further research are suggested.

Finally, Appendix A contains a copy of the *script* which was used to screen eligible respondents for the food survey used in this thesis and Appendix B shows the full questionnaire which was developed to elicit joint preferences for food. Appendix C concludes the thesis with a display of the choice tasks that were used in the questionnaire; including an example choice task, used for demonstration purposes.

1.3.1 Part I summary

The first paper: Chapter 2 focuses on the case of one member of a two person household being asked to make choices affecting the travel time and salary of both members. The paper highlights the presence of significant heterogeneity across individuals, not just in their underlying sensitivities, but also in the relative weight they assign to their partner and shows how this weight varies across attributes. Interestingly, findings show that male respondents place more weight on their partner's travel time, while female respondents place more weight on their partner's salary. From a modelling perspective, clear evidence is shown of a risk of confounding between heterogeneity in marginal sensitivities and heterogeneity in the weights assigned to each member. The paper shows how this can lead to misleading model results and argues that this may also explain prior results showing bargaining or weight parameters outside the expected $[0, 1]$ range in more traditional joint decision making contexts.

The second paper: Chapter 3 focuses on the accuracy of *proxy* preferences. Traditional approaches to discrete choice modelling make use of an individual's preferences as a proxy for the preferences held by the household of which he or she is a member. This method has consistently been proven to be less accurate than studies where individual and joint choices are modelled at the same time, with the joint choices being driven by a weighted average of the sensitivities of the individual decision makers. Whilst it is not a novel phenomenon that members within a household may not always have identical preferences, traditional methods still prevail in most discrete studies today.

This paper considers which key factors (for example, socio-demographics) can aid a members' ability to correctly act as a proxy for the household of which he or she is a representative. In line with the literature, findings suggest that women have a greater overall ability to represent their *household's* choices, whereas interestingly men far outperform when the questions are more compartmentalized.

1.3.2 Part II summary

To introduce the second part of the thesis, Chapter 4 details the history and development of the integrated choice and latent variable Model and also provides a review of the current literature.

The third paper: Chapter 5 introduces an empirical application making use of stated choice data looking at important factors within food choices. The data contains information about people's preferences for calories, cooking time, food types and cost, when considering an evening meal. The paper makes use of the innovative integrated choice and latent variable model (ICLV), which has had growing interest of late.

Within the ICLV model, responses to attitudinal questions are modelled jointly with the actual choice processes, whilst maintaining the assumption that both processes are at least in part influenced by these latent attitudes. This approach integrates choice models with latent variable models resulting in an improvement in the understanding of preferences as well as an improvement in the explanatory power of the model. One of the major benefits of using this latent approach is that the model is able to overcome bias inherent in the direct incorporation of indicators of attitudes (or other subjective measures) in the utility function. Hence, ICLV models avoid the risk of endogeneity bias that would arise in a deterministic treatment (Ben-Akiva et al., 2002a,b).

Within this application, the model makes use of seven latent variables, which both drive the sensitivities in the choice models and help to explain the answers to the attitudinal questions. Additionally, the model makes use of the respondents' reported rankings of attribute levels, a somewhat novel use of latent variables.

The hypothesis put forward in **the final paper**, Chapter 6, is that just as with individual choice processes, joint decisions are similarly driven in part by unobserved attitudes. Different possibilities may arise. The attitudes of the different decision makers may all play a role, or the attitudes of one decision maker may be dominant. Similarly, one decision maker may know the attitudes of another decision maker and either try to take them into account, or act against them.

Hence, in addition to socio-economic variables, the decision making structure within a household is likely to have a bearing on the 'household choice'. There are likely to be at least three subgroups of household decision-making structures: a household in which a dictator makes the decisions (akin to the Unitary model); a household wherein the dominance oscillates in accordance with whichever household member maintains the strongest attitude for the specific decision; and finally, a household where for each decision there is a compromise between the household members. In this paper a series of attitudinal questions are asked to both decision makers aimed at determining in which of these categories the household falls. The theoretical part of the paper thus presents a framework for the joint modelling of latent attitudes and decision processes within the context of a multi-agent decision environment.

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Part I

Intra-Household Choices

Chapter 2

I'll take the money and you can have the short commute: a study of household level work and travel decisions[1]

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Abstract

With many real world decisions being made in conjunction with other decision makers, or single agent decisions having an influence on other members of the decision maker's immediate entourage, there is strong interest in studying the relative weight assigned to different agents in such contexts. In the present paper, we focus on the case of one member of a two person household being asked to make choices affecting the travel time and salary of both members. We highlight the presence of significant heterogeneity across individuals not just in their underlying sensitivities, but also in the relative weight they assign to their partner, and show how this weight varies across attributes. Interestingly, we find that male respondents place more weight on their partner's travel time, while female respondents place more weight on their partner's salary. From a modelling perspective, we show clear evidence of a risk of confounding between heterogeneity in marginal sensitivities and heterogeneity in the weights assigned to each member. We show how this can lead to misleading model results, and argue that this may

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also explain results showing bargaining or weight parameters outside the usual $[0, 1]$ range in more traditional joint decision making contexts.

Keywords: household decisions; distributional assumptions; random coefficients; joint decisions; bargaining coefficient

2.1 Introduction

The field of choice modelling has evolved dramatically over recent years, with numerous developments that aim to realign modelled behaviour with real world behaviour. A key focus has been the representation of variations across respondents in their sensitivities and their choice processes, as well as studying the influence that underlying attitudes may have on behaviour.

Data on choice behaviour is routinely used to derive individuals' preferences for goods and services. However, there is a growing recognition that many real life decisions are made not by a single person, but in consultation with other actors (see, for example Ben-Akiva et al., 2002a). Similarly, a single person may make choices that affect other members of their household or peer group. The work described in the present paper falls into this last category.

In line with the majority of the literature, the emphasis in this paper is on decisions at the household level, although the methodological discussions arguably also have relevance in other joint decision-making contexts. If choices are made jointly by a number of household members, then it is likely that they take part in a negotiation process in order to maximise some joint-utility function. Similarly, when an individual is making a decision that will affect more than just themselves, the expectation is that, at least to some degree, they will take into consideration the preferences held by other household members (or perceived to be held), in addition to their own. They are also likely to give differential weight to their own preferences across different attributes.

Classically, household data collection involves selecting a single respondent from the household to act as a reliable proxy for the household choices when completing the choice experiment tasks. This representative respondent could be selected on the assumption that he or she is the main decision maker within the household and it is likely that his or her decision would be the one that prevailed. Alternatively, it could be assumed that he or she would be able to realistically approximate the decisions that the household would make, were they to be asked as a group.

There are mixed views about the ability of a single member to accurately represent the preferences held by all members within their household. For instance, findings by Corfman (1991) suggest that a response from just a single member on their perceptions of each of the other group member's relative influence does not necessarily reflect the actual perceptions of the other group members. Corfman (1991) further tested the hypothesis that the potential sources of error affecting the accuracy with which a person will report their perceived preferences could be due to poor memory, inferential ability, perceptual bias, reporting bias, as well as the joint choice process itself. In contrast, a study by Strand (2007) found that when an individual from a two-person household was asked to value the *household's* willingness to pay for public goods, they tended to represent the household's willingness to pay correctly. Strand (2007) also found that in a large sample, respondents will represent the household preferences correctly, even if the members surveyed are selfish or altruistic. Conversely, Bateman and Munro (2009) found significant differences between the responses from a single randomly selected individual providing responses on behalf of the couple from which they were chosen and responses where both partners were asked the household choice questions jointly. Crucially, they also found that the values elicited from the joint responses were not a simple weighted average of those values elicited from the separate male and female responses. They postulate that the difference in these responses could be due to the opportunity to exchange information, not only about the good in question but also about each member's preferences for this good, which could contribute substantially to the individual's prior knowledge base about the good, especially when the good to be valued is unfamiliar. Hensher et al. (2011) also find that for vehicle purchase, sampling an individual as a representative of the household's preferences is less appropriate than utilising preference information from the relevant group of decision makers in the household.

The recognition of the differential influence of individual players in such a multi-agent context has moved us away from the unitary household model or 'common preference model' which assumes that, irrespective of the members of a household, it will act as a single-decision-making unit, wherein a single preference function will represent all members of the group (see, for example, discussions in Adamowicz et al., 2005, Katz, 1997, Lampietti, 1999 and Vermeulen, 2002). This assumption could either force the preferences of different members of the household to be the same, or constrain the preferences being estimated to be an equally weighted average of members' preferences. These are two very different, though equally unrealistic, implications.

In reality, it is unlikely that households comprise of individuals with *identical* (homogeneous) tastes (Samuelson, 1956). Adamowicz et al. (2005) list further assumptions associated with the unitary model, including the fact that the model imposes the choice of a benevolent dictator on the household, that it does not allow for bargaining/negotiation to take place and that it does not permit the differences between its members' knowledge or experience to create an opportunity for the use of different decision-making strategies. Another supposition of the unitary model is that all of the resources in the household are pooled and that all members share in these in equal measure.

The growing recognition that this model does not sufficiently reflect the reality of household decision making (see, for example Dosman and Adamowicz, 2006) has led to a significant body of work looking at how members of a household may engage in a process of joint deliberation in order to maximise both their individual and joint utility functions (see, for example Adamowicz et al., 2005, Marcucci et al., 2011 and Munro, 2009 for a comprehensive review, as well as key developments in Aribarg et al., 2002, Arora and Allenby, 1999, Browning and Chiappori, 1998, Dellaert et al., 1998, Dosman and Adamowicz, 2006 and Hensher et al., 2008). Within the literature, it is clearly evident that there is not only disparity between household member's preferences, but also between the choices made by individuals and the choices made by households collectively.

While the focus in the literature is increasingly on joint decisions, rather than decisions by a single person affecting multiple individuals, a key interest, and the topic of this paper, is in understanding how individual respondents may give more or less weight to their own sensitivities than to those of their fellow decision makers. For the purpose of studying such heterogeneity, data collected from one spouse but concerning choice situations affecting both partners is in fact more suitable as it avoids the need to attempt to mathematically represent the actual bargaining process taking place in a joint decision making context. From a behavioural perspective, such scenarios also align themselves with numerous real world situations, where the expectation is that individuals would consider their choice impact on others simultaneously with the choice impact on themselves. This is arguably a more frequent occurrence than is the case for *collective* decision making.

The present paper makes the case that, just as in more traditional choice data (i.e. choices by a single agent affecting only themselves), there exist significant differences across people in the context of household level decisions. The assertion is that not adequately representing such heterogeneity, both in the underlying sensitivities and the relative weight assigned to a person's own sensitivities and those of their partner, may lead to misguided findings. Crucially, there is significant risk of confounding between heterogeneity in the marginal utility coefficients and the bargaining or weight parameters, where inappropriate specifications are likely to exacerbate problems with the latter falling outside the traditionally imposed $[0,1]$ range. We support these claims through an empirical analysis using stated choice data examining the intra-household preferences for commuting time and salary collected in the Stockholm region of Sweden. Specifically, in this survey, each member of a dyadic household was individually asked to trade between their own commuting time and salary and also their partner's commuting time and salary. Results suggest the presence of significant levels of heterogeneity both in the underlying sensitivities of individual respondents as well as in the weights they assign to their partners. A failure to jointly account for both types of heterogeneity leads to inferior results and possibly misguided interpretations.

The remainder of this paper is organised as follows. Section 2.2 presents an overview of the models that are applicable in this context, with a particular emphasis on the specification of bargaining or weight parameters. This is followed by our empirical application in Section 2.3, and a concluding discussion is presented in Section 2.4.

2.2 Theory

To express household decisions within a random utility framework, the utility that household h obtains from choosing alternative j is represented as:

$$U_{hj} = V_{hj} + \varepsilon_{hj}, \tag{2.1}$$

where V_{hj} is the deterministic component of utility and ε_{hj} is the random component. In the unitary model, we would simply have that $V_{hj} = f(\beta, x_{hj})$, where x_{hj} is a vector of attributes describing alternative j as faced by household h, with β being a vector of estimated parameters, and where the specification of the functional form of $f(\cdot)$ is a decision to be made by the analyst. This approach not only assumes homogeneity in the β parameters across household members, but also an aggregation of the values for any elements in x_{hj} that may in fact vary across household members.

Moving on from the unitary model, and focussing on a two-person context, we recognise that the different members of a household potentially have different marginal sensitivities (i.e. we have β_1 for person 1 and β_2 for person 2), carry different weight in the joint decision process (or indeed are given different weight by the person making the decision), and possibly also experience different values for a given attribute within the vector x. As such, we now have that:

$$V_{hj} = \lambda_1 f(\beta_1, x_{1j}) + \lambda_2 f(\beta_2, x_{2j}), \tag{2.2}$$

where x_{1j} and x_{2j} relate to the possibly different values for the vector x for alternative j for the two household members. The two additional parameters λ_1 and λ_2 give the weights of the two household members (either in the joint decision making process or differences in the weight assigned by the single decision maker), where we have that $\lambda_1 + \lambda_2 = 1$. Usually, the assumption is also made that $0 \leq \lambda_p \leq 1$, $p = 1, 2$, a point we will return to below.

In order to estimate a model of the form described in Equation 2.2, we would generally expect to make use of data on both individual choices and joint choices (or choices affecting both partners), where, as above, the latter are driven by a weighted average of the sensitivities of the individual household members.

A significant amount of research has gone into the specification of the λ parameters in such models. Initially, researchers suggested that the use of equal weights should be a starting point (Steckel et al., 1991). Whilst Curry and Menasco (1979) prove that using equal weights (i.e. $\lambda_1 = \lambda_2 = 0.5$) results in a group (a man-woman dyad in their case) selecting the alternative that maximised their total joint utility, the use of equal weights imposes the assumption that every member of the group has an equal influence on the outcome of the group's decision, or that, with a single decision maker, equal weight is given to the second person. Here, it is worth recognising that even with $\lambda_1 = \lambda_2 = 0.5$, there is a possibility for differential impact by the two partners given possible differences between β_1 and β_2. Setting $\lambda_1 = \lambda_2 = 0.5$ simply means that equal weight is given to the sensitivities of the two agents, but it remains reasonable to expect that different group members will exert varied levels of influence on the different attributes of the decision, depending on their individual utility functions (Aribarg et al., 2002; Arora and Allenby, 1999; Dellaert et al., 1998; Rose and Hensher, 2004). It would be consistent to assume that whoever cares more about a given attribute is likely to have a greater influence on the joint sensitivity for this attribute.

The assumption of $\lambda_1 = \lambda_2 = 0.5$ is generally rejected on theoretical as well as empirical grounds. With the weights being freely estimated rather than constrained to be equal, an important question then arises as to the range for these weights. Although it seems reasonable to think that joint taste intensities should be intermediate between individual taste intensities, i.e. within the $[0, 1]$ range, this may not always be the case (cf. Adamowicz et al., 2005), and there are examples of estimates outside this range (see, for example Beharry-Borg et al., 2009).

A number of interpretations for a λ estimate outside the $[0, 1]$ interval have been put forward. For instance, Dellaert et al. (1998) describes a negative value for λ as the "systematic denial of the individual's preference in the joint evaluation", whilst Beharry-Borg et al. (2009) suggest that when an individual is a member of a group, their responses may be even more extreme than their individual responses would have been if they were not part of the group. This is known as the group polarization phenomenon (cf. Arora and Allenby, 1999; Myers and Lamm, 1976; Rao and Steckel, 1991; Steckel et al., 1991). As an illustration, consider this simple example: If the *female* coefficients are more positive than the *male* ones, a negative λ_m (i.e. for the male respondent) would make the *joint* coefficients even more positive than either of the individual's coefficients. A possible interpretation for this example would be that the *male* respondent has been influenced by the *female* partner, and that their joint view is now even stronger. These findings are contrary to the belief that the joint preferences should be intermediate between the individuals' preferences. Similarly, Bateman and Munro (2005) find couples making more risk adverse choices when facing tasks together compared to when the partners faced the same decision-making tasks individually.

The aim of the present paper is to look further into the role of bargaining or weight parameters and their interaction with the marginal utility coefficients, with a particular emphasis on the role of heterogeneity. We argue that there are likely to exist differences not just across agents in their marginal sensitivities, but also differences across households in the values of the weight parameters. We argue that a failure to adequately deal with such heterogeneity may lead to misguided findings. A key hypothesis put forward in the present paper is that λ parameters outside the $[0, 1]$ interval may be caused in part by unaccounted or incorrectly modelled heterogeneity, especially in β, with the same applying for findings where the λ parameter goes to (or beyond) either bound of the $[0, 1]$ interval (Dosman and Adamowicz, 2006). We specifically make the case for an approach that uses different λ parameters for different attributes, thus recognising that the relative weights of individuals in a household may differ across attributes.

Before proceeding, it is important to acknowledge once again that in situations where a single agent makes choices affecting multiple individuals, such as the data used here, the bargaining parameter takes on the role of a weight parameter. Nevertheless, we feel that the same issues will also arise in both types of *joint* decision making scenarios.

2.3 Empirical application: a work place location study in Sweden

This section presents the results from a case study aimed at studying the role of heterogeneity in a multi-agent context, with a particular emphasis on the interaction between marginal utility coefficients and bargaining coefficients. The study makes use of data from an experiment where a single household member is asked to make decisions affecting both members of the household. This specific context changes the interpretation of the bargaining coefficient to that of a weight parameter, but allows us to study the issues of interest without a need to specify a detailed model for negotiation between household members. We argue that the potential issues of confounding between heterogeneity in marginal utility coefficients and bargaining/weight coefficients in multi-agent models similarly arise in the context where a single household member makes decisions for both partners.

2.3.1 Data

The data used for this application come from a survey conducted in the Stockholm region of Sweden in 2005. The specific interest of the survey was a study of the trade-offs between salary and commuting time. As already mentioned earlier, the survey collected responses from dyadic households; with each member of the dyad answering the survey individually.

The study was conducted in two parts. First, each member of the household was asked to consider the trade-off between an increase in the length of time that it would take them individually to travel to work and an increase in their personal monthly salary. An example choice task for this first game is shown in Figure 2.1(a), where travel time is in minutes, and salary is in Swedish Kronor[2].

Once the respondent had completed a series of these choice tasks they were then asked to complete the second part of the survey. In the second game, each respondent was asked in addition to consider the trade-off between increasing the length of time that it would take their partner to travel to work and an increase in their partner's monthly salary. An example choice task for this second game is shown in Figure 2.1(b). Unlike in game 1, respondents were now expected to choose between an increase in the length of time that it would take to travel to work and an increase in monthly salary for both themselves and their respective partner simultaneously. Crucially, the adjustments presented in this second task were not necessarily identical in proportion for the respondent and their partner.

[2]The 2005 exchange is approximately £0.07 per SEK1.

Which alternative would you prefer if the company offered the following options in the choice of workplace location?

Alternative 1	**Alternative 2**
Today's travel time	25 minutes longer travel time than today
Today's salary	The salary is 1000 kronor more per month than today (after tax)

☐ **Alternative 1** ☐ **Alternative 2**

☐ **Indifferent**

(a) Example of first choice task

Which alternative would you prefer if the company offered the following options in the choice of workplace location?

Alternative 1		**Alternative 2**	
You	Your partner	You	Your partner
Today's location *(Travel time and salary as today)*	Today's location *(Travel time and salary as today)*	25 minutes longer travel time than today The salary is 1000 kronor more per month than today (after tax)	10 minutes longer travel time than today The salary is 500 kronor more per month than today (after tax)

☐ **Alternative 1** ☐ **Alternative 2**

☐ **Indifferent**

(b) Example of second choice task

Figure 2.1: Example stated choice scenarios

Both games used a choice set of three alternatives, namely a status quo option, an alternative option (i.e. increase in salary in return for increased travel time), and an "indifferent" option. Each respondent was given four scenarios to complete in the first game, and an additional four or five tasks in the second game, depending on which version of the design was used. Within each household, the man and the woman usually received different versions of the survey. In total, responses were collected from 2,358 respondents, i.e. 1,179 couples. This provided us with a total of 20,041 observations. For more detailed information on the data the reader is directed to Swärdh and Algers (2009).

2.3.2 Model specification

A number of different models were estimated, each time combining the data from the choice tasks concerning only the household member completing the survey with the data from the choice tasks concerning both members. All models were estimated in Biogeme (Bierlaire, 2003). To recognise the repeated choice nature of the data, the standard errors in all models were computed using the panel specification of the sandwich matrix. Additionally, in those models accommodating random heterogeneity in β and/or λ, the distribution was across households, whilst maintaining intra-respondent homogeneity. For these models the log-likelihood was simulated using 500 Halton draws.

For the first game, as shown in Figure 2.1(a), the observable component of the utility function for the three alternatives and individual n in choice scenario t is given by:

$$\begin{aligned} V_{nt1} &= \alpha_{1,1} + \beta_{\text{TT}}\text{TT}_{nt1} + \beta_{\text{L-Sal}}\text{L-Sal}_{nt1} \\ V_{nt2} &= \beta_{\text{TT}}\text{TT}_{nt2} + \beta_{\text{L-Sal}}\text{L-Sal}_{nt2} \\ V_{nt3} &= \alpha_{1,3} \end{aligned} \tag{2.3}$$

where β_{TT} and $\beta_{\text{L-Sal}}$ give the marginal utility coefficients for travel time (TT) and the logarithm of salary (L-Sal), where this gave superior results to a linear specification. Furthermore, $\alpha_{1,j}$ is the constant for alternative j in game 1, where, for identification reasons, we set $\alpha_{1,2} = 0$, thus estimating constants for the status quo alternative and the "indifferent" alternative. For the travel time and salary attributes, the actual values were used, rather than the changes as presented in the survey, as this gave better results.

For the second set of choices, hereafter referred to as "game 2" as shown in Figure 2.1(b), (i.e., the *'joint'* game), the alternatives are now described by the travel time and salary for both partners, and the utilities are given by:

$$\begin{aligned} V_{nt1} &= \nu\left[\alpha_{2,1} + \lambda\left(\beta_{\text{TT}}\text{TT}_{nt1} + \beta_{\text{L-Sal}}\text{L-Sal}_{nt1}\right)\right. \\ &\qquad\qquad \left. + (1-\lambda)\left(\beta_{\text{TT}}\text{TT}_{pt1} + \beta_{\text{L-Sal}}\text{L-Sal}_{pt1}\right)\right] \\ V_{nt2} &= \nu\left[\lambda\left(\beta_{\text{TT}}\text{TT}_{nt2} + \beta_{\text{L-Sal}}\text{L-Sal}_{nt2}\right)\right. \\ &\qquad\qquad \left. + (1-\lambda)\left(\beta_{\text{TT}}\text{TT}_{pt2} + \beta_{\text{L-Sal}}\text{L-Sal}_{pt2}\right)\right] \\ V_{nt3} &= \nu\alpha_{2,3} \end{aligned} \tag{2.4}$$

This incorporates first a multiplication of the utility by ν, which gives the scale parameter for the second set of choices, with the scale for game 1 being normalised to 1. As in game 1, we estimate constants specific to game 2, namely $\alpha_{2,j}$, where $\alpha_{2,2} = 0$. The marginal utility coefficients are identical to those defined for Equation 2.3, while the associated attributes are now distinct for person n and their partner, indexed by p. The additional parameter λ plays a somewhat different role from the bargaining coefficient in traditional joint choice models; it gives the weight respondent n assigns to the circumstances affecting himself or herself, relative to those affecting their partner.

The specification in Equation 2.4 allows for respondent n to assign different weights to his/her own circumstances than those of his/her partner. However, it is conceivable that such differences also arise at the level of individual attributes, i.e. allowing for a greater disparity between the self and partner valuations for one attribute than for another. For this purpose, Equation 2.4 can be adapted to:

$$\begin{aligned}
V_{nt1} &= \nu \left[\alpha_{2,1} + \lambda_{\mathrm{TT}}\beta_{\mathrm{TT}}\mathrm{TT}_{nt1} + (1-\lambda_{\mathrm{TT}})\,\beta_{\mathrm{TT}}\mathrm{TT}_{pt1}\right.\\
&\qquad\qquad\qquad \left. + \lambda_{\text{L-Sal}}\beta_{\text{L-Sal}}\text{L-Sal}_{nt1} + (1-\lambda_{\text{L-Sal}})\,\beta_{\text{L-Sal}}\text{L-Sal}_{pt1}\right]\\
V_{nt2} &= \nu \left[\lambda_{\mathrm{TT}}\beta_{\mathrm{TT}}\mathrm{TT}_{nt2} + (1-\lambda_{\mathrm{TT}})\,\beta_{\mathrm{TT}}\mathrm{TT}_{pt2}\right.\\
&\qquad\qquad\qquad \left. + \lambda_{\text{L-Sal}}\beta_{\text{L-Sal}}\text{L-Sal}_{nt2} + (1-\lambda_{\text{L-Sal}})\,\beta_{\text{L-Sal}}\text{L-Sal}_{pt2}\right]\\
V_{nt3} &= \nu\alpha_{2,3}
\end{aligned} \tag{2.5}$$

From Equation 2.5, it becomes clear that a corresponding specification could have been obtained without the λ parameters by instead using separate marginal utility coefficients for respondent n and their partner p. We chose the above specification partly as it will facilitate interpretation in the models incorporating random heterogeneity, and avoids the need to specify correlation between β_n and β_p. The λ parameters now have even more importance than in Equation 2.4. Two views arise. They could be interpreted as differences the respondent perceives between his/her valuations of the attributes and those of his/her partner. Arguably more realistically, they could also be interpreted as the importance rating the respondent places on his/her own circumstances compared to those of their partner.

The specifications in Equations 2.3, 2.4 and 2.5 serve as the basis for the first three of our models. In particular:

Model 1 uses Equation 2.3 for the game 1 choices and Equation 2.4 for the game 2 choices, keeping λ fixed at 0.5, i.e. assuming that the decision maker gives equal weight to his/her partner.

Model 2 expands on model 1 by estimating λ.

Model 3 replaces Equation 2.4 with Equation 2.5, thus estimating separate λ parameters for travel time and salary.

The three base models make the assumption of complete homogeneity across all respondents in all households for both the β and λ parameters. This assumption is gradually relaxed in the subsequent four models, as follows:

Model 4 expands on model 3 by accounting for deterministic heterogeneity by estimating separate β coefficients and separate λ coefficients for male and female respondents. This allows us to investigate whether there are any distinct differences by gender regarding how the members of the household dyad valued an increase in their own salary compared with how they valued an increase in their partner's salary, and in their willingness to accept a longer commute in return.

Model 5 expands on model 4 by allowing for additional random heterogeneity in the β parameters, using Lognormal distributions in a mixed logit model, where we allow for correlation between the travel time and salary coefficients, while still using separate coefficients for male and female respondents.

Model 6 is a different generalisation of model 4 in that is allows for random heterogeneity in the λ parameters, using Uniform distributions.

Model 7 combines models 5 and 6, allowing for heterogeneity in both the β and λ parameters, using the same distributional assumptions as in these models, while still using separate parameters for male and female respondents.

2.3.3 Estimation results

The estimation results for the first three models are summarised in Table 2.1, where these models do not accommodate any heterogeneity across respondents, either deterministically or randomly. Looking at model 1, we see that all else being equal, there is some evidence of a preference for the status quo option (estimates for $\alpha_{1,1}$ and $\alpha_{2,1}$), while a lack of differences between alternatives (i.e. all else being equal) also leads to increased probability of choosing the "indifferent" option. The impact of increases in travel time is negative while the impact of increases in the salary is positive, with the log-transform ensuring decreasing marginal returns. This model imposes the assumption that a respondent gives equal weight to both members of the household ($\lambda = 0.5$), while the scale parameter for the second game is not significantly different from the base of 1,

Table 2.1: Results: models 1 - 3

	Model 1 Equal weights		Model 2 Generic λ		Model 3 Attribute-specific λ	
	est.	t-rat.	est.	t-rat.	est.	t-rat.
$\alpha_{1,1}$	0.5370	9.67	0.5370	9.68	0.5370	9.67
$\alpha_{1,3}$	4.2100	2.76	4.2000	2.76	4.2100	2.76
$\alpha_{2,1}$	0.9210	7.03	0.9220	7.03	0.9240	7.04
$\alpha_{2,3}$	4.4000	2.78	4.3900	2.77	4.4000	2.77
β_{TT}	-0.0323	12.34	-0.0323	12.36	-0.0323	12.34
$\beta_{\text{L-Sal}}$	0.7330	4.91	0.7320	4.90	0.7330	4.91
λ	0.5	-	0.4870	12.98 *(0.35)*§	-	-
λ_{TT}	-	-	-	-	0.4730	11.89 *(0.54)*§
$\lambda_{\text{L-Sal}}$	-	-	-	-	0.5690	4.48 *(0.68)*§
ν	0.9240	11.42 *(0.94)*†	0.9240	11.42 *(0.94)*†	0.9230	11.43 *(0.95)*†
$\mathcal{L}\left(\hat{\beta}\right)$	-14,136.007		-14,135.945		-14,135.505	
$\bar{\rho}^2$	0.358		0.358		0.358	

† Note: t-rat. are relative to 1.
§ Note: t-rat. are relative to 0.5.

suggesting no significant differences in the relative weight of the modelled and random utilities in the two games.

Looking next at model 2, which freely estimates λ, we note only a minor and not statistically significant improvement in model fit. This is in line with the estimate for λ changing only from 0.5 to 0.4870, where this change is not significant at usual confidence levels. The remaining estimates remain unaffected.

A similar observation can be made for model 3, where the gains in fit obtained by allowing for attribute specific λ parameters are once again not significant at usual levels. Indeed, while the estimated values might imply differences in the relative weights assigned to a partner's travel time and income, it should be noted that neither of the two λ parameters are significantly different from the base value of 0.5.

We now turn our attention to models accommodating differences across respondents, where results for models 4 to 7 are summarised in Table 2.2. Model 4 expands on model 3 by allowing for differences between male and female respondents in the β and λ parameters, using subscripts m and f. This leads to an improvement in model fit by 4.11 units, which, at the cost of 4 additional parameters, is only significant at the 92% level. A detailed study of the results, using an asymptotic t-ratio for differences in parameters, reveals that the main differences arise in the β and λ parameters for travel time. Although these differences are only significant at the 82% level for λ_{TT} and the 90% level for β_{TT}. Overall, this model would suggest only small differences between male and female respondents when accommodating deterministic heterogeneity alone.

The next step was to allow for random heterogeneity across respondents in the β parameters, where this is accommodated in model 5. In particular, we use Lognormal distributions, i.e. we have that $\ln(\beta_{f,\text{L-Sal}})$ and $\ln(\beta_{f,\text{TT}})$ follow Normal distributions. Here, $\mu_{\ln\left(\beta_{f,\text{L-Sal}}\right)}$ and $\mu_{\ln\left(\beta_{f,\text{TT}}\right)}$ give the means of the underlying Normal distributions in the case of female respondents (where a corresponding notation with m applies to male respondents). We allow for correlation between the travel time and salary sensitivities and hence estimate three parameters for the Cholesky matrix. Here, $|s_{11,\ln\left(\beta_{f,\text{L-Sal}}\right)}|$ gives the standard deviation for the underlying Normal distribution for $\ln(\beta_{f,\text{L-Sal}})$, while the corresponding standard deviation for $\ln(\beta_{f,\text{TT}})$ is given by $\sqrt{s^2_{21,\ln\left(\beta_{f,\text{TT}}\right)} + s^2_{22,\ln\left(\beta_{f,\text{TT}}\right)}}$, with the covariance being equal to $s_{11,\ln\left(\beta_{f,\text{L-Sal}}\right)} s_{21,\ln\left(\beta_{f,\text{TT}}\right)}$. No sign constraint is imposed on any of the elements in the Cholesky matrix so as to allow for positive as well as negative covariances. A corresponding approach was used for travel time, with an appropriate sign change for the attribute (given that increases in time lead to losses rather than gains in utility).

We see that model 5 obtains a dramatic improvement in log-likelihood over model 4, with a hugely significant increase by $2,993.32$ units at the cost of 6 additional parameters. This is a result of allowing for random heterogeneity as well as explicitly capturing the correlation across choices for the same respondent. The first observation to be made from the estimates for model 5 is that the constants for the first and third alternatives are now negative, possibly as a result of some of the behaviour previously captured by positive constants for the first and third alternative now being captured by the tails of the Lognormal distribution (remembering that the values for both the travel time and salary attributes are largest for the second alternative, which does not have a constant). Turning to the λ parameters, we see that $\lambda_{f,\mu_{\text{TT}}}$ and $\lambda_{m,\mu_{\text{TT}}}$ are now significantly different from 0.5, while the differences between male and female respondents for $\lambda_{\mu_{\text{TT}}}$ are also statistically significant at high levels. Across all four λ parameters, we see an indication of greater weight being assigned to the respondent's attributes than to those of their partner.

All parameters relating to the lognormally distributed β coefficients are statistically significant and show high levels of random heterogeneity, a point we will return to below in the discussion of relative valuations. Using an asymptotic t-ratio for differences in parameters, we find that the differences between male and female respondents for salary, $\beta_{\text{L-Sal}}$, are significant with a confidence level of 97%. This observation, in line with a similar observation for the λ parameters, suggests that the recovery of significant differences between male and female respondents is facilitated by additionally allowing for random heterogeneity across respondents. Finally, we see that the results for model 5 show significantly higher scale for game 2, i.e. the joint decisions, than for game 1. This was not the case in models 1 to 4, and could suggest that a failure to accommodate random variations in sensitivities led to an inability to adequately model the choices for game 2 in these earlier models.

Model 6 takes a different approach to model 5 by allowing for heterogeneity in the λ parameters rather than the β parameters, where Uniform distributions are used, with e.g. $\lambda_{\text{f,L-Sal}}$ having a mean of $\lambda_{f,\mu_{\text{L-Sal}}}$, with Uniform variation between $\lambda_{f,\mu_{\text{L-Sal}}} - \lambda_{f,s_{\text{L-Sal}}}$ and $\lambda_{f,\mu_{\text{L-Sal}}} + \lambda_{f,s_{\text{L-Sal}}}$. This model obtains an improvement in log-likelihood by 124.19 units over model 4, which is statistically significant coming at the cost of 4 additional parameters, but is clearly far more modest than the improvement obtained by model 5. As in model 5, we again see heightened scale for game 2. However, a further inspection of the estimates shows that with the exception of $\lambda_{f,\text{TT}}$, the range of the λ parameters falls outside the $[0, 1]$ boundary, where, for $\lambda_{f,\text{L-Sal}}$, we even obtain a negative mean. As highlighted earlier, a number of interpretations have been put forward for such estimates, but we believe that at least in some cases, this is a result of confounding with other heterogeneity, a point we investigate further in model 7. Additionally, in the present case, negative λ parameters would lead to a change in the sign of the marginal utility coefficients, which is clearly nonsensical.

Model 7 presents a generalisation of both model 5 and model 6. In comparison with model 5, we obtain gains in log-likelihood by 19.40 where this is statistically significant coming at the cost of 4 additional parameters. Similarly, model 7 obtains a hugely significant improvement in log-likelihood by $2,888.52$ units over model 6, at the cost of 6 additional parameters. This shows the benefit of allowing jointly for heterogeneity in β and λ, although some of the gains over model 5 could be the result of the more flexible distributional assumptions (Uniform multiplying a Lognormal, instead of a Lognormal alone). As was the case in model 5, the constants for the first two alternatives are once again negative. The parameters for the lognormally distributed β coefficients again all attain high levels of significance. Crucially, in contrast with model 6, all λ parameters

Table 2.2: Results: models 4 - 7

	Model 4 Det. heterogeneity		Model 5 Random β		Model 6 Random λ		Model 7 Random β and λ	
	est.	t-rat.	est.	t-rat.	est.	t-rat.	est.	t-rat.
$\alpha_{1,1}$	0.5330	9.54	-0.8470	7.29	0.5420	9.62	-1.0300	6.91
$\alpha_{1,3}$	4.3100	2.74	-1.7700	5.59	4.7400	2.75	-1.9100	5.22
$\alpha_{2,1}$	0.9390	7.06	-1.0200	11.16	0.3050	1.92	-1.1200	10.32
$\alpha_{2,3}$	4.4800	2.77	-1.6300	5.84	5.4600	3.01	-1.7400	4.87
$\lambda_{f,\mu_{\text{L-Sal}}}$	0.5890	2.27 *(0.34)*§	0.5330	18.29 *(1.13)*§	-0.4870	1.56 *(3.16)*§	0.5340	12.67 *(0.81)*§
$\lambda_{f,s_{\text{L-Sal}}}$	-	-	-	-	4.0200	4.25	0.1230	0.89
$\lambda_{f,\mu_{\text{TT}}}$	0.5480	9.60 *(0.84)*§	0.6050	40.80 *(7.09)*§	0.5220	13.93 *(0.59)*§	0.6180	36.01 *(6.86)*§
$\lambda_{f,s_{\text{TT}}}$	-	-	-	-	0.0173	0.11	0.2620	5.66
$\lambda_{m,\mu_{\text{L-Sal}}}$	0.5720	2.77 *(0.35)*§	0.5580	16.76 *(1.74)*§	1.3700	3.89 *(2.47)*§	0.6260	13.00 *(2.61)*§
$\lambda_{m,s_{\text{L-Sal}}}$	-	-	-	-	3.4900	2.60	0.1720	3.68
$\lambda_{m,\mu_{\text{TT}}}$	0.4080	5.67 *(1.28)*§	0.5400	34.81 *(2.58)*§	0.4070	8.08 *(1.85)*§	0.5440	9.59 *(0.78)*§
$\lambda_{m,s_{\text{TT}}}$	-	-	-	-	0.8610	4.60	0.1250	0.26
$\beta_{f,\text{L-Sal}}$	0.7360	4.68	-	-	0.7770	4.56	-	-
$\beta_{f,\text{TT}}$	-0.0306	11.26	-	-	-0.0305	11.48	-	-
$\mu_{\ln(\beta_{f,\text{L-Sal}})}$	-	-	1.8300	22.42	-	-	1.4300	20.54
$\mu_{\ln(\beta_{f,\text{TT}})}$	-	-	-1.6300	28.20	-	-	-1.6300	22.25
$s_{11,\ln(\beta_{f,\text{L-Sal}})}$	-	-	2.6600	39.22	-	-	2.6100	51.39
$s_{21,\ln(\beta_{f,\text{TT}})}$	-	-	0.5860	11.82	-	-	0.5630	12.66
$s_{22,\ln(\beta_{f,\text{TT}})}$	-	-	-0.3370	14.83	-	-	0.3060	16.15
$\beta_{m,\text{L-Sal}}$	0.7520	4.92	-	-	0.7900	4.74	-	-
$\beta_{m,\text{TT}}$	-0.0344	11.15	-	-	-0.0337	11.06	-	-
$\mu_{\ln(\beta_{m,\text{L-Sal}})}$	-	-	1.5500	13.26	-	-	1.6300	19.53
$\mu_{\ln(\beta_{m,\text{TT}})}$	-	-	-1.6400	24.19	-	-	-1.5600	22.68
$s_{11,\ln(\beta_{m,\text{L-Sal}})}$	-	-	-2.7000	26.99	-	-	-2.6000	23.88
$s_{21,\ln(\beta_{m,\text{TT}})}$	-	-	-0.6400	7.24	-	-	-0.5740	10.38
$s_{22,\ln(\beta_{m,\text{TT}})}$	-	-	-0.3580	13.84	-	-	-0.4410	6.63
ν	0.9110	11.35 *(1.11)*†	2.0800	12.53 *(6.51)*†	1.6800	4.81 *(1.94)*†	1.9800	11.84 *(5.87)*†
$\mathcal{L}\left(\hat{\beta}\right)$	-14,131.392		-11,138.076		-14,007.193		-11,118.674	
$\bar{\rho}^2$	0.358		0.493		0.363		0.494	

† Note: t-rat. are relative to 1.

§ Note: t-rat. are relative to 0.5.

Table 2.3: Results: trade-offs

WTA extra mins per trip for 1,000K extra a month

	Female respondents					
	Self			**Partner**		
	mean	s.d.	cv	mean	s.d.	cv
Model 1	1.1016	0.81	0.74	0.7927	0.49	0.62
Model 2	1.1001	0.81	0.74	0.7916	0.49	0.62
Model 3	1.3251	0.98	0.74	0.6483	0.40	0.62
Model 4	1.2549	0.93	0.74	0.7640	0.47	0.62
Model 5	12.3723	122.79	9.92	11.9482	150.41	12.59
Model 6		*undefined*			*undefined*	
Model 7	9.5305	105.23	11.04	7.6079	88.15	11.59
	Male respondents					
	Self			**Partner**		
	mean	s.d.	cv	mean	s.d.	cv
Model 1	0.7897	0.48	0.61	1.1200	0.86	0.76
Model 2	0.7887	0.48	0.61	1.1184	0.85	0.76
Model 3	0.9500	0.58	0.61	0.9160	0.70	0.76
Model 4	1.0666	0.65	0.61	0.7800	0.60	0.76
Model 5	7.7722	83.28	10.71	10.2491	109.88	10.72
Model 6		undefined			undefined	
Model 7	8.6593	88.47	10.22	8.4555	95.26	11.27

now have a range that is strictly within the $[0, 1]$ interval. This final model is also more successful in retrieving significant differences between male and female respondents, in line with similar observations for model 5.

2.3.4 Implied trade-offs

As a next step in our comparison between the different models, we now look at relative valuations of the two attributes. The context of the survey was a study of the willingness by respondents to accept higher travel time in return for higher salary, and as such, the focus in this section is specifically on that ratio (as opposed to the willingness to accept lower salary in return for shorter travel times).

The calculation of the ratios between the two coefficients is complicated by the use of the log-transform for salary in all models, meaning that the willingness to accept (WTA) reduces with increasing income. In a model with fixed coefficients only, the trade-off would be given by $\frac{\beta_{\text{L-Sal}}}{\beta_{\text{TT}}} \cdot \frac{1}{\text{Sal}}$, i.e. the trade-off is divided by the salary. For this reason, our analysis calculated individual WTA values for each observation in the data, using the salary for the chosen alternative, and our results look at the distribution of the resulting WTA measures in the sample population. The calculation becomes somewhat more complicated once we introduce λ parameters as well as deterministic and random heterogeneity across respondents. Here, the mean and standard deviations are calculated analytically rather than using simulation, which would be unreliable due to the long tails of the Lognormal distribution. An important issue arises in model 6. The fact that the distribution of the λ parameters falls outside the $[0, 1]$ range means that the moments of the resulting WTA distribution are undefined (cf. Daly et al., 2012b), and as such are not reported. This is a further reason for attempting to ensure constant signs across respondents in the λ parameters, a point seemingly not recognised in earlier work.

A number of key observations can be made from the results in Table 2.3. Accommodating random heterogeneity across respondents in the β parameters obviously leads to a very significant increase in heterogeneity in the WTA measures, whereas the heterogeneity in the initial models is merely a result of the non-linear specification (using the logarithm of salary). At the same time, we also see a significant increase in the mean WTA measures, leading to far more realistic values than was the case in the first four models.

Focussing on the results from model 7, which gave the best overall performance, we can see that for female respondents, the WTA measures for the respondents themselves are higher than those they assign to their male partners. Although female respondents assign more weight to their partner's salary than his travel time, which would imply higher WTA, the actual salary for male respondents is higher in this sample, leading to lower WTA measures. Male respondents on the other hand assign more weight to their partner's travel time than to her salary, which would lead to low WTA measures, but this is compensated for by the lower salary for female respondents in the data, meaning that the final WTA measures assigned by male respondents to themselves and their partner are very similar.

2.4 Conclusions

This paper has focussed on the issue of the representation of heterogeneity in choice models that are either estimated on data from joint decisions or data on decisions made by a single person but affecting multiple individuals. Our empirical example has focussed on the latter, primarily as this avoids the need for an explicit representation of the bargaining process.

A number of central ideas are put forward in the paper, and tested in an empirical study using a stated choice dataset in which each partner was asked to evaluate scenarios leading to changes in travel time and salary for both themselves and their partner.

Firstly, we argue that differences in weights assigned to individual partners of a household may vary across attributes. Our results show that the weights respondents assign to their partners do indeed vary across attributes, although such differences are only properly retrieved when allowing for heterogeneity in the marginal utility coefficients[3]. For example, using an asymptotic t-ratio for differences in parameters, we find significant differences between the mean female allocation of salary and travel time weights, $\lambda_{f,\mu_{\text{TT}}}$ and $\lambda_{f,\mu_{\text{L-Sal}}}$ respectively, in both model 5 and model 7, with a confidence level of 92% applying to the differences in model 7.

Secondly, we argue that there is scope for significant heterogeneity across respondents in underlying sensitivities as well as the relative weights assigned to themselves and their partners. This is once again confirmed in the empirical example, showing significant improvements in model fit when allowing for random heterogeneity in the β parameters, and to a lesser extent in the λ parameters. We also retrieve differences between male and female respondents in both sets of parameters, but here there is evidence that such differences can only be adequately captured if simultaneously accommodating random variations.

Thirdly, and most importantly, we argue that there is potentially significant scope for confounding between heterogeneity in marginal sensitivities and heterogeneity in bargaining or weight parameters. Additionally, there is a risk of inappropriate assumptions for the distribution of randomly distributed bargaining or weight parameters leading to misguided results and interpretations. These claims are strongly supported by the evidence from model 6. This model shows that only allowing for heterogeneity in λ without accounting for heterogeneity in β leads to overstated heterogeneity in the former, along with suggesting a significant share of the distribution for λ falling outside the conventional $[0, 1]$ range. While arguments have been put forward to justify such values, we argue here that an incomplete or inappropriate treatment of heterogeneity in the β parameters may exacerbate such problems; a claim entirely supported by the differences in results between model 6 and model 7, notwithstanding the slightly different role for λ in our models. It may also play a role in results showing a dominant role for one partner, e.g. as in Dosman and Adamowicz (2006). Clearly, it is also crucial not to use distributional assumptions that would a priori postulate the

[3]Note that efforts to study differences between λ_{TT} and $\lambda_{\text{L-Sal}}$ were only moderately successful in models 3 and 4.

Table 2.4: Results: weight parameters

	Travel time					
	Female			**Male**		
	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound
Model 1	-	0.5	-	-	0.5	-
Model 2	-	0.4870	-	-	0.4870	-
Model 3	-	0.4730	-	-	0.4730	-
Model 4	-	0.5480	-	-	0.4080	-
Model 5	-	0.6050	-	-	0.5400	-
Model 6	0.4507	0.5220	0.5933	-0.4540	0.4070	1.2680
Model 7	0.3560	0.6180	0.8800	0.4190	0.5440	0.6690
	Salary					
	Female			**Male**		
	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound
Model 1	-	0.5	-	-	0.5	-
Model 2	-	0.4870	-	-	0.4870	-
Model 3	-	0.5690	-	-	0.5690	-
Model 4	-	0.5890	-	-	0.5720	-
Model 5	-	0.5330	-	-	0.5580	-
Model 6	-4.5070	-0.4870	3.5330	-2.1200	1.3700	4.8600
Model 7	0.4110	0.5340	0.6570	0.4540	0.6260	0.7980

presence of such values, such as in the use of a normally distributed λ parameter (cf. Beharry-Borg et al., 2009); here the same argument applies as for marginal utility coefficients with strong a priori sign expectations (cf. Hess et al., 2005). In a specification such as used here, a negative λ parameter would also lead to sign violations for the marginal utility coefficients.

The greater ability of retrieving heterogeneity in the λ parameters when additionally accommodating random heterogeneity in the marginal utility coefficients is highlighted again in Table 2.4, which also again shows the problems arising with model 6 due to its failure to account for such heterogeneity in β while allowing for heterogeneity in λ.

In terms of actual empirical findings for the data at hand, there is evidence of significant heterogeneity across respondents in their own trade-offs between salary and travel time, as well as the weight they assign for those two attributes for their partner. Most of this heterogeneity is random, but some is also linked to differences between men and women. Here, there is evidence that male respondents give more weight to their partner's travel time than to her salary, with the opposite applying to female respondents. These differences do not translate directly into the WTA patterns though, given the non-linear valuation of increases in salary and the higher overall salary for male respondents.

There is significant scope for future work. This includes attempts to validate our findings on other data, as well as looking into the impact of heterogeneity assumptions in a more traditional joint decision making context. Future work should also concentrate more on linking heterogeneity in λ to underlying respondent characteristics, where the main emphasis thus far has been on income, but where scope also exists to study the role of gender ideology, the relative levels of education of each of the household members, and their employment status and patterns. In general, greater effort should go into explaining heterogeneity in both λ and β in such a deterministic manner, but in the present case, gender was the main discriminator. Similarly, there is scope for testing non-linear formulations for the weight parameters in future work, where in the present paper, we restricted ourselves to a standard linear specification.

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Chapter 3

Factors affecting the accuracy of proxy responses in a dyadic household: Can you predict you partners meal preferences?

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Abstract

This paper focuses on the accuracy of *proxy* preferences. Traditional approaches to discrete choice modelling make use of a single individual's responses from a household, regardless of the household structure. These individual responses may represent self-reported preferences, or as is commonly assumed, preferences provided on behalf of any or all other members of the household, namely proxy preferences. This paper considers which key factors (for example, socio demographics) can aid a persons ability to correctly provide reliable proxy responses. Making use of an empirical dataset on household food choices, we test the strength of proxy reporting between couples living in Northern Ireland. In line with the literature, findings suggest that women have a greater overall ability to provide proxy responses, whereas interestingly men far outperform when the questions are more compartmentalised.

Keywords: household decisions; self/proxy response; response quality

3.1 Introduction

Traditionally, household data collection has involved selecting a respondent from a household. This respondent is often required to accurately represent the hypothetical choices that any or all other members of the household would make. Given that the cost of 'target' interviewing a specific member, or interviewing each and every member individually (or sometimes as a group) can not only be expensive, but also an impractical/infeasible use of resources and/or time (Beck et al., 2012; Kojetin and Miller, 1993; Moore, 1988) the ability to act as a reliable proxy evidently becomes invaluable[1].

Historically, there have been many criteria which have been used to select the 'best' proxy reporter. For example, this representative member could be selected on the assumption that he or she is the main decision maker within the household and it is most likely that it will be his or her decision which is upheld. Becker's (1981) unitary model presents a specific example of this, suggesting that the representative decision maker should be the person who has the highest income, as it is likely that he or she will have the most influence within his or her household. An alternative selection criterion could be to select the person who is most likely to be able to realistically approximate the decisions that the household would make, were they to be asked collectively. A considerable proportion of studies undertaken during the 1960's to 1980's, based their research findings on family/marital decision-making solely on the wives' responses to family or marital decision-making questions (Blood and Wolfe, 1960; Monroe et al., 1985). For a much more detailed review of household respondent selection criteria, see Marcucci et al. (2011). There are mixed views about a persons ability to accurately represent the preferences held by other members of their household (see, for example Adamowicz et al., 2005, Corfman, 1991 and Strand, 2007).

In a recent controversial paper, Beck et al. (2012) found that models estimated on *proxy* data and *actual* data produced very similar results leading them to the conclusion that proxy responses are indeed a suitable replacement for actual choice information. Conversely, Davis et al. (1986) found that, when compared with the average gender-specific preferences, only 53% of people were able to provide more accurate predictions for their partner's preferences.

Many studies find similarities between the responses obtained from husbands and wives at the aggregate level, but also find significant discrepancies when comparing responses at the household level (Granbois and Willett, 1970; Monroe et al., 1985; Quarm, 1981). In the next section, we consider some of the potential

[1]There are of course, recognised exceptions to collecting proxy responses; for children and for those who are too mentally or physically infirm to respond (Moore, 1988).

causes and corresponding hypothesis that have been tested in the literature, as to why spouses sometimes struggle to predict their partners preferences.

3.1.1 Why are we so bad at predicting?

Too much time together?

When it comes to making a decision, the first step for many individuals will be to try to consider the attitudes and perceptions held by any other members considered to be *stakeholders* in the outcome of the decision (Lerouge and Warlop, 2006). However, in as much as the other *stakeholders* will have provided this individual decision maker with accurate and specific information about their preferences, it has been shown that commonly the individual will distort this information when utilising it. This scenario of inaccurate predictors seems to ring true, even when the *stakeholders* may be very intimately related to the decision-maker (Lerouge and Warlop, 2006).

Lerouge and Warlop (2006) test the seemingly instinctive expectation that the more familiar the proxy reporter is with the stakeholder for whom they are making the decision, the more accurate their prediction will be. In their counter-intuitive findings, considerable evidence is provided that familiarity generates an *increase* in prediction problems, to the extent that familiarity with the stakeholders' product-specific attitudes and preferences, will even lead to a negative effect on prediction accuracy.

Similarly, Menon et al. (1995) test the hypothesis that increased joint participation in a behaviour or discussion relating to a certain topic could be a contributing factor to increased knowledge about the other person's behaviours and opinions, correspondingly increasing the ability for proxy reporting. Menon et al. (1995) found, however, that the number of years a couple had been together had no effect on increased proxy reporting. A study by Swann and Gill (1997) further demonstrated that whilst relationship length and the degree of involvement increased the *confidence* with which people answered questions about their partner, neither of these factors consistently had an effect in improving the overall accuracy of the predictions. In addition Van Es and Shingi (1972) found that occupation and education also had no effect on the agreement between spouses responses. In conclusion the amount of discussion between a couple on a specific topic and their level of joint participation relating to this topic have been found to be better indicators for accurate proxy reporting than the number of years that the couple have been together (Menon et al., 1995).

Report *(anchor on)* their own preferences

Lerouge and Warlop (2006) suggest that a possible explanation for the lack of predictive accuracy (even when the couple may consider themselves to be well established as a unit) could be that a *predictor* may project their own attitudes and preferences onto their partners, irrelevant of how much information they already hold on their partner. Lerouge and Warlop (2006) provide empirical evidence to support this conclusion; their finding was especially strong, when the household's members have dissimilar attitudes towards a product. Likewise, Kenny and Acitelli (2001) found that information held about the person's partner was often replaced with projections of one's own preferences and attitudes, when asked to make predictions about their partner. Kenny and Acitelli (2001) conclude that this could be due to the person being uncertain about how to respond for their partner and, consequently, using their own *feelings* to infer their partners *feelings*.

The concept that a person will utilize his or her own attitudes and perceptions as projections for the preferences and attitudes of a known, but dissimilar other, is well documented in the false consensus literature (see, for example Marks and Miller, 1987, Ross et al., 1977 and Yadav et al., 2010) and the projection hypothesis literature (see, for example Goel et al., 2010, Krueger, 2007 and Krueger and Stanke, 2001). An exception to this can be found in Dellaert et al. (1998), who found that respondents were not only able to discern that other individuals have differing preferences, but also attempted to provide estimates for these preferences rather than projecting their own.

It should be noted here that if the household members have similar preferences to begin with, then collecting proxy reports based on anchored procedures is considered better than asking the respondent to try to predict the other persons preferences 'freely'. Problems with this method arise, when anchoring leads to overestimating the similarity between household members (see discussion in Bickart et al., 1994).

Survey issues

We have considered above some of the potential causes for poor proxy reporting ability, which stem directly from respondents. We now examine some scenarios where the bias could have been introduced as a result of the survey method used. Quarm (1981) consider two very different sources of between-spouse discrepancies in their study on 'power' in marital decision-making and task allocation:

- *Random measurement error.* Spouses asked identical questions may interpret them differently, as a result of the questions being too general or ambiguous (see also, Monroe et al., 1985).

- *Response reliability.* Although, a respondent may understand the question(s) completely, they could be unsure of their answer(s). After examining responses both concerning similar items, and concerning the same item at two different points in time, they found low correlation[2].

Just a guess?

In their study, Beck et al. (2012) examine potential sources of error in prediction. They found a general lack of significant parameters in instances where the proxy responses were incorrect. This lead them to the conclusion that when an individual was faced with a choice that they felt they could not correctly predict for their partner, they provided a simple guess instead of a "systematic evaluation" of the attributes provided.

3.1.2 Explanatory factors

There is a wide array of factors that have been found to be related to how much one person knows about another, and subsequently how well this person can accurately predict the other's preferences/choices. Kojetin and Miller (1993), detail some of the explanatory factors, which have been previously found to have a *stake* in this ability. In their paper, Kojetin and Miller (1993) discuss the idea that there is likely to be two levels of analysis needed: one which takes into consideration *individual characteristics*, and one which considers the *household* or *family characteristics*. Kojetin and Miller (1993) suggest that *individual characteristics* could be used to distinguish people who:

- are likely to be well informed about the types, categories and amounts of expenditure the other household members are likely to engage in[3],
- may have acquired knowledge or learnt information about particular household members as a result of the type or amount of direct (or indirect) *interaction* they have had with these other household members,
- may also know quite a lot about a particular household member because of their *relationship* or their *interest and involvement* in the activities which that particular household member partakes in.

Kojetin and Miller (1993) further suggest that there may also be *household* or *family characteristics* that distinguish households in which all members are

[2] Davis et al. (1986) also found very low response reliability in their survey.

[3] This information is likely to be gained through their role or status in the household.

well-informed about each other, from households in which each person will only be able to accurately report preferences/choices for themselves.

The remainder of this paper is organised as follows. Section 3.2 presents an overview of the empirical data used in this study. This is followed in Section 3.3 by a discussion of the factors affecting the reliability of spousal proxy responses that are applicable in this context. Section 3.4 presents a latent class model, while conclusions are presented in Section 3.5.

3.2 Household food decisions

Recently, there has been a surge of interest in why people choose to eat what they do. It is commonly believed that we are on the verge of an obesity crisis (Gortmaker et al., 2011; Sassi, 2010; Swinburn et al., 2011; Wang et al., 2011). Much time and resources have been invested into the development of both dietary recommendations and food guides specifically tailored for several different audiences (Asp, 1999). These have been utilised by many health-related organizations and governmental agencies (see, for example Porter et al., 1998 and Senauer et al., 1991). However, even though significant efforts have been made to communicate guidance on food choices to the general public, much research is finding that consumers are having problems utilising this information (Nestle et al., 1998; Porter et al., 1998; Willett, 1994, 1998).

Hence, in this study we make use of an empirical dataset on household food choices, specifically containing households with both a male and female household 'head', which we will refer to as *dyadic* households. Within this data we examine the frequency with which the household members interact with the 'food' and how often they take responsibility for different food related choices. We use this data to test the strength of proxy reporting between couples living in Northern Ireland.

3.2.1 Empirical data

Data were collected from a random sample of Northern Ireland households during early 2011. The survey was conducted as a face-to-face Computer Aided Personal Interview (CAPI) by MRNI Research. Given the research goals, the data collection had to be centred on only those households, which contained two 'household heads'. Hence, selection criteria had to be implemented *at the door* before each household could be included in the sample. The selection process which was used is detailed in Appendix A. In addition, a copy of the full questionnaire is shown in Appendix B. A total of 324 households were interviewed. However, after some extensive data cleaning, only 290 households were included in the present analysis[4].

The data were collected to elicit intra-household trade-offs between meal options. Questions were asked to obtain information on weekly food habits, preferences and in addition relationship status and attitudes between household members. The structure of the interviews was such that each *household head* was asked to complete an individual questionnaire separately and also complete together a *joint* questionnaire. Throughout this paper we will consider both the responses to the choice tasks and also other food related questions, in which each respondent was asked to provide proxy responses for his or her partner; this enables us to compare the accuracy with which the answers were provided.

3.2.2 Food patterns

For this next section we will consider the frequency with which each household (and its members) interact with food. During the survey, several questions were asked to try to establish an understanding of the intra-household *food* dynamics. Questions related not only to the frequency of eating together and purchasing food, but also to the food related attributes which members felt were the most important.

Frequency of interactions

Each member of the household was asked individually, who they felt was typically responsible for buying the food that is bought for both themselves and their partner to cook and eat at home. The answers to this question are shown in Table 3.1. From this table, we can see that when it comes to food purchases there is a clear female dominance, with 67% women stating that they would be responsible for buying the food more often than their partner and 64% men concurring. What is also noticeable is the lack of symmetry in Table 3.1. For example; given that each household contained both a male and female member, we would have expected an equal number of Female "Always me" and Male "Always my Partner". Subsequently, there seems to be agreement on the general task distribution, but some discrepancies about the specific frequencies. These results provide some support for Quarm's (1981) random measurement error postulation.

Given the nature of the survey, it was important to elicit the frequency with which the household members not only ate together, but ate the same meal.

[4]For Table 3.5 and Table 3.6 a reduced sample size is used, due to missing data.

Table 3.1: Typically who in your household is responsible for buying the food that is bought for you and your partner to cook and eat at home?

	Female		Male	
	Count	%	Count	%
Always me	94	32.41	7	2.41
Usually me	99	34.14	18	6.21
Shared (50/50)	75	25.86	78	26.90
Usually my Partner	11	3.79	84	28.97
Always my Partner	10	3.45	101	34.83
Someone Else	1	0.34	2	0.69

Additionally, a high level of *involvement* would increase the level with which the respondents found the survey realistic.

The first two columns in Table 3.2 show the responses to the question: *"During a typical week, how many days would you and your partner eat an evening meal together that was prepared and cooked at home?"*. The last two columns in Table 3.2 show the responses to the question: *"During a typical week, how many days would you and your partner, eat the same evening meal?"*. As with Table 3.1 we see some asymmetry in the responses, with 120 females and 111 males stating that they eat an evening meal that was prepared at home together at least 6 times a week. Also, if we consider the number of times respondents stated they ate the same evening meal as their partner, a higher frequency of males stated that they ate the same meal as their partner less often than their female counterparts.

Table 3.2: During a typical week, how many days would you and your partner ...

	Cook at home				*Eat the same meal*			
	Female		Male		Female		Male	
	Count	%	Count	%	Count	%	Count	%
Never	2	0.69	2	0.69	12	4.14	14	4.83
1-2 times	20	6.90	22	7.59	61	21.03	82	28.28
3-5 times	148	51.03	155	53.45	139	47.93	116	40.00
6-7 times	120	41.38	111	38.28	78	26.90	78	26.90

Finally, household members were asked how frequently they would be responsible for preparing and cooking the evening meal that they ate together with their partner. Table 3.3 shows that, in line with expectations, females have a much higher prevalence of responsibility for cooking, with 28% of females (and only 11% of males) stating that they would be responsible for cooking and preparing the food at least $6-7$ times a week. In addition, just 3% of females stated that they never cook the evening meal compared with 30% of males.

Table 3.3: During a typical week, how many days do you prepare and cook the evening meal that you and your partner eat together at home?

	Female		Male	
	Count	%	Count	%
Never	9	3.10	88	30.34
1-2 times	33	11.38	98	33.79
3-5 times	168	57.93	73	25.17
6-7 times	80	27.59	31	10.69

3.2.3 Choice Tasks

In the stated choice component of the survey, respondents were presented with the choice between three different meal options, described in terms of calories, cooking time, food type and cost. Taste was not included as a direct variable in the choice tasks as it was deemed subject to *interpretation* by the respondent. Instead, "food type" was used as a proxy for taste. Table 3.4 shows the three levels used for the different attributes, where the specific combinations presented in a given choice scenario were obtained from a D-efficient experimental design with Bayesian priors.

Table 3.4: Attribute levels

Attribute	Levels
Calories *(per portion)*	Less than 400 calories
	Between 400 and 600 calories
	Over 600 calories
Cooking Time	Less than 30 minutes
	Between 31 and 60 minutes
	Over 60 minutes
Food Type *(proxy for taste)*	Asian
	Italian
	Local
Cost	£5
	£10
	£15

To allow respondents to better relate to the attribute levels for calories, cooking time and food type, they were provided with illustrative reference cards that showed what type of meal could be expected for given attribute combinations. In each choice task, respondents were asked to choose both their most preferred option and their least preferred option for a typical evening meal, which would be cooked at home that they would share together with their partner. Respondents

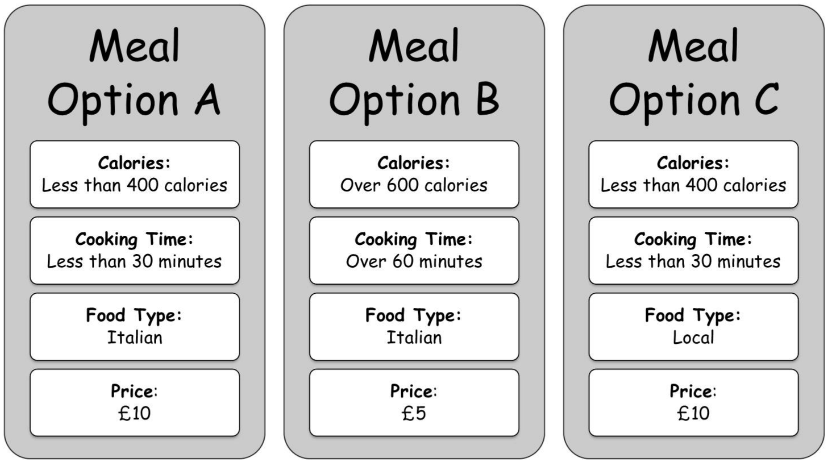

Figure 3.1: Example choice task

were also asked which of the meal options they thought would be most preferred and least preferred by their partner.

Each member of the household was asked 8 choice tasks individually. An example choice scenario is shown in Figure 3.1. There were 3 different block designs which were used for the survey[5]. These were randomised across households. Respondents were told that each option represented a typical evening meal that they would share with their partner at home. In the choice tasks a "no choice" option was not explicitly included, however if the respondents could not decide, then this was recorded as a "don't know" by the interviewer, but if the respondents could not jointly *agree* this was recorded by the interviewer as a "can't agree" instead.

3.3 Predictive power

We will now look in more detail at the household level of accuracy. For each of the questions, where a respondent was asked to provide an answer on behalf of their partner, specifically the cases where they were asked their partners' most and least preferred; we consider 5 different scenarios:

Scenario 1: The respondent correctly predicted his or her partners' choices.

Scenario 2: The respondent actually predicted his or her partners' *opposite* choices (for example; when asked for his partners most preferred, the respondent reported the option that his partner had chosen as her least preferred).

[5]A complete list of all choice tasks is shown in Appendix C, grouped by block design.

Scenario 3: The respondent stated "Don't Know" when asked his or her partners preference[6].

Scenario 4: The respondent gave an incorrect prediction for his or her partners choice, though it was not his or her partners *opposite* choice *(Scenario 2)*. For example; the female member of the household stated that her most preferred option was A and her least preferred option was B, but when asked to predict his partners most preferred option, the male respondent stated C.

Scenario 5: The respondent gave an answer for his or her partners' preferences, but his or her partner had stated that he or she didn't know which option he or she preferred.[7]

3.3.1 Attributes/food preferences

Both members of the household were asked to indicate, out of the attributes, Calorie Content, Time Spent to Prepare and Cook, Food Type and Cost, which was the most and least important to themselves. Respondents were also asked which features they felt were the most and least important to their partner. Looking at Table 3.5[8] we see that compared with females, of whom only 105 answered correctly, when asked to predict the attribute which was most important to their partner, 147 males answered correctly.

Table 3.6[9] contains the results when each member of the household was asked to indicate which type of food, out of Local, Italian and Asian was the most and least important to their partners. Whilst again, we see a higher proportion of males in the Scenario 1 category than female, this is now a marginal difference. In fact, across all Scenarios, there is minimal differences between the numbers of males and females, except for Scenarios 4 and 5 when reporting on least preferred food type. For example, in Scenario 5, 22 men gave an answer for their partner, when they said "Don't Know", compared with 40 women who gave an answer for their partner, when they said "Don't Know". What is most noticeable about Table 3.6 is the high proportion of people in Scenario 1, with 68.64% of people correctly able to predict their partners most preferred food type. When we consider the least favourite food type, this drops to 40.07% with a corresponding

[6]If the respondents partner also stated "Don't Know" we still treat this as Scenario 3; as we are measuring *uncertainty*. This is in contrast to the concept that a mutual "Don't Know" response could suggest that the proxy reporter has knowledge about their partners uncertainty

[7]Scenario 5 was only applicable if all of the other scenarios had been exhausted; this avoided the issue of double counting.

[8]Table 3.5 shows information for just 249 couples due to missing/incorrect data.

[9]Table 3.6 shows information for just 287 couples due to missing/incorrect data.

Table 3.5: Which of these four features is the most/least important to your partner?

	Scenario 1 *Correct*		Scenario 2 *Opposite*		Scenario 3 *Don't Know*		Scenario 4 *In between*		Scenario 5 *Partner DK*	
	Most	Least	Most	Least	Most	Least	Most	Least	Most	Least
Male	147	72	17	17	40	68	33	61	12	31
Female	105	84	20	17	83	70	22	60	19	18
Total	252	156	37	34	123	138	55	121	31	49

Table 3.6: Thinking about preferences for food types, which of the three groups would your partner most/least prefer your typical evening meal to be?

	Scenario 1 *Correct*		Scenario 2 *Opposite*		Scenario 3 *Don't Know*		Scenario 4 *In between*		Scenario 5 *Partner DK*	
	Most	Least	Most	Least	Most	Least	Most	Least	Most	Least
Male	198	117	14	10	30	108	35	30	10	22
Female	196	113	13	12	24	103	38	19	16	40
Total	394	230	27	22	54	211	73	49	26	62

increase in the number of people who stated they don't know their partners least preferred food type (Scenario 3).

3.3.2 Meal preferences

Table 3.7 shows the frequency with which proxy responses to the choice tasks[10] falls into the different scenarios outlined in Section 3.3. We can see that across the different scenarios, the differences between the male predictors and female predictors is minimal, with the exception of Scenario 3 (*Don't Know*), where, in 140 choice tasks males stated they did not know their partners' most preferred (341 when asked least preferred) compared with 75 choice tasks where females stated they did not know their partners' most preferred (237 when asked least preferred). We also see a slightly higher rate of female choice tasks falling into Scenario 1 (*Correct*).

However, Table 3.7 only considers the aggregate predictive ability of males and females across the sample. It does not inform us of the 'within household' predictive ability; specifically, information about *who* in each household is the better predictor. Of clear interest is who in the household would be the *better* or rather, most accurate predictor. This information is shown in Table 3.8, where for each household the number of times each member was able to 'out-predict' their partner is shown. We see that when predicting his or her partners most preferred meal option, there are 70 households in which males outperform their partners, compared with 61 households in which females outperform. This difference is reduced when predicting his or her partners least preferred meal option, with 62 households containing males who outperform their partners, compared with 58 households containing female outperformers. As with Table 3.7, the differences between male and female predictors are minimal. These tables show that gender alone is not sufficient criteria for selecting the best 'representative' member, on the basis of them being the best predictor. Hence, we now consider some other factors which could influence a person's predictive ability.

3.3.3 Other factors

In Table 3.9 we see that the overall average predictive ability for females is higher than the predictive ability for males, both when asked to predict their partner's most preferred meal option and when asked to predict their partner's least preferred meal option. Although these differences are only slight. However, for both

[10]Each individual conducted a series of 8 choice tasks.

Table 3.7: Choice task predictive scenarios

Predictor:	Male				Female			
Predicting:	Partners most preferred		Partners least preferred		Partners most preferred		Partners least preferred	
Scenario	Percentage	Count	Percentage	Count	Percentage	Count	Percentage	Count
1: *Correct*	69.96	1623	59.48	1380	70.82	1643	61.12	1418
2: *Opposite*	8.71	202	7.84	182	8.15	189	8.62	200
3: *Don't Know*	6.03	140	14.70	341	3.23	75	10.22	237
4: *In-between*	14.44	335	14.91	346	16.94	393	15.30	355
5: *Partner DK*	0.86	20	3.06	71	0.86	20	4.74	110

Table 3.8: Predicting right

(a) Predicting your partner's most preferred

Scenario:	Predicted correctly	Percentage
Male predicts his partner's choice right more often than female	70	24.14%
Female predicts her partner's choice right more often than male	61	21.03%
Both equal frequency	159	54.83%

(b) Predicting your partner's least preferred

Scenario:	Predicted correctly	Percentage
Male predicts his partner's choice right more often than female	62	21.38
Female predicts her partner's choice right more often than male	58	20.00
Both equal frequency	170	58.62

males and females, we find highly significant differences between the average ability to correctly predict their partner's most preferred meal option and the average ability to correctly predict their partner's least preferred meal option.

Table 3.9 also shows the average predictive ability, classified by varying food interactions. We specifically look at the responses to the questions[11]:

- *"During a typical week, how many days would you and your partner eat an evening meal together that was prepared and cooked at home?"*.
- *"During a typical week, how many days do you prepare and cook the evening meal that you and your partner eat together at home?"*.
- *"During a typical week, how many days would you and your partner, eat the same evening meal?"*.

We can see that, for both males and females, the average predictive ability when asked their partner's preferences for meal options, often follows a non-linear trend as their food involvement increases. For many females their predictive ability is weakest for food involvement measures of '3-5 times a week'. In contrast, this level of involvement is often when males have the highest level of predictive ability. Another non-linear trend is found when we compare the average predictive ability across varying ages. What is also noticeable is that, if we consider the effect of education, we see that those with a higher education, namely at least a degree, have the least average predictive ability, which may seem a counter-intuitive, given Corfman's (1991) earlier findings. Finally, we find for all categories, for both males and females, that the average ability to correctly predict their partner's most preferred meal option is higher than the average ability to correctly predict their partner's least preferred meal option, with the exception of males who prepare and cook the evening meal at least 6 times a week.

In Table 3.10 we see that the overall predictive ability for females is significantly different than the predictive ability for males, when asked to predict the attribute which they think would be most important to their partner, but not when asked to predict the attribute which they think would be least important to their partner. Looking again, at the average predictive ability, classified by varying food interactions in Tables 3.10, which now consider the ability to predict the most and least important food attribute, we now see that the average predictive ability increases for males as their food involvement increases. However, this time for females, we see some non-linear trends. When we compare the average predictive ability across varying ages, there does not seem to be any clear trend for either males or females. Similarly, the effect of education does not seem to

[11] Results for these questions also featured previously in Table 3.2 and Table 3.3

Table 3.9: Average ability to correctly predict most/least preferred choice tasks

	Female			Male		
		Mean correct (%)			Mean correct (%)	
	Count	Most	Least	Count	Most	Least
Overall	290	70.82	61.12	290	69.96	59.48
Food cooked at home						
Less than 2 times	22	71.59	59.09	24	64.06	52.08
3-5 times	148	70.69	58.11	155	72.18	61.45
6-7 times	120	70.83	65.21	111	68.13	58.33
You prepare food						
Less than 2 times	42	75.30	67.56	186	70.16	57.26
3-5 times	168	70.16	59.08	73	71.75	62.67
6-7 times	80	69.84	62.03	31	64.52	65.32
Eat the same meal						
Less than 2 times	73	73.29	62.33	96	71.61	58.59
3-5 times	139	72.30	60.25	116	72.41	58.30
6-7 times	78	65.87	61.54	78	64.26	62.34
Age						
18-24	30	75.42	65.42	27	73.61	55.09
25-34	72	72.22	59.90	66	71.21	60.80
35-50	96	69.92	60.03	98	68.24	58.93
51-59	36	64.58	63.89	40	68.13	63.75
60-64	24	65.63	59.38	20	69.38	61.25
65-75+	32	76.95	61.33	39	71.79	56.41
Education						
None	57	73.90	61.62	49	71.68	59.69
GCSE	143	72.99	64.69	142	72.27	62.24
ALevel	42	69.64	59.52	32	64.06	56.25
Vocational	19	71.05	45.39	37	73.65	54.39
Degree+PG	29	55.60	55.17	30	57.92	55.83

Table 3.10: Average ability to correctly predict the most/least important food attributes to their partner.

	Female			Male		
		Mean correct (%)			Mean correct (%)	
	Count	Most	Least	Count	Most	Least
Overall	290	39.31	33.10	290	53.79	30.00
Food cooked at home						
Less than 2 times	22	40.91	40.91	24	29.17	16.67
3-5 times	148	32.43	27.70	155	49.68	29.68
6-7 times	120	47.50	38.33	111	64.86	33.33
You prepare food						
Less than 2 times	42	33.33	38.10	186	49.46	27.42
3-5 times	168	37.50	29.76	73	53.42	32.88
6-7 times	80	46.25	37.50	31	80.65	38.71
Eat the same meal						
Less than 2 times	73	27.40	36.99	96	43.75	20.83
3-5 times	139	35.97	28.78	116	49.14	32.76
6-7 times	78	56.41	37.18	78	73.08	37.18
Age						
18-24	30	46.67	23.33	27	51.85	37.04
25-34	72	43.06	36.11	66	48.48	33.33
35-50	96	40.63	30.21	98	62.24	30.61
51-59	36	44.44	41.67	40	62.50	32.50
60-64	24	20.83	29.17	20	20.00	25.00
65-75+	32	28.13	37.50	39	51.28	17.95
Education						
None	57	28.07	36.84	49	44.90	22.45
GCSE	143	46.15	31.47	142	59.86	29.58
ALevel	42	26.19	30.95	32	62.50	21.88
Vocational	19	42.11	47.37	37	37.84	51.35
Degree+PG	29	44.83	27.59	30	50.00	26.67

Table 3.11: Average ability to correctly predict your partners most/least preferred food type.

		Mean correct (%)	
	Count	Most	Least
Overall	580	68.62	40.00
Food cooked at home			
Less than 2 times	46	47.83	21.74
3-5 times	303	68.98	33.99
6-7 times	231	72.29	51.52
You prepare food			
Less than 2 times	228	67.98	39.04
3-5 times	241	68.05	35.27
6-7 times	111	71.17	52.25
Eat the same meal			
Less than 2 times	169	68.05	29.59
3-5 times	255	68.24	39.22
6-7 times	156	69.87	52.56
Age			
18-24	57	68.42	29.82
25-34	138	68.12	31.88
35-50	194	65.46	48.45
51-59	76	55.26	43.42
60-64	44	70.45	27.27
65-75+	71	91.55	45.07
Education			
None	106	83.96	40.57
GCSE	285	61.75	36.84
ALevel	74	64.86	39.19
Vocational	56	73.21	53.57
Degree+PG	59	74.58	42.37

produce an obvious influence on predictive ability. Conversely to Table 3.9, we are now seeing a more dominant predictive ability for males. This is especially prominent when males with a high level of food involvement are asked which food attribute is most important to their partner.

In Table 3.11 we found no significant difference between the overall predictive ability for females compared with males, when asked to predict either their partner's most preferred food type or their partner's least preferred food type. Consequently, we have aggregated the household members in this table. As with Tables 3.9 we can see a positive relationship between food involvement and average predictive ability, when asked their partners preferences for different types of food. Once again, we find no effect for age or education on predictive ability.

3.4 Men vs. women

In this last section, we return to the concept of proxy reports based on anchored procedures. Beck et al. (2012) found in their data on the choice of motor vehicle that in 59% of the choices made a respondent predicted that the other person would choose the same option. Consequently, when they checked this against the number of choices which actually represented a convergence of choices, namely where both members had indeed selected the same option, this percentage fell to 52%.

For our food survey, we find a much higher rate of respondents who believe that their partners preferences are aligned to their own. When asked which of the meal options they thought their partner would prefer most, 83.60% of the responses were the same as those which were provided when asked their own most preferred option. Similarly, when asked which of the meal options they thought their partner would prefer least, 84.59% of the responses were the same as those which were provided when asked their own least preferred option. However, only 67.63% of the responses for most preferred meal option corresponded to both household members individually choosing the same option, with this figure dropping to 63.06% for their least preferred meal option.

Given the extensive amount of literature on these findings, we would suggest that for our *'scenario'* of food choices, there could be many possible reasons for such a high rate of anchoring on ones own preferences:

- When taking into consideration that eating a meal together in most households can occur many times during the course of a week; for many people, the dis-utility associated with the added complexity of having to cook more than one 'meal type' is compounded and can far outweigh the dis-utility of *compromising* and eating a 'meal type' that would not be otherwise chosen by the *chef*. The result of this could be that many household members responsible for the cooking, are perceived by their partners to like/dislike the same meal types.

- Conversely it could be, as is suggested by Kenny and Acitelli (2001), that information held about the person's partner was often replaced with projections of one's own preferences and attitudes, due to the person being uncertain about how to provide answers on behalf of their partner.
- Given the repeated nature of eating a meal together, respondents found it difficult to establish an 'average' for their partners preferences.
- The household members genuinely have similar preferences.

It is this last hypothesis that we explore below. In order to best represent the degree of similarity between the preferences of male and female household members, we make use of a latent class model specification, which has been adjusted to also account for scale differences.

3.4.1 Latent class model

The latent class model (LCM), whilst considered by some as a less flexible mixed logit model[12], has a major advantage in that it does not require the analyst to make prior assumptions about the distributions of parameters across individuals (Greene and Hensher, 2003). The basic principle of the LCM is that an individuals' behaviour will depend not only on the observable attributes but also on some latent heterogeneity which varies across unobserved attributes. The development of the LCM is detailed in Greene and Hensher (2003), including comparison with the mixed logit model. We reproduce here the LCM specification.

An individual n, is probabilistically assigned[13] to a specific latent class c, based on his or her preferences and/or characteristics. The share of the population in class c is given by the membership probability π_c:

$$\pi_c = \frac{exp\left(\mathrm{CTE}_c\right)}{\sum\limits_{c=1}^{C} exp\left(\mathrm{CTE}_c\right)} \tag{3.1}$$

[12]The latent class model assumes discrete mixing distributions, whereas the more commonly known random parameter model assumes continuous mixing distributions for the parameters.

[13]Membership probability can be based only on a constant (Scarpa and Thiene, 2005) or be informed by socio-economic covariates (Boxall and Adamowicz, 2002). In this paper, we follow the former approach.

where CTE_c can be estimated in the model along with the parameter coefficients, β, for each class. Thus, the probability that individual n will choose alternative i over alternative j, in a choice task is given by:

$$P_{ni} = \sum_{c=1}^{C} \pi_c \left(\frac{exp\left(\beta_c x_{ni}\right)}{\sum_j \left(\beta_c x_{nj}\right)} \right) \tag{3.2}$$

The assumption in the LCM is that individuals in the same class will all have similar preferences, but individuals in different classes will have differing preferences (Swait and Adamowicz, 2001). LCMs have been widely used to identify preference segments among users (see, for example Boxall and Adamowicz, 2002, Greene and Hensher, 2003, Hess and Rose, 2007, Hess et al., 2009, Provencher et al., 2002, Scarpa and Thiene, 2005 and Scarpa et al., 2008).

To best establish if the household members genuinely have similar preferences, we compare three different MNL specifications, with a LCM:

Model 1: Same preferences and same scale. In this model we assume that males and females have identical preferences and subsequently only estimate one set of coefficients, β, to represent both members of the household.

Model 2: Same preferences, but different scale. In this second model we again assume that males and females have identical preferences, but we consider the possibility that they have different levels of scale heterogeneity[14] (also referred to as heteroskedasicity). Thus, we estimate one set of coefficients, β and an additional scale coefficient for females, μ_f.

Model 3: Different preferences. Thirdly, we assume that males and females have different preferences and subsequently, we estimate separate coefficients for them. For males we estimate β^m and for females β^f.

Model 4: Heteroskedasic latent class model (HLCM). In this final model we use the specifications of the previous three models as our different latent classes and estimate the corresponding class probabilities, π_c. Hence, accounting for both taste and scale heterogeneity.

If we now consider only the deterministic component of utility that an individual n obtains from choosing alternative i. Equation 3.3 shows the specification for our first model and also class 1 in the HLCM model, where x_{ni} is a vector of

[14]Scale heterogeneity refers to heterogeneity in the variance associated with the random component of utility, ε (c.f. Swait and Louviere, 1993). Additionally, Swait and Adamowicz (2001) define the scale parameter as the *ability* to choose, which they specify as a function of choice task complexity and respondent effort.

attributes describing alternative i as faced by individual n, and β is a vector of estimated parameters:

$$V_{ni}^{C_1} = \beta x_{ni} \tag{3.3}$$

If we expand Equation 3.3 to account for females and males having different levels of scale heterogeneity, we have Equation 3.4 below, which represents the specification for both model 2 and class 2:

$$V_{ni}^{C_2} = \left(\delta^m \mu_m + \delta^f \mu_f\right) \beta x_{ni} \tag{3.4}$$

where, μ_f is scale coefficient for females, with the equivalent scale coefficient for males (μ_m) being fixed to 1 and δ^m is an indicator equal to 1 if the respondent is male and 0 otherwise. Similarly, δ^f is equal to 1 if the respondent is female. Given that our interest is in how the scale parameter for females differs from the male scale parameter[15], we specify $\mu_f = 1 + \eta_f$, subject to the constraint[16] $\eta_f \geq -1$.

Additionally, we have Equation 3.5 below, which represents our final specification for model 3 and class 3, in which we assume that males and females have different preferences:

$$V_{ni}^{C_3} = \delta^m \beta^m x_{ni} + \delta^f \beta^f x_{ni} \tag{3.5}$$

where, β^f represents the estimated coefficients for females and β^m represents the estimated coefficients for males.

Finally, we have Equation 3.6 representing our heteroskedasic latent class model (HLCM), which is a combination of Equation 3.3, Equation 3.4 and Equation 3.5, weighted by their associated class probabilities π_c, where $c = \{C1, C2, C3\}$:

$$V_{ni} = \pi_{C_1} V_{ni}^{C_1} + \pi_{C_2} V_{ni}^{C_2} + \pi_{C_3} V_{ni}^{C_3} \tag{3.6}$$

We make use of the cases in which individuals were asked *"Which of the meal options you would prefer most?"* and estimate the proportion of household members having similar (or the same) preferences.

[15]We specify males as our baseline group, for which the scale parameter is fixed to one to avoid specification problems.

[16]Note that by enforcing the constraint $\eta_f \geq -1$ the scale factor is subsequently constrained to $\mu_f \geq 0$. This is possible as the algorithm used in the maximization, namely the CFSQP algorithm (Lawrence et al., 1997) is able to manage these types of constraints.

3.4.2 Results

The models were estimated with Pythonbiogeme (c.f. Bierlaire, 2003, 2008) using the CFSQP algorithm (Lawrence et al., 1997). In order to deal with the problem of local maxima in discrete mixture of parameters (LC models), between 50-100 random starting values were used[17].

Table 3.12 shows the results for models $1-3$ and the HLCM. Comparing first models 1 and 2, we see minimal differences between the two models in both the parameter coefficients β and the log-likelihood $\mathcal{L}\left(\hat{\beta}\right)$. This is due to the small and non-significant effect of the scale coefficient for females, η_f, suggesting that there is no difference between members' *ability* to choose.

Looking now at the results for model 3, where we have estimated separate coefficients for males β^m and females β^f, we start to notice some gender related preference differences, however these are still relatively small. Again, we do not see a significant improvement in log-likelihood with model 3 only improving on model 1 by 5.2 units and model 2 by 5.17 units, which at the cost of 7 parameters compared with model 1 and 6 parameters compared with model 2 is only significant at the 83% and 89% level respectively.

However, when we consider model 4, we see a highly significant improvement over the three previous models. This improvement is largely due to model 4 taking into account the panel nature of the data. There are some small changes in sign and significance across all coefficients. Most noticeable is the change in the scale parameter η_f, which has increased to 11 and is significant. This very high scale could imply that the females in that class (i.e. the ones that have the same preferences as their male counterparts, but a different level of scale) have more stable and defined preferences. Additionally, as we see in Table 3.13 the proportion of people in this class (just 10.44%) is very small, whereas the scale difference calculated in model 2 included the whole sample, most of which (64.31%) have similar (the same) preferences and scale.

Finally, we also notice that in models $1-3$, the coefficients for low time and Italian are not significant. High calories was combined with the base medium calories in all models, as it was not found to be significantly different from medium in any of the models. Although, β_{Cost} for class 1 in the HLCM is positive, it very small and not significant.

[17]This was coded in 'PERL' and used in combination with Pythonbiogeme run under Ubuntu 10.04 LTS - the Lucid Lynx. For a more in-depth discussion, see Boeri (2011)

Table 3.12: Results: models 1 - 3 and HLCM

	Model 1: same		Model 2: scale		Model 3: different		Model 4: HLCM	
	est.	rob. t-rat.	est.	rob. t-rat.	est.	rob. t-rat.	est.	rob. t-rat.
β_{LowCal}	0.2280	6.79	0.2270	6.84	-	-	0.3170	6.39
β_{LowTime}	0.0043	0.11	0.0044	0.11	-	-	0.0434	1.90
β_{HighTime}	-0.2050	-4.72	-0.2030	-4.64	-	-	-0.0768	-2.45
β_{Asian}	-0.3570	-9.21	-0.3550	-8.86	-	-	-0.1800	-3.31
β_{Italian}	-0.0769	-1.81	-0.0763	-1.81	-	-	0.0492	1.40
β_{Cost}	-0.0490	-12.17	-0.0486	-11.07	-	-	0.0043	1.17
β_{DK}	-3.7700	-27.96	-3.7400	-20.61	-	-	-2.8700	-16.16
η_{f}	-	-	0.0153	0.23	-	-	11.0000	4.29
β^m_{LowCal}	-	-	-	-	0.1280	2.69	0.2880	1.13
β^m_{LowTime}	-	-	-	-	-0.0108	-0.19	0.4100	1.95
$\beta^m_{\text{HighTime}}$	-	-	-	-	-0.2180	-3.58	0.0976	0.41
β^m_{Asian}	-	-	-	-	-0.3440	-6.24	-1.0400	-3.22
β^m_{Italian}	-	-	-	-	-0.0825	-1.36	-1.2000	-2.83
β^m_{Cost}	-	-	-	-	-0.0519	-9.19	-0.3760	-10.37
β^m_{DK}	-	-	-	-	-3.8900	-19.95	-7.4700	-12.35
β^f_{LowCal}	-	-	-	-	0.3260	6.88	0.5780	1.70
β^f_{LowTime}	-	-	-	-	0.0197	0.34	0.6570	3.26
$\beta^f_{\text{HighTime}}$	-	-	-	-	-0.1920	-3.10	0.3580	1.91
β^f_{Asian}	-	-	-	-	-0.3720	-6.82	-0.9210	-3.30
β^f_{Italian}	-	-	-	-	-0.0727	-1.21	-1.2600	-3.29
β^f_{Cost}	-	-	-	-	-0.0459	-8.02	-0.3640	-7.88
β^f_{DK}	-	-	-	-	-3.6500	-19.55	-6.7600	-7.30
$\mathcal{L}\left(\hat{\beta}\right)$	-5,169.712		-5,169.683		-5,164.511		-4,749.827	

Table 3.13: HLCM class membership probabilities

	est.	rob. t-rat.
CTE_1	0.935	5.40
π_{C_1}	64.31%	-
CTE_2	-0.883	-2.99
π_{C_2}	10.44%	-
CTE_3	0	-
π_{C_3}	25.25%	-

3.5 Conclusions

During this chapter, we have looked at previous findings in the literature on the ability of a household member to accurately represent his or her partners preferences through the medium of proxy reporting. There are clearly mixed views in the literature about an individuals ability to provide accurate proxy responses.

We made use of an empirical data set, which was collected to elicit intra-household trade-offs between meal options. Through the investigation of different prediction scenarios, we have found that generally it would seem females have not only a higher level of accuracy, but a more stable level of accuracy, with few situations arising where they are not able to 'out-predict' their partner. However, these finding must be taken in the context of food choices; a context in which we found a clear female dominance, namely it was found that females interacted with the food much more than males.

An alternative hypothesis, could be that even though men had the better ability to predict the level of importance the that their partner's attributed to the food related attributes, women were better at predicting the overall actual choices. This could mean that the women were better able to integrate the trade-offs involving multiple attributes, or were more aware of some external parameters driving their partners actual choices.

With regards to the predictive ability of household members, there are still some unanswered questions. Additionally, an avenue for further work could be to investigate how this predictive accuracy affects joint household decisions. For example; if my prediction of my partners choices is more accurate than my partners prediction of my choices, does this result in me getting more *weight* when it comes to making choices together?

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Part II

Integrated Choice and Latent Variable (ICLV) Models

Chapter 4

Review of integrated choice and latent variable (ICLV) models

4.1 Introduction

Discrete choice models have been used extensively in many research fields to understand the preferences of decision makers. They are based on the notion that when presented with a choice, a respondent will consider the utilities he or she perceives to gain for each of the different alternatives and subsequently, will choose the alternative which maximises his or her utility (or minimizes his or her anticipated regret, c.f. Chorus, 2010, Chorus et al., 2008 and Thiene et al., 2012).

Significant progress has been made recently in the development of discrete choice models that are better able to reproduce *real world* behaviour. There has been a particular emphasis in this context on developing models that are able to incorporate the specifics of the cognitive processes that respondents go through in order to reason about choices they make. This has been a result of the growing realisation that decision makers' attitudes affect their parameter estimates, which will in turn have an impact on their behaviour. Hence many surveys now collect responses to attitudinal questions hoping to best capture these important cognitive processes.

There have been several approaches that researchers have used to order to best make use of attitudinal data. Some have included indicators of attitudes directly in their utility functions (Green, 1984; Harris and Keane, 1998; Koppelman and Hauser, 1978; Milon and Scrogin, 2006; Morey, 1981). This technique not only ignores possible measurement error but also puts the analyst at risk of endogeneity bias. Similarly, studies have made use of factor analysis on the indicators and then used these fitted latent variables in the utility function (Madanat et al., 1995; Morikawa, 1989; Prashker, 1979a,b).

Other work has made use of a latent class approach; with class allocation a function of attitudinal indicators. Hess and Beharry-Borg (2012) detail the different approaches which have been used within this latent class specification:

Approach 1: The approach taken by Boxall and Adamowicz (2002) and Swait and Sweeney (2000) assumes that the probability that an individual belongs to a certain class is a function of his or her attitudinal questions. In other words, they use responses to preference statements as exogenous variables to explain the observed choices.

Approach 2: The approach suggested by Morey et al. (2006) is to sequentially estimate a latent-class choice model. This approach utilizes only the attitudinal data without the choice data to estimate the latent classes, under the assumption that class membership is formed exogeneously and the probability of a response to an attitudinal question is a function of the class to which that person belongs. This approach has been widely used across different research areas (see, examples in de Menezes and Bartholomew, 1996, Eid et al., 2003, Morey et al., 2006, 2008, Thacher et al., 2005 and Yamaguchi, 2000).

Approach 3: As an extension of the approach used by Boxall and Adamowicz (2002), Breffle et al. (2011) estimate a model where both the choice data and attitudinal data are used to estimate the probability that an individual belongs to a certain class. In addition, all the parameters in the *joint* model are jointly determined by both the choice data and the preference-statement data. A similar approach was used in Atasoy et al. (2011).

Approach 4: Another approach that has been used to incorporate attitudinal data is cluster analysis. Cluster analysis deterministically allocates each individual to a specific group, in comparison to the probabilistic assignment achieved through a traditional latent-class model (Morey et al., 2008). Aldrich et al. (2007), Baker and Burnham (2001) and Pennings and Leuthold (2000) are just some examples of studies which have used cluster analysis.

4.1.1 Measurement error

There are examples in the literature which make use of *attitudinal* data. Typically they use the answers to attitudinal questions and group them together into a variable I_n. However, answers to attitudinal questions are not a direct measure of attitudes, but *functions* of underlying latent attitudes. Direct incorporation of them into the utility function can lead to measurement error.

Problems with measurement errors can be overcome by looking at a set of indicators that have their origin in a latent variable, rather than a simple one-to-one correspondence.

4.1.2 Endogeneity

Answers to attitudinal questions may be correlated with other unobserved factors, i.e. $corr\,(I_n, \varepsilon_n) \neq 0$. This can lead to endogeneity bias.

Given the recognition that an analyst doe not observe attitudes, but only captures responses to attitudinal questions in addition to the stated choice behaviour, one of the major benefits of using this latent approach is that the model is able to overcome bias inherent in the direct incorporation of indicators of attitudes (or other subjective measures) in the utility function. Hence, integrated choice and latent variable models avoid the risk of endogeneity bias that would arise in a deterministic treatment (Ben-Akiva et al., 2002a,b).

4.1.3 Integrated choice and latent variable (ICLV) models

Integrated choice and latent variable (ICLV) models represent a promising new generation of discrete choice models that take into account the impact of attitudes on the decision making process, by combing the traditional discrete choice models with the structural equation approach for latent variables (Ben-Akiva et al., 2002b; Temme et al., 2008). Above and beyond, looking at the impacts of directly observable variables, ICLV models show how the attitudes and conceptual motivations held by an individual, such as altruism, impact on their choices. This provides the model with better explanatory power (Hess and Beharry-Borg, 2012; Walker and Ben-Akiva, 2002).

Theoretical discussions for such hybrid choice models centre on the work of Ben-Akiva et al. (2002a,b) and Bolduc et al. (2005), with numerous applications, for example Abou-Zeid et al. (2010), Alvarez-Daziano and Bolduc (2009), Daly et al. (2012a), Fosgerau and Bjørner (2006), Hess and Beharry-Borg (2012), Johansson et al. (2006) and Yáñez et al. (2010).

Within the ICLV model, responses to attitudinal questions are modelled jointly with the actual choice processes, whilst maintaining the assumption that both processes are at least in part influenced by these latent attitudes. This approach integrates choice models with latent variable models resulting in an improvement in the understanding of preferences as well as an improvement in the explanatory power of the model.

4.2 Theory

In line with the foundations of choice models, we first consider representing an individual's decisions within a random utility framework; the utility that the individual n obtains from choosing alternative i, in choice task t is represented as:

$$U_{i,n,t} = V_{i,n,t} + \varepsilon_{i,n,t}, \tag{4.1}$$

where $V_{i,n,t}$ is the deterministic component of utility and $\varepsilon_{i,n,t}$ is the random component.

Considering only the deterministic part, we would simply have that $V_{i,n,t} = f\left(\beta_n, x_{i,n,t}, z_n\right)$, where $x_{i,n,t}$ is a vector of attributes describing alternative i as faced by individual n in choice task t, β_n being a vector of estimated parameters for the sensitivities of respondent n, and z_n being a vector of measured attributes (usually socio demographics) of respondent n. The specification of the functional form of $f(\cdot)$ is a decision to be made by the analyst.

4.2.1 MNL

In the simple MNL model, we fix $\beta_n = \beta, \quad \forall n$. This approach assumes homogeneity in the β parameters across individuals. Deterministic heterogeneity can still be induced into the model, through interactions with z_n. For example, taste heterogeneity can be linked to gender, income, age, etc.

$$P_{i,n,t} = \frac{e^{V_{i,n,t}}}{\sum\limits_{J=1}^{J} e^{V_{j,n,t}}} \tag{4.2}$$

Hence the deterministic component is now, $V_{i,n,t} = f\left(\beta, x_{i,n,t}, z_n\right)$.

4.2.2 Mixed Logit

In more advanced Mixed Logit models, we allow for additional random variations across respondents, i.e. $\beta \sim f\left(\beta \mid \Omega\right)$. Which gives:

$$P_{i,n,t} = \int\limits_{\beta} \frac{e^{V_{i,n,t}}}{\sum\limits_{J=1}^{J} e^{V_{j,n,t}}} f\left(\beta \mid \Omega\right) \mathrm{d}\beta \tag{4.3}$$

4.2.3 ICLV

Let us assume that we have a latent variable α, which for respondent n takes the value α_n, with:

$$\alpha_n = f(z_n, \gamma) + \eta_n \tag{4.4}$$

where $f(z_n, \gamma)$ represents the deterministic part of α_n, with, z_n being a vector of socio-demographic variables, γ being a vector of estimated parameters and η_n is a random disturbance, which follows a standard Normal distribution across respondents.

Consider Equation 4.5 below, which shows the latent variables used as explanatory variables in the utility function:

$$V_{i,n,t} = f(\beta, x_{i,n,t}, \alpha_n, \tau, z_n) \tag{4.5}$$

where τ is a vector of parameters that explains the impact of the vector of latent variables α_n on the utility of alternative i, possibly in interaction with the attributes $x_{i,n,t}$ and the parameters β. Together the latent variable equation and the utility function, give the structural equations. At the same time, they are used to explain the responses to the attitudinal questions. This gives us a specification which is very similar to the mixed logit model, where the random component is now interacted with respondents' socio-demographic characteristics:

$$LL(\beta, \gamma, \tau, z_n) = \sum_{n=1}^{N} \ln \int_{\eta} L(y_n \mid \cdot)\, g(\eta)\, \mathrm{d}\eta \tag{4.6}$$

where, $L(y_n \mid \cdot) = \prod_{t=1}^{T} P_{i^*,n,t}$, i^* is the chosen alternative and $P_{i^*,n,t}$ is a function of β, which is interacted with the vector of latent variables α_n through τ.

The next step is to include the indicators; we do this by treating them as *dependent* variables instead of *explanatory* variables. This forms the basis of the other component of the model, which is given by the measurement equations for the indicator variables, which we consider below.

Continuous indicators

Indicators are typically responses to attitudinal questions, which have a finite number of possible answers. One of the most frequent is the use of a Likert Scale (see, for example Alvarez-Daziano and Bolduc, 2009, Hess and Beharry-Borg, 2012 and Yáñez et al., 2010). For each respondent n, we will have k indicators, forming $I_{k,n}$.

Indicators are often modelled as continuous indicators:

$$I_{kn} = \delta_{I_k} + \zeta_{I_{k,n}} \alpha_n + \upsilon_{k,n} \tag{4.7}$$

where δ_{I_k} is a constant for the k^{th} indicator, $\zeta_{I_{k,n}}$ is the estimated effect of the latent variable α_n on this indicator and $\upsilon_{k,n}$ is a Normally distributed disturbance, with a mean of zero and a standard deviation of σ_{I_k}.

Indicators have typically been responses to attitudinal questions with a finite number of possible values (e.g. Likert Scales ranging from 1 to 5). However, many practitioners commonly use a continuous specification, regardless of the discrete nature of outcomes of the indicator variables.

Subtracting the mean of each indicator from the original indicator variables obviates the need to estimate δ_{I_k} $\forall k$. This gives us $L\left(I_n \mid \zeta_I, \sigma_I, \alpha_n\right)$, the probability of observing the specific responses given by respondent n to the various attitudinal questions, which is a product of Normal density functions:

$$L\left(I_n \mid \zeta_I, \sigma_I, \alpha_n\right) = \prod_{k=1}^{K} \phi\left(I_{k,n}\right) \tag{4.8}$$

with:

$$\phi\left(I_{k,n}\right) = \frac{1}{\sigma_{I_k}\sqrt{2\pi}}\, e^{-\frac{\left(I_{k,n} - \zeta_{I_k}\alpha_n\right)^2}{2\sigma_{I_k}^2}} \tag{4.9}$$

In combination, the Log-likelihood function is thus given by:

$$LL\left(\beta, \gamma, \tau, \zeta_I, \sigma_I\right) = \sum_{n=1}^{N} \ln \int_{\eta} L\left(y_n \mid \cdot\right) L\left(I_n \mid \cdot\right) g\left(\eta\right) \mathrm{d}\eta \tag{4.10}$$

Hence, in addition to the parameters estimated for the standard model, the estimation of this model thus entails the estimation of the vector of interaction terms τ, the parameters of the measurement equations ζ_{I_k} $\forall k$, the socio-demographic interaction terms γ, and the standard deviation of the Normally distributed $\upsilon_{k,n}$ terms (having normalised the standard deviation of η_n to 1).

If we also wanted to allow for random taste heterogeneity, we would need additional layers of integration, giving us:

$$LL\left(\Omega, \gamma, \tau, \zeta_I, \sigma_I\right) = \sum_{n=1}^{N} \ln \int_{\beta} \int_{\eta} L\left(y_n \mid \cdot\right) L\left(I_n \mid \cdot\right) g\left(\eta\right) m\left(\beta \mid \Omega\right) \mathrm{d}\beta \mathrm{d}\eta \tag{4.11}$$

where $\beta \sim m(\beta \mid \Omega)$.

Ordered indicators

However, given the ordered nature of many indicators, it would be more appropriate to use a specification which recognises this, such as an ordered logit model (c.f. Daly et al., 2012a).

Using an ordered logit, we find that the probability of observing a specific response s, for the k^{th} indicator and respondent n is now given by:

$$P(I_{k,n}=s) = P(\alpha_n \leq \mu_{k,s}) - P(\alpha_n \leq \mu_{k,s-1}) \tag{4.12}$$

$$= \frac{e^{\mu_{k,s}-\zeta_{I_k}\alpha_n}}{1+e^{\mu_{k,s}-\zeta_{I_k}\alpha_n}} - \frac{e^{\mu_{k,s-1}-\zeta_{I_k}\alpha_n}}{1+e^{\mu_{k,s-1}-\zeta_{I_k}\alpha_n}} \tag{4.13}$$

where the estimated effect of the latent variable α_n on this indicator is given by ζ_{I_k}, and the probability of the actual observed response is then given by:

$$L_{I_{k,n}} = \sum_{s=1}^{S} \mathbb{I}_{\mathrm{s}}^{k,n} \left[\frac{e^{\mu_{k,s}-\zeta_{I_k}\alpha_n}}{1+e^{\mu_{k,s}-\zeta_{I_k}\alpha_n}} - \frac{e^{\mu_{k,s-1}-\zeta_{I_k}\alpha_n}}{1+e^{\mu_{k,s-1}-\zeta_{I_k}\alpha_n}} \right] \tag{4.14}$$

where $\mathbb{I}_{\mathrm{s}}^{k,n} = 1$ if respondent n gives level s as the answer to the k^{th} attitudinal question, and zero otherwise. For normalisation, we set $\mu_{k,0} = -\infty$ and $\mu_{k,S} = +\infty$ and estimate the intermediate values, imposing the constraint that $\mu_{k,s} \geq \mu_{k,s-1}$. Finally, we set $L_{I_n} = \prod L_{I_{k,n}}$.

Binary indicators

Also, some indicators can simply be binary statements. For example: yes/no, agree/disagree, present/absent.

In which case, the ordinal probability equation 4.14 reduces to:

$$L_{I_{k,n}} = \mathbb{I}_0^{k,n} \frac{1}{1+e^{\mu_k-\zeta_{I_k}\alpha_n}} + \mathbb{I}_1^{k,n} \frac{e^{\mu_k-\zeta_{I_k}\alpha_n}}{1+e^{\mu_k-\zeta_{I_k}\alpha_n}} \tag{4.15}$$

where, for example, $\mathbb{I}_0^{k,n} = 1$ if respondent n states *disagree* as the answer to the k^{th} question, and $\mathbb{I}_1^{k,n} = 1$ if respondent n states *agree*.

μ_k is now the sample level constant of *agree* (or 'yes', 'present', etc.) and ζ_{I_k} again, is the estimated effect of the latent variable α_n on this indicator.

Ranking indicators

In Chapter 5 we make use of an indicator related to the respondents rankings of various attributes. An detailed explanation of this specification is given in Section 5.4.1.

Combination log-likelihood

When using an ICLV model, the log-likelihood function is composed of two different components:

Choice component: $L(y_n \mid \beta, \tau, \alpha_n, z_n)$, which gives the likelihood of the observed sequence of choices of respondent n, (y_n), which is a product of logit probabilities; and

Attitude component: $L(I_n \mid \ldots, \alpha_n)$, which gives the probability of observing the specific responses given by respondent n to the attitudinal questions; the form of which will be depend on the specific model assumptions (i.e. continuous, ordinal, etc.).

In combination, the $\mathcal{LL}$ function is thus given by:

$$LL(\beta, \gamma, \tau, \ldots) = \sum_{n=1}^{N} \ln \int_{\eta_n} L(y_n \mid \cdot)\, L(I_n \mid \cdot)\, g(\eta_n)\, \mathrm{d}\eta_n \tag{4.16}$$

Hence, in addition to the parameters estimated for the standard model, the estimation of this model thus entails the estimation of the vector of interaction terms τ, the socio-demographic interaction terms γ, and the parameters of the measurement equations. Again for the inclusion of random taste heterogeneity, we expand Equation 4.16 to allow for the additional layers of integration:

$$LL(\Omega, \gamma, \tau, \ldots) = \sum_{n=1}^{N} \ln \int_{\beta} \int_{\eta} L(y_n \mid \cdot)\, L(I_n \mid \cdot)\, g(\eta)\, m(\beta \mid \Omega)\, \mathrm{d}\beta \mathrm{d}\eta \tag{4.17}$$

where $\beta \sim m(\beta \mid \Omega)$.

4.3 Empirical applications

As mentioned above, key theoretical discussions for such hybrid choice models centre on the work of Ben-Akiva et al. (2002a,b) and Bolduc et al. (2005). Below we detail some of the key empirical examples found in the literature.

Integrated choice and latent variable (ICLV) models owe much of their development to the field of transportation economics. As a result, this section draws heavily on the transportation economics literature, in the provision of examples of empirical applications. The studies summarised below are by no means an exhaustive list. There exist numerous other applications; for example Abou-Zeid et al. (2010), Ashok et al. (2002), Daly et al. (2012a), Golob (2001) and Pendleton and Shonkwiler (2001) to name just a few.

Transport

Yáñez et al. (2010) make use of the last wave of the Santiago Panel; a 5-day pseudo diary which was collected after the implementation of Transantiago; a new urban public transport system for Santiago de Chile. They considered 3 latent variables. The first related to *accessibility*, the second related to *reliability* and the third related to *comfort/safety*. The effects of these variables were captured through the responses to 7 perception indicators, based on the respondents evaluation of different aspects of what they considered to be 'pure modes' (i.e. Bus, Metro, Share Taxi, Car-Driver and Car-Passenger). These perception indicators were recorded on a scale from 1 to 7, with 7 corresponding to *'very satisfactory'* and 1, *'least satisfactory'*. The 7 indicators were constructed using a continuous specification.

Using data on stated choices made by Canadian consumers faced with 'green' personal vehicle alternatives, Alvarez-Daziano and Bolduc (2009) make use of an 'environmental concern' latent variable related to transportation and its environmental impact. Their latent variable for environmental concern, was used to model the answers to 14 different indicators; 8 relating to a respondents support for transport policies or government actions that would influence the transportation system varying across 5 levels from *Strongly Opposed* to *Strongly Supportive*; and 6 relating to a respondents evaluation of problems related to transportation according to degree of seriousness, again varying across 5 levels from *Not a Problem* to *Major Problem*. The 14 indicators were constructed using a continuous specification.

With a sample of Swedish commuters, Johansson et al. (2006) collected data on respondent's travel mode choice and additionally, on attitudinal and behavioural indicator variables. They then used these to construct 5 latent variables; concerning environmental preferences and preferences for safety, flexibility, comfort and convenience. They used two different methods to construct the latent variables: for the latent variables concerning preferences for comfort, convenience and flexibility, they made use of attitudinal indicator variables; and for the latent variables relating to preferences for safety and environmental variables, they made use of behavioural indicator variables. Johansson et al. (2006) found that both attitudes towards flexibility and comfort, as well as being pro-environmentally inclined, influenced the individual's choice of travel mode (of which they considered a maximum of three alternative travel modes per respondent).

Fosgerau and Bjørner (2006) make use of a contingent valuation (CV) dataset from Copenhagen, where information on stated annoyance is utilised to estimate WTP for noise reduction. They over-sampled respondents who lived in areas with relatively high traffic levels, such that they could obtain a large enough number of respondents exposed to medium and high noise levels. Respondents were asked to indicate on a five-level scale *(not at all annoyed, slightly annoyed, moderately annoyed, very annoyed or extremely annoyed)* their level of noise annoyance. Using an open-ended elicitation format, which yielded a continuous variable for WTP (that was censored at zero), Fosgerau and Bjørner (2006) combined the questions on noise annoyance with questions on the WTP for avoiding the noise annoyance. They made use of an ordered probit to model noise annoyance, and a linear model to estimate log(WTP).

Environmental economics

One of the first applications of ICLV models within the environmental economics field was by Hess and Beharry-Borg (2012). In this study, they applied an ICLV model to analyse respondents' answers about their attitudes to coastal water quality in Tobago. The survey was focussed on establishing respondents' WTP for visiting beaches with improved water quality. In their study, Hess and Beharry-Borg (2012) made use of a single latent variable, which represented a respondents underlying attitude towards policy intervention. This attitude was then used to model respondents' answers to 6 indicator questions, about coastal water quality protection. Each of these indicator questions were recorded on five-point Likert scales ranging from *strongly agree* to *strongly disagree*. However, the 6 indicators were constructed using a continuous specification.

4.4 Multi-agent ICLV models

It is well recognised that *attitudes* towards different attributes of the alternatives are also an important determinant of an individual's choices and underlying preferences. What is less well understood is the consideration that individuals give to the attitudes held by other actors/agents. Therefore, inclusion of the individual's and their respective partner's attitudinal data may contribute to richer discrete choice models. In this context, integrated choice and latent variable models may be advantageous. Moreover, when making a decision it is quite likely that an individual will consider the attitudes held by their partner. Inclusion of the individual's and their respective partner's attitudinal data may, therefore, contribute to richer discrete choice models.

In conclusion, there is now considerable empirical evidence to reject the misconception that group interactions produce joint deliberations consistent with a weighted average of the individual members' preferences and sensitivities (Beharry-Borg et al., 2009). Beharry-Borg et al. (2009) further suggest that:

> "more research is needed to tease out the interactions mechanisms in this context, rather than passively relying on the assumption of joint decision making being an outcome that can be assimilated to 'bargaining' across the two sexes' utilities."

In Chapter 6 we *tease out the interaction mechanisms* though the incorporation of latent attitudes relating to the household members' relationship.

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Chapter 5

A question of taste: recognising the role of latent preferences and attitudes in analysing food choices

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Abstract

Despite substantial interest in understanding consumer food choices, only a limited number of modelling applications have been conducted to date. A key complexity in this context is the potentially large amount of heterogeneity in tastes across individual consumers, as well as the role of underlying attitudes towards cooking. With both tastes and attitudes being unobserved, the present paper makes the case for a latent variable treatment of these components. Using empirical data collected as part of a wider study to elicit intra-household trade-offs between meal options, we show how these latent underlying preferences and attitudes drive both the choice behaviour as well as the answers to supplementary questions. We find significant heterogeneity across respondents in these underlying factors and show how incorporating them in our models leads to highly significant improvements in model fit.

Keywords: food preferences; latent variables; stated choice; taste heterogeneity

5.1 Introduction

There has long been interest in better understanding consumers' food choices, with a focus on people's motivations, preferences and habits. Recently, particular emphasis has been put on eating habits with an obesity risk context.

Food choices are complex as well as frequent. In a recent study, Wansink and Sobal (2007) estimated that a person can make over 200 food and beverage related decisions every day. Asp (1999) in turn discusses in detail some of the factors which effect consumers when they are deciding what to eat, particularly cultural, psychological and lifestyle factors as well as food trends to name but a few. Work by Lennernäs et al. (1997) has highlighted the role of quality/freshness, price, taste, as well as family preferences and trying to eat healthy, while Drewnowski and Darmon (2005) consider the effects of taste, convenience and economic constraints on food choices. Lennernäs et al. (1997) also found that respondents in different socio-economic categories select different factors as contributing a large portion of influence on their food choices. The extent of heterogeneity in preferences is also highlighted in other work. For example, Logue and Smith (1986) indicate that women have higher preferences for low-calorie foods than men and Rappoport et al. (1993) found that insofar as the *health* value of food was concerned, males had a much simpler cognitive structure than females. Consumer information and market research companies are continually developing classification systems which aim to identify different consumer segments and consequently try to predict consumer behaviour (Asp, 1999). These systems make use of important lifestyle factors to describe how consumers make food decisions (Asp, 1999). However, most food studies focus on a limited socio-geographic based population (Glanz et al., 1998; Jaeger and Meiselman, 2004; Marshall and Bell, 2004).

A large body of work has focussed on respondent reported measures of importance of key attributes. For example, Glanz et al. (1998) examine the self-reported importance of taste, nutrition, cost, convenience, and weight control on personal dietary choices and whether these factors vary across demographic groups, are associated with lifestyle choices related to health, and actually predict eating behaviour. They found the importance placed on taste, nutrition, cost, convenience, and weight control helped predict types of food consumed. A proportion of studies which have investigated adult preferences for a variety of foods have involved the respondent rating individual food items on either a nine, five or four point scale, wherein the studies reported the mean preferences of ratings for each food item (see, for example Bell and Marshall, 2003, Drewnowski and Hann, 1999, Jaeger and Meiselman, 2004 and Rappoport et al., 1993).

Whilst simple rating methods can provide rich information about specific food preferences, they do not examine food preference *patterns* which would help to elicit more general food preferences. For example, a person's preference for one type of food could be a predictive indicator of that person's preference for another type of food (Logue and Smith, 1986). It is in this context where there exists a significant difference between the methods used to study food preferences and the tools used to analyse other types of consumer decisions. Across a number of fields, mathematical structures belonging to the family of random utility models have established themselves as the preferred method for the study of choice behaviour at the disaggregate level (Train, 2009). These models quantify the relative importance of the different attributes describing each alternative and are used across fields as diverse as transport, marketing and health economics. However, their use in the area of consumer food choices has been far more limited, with only a handful of applications, (for example in the work of Jaeger and Rose, 2008 and Jaeger et al., 2008).

The present paper illustrates how advanced choice models can be used to obtain a better understanding of consumer food choices. In particular, we recognise, in line with previous work, that there exist significant differences in preferences across individual consumers. We hypothesise that while some of these differences can be linked to socio-demographic characteristics, others cannot. The standard modelling approach for such "unexplained" differences would be a model allowing for random taste heterogeneity. Any information about sensitivities and differences in sensitivities would be inferred solely on the basis of the choices made by respondents. We use a more refined approach that allows us to make use of the supplementary information provided by respondents in ranking questions and attitudinal questions within a hybrid choice model making use of latent variables (Ben-Akiva et al., 2002a,b; Bolduc et al., 2005). We show that the use of these additional model components leads to important gains in fit as well as a better understanding of what drives food choices, and the differences in these drivers across the population.

The remainder of this paper is organised as follows. Section 5.2 presents an overview of the empirical data used in this study. This is followed in Section 5.3 by a discussion of the results for the base models, and in Section 5.4 by a discussion of the results for the latent variable models. Section 5.5 shows the implied marginal rates of substitution, while conclusions are presented in Section 5.6.

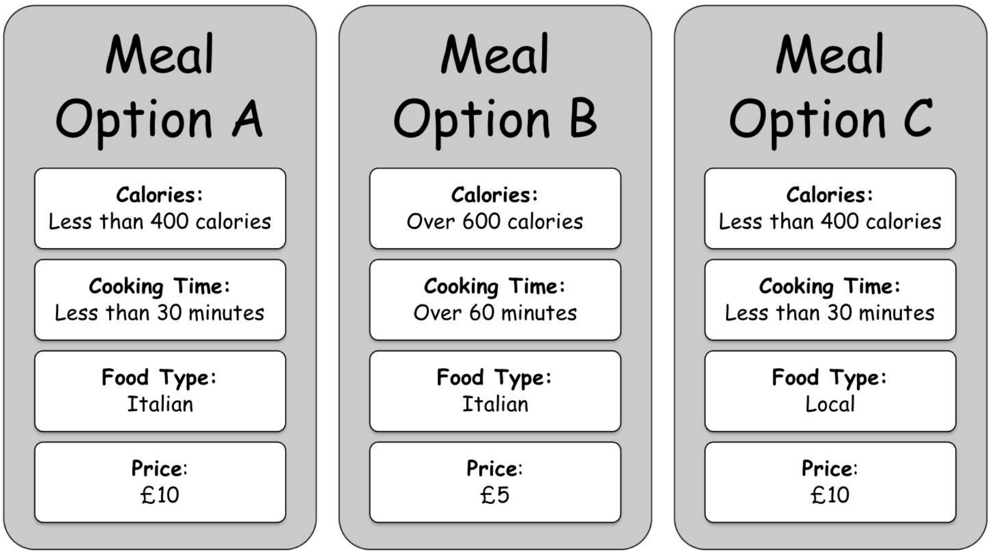


Figure 5.1: Example choice task

5.2 Survey work

Data were collected as part of a wider study to elicit intra-household trade-offs between meal options. The respondents used for the survey formed a random sample of Northern Ireland households, and face-to-face interviews were used for preference elicitation.

5.2.1 Stated choice component

In the actual stated choice component of the survey, respondents were presented with the choice between three different meal options, described in terms of calories, cooking time, food type and cost. Taste was not included as a direct variable in the choice tasks as it would be subject to *interpretation* by the respondent. Instead, "food type" was used as a proxy for taste. Three levels were used for each attribute, where the specific combinations presented in a given choice scenario were obtained from a D-efficient experimental design with Bayesian priors. An example choice scenario is shown in Figure 5.1. We decided against explicitly including a "no choice" option, but if a respondent could not decide, then this was recorded as a "don't know" by the interviewer.

Table 5.1 shows the three levels used for the different attributes. To allow respondents to better relate to the attribute levels for calories, cooking time and food type, they were provided with illustrative reference cards that showed what type of meal could be expected for given attribute combinations. In each choice task, respondents were asked to choose their most preferred option for a typical evening meal that they would share together with their partner at home, and

Table 5.1: Attribute levels

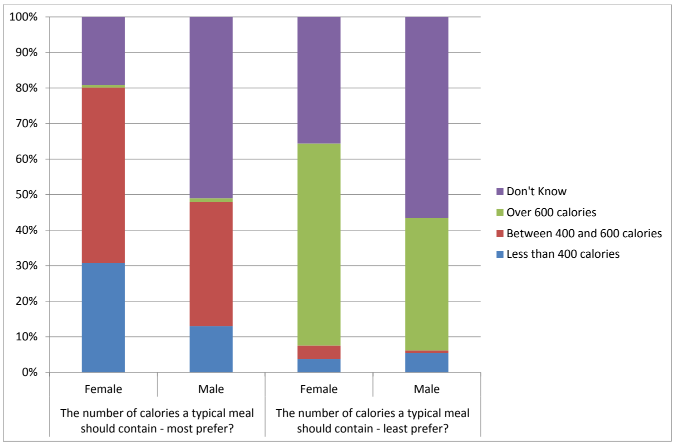
Attribute	Levels
Calories *(per portion)*	Less than 400 calories
	Between 400 and 600 calories
	Over 600 calories
Cooking Time	Less than 30 minutes
	Between 31 and 60 minutes
	Over 60 minutes
Food Type *(proxy for taste)*	Asian
	Italian
	Local
Cost	£5
	£10
	£15

which would be cooked at home. For the present study, we made use of responses from 584 individuals, giving $4,672$ observations in total.

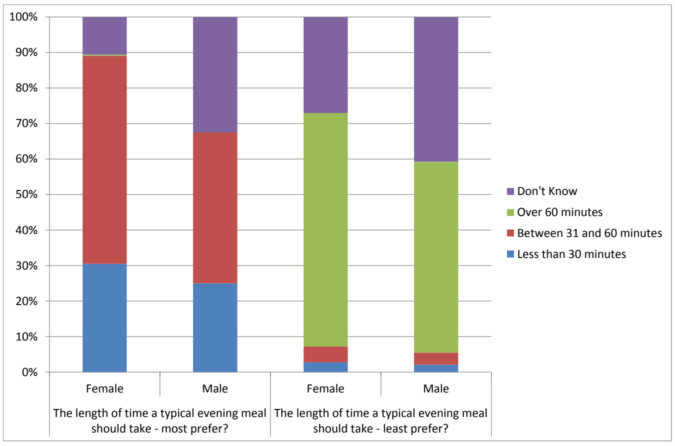
5.2.2 Supplementary questions

In addition to completing the choice tasks, respondents were also asked to state their most preferred and least preferred level of each of the three non-cost attributes. A summary of the information obtained in this manner is shown in Figure 5.2.

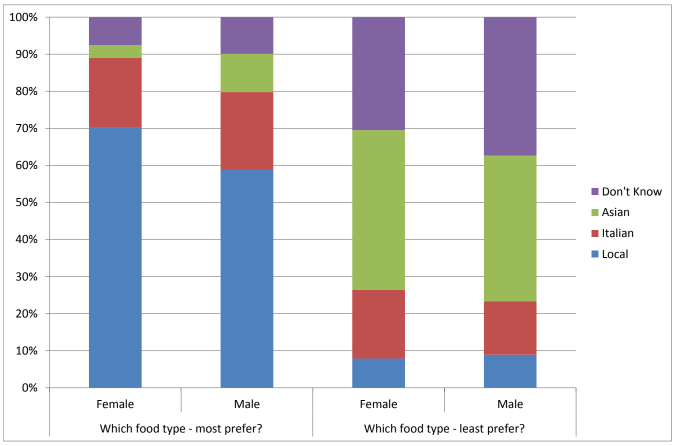
The results from this exercise are in line with expectations and the prior literature. We can see that for Calories, 49% of the interviewed women prefer the medium calories range, with a total of 80% preferring fewer than 600 calories in their meal. Whilst this preference pattern is reflected by the male respondents, the level of uncertainty ("don't know") is increased, especially for the least preferred calorie level. With regards to cooking time, medium cooking time is again the most preferred, while high cooking time is generally the least preferred. Overall the question which encountered the fewest "don't know" responses was the question which asked respondents their most preferred food types. Local food was the most popular choice; this is in line with findings by McIlveen and Chestnutt (1999), where they conclude that greater product awareness needs to be instigated by retailers in Northern Ireland in order to inform consumers of the larger range of food products available to them and consequently encourage greater usage. McIlveen and Chestnutt (1999) found that the Italian food sector represented a growth area, whereas Indian and other newly developing GB food sectors were not yet evident in Northern Ireland.



(a) Calories



(b) Cooking Time



(c) Food Type

Figure 5.2: Attribute importance rankings

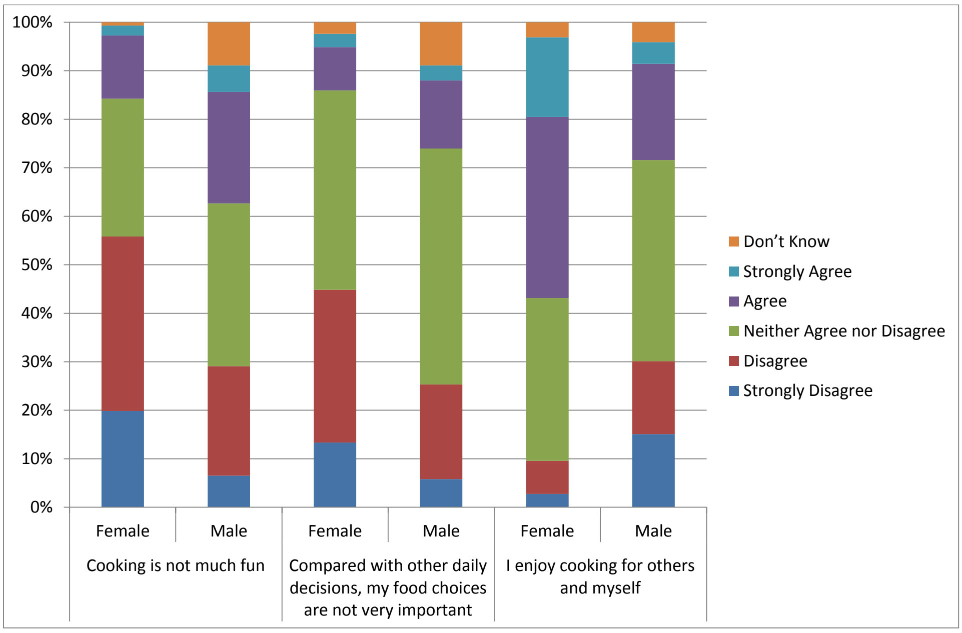


Figure 5.3: Cooking attitudes

As a final component, respondents were also presented with three questions relating to attitudes towards cooking. In particular, respondents were asked to indicate their level of agreement (on a five-point Likert scale) with three statements, namely:

- *"Cooking is not much fun"*;
- *"Compared with other daily decisions, my food choices are not very important"*; and
- *"I enjoy cooking for others and myself"*.

Figure 5.3 shows a summary of the responses to the three attitudinal questions, highlighting a more positive attitude towards cooking for female respondents, along with a higher prevalence of "don't know" responses for male respondents.

The inclusion of these statements was driven in part by the success achieved in Bell and Marshall (2003) and Marshall and Bell (2004) at being able to classify differences in food choices and food choice patterns by using a measure of food involvement, namely the "Food Involvement Scale" (FIS). Bell and Marshall (2003) define food involvement as 'the level of importance of food in a person's life'. They also assume that as a result of this the level of food involvement will vary across individuals. Bell and Marshall (2003) and Laaksonen (1994, pg. 8-9) suggest that food involvement is a mediating variable, acting between stimulus objects and response, depending on both the characteristics of the stimulus object and those of the consumer.

5.3 Base models

5.3.1 Specification

As a first step, we estimate simple Multinomial Logit (MNL) models on our data, where we use the panel specification of the sandwich estimator to recognise the repeated choice nature of the data in the computation of standard errors. All models were coded in Ox 6.2 (Doornik, 2007).

Two different specifications are used. In the first model, the deterministic component of utility[1] for respondent n and alternative j in choice task t (out of 8) is written as:

$$\begin{aligned} V_{njt} = & \beta_{\text{LowCal}}\text{LowCal}_{njt} + \beta_{\text{HighCal}}\text{HighCal}_{njt} + \\ & \beta_{\text{LowTime}}\text{LowTime}_{njt} + \beta_{\text{HighTime}}\text{HighTime}_{njt} + \\ & \beta_{\text{Asian}}\text{Asian}_{njt} + \beta_{\text{Italian}}\text{Italian}_{njt} + \\ & \beta_{\text{Cost}}\text{Cost}_{njt} \qquad \forall 1 \leq j \leq 3 \end{aligned} \tag{5.1}$$

$$V_{n4} = \delta_{\text{DK}}\text{DK}_{n4} \tag{5.2}$$

where, as an example, LowCal_{njt} is set to 1 if alternative j has the low calories level (and is set to 0 if alternative j has a calories level other than low), and where β_{LowCal} is the associated marginal utility coefficient, which is to be estimated. Equation 5.1 shows the utility individual n will receive if they select any of the first three alternatives, whereas Equation 5.2 shows the utility individual n will receive through the selection of the “don’t know” option (displayed as alternative 4, in this case). Other than cost, the attributes were entered as dummy variables so as to allow us to capture any non-linear preference structures for these attributes, where the middle level was used as the base (i.e. sensitivity fixed to zero).

The specification thus far has assumed that the sensitivities to the different attribute levels (i.e. the preferences) are constant across individuals in our sample. To address this shortcoming, we make use of a revised specification that allows for differences in sensitivities for the three non-cost attributes by age group as

[1] In the MNL specification, the random component of the utility function follows a type I extreme value distribution.

well as by gender. For each level (other than middle), we thus estimate a base coefficient, along with offsets for male respondents, respondents under the age of 35 and respondents over the age of 50, using the middle age group as the base. This specification is shown in Equation 5.3, where, for example, $\Delta_{\text{Italian;Male}}$ shows the shift in the utility for Italian food for a male respondent relative to a female respondent.

$$
\begin{aligned}
V_{njt} =& \beta_{\text{LowCal;Base}}\text{LowCal}_{njt} + \Delta_{\text{LowCal;Male}}\text{LowCal}_{njt} + \\
& \Delta_{\text{LowCal;Under 35}}\text{LowCal}_{njt} + \Delta_{\text{LowCal;Over 50}}\text{LowCal}_{njt} + \\
& \beta_{\text{HighCal;Base}}\text{HighCal}_{njt} + \Delta_{\text{HighCal;Male}}\text{HighCal}_{njt} + \\
& \Delta_{\text{HighCal;Under 35}}\text{HighCal}_{njt} + \Delta_{\text{HighCal;Over 50}}\text{HighCal}_{njt} + \\
& \beta_{\text{LowTime;Base}}\text{LowTime}_{njt} + \Delta_{\text{LowTime;Male}}\text{LowTime}_{njt} + \\
& \Delta_{\text{LowTime;Under 35}}\text{LowTime}_{njt} + \Delta_{\text{LowTime;Over 50}}\text{LowTime}_{njt} + \\
& \beta_{\text{HighTime;Base}}\text{HighTime}_{njt} + \Delta_{\text{HighTime;Male}}\text{HighTime}_{njt} + \\
& \Delta_{\text{HighTime;Under 35}}\text{HighTime}_{njt} + \Delta_{\text{HighTime;Over 50}}\text{HighTime}_{njt} + \\
& \beta_{\text{Asian;Base}}\text{Asian}_{njt} + \Delta_{\text{Asian;Male}}\text{Asian}_{njt} + \\
& \Delta_{\text{Asian;Under 35}}\text{Asian}_{njt} + \Delta_{\text{Asian;Over 50}}\text{Asian}_{njt} + \\
& \beta_{\text{Italian;Base}}\text{Italian}_{njt} + \Delta_{\text{Italian;Male}}\text{Italian}_{njt} + \\
& \Delta_{\text{Italian;Under 35}}\text{Italian}_{njt} + \Delta_{\text{Italian;Over 50}}\text{Italian}_{njt} + \\
& \beta_{\text{Cost}}\text{Cost}_{njt} \qquad \forall 1 \leq j \leq 3
\end{aligned} \tag{5.3}
$$

5.3.2 Results

The results for the two base models are summarised in Table 5.2. Looking first at the model without socio-demographic interactions, we can see that the coefficients for low calories (β_{LowCal}) is positive and significant while the coefficient for high time (β_{HighTime}) is negative and significant. This indicates that low levels of calories are preferred to medium levels of calories, while medium time is preferred to high time. The signs for the coefficients for high calories (β_{HighCal}) and low time (β_{LowTime}) are not in line with this, but the coefficients are not statistically significant, making the sign irrelevant and showing that there is no difference from the sensitivity for the medium level in these cases; at the aggregate level, the respondents are not distinguishing between high calories and the base level medium calories, or between low time and the base level of medium time. We can also see that as expected, the coefficients for Italian (β_{Italian}) and Asian (β_{Asian}) food are negative, meaning that respondents prefer the base of Local food to these alternatives, albeit that the difference with Italian food is not statistically signif-

Table 5.2: Base MNL model and MNL with age and gender effects

	Base MNL		MNL with age and gender	
	est.	rob. t-rat.	est.	rob. t-rat.
$\beta_{\text{LowCal;Base}}$	0.2468	4.74	0.5050	4.97
$\Delta_{\text{LowCal;Male}}$	-	-	-0.1970	-2.00
$\Delta_{\text{LowCal;Under 35}}$	-	-	-0.3231	-2.66
$\Delta_{\text{LowCal;Over 50}}$	-	-	-0.1652	-1.36
$\beta_{\text{HighCal;Base}}$	0.0341	0.69	0.0341	0.35
$\Delta_{\text{HighCal;Male}}$	-	-	0.0310	0.33
$\Delta_{\text{HighCal;Under 35}}$	-	-	0.1261	1.08
$\Delta_{\text{HighCal;Over 50}}$	-	-	-0.1826	-1.56
$\beta_{\text{LowTime;Base}}$	-0.0142	-0.34	0.1048	1.22
$\Delta_{\text{LowTime;Male}}$	-	-	-0.0061	-0.07
$\Delta_{\text{LowTime;Under 35}}$	-	-	-0.1402	-1.28
$\Delta_{\text{LowTime;Over 50}}$	-	-	-0.2086	-2.00
$\beta_{\text{HighTime;Base}}$	-0.2197	-6.52	-0.1220	-1.57
$\Delta_{\text{HighTime;Male}}$	-	-	-0.0319	-0.45
$\Delta_{\text{HighTime;Under 35}}$	-	-	-0.2219	-2.42
$\Delta_{\text{HighTime;Over 50}}$	-	-	-0.0182	-0.21
$\beta_{\text{Italian;Base}}$	-0.0599	-1.20	0.1852	2.00
$\Delta_{\text{Italian;Male}}$	-	-	-0.0357	-0.37
$\Delta_{\text{Italian;Under 35}}$	-	-	-0.2900	-2.57
$\Delta_{\text{Italian;Over 50}}$	-	-	-0.4213	-3.34
$\beta_{\text{Asian;Base}}$	-0.3275	-6.65	-0.0888	-0.95
$\Delta_{\text{Asian;Male}}$	-	-	0.0247	0.26
$\Delta_{\text{Asian;Under 35}}$	-	-	-0.5272	-4.62
$\Delta_{\text{Asian;Over 50}}$	-	-	-0.2605	-2.12
β_{Cost}	-0.0493	-7.92	-0.0504	-8.07
δ_{DK}	-3.8274	-20.87	-3.8540	-20.97
$\mathcal{LL}$	-5,192.85		-5,141.8	

icant. The cost coefficient (β_{Cost}) has the expected negative estimate, while the strong negative estimate for the constant for the "don't know" alternative (δ_{DK}) reflects the low rate of respondents indicating indecision between alternatives.

Turning to the model incorporating socio-demographic interactions, we obtain an improvement in log-likelihood by 51.85 units over the base model, where this is highly significant at the cost of 18 additional parameters. While we note a significant negative shift in preferences towards low calories for males, we do not find significant differences between males and females for any of the other attributes, a finding which is contrary to much of the food preference literature. On the other hand, we observe a number of significant age interactions. Notably, we observe a lower preference for low calorie levels for respondents under the age of 35, along with reduced preferences (or increased dislike) of high time as well as Italian and Asian food. For respondents over 50 years of age, we note a significant negative shift in preferences for low time, as well as once again Italian and Asian food.

5.4 Integrated Choice and Latent Variable (ICLV) model

The findings from the base models give us an indication of heterogeneity in preferences as a function of age and gender. However, it is easily conceivable that additional differences exist which cannot entirely be linked to socio-demographic characteristics. Rather than relying on a simple random coefficients specification, we propose to make use of the additional information collected from respondents in terms of attribute rankings as well as attitudinal questions. Specifically, we hypothesise that these additional data can serve as proxies for the underlying differences in sensitivities. However, it is important to recognise that answers to attribute ranking questions and attitudinal questions do not provide us with a direct error-free measure of the actual underlying sensitivities. Indeed, they are merely a function of these sensitivities. Similarly, these data points are likely to be correlated with other unobserved effects, and their incorporation as explanatory variables in our choice models would thus put us at risk of endogeneity bias.

To allow us to use the additional data while not exposing ourselves to the risk of measurement error and endogeneity bias, we make use of a hybrid model specification in which the answers to ranking questions and attitudinal questions are treated as dependent rather than explanatory variables. A number of latent variables are then used to create a link between a given respondent's choices and his/her answers to these additional questions. Within such an Integrated Choice and Latent Variable (ICLV) model, the responses to the subjective questions are modelled jointly with the actual choice processes, all the while maintaining the assumption that *both* processes are at least in part influenced by the latent attitudes. This approach integrates choice models with latent variable models resulting in an improvement in the understanding of preferences as well as an improvement in the explanatory power of the model. The theoretical discussions for such hybrid choice models centre on the work of Ben-Akiva et al. (2002a,b) and Bolduc et al. (2005), with numerous applications, for example Abou-Zeid et al. (2010), Alvarez-Daziano and Bolduc (2009), Daly et al. (2012a), Fosgerau and Bjørner (2006), Hess and Beharry-Borg (2012), Johansson et al. (2006) and Yáñez et al. (2010).

5.4.1 Model specification

Let us assume that we have a latent variable α, which for respondent n takes the value α_n, with:

$$\alpha_n = f(z_n, \gamma) + \eta_n \tag{5.4}$$

where $f(z_n, \gamma)$ represents the deterministic part of α_n, with, z_n being a vector of socio-demographic variables, γ being a vector of estimated parameters and η_n is a random disturbance, which follows a standard Normal distribution across respondents.

Our work makes use of seven latent variables:

- two latent variables linked to the underlying sensitivities to the high and low levels for calories, α_1 and α_2;
- two latent variables linked to the underlying sensitivities to the high and low levels for cooking time, α_3 and α_4;
- two latent variables linked to the underlying sensitivities to Italian and Asian food, α_5 and α_6; and
- one latent variable linked to general attitudes towards food, hereafter known as the *'cooking'* attitude, α_7.

We use a linear in attributes specification for the deterministic part, and write:

$$\alpha_{k,n} = \gamma_{\alpha_k} z_n + \eta_{k,n}, \qquad k = 1, \ldots, 7 \tag{5.5}$$

Hereafter, α_n represents the vector of latent attitudes for respondent n.

These latent variables are now used as explanatory variables in the utility function, which is rewritten as:

$$V_{int} = f(\beta, x_{int}, \delta, \alpha_n, \tau) \tag{5.6}$$

where τ is a vector of parameters that explain the impact of the vector of latent variables α_n on the utility of alternative i, possibly in interaction with the attributes x_{int} and the parameters β.

At the same time, we use the latent variables to explain the responses to the ranking questions and the attitudinal questions. In particular, the first two latent

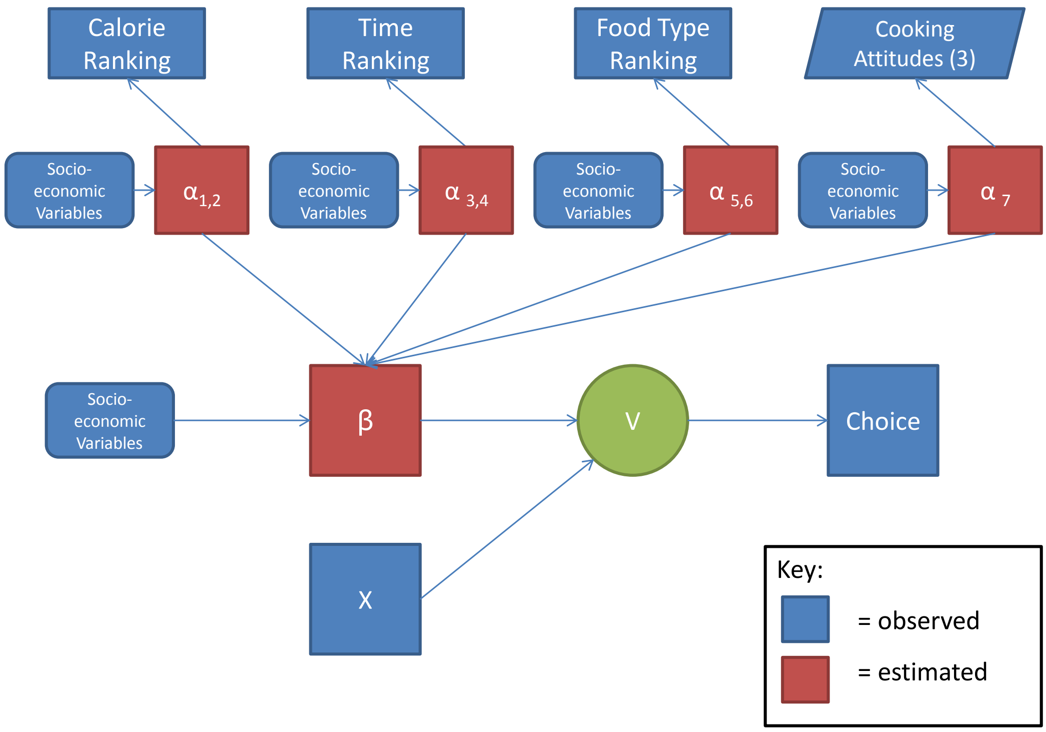


Figure 5.4: ICLV model outline

variables are used to explain the ranking of the three different calorie levels, the following two latent variables are used for the ranking of the three different time levels, and the fifth and sixth latent variable are used to explain the ranking of the three different food types. Finally, the seventh latent variable is used to explain the answers to the three attitudinal questions.

The entire structure of the model is represented graphically in Figure 5.4. At the top of the graph we have the indicators, I_k; "Calorie Ranking", "Time Ranking", "Food Type Ranking" and "Cooking Attitudes" (for which we have three indicator functions). These indicators are explained using the seven latent variables, which in turn are a function of socio-demographic variables (in addition to having a random component). The latent variables are then at the same time interacted with the coefficients of the choice model (β), which are possibly also interacted with socio-demographic indicators, and which, in interaction with the attribute levels, explain the choices observed in the data.

We now look in detail at the measurement component of the overall structure, i.e. explaining the observed attribute rankings as well as answers to attitudinal questions. For each of the three non-cost attributes, respondents were asked to state their most preferred and least preferred level (i.e. *best* and *worst* level respectively). We represent the underlying sensitivities to the different levels of these attributes through the use of a simple logit model, where, for the example of the calories attribute, we have that:

- the utility for *low* calories is given by the latent variable for the underlying sensitivity to low calories, i.e. α_1, plus a parameter $\mu_{R,\text{LowCal}}$ to capture the mean ranking in the sample;
- the utility for *high* calories is given by the latent variable for the underlying sensitivity to high calories, i.e. α_2, plus a parameter $\mu_{R,\text{HighCal}}$ to capture the mean ranking in the sample; and
- the utility for *medium* calories is set to zero.

For the response to the *worst* attribute level, the sign of the utilities was reversed. Respondents were also allowed to opt out of each ranking question, by giving a "don't know" response to either their best or worst preferred level. The utilities for such responses are given by constants, where separate constants are used for the best and worst rankings, given the differential rates of "don't know".

The actual probabilities for the observed responses to the best and worst ranking questions are now given by:

$$P_{\text{cal-best,n}} = \frac{\mathbb{I}^{B}_{\text{LC,n}} e^{\mu_{R,\text{LowCal}}+\alpha_{1,n}} + \mathbb{I}^{B}_{\text{MC,n}} + \mathbb{I}^{B}_{\text{HC,n}} e^{\mu_{R,\text{HighCal}}+\alpha_{2,n}} + \mathbb{I}^{B}_{\text{DK BC,n}} e^{\delta_{R,\text{DK BestCal}}}}{e^{\mu_{R,\text{LowCal}}+\alpha_{1,n}} + e^{\mu_{R,\text{HighCal}}+\alpha_{2,n}} + e^{\delta_{R,\text{DK BestCal}}} + 1} \tag{5.7}$$

$$P_{\text{cal-worst,n}} = \frac{\mathbb{I}^{W}_{\text{LC,n}} e^{-\mu_{R,\text{LowCal}}-\alpha_{1,n}} + \mathbb{I}^{W}_{\text{MC,n}} + \mathbb{I}^{W}_{\text{HC,n}} e^{-\mu_{R,\text{HighCal}}-\alpha_{2,n}} + \mathbb{I}^{W}_{\text{DK WC,n}} e^{\delta_{R,\text{DK WorstCal}}}}{e^{-\mu_{R,\text{LowCal}}-\alpha_{1,n}} + e^{-\mu_{R,\text{HighCal}}-\alpha_{2,n}} + e^{\delta_{R,\text{DK WorstCal}}} + 1} \tag{5.8}$$

where:

- $\mathbb{I}^{B}_{\text{LC,n}}$ is an indicator variable, equal to 1 if respondent n choose 'Low' as his/her most preferred calorie level and 0 otherwise;
- $\mathbb{I}^{B}_{\text{MC,n}}$ is an indicator variable, equal to 1 if respondent n choose 'Medium' as his/her most preferred calorie level and 0 otherwise;
- $\mathbb{I}^{B}_{\text{HC,n}}$ is an indicator variable, equal to 1 if respondent n choose 'High' as his/her most preferred calorie level and 0 otherwise; and
- $\mathbb{I}^{B}_{\text{DK BC,n}}$ is an indicator variable, equal to 1 if respondent n did not know his/her most preferred calorie level and 0 otherwise.

Equivalently $\mathbb{I}^{W}$ is an indicator variable for the least favourite rankings. The parameters $\delta_{R,\text{DK BestCal}}$ and $\delta_{R,\text{DK WorstCal}}$ give the utility for the "don't know" choices.

A corresponding specification was used for the ranking questions for time and food type. From this, we then obtain:

$$L\left(R_n\right) = P_{\text{cal-best,n}} P_{\text{cal-worst,n}} P_{\text{time-best,n}} P_{\text{time-worst,n}} P_{\text{type-best,n}} P_{\text{type-worst,n}} \quad (5.9)$$

which gives the probability of observing the specific responses given by respondent n to the ranking questions a product of logit probabilities which is conditional on the first six latent variables.

Now let us consider the cooking indicators. In line with Daly et al. (2012a), we treat the responses to these three attitudinal questions using an ordered logit model specification. The probability of observing a given value s, with $s = 1, \ldots, 5$ for the k^{th} indicator (with $k = 1, 2, 3$) for respondent n is now given by:

$$P\left(I_{k,n}\right) = \frac{e^{\mu_{k,s} - \zeta_{I_k} \alpha_{7,n}}}{1 + e^{\mu_{k,s} - \zeta_{I_k} \alpha_{7,n}}} - \frac{e^{\mu_{k,s-1} - \zeta_{I_k} \alpha_{7,n}}}{1 + e^{\mu_{k,s-1} - \zeta_{I_k} \alpha_{7,n}}} \quad (5.10)$$

where the estimated effect of the latent variable $\alpha_{7,n}$ on this indicator is given by ζ_{I_k}, and the probability of the actual observed response is then given by:

$$L_{I_{k,n}} = \sum_{s=1}^{S} \mathbb{I}_{\text{s}}^{k,n} \left[\frac{e^{\mu_{k,s} - \zeta_{I_k} \alpha_{7,n}}}{1 + e^{\mu_{k,s} - \zeta_{I_k} \alpha_{7,n}}} - \frac{e^{\mu_{k,s-1} - \zeta_{I_k} \alpha_{7,n}}}{1 + e^{\mu_{k,s-1} - \zeta_{I_k} \alpha_{7,n}}} \right] \quad (5.11)$$

where $\mathbb{I}_1^{k,n} = 1$ if respondent n gives level 1 as the answer to the k^{th} attitudinal question, and zero otherwise. For normalisation, we set $\mu_{k,0} = -\infty$ and $\mu_{k,5} = +\infty$ and estimate the four intermediate values, imposing the constraint that $\mu_{k,s} \geq \mu_{k,s-1}$. Finally, we set $L_{I_n} = \prod_{k=1}^{3} L_{I_{k,n}}$.

Our joint model now has three components, a choice model, a measurement model for the ranking questions, and a measurement model for the three attitudinal questions. The likelihood for the observed sequence of choices for respondent n is given by $L\left(y_n \mid \beta, \delta, \tau, \alpha_n\right)$, which is a product of logit probabilities, and a function of the parameters of the base choice model (grouped together into β), the interaction terms τ and the vector of seven latent variables α. The likelihood for the measurement model for the ranking question is given by $L\left(R_n \mid \mu_R, \delta, \alpha_{1-6,n}\right)$ which is a function of the first six latent variables as well as a set of constants and the mean ranking parameters. Finally, the likelihood for the measurement model for the attitudinal questions is given by $L\left(I_n \mid \zeta_I, \mu, \alpha_{7,n}\right)$, which is a function of interaction terms ζ, the threshold parameters μ, and the seventh latent variable.

In combination, the log-likelihood function is thus given by:

$$LL\left(\beta,\gamma,\tau,\zeta_I,\mu,\mu_R,\delta\right)=\sum_{n=1}^{N}\ln\int_{\eta}L\left(y_n\mid\cdot\right)L\left(I_n\mid\cdot\right)L\left(R_n\mid\cdot\right)g\left(\eta\right)\mathrm{d}\eta \quad (5.12)$$

where integration over the random component of α is needed. In addition to the parameters estimated for the standard model, the estimation of this model thus entails the estimation of the vector of interaction terms τ, the parameters of the various measurement equations, and the socio-demographic interaction terms γ.

5.4.2 Results

The specification for our latent variable model made use of the base specification from the MNL model without socio-demographic interactions, given that these are now dealt with in the latent variable specification.

In the choice model, the first six latent variables were interacted with the associated parameter, e.g. the latent variable for low calories was interacted with the β parameter for low calories. The latent variable for general cooking attitude was interacted with all non-cost coefficients in the choice model, with the exception of high time where no meaningful effect was retrieved. The specification of the measurement equations is as discussed in Section 5.4.1. The means of the latent variables were set to zero, and an extensive amount of testing was conducted to establish significant socio-demographic interactions, focussing on age and gender, where only the most significant interactions were retained, as discussed later in this section.

The estimation results for the choice model component are shown in Table 5.3. The overall fit for the hybrid model cannot be compared to that for the MNL model as it jointly models the choices and responses to attitudinal and ranking questions. However, it is possible to factor out the component of the log-likelihood relating to the choice model, conditional on the other components. This gives us a log-likelihood of $-5,044.01$, which offers a highly significant improvement over the base model by 148.84 units for 11 additional parameters.

We first observe that β_{HighCal} has changed in sign and has also become significant compared with the base model. This is in line with the preferences found above in Figure 5.2. Two additional parameters, namely β_{LowTime} and β_{Italian}, also undergo sign changes, but the coefficients remain insignificant. For the first six latent variable interaction terms, we can see that, in line with expectations, a higher value for the underlying attribute sensitivity leads to a more positive parameter in the choice model, albeit that this is not statistically significant for

Table 5.3: Estimation results for choice model component

	est.	rob. t-rat.
β_{LowCal}	0.4103	4.57
β_{HighCal}	-0.2388	-2.79
β_{LowTime}	0.0258	0.42
β_{HighTime}	-0.2444	-6.38
β_{Italian}	0.0444	0.55
β_{Asian}	-0.3197	-3.19
β_{Cost}	-0.0532	-7.55
δ_{DK}	-3.9231	-20.61
$\tau_{\alpha_{\text{LowCal}},\beta_{\text{LowCal}}}$	0.6740	7.50
$\tau_{\alpha_{\text{HighCal}},\beta_{\text{HighCal}}}$	0.3783	2.78
$\tau_{\alpha_{\text{LowTime}},\beta_{\text{LowTime}}}$	0.6065	7.78
$\tau_{\alpha_{\text{HighTime}},\beta_{\text{HighTime}}}$	0.0303	0.75
$\tau_{\alpha_{\text{Italian}},\beta_{\text{Italian}}}$	0.3187	5.53
$\tau_{\alpha_{\text{Asian}},\beta_{\text{Asian}}}$	0.6476	6.80
$\tau_{\alpha_{\text{Cooking}},\beta_{\text{LowCal}}}$	-0.2089	-3.04
$\tau_{\alpha_{\text{Cooking}},\beta_{\text{HighCal}}}$	0.0779	1.21
$\tau_{\alpha_{\text{Cooking}},\beta_{\text{LowTime}}}$	-0.0519	-1.17
$\tau_{\alpha_{\text{Cooking}},\beta_{\text{Italian}}}$	-0.0707	-1.21
$\tau_{\alpha_{\text{Cooking}},\beta_{\text{Asian}}}$	-0.0080	-0.12
Choice component $\mathcal{LL}$	-5,044.01	
Overall $\mathcal{LL}$	-10,666.60	

high time. For the final latent variable, i.e. the general cooking attitude, only one interaction is significant, indicating that a higher value for the latent attitude equates to a less positive value for the associated low calorie coefficient. As we will see later, this latent variable in fact equates to an *anti-cooking* attitude, meaning that respondents who have a more positive attitude towards cooking also prefer cooking lower calorie meals.

As a next step, we look at the structural equations for the seven latent variables, with estimates summarised in Table 5.4. These results show that male respondents have a more positive value for the latent variables for high calories, high time and Italian and Asian food types. The result for high time may seem counter-intuitive, but a possible explanation could be that whilst they would prefer to have meals that take longer to cook, they do not necessarily want to be responsible for creating the meal. We also see that male respondents have a more positive value for the general latent cooking attitude, where it is important to remember that this is in fact an *anti-cooking* attitude, which explains the sign. The same applies for the low and high age groups. In addition, being under the age of 35 has a negative effect on the latent variable for low calories, as well as

Table 5.4: Estimation results for structural equation model for latent attitudes

		est.	rob. t-rat.
Calories			
	$\gamma_{\text{Low\_Cal}_{<35}}$	-0.2594	-1.95
	$\gamma_{\text{High\_Cal}_{\text{Male}}}$	0.5171	2.08
	$\gamma_{\text{High\_Cal}_{<35}}$	0.5011	3.03
Cooking Time			
	$\gamma_{\text{Low\_Time}_{50+}}$	-0.2595	-1.85
	$\gamma_{\text{High\_Time}_{\text{Male}}}$	0.5171	2.56
Food Type			
	$\gamma_{\text{Italian}_{\text{Male}}}$	0.3186	1.76
	$\gamma_{\text{Italian}_{<35}}$	-0.5442	-2.54
	$\gamma_{\text{Italian}_{50+}}$	-0.9269	-4.24
	$\gamma_{\text{Asian}_{\text{Male}}}$	0.2087	1.39
	$\gamma_{\text{Asian}_{<35}}$	-0.5072	-2.99
	$\gamma_{\text{Asian}_{50+}}$	-0.3310	-1.86
Cooking			
	$\gamma_{\text{Cooking}_{\text{Male}}}$	0.6713	5.98
	$\gamma_{\text{Cooking}_{<35}}$	0.5018	3.67
	$\gamma_{\text{Cooking}_{50+}}$	0.2534	1.80

Table 5.5: Estimation results for measurement model for rankings of attributes

		est.	rob. t-rat.
Calories			
	$\mu_{R,\text{LowCal}}$	-0.7629	-5.54
	$\mu_{R,\text{HighCal}}$	-4.0481	-15.30
	$\delta_{R,\text{DK Most Cal}}$	-0.1595	-1.65
	$\delta_{R,\text{DK Least Cal}}$	3.5868	17.00
Cooking Time			
	$\mu_{R,\text{LowTime}}$	-0.5965	-4.73
	$\mu_{R,\text{HighTime}}$	-4.2649	-16.80
	$\delta_{R,\text{DK Most Time}}$	-0.7959	-7.30
	$\delta_{R,\text{DK Least Time}}$	3.3050	14.61
Food Type			
	$\mu_{R,\text{Italian}}$	-0.9207	-4.91
	$\mu_{R,\text{Asian}}$	-2.1267	-10.59
	$\delta_{R,\text{DK Most Type}}$	-1.9328	-12.79
	$\delta_{R,\text{DK Least Type}}$	2.0953	13.74

Table 5.6: Estimation results for measurement model for latent attitude to Cooking, α_1

		est.	rob. t-rat.
Cooking is not much fun			
	$\zeta_{\text{Cooking 1}}$	3.1146	7.13
	Threshold 1	-2.2387	-4.84
	Threshold 2	1.3287	2.88
	Threshold 3	4.7295	7.00
	Threshold 4	8.3355	8.82
Compared with other daily decisions, my food choices are not very important			
	$\zeta_{\text{Cooking 2}}$	1.6174	8.51
	Threshold 1	-2.1674	-8.41
	Threshold 2	0.2199	0.88
	Threshold 3	3.4837	9.70
	Threshold 4	5.6278	12.32
I enjoy cooking for others and myself			
	$\zeta_{\text{Cooking 3}}$	-2.8201	-8.87
	Threshold 1	-6.2423	-9.38
	Threshold 2	-4.6090	-8.10
	Threshold 3	-0.8788	-2.21
	Threshold 4	2.6166	5.76

for Italian and Asian food types, but a positive affect on the latent variable for high calories. Lastly, respondents aged over 50 have a less positive value for the latent variable for low time, as well as non-local food.

The results for the measurement model for attribute rankings are summarised in Table 5.5. The negative signs for the six mean ranking parameters are a reflection of the fact that, across attributes, the middle level tended to be ranked highest by respondents. The signs for the "don't know" constants reflect the low rates for choosing "don't know" in response to the *best* level question, and the high rate for choosing it in response to the *worst* level question. This is an indication that respondents find it harder to evaluate their least preferred option and as a result, are more inclined to state "don't know".

We finally turn to the results for the measurement model for the three attitudinal questions, which are shown in Table 5.6. We can see that the thresholds are all increasing in magnitude, as is required by the model. Additionally, we see positive estimates for the interaction terms in the first two equations, and a negative effect in the third model. This means that a more positive value for the seventh latent variable leads to stronger agreement with the statements that *"Cooking is not much fun"* and *"Compared with other daily decisions, my food* *choices are not very important"*, but increased disagreement with the statement that *"I enjoy cooking for others and myself"*. This is in line with an interpretation of this latent variable as an *anti-cooking* attitude, which explains the role of this latent variable in the choice model as well as the signs of the socio-demographic interactions in its structural equation.

5.5 WTP / Marginal Rates of Substitution

As a final step, we turn our attention to implied willingness to pay (WTP) patterns and other marginal rates of substitution.

We first look at the WTP patterns from our base MNL model without socio-demographic interactions, shown in Table 5.7(a). Each time, the WTP measures relate to a shift away from the middle (base) level. In these results, negative WTP measures reflect the fact that some attribute levels are undesirable when compared to the middle level. We note a positive WTP for moving from middle calorie to low calorie meals, while cost reductions are required at the aggregate level to accept a move to high time or Asian food. The remaining WTP measures relate to parameters that were not statistically significant.

Table 5.7(b) and Table 5.7(c) show the corresponding results for the MNL model with gender and age interactions as well as for the ICLV model. In both cases, we now have variation across respondents. While the signs and size of the mean WTP measure remain in line with the simple MNL results, most WTP measures now show tails of opposing signs. This reflects the high degree of heterogeneity in the data, where, for the ICLV model, it is also important to acknowledge the potential impact of the Normal distribution on results.

For the marginal rate of substitution, we focus on a shift from medium calories to low calories, and in particular respondents' willingness to accept a move to high time (from medium time) or Asian food (from local food) in return for such a change. For the simple MNL model, Table 5.8(a) shows that the desire to shift to low calories is stronger than the desire to avoid a shift from medium time to high time, but is not as strong as the desire to avoid a shift from local food to Asian food. For the model with socio-demographic interactions (cf. Table 5.8(b)), we see strong heterogeneity, where sign changes are a result of some segments disliking low calories or having a positive preference for high time or Asian food. While the mean is greater than one for both marginal rates of substitution, the medians are both lower than one. This implies that while some respondents have a very strong preference for a move to low calories, the relative preference for avoiding a move to high time or Asian food is stronger for over fifty percent

Table 5.7: Willingness to pay (WTP) measures

(a) Base MNL model:

	WTP
LowCal	5.0033
HighCal	0.6922
LowTime	-0.2879
HighTime	-4.4543
Italian	-1.2144
Asian	-6.6393

(b) MNL with age and gender effects:

	Quantiles								
	5	10	25	50	75	90	95	Mean	SD
LowCal	-0.3012	-0.3012	2.8297	3.6060	6.7369	10.0130	10.0130	4.8546	3.2509
HighCal	-2.9429	-2.9429	-2.3284	1.2916	3.1780	3.7925	3.7925	0.6584	2.4983
LowTime	-2.1777	-2.1777	-2.0576	-0.7020	1.9576	2.0777	2.0777	-0.2465	1.7258
HighTime	-7.4542	-7.4542	-6.8207	-3.4151	-2.7816	-2.4200	-2.4200	-4.3301	2.0148
Italian	-5.3884	-5.3884	-4.6815	-2.0768	2.9661	3.6730	3.6730	-1.2996	3.5191
Asian	-12.2160	-12.2160	-11.7260	-6.4369	-1.7617	-1.2712	-1.2712	-6.6882	4.3165

(c) ICLV Model:

	Quantiles								
	5	10	25	50	75	90	95	Mean	SD
LowCal	-17.9600	-13.0450	-4.7716	4.2969	13.4660	21.6380	26.5340	4.3145	13.5180
HighCal	-13.4810	-10.6690	-5.9076	-0.6057	4.7024	9.4805	12.3330	-0.5976	7.8423
LowTime	-20.0340	-15.8180	-8.8154	-1.0288	6.7450	13.7280	17.9000	-1.0387	11.5300
HighTime	-5.4120	-5.1990	-4.8423	-4.4456	-4.0490	-3.6924	-3.4791	-4.4456	0.5874
Italian	-12.7070	-10.3380	-6.3563	-1.8941	2.5852	6.6651	9.0530	-1.8689	6.6220
Asian	-28.7650	-24.2330	-16.6410	-8.1990	0.2410	7.8408	12.4050	-8.1956	12.5080

Table 5.8: Marginal rates of substitution (MRS)

(a) Base MNL model:

	MRS
Move to Low Cal and accept high time	1.1233
Move to Low Cal and accept Asian	0.7536

(b) MNL with age and gender effects:

	MRS: Quantiles								
	5	10	25	50	75	90	95	Mean	SD
Move to Low Cal and accept high time	-0.0404	-0.0404	0.5287	0.8286	2.4220	4.1378	4.1378	1.6473	1.4010
Move to Low Cal and accept Asian	-0.0257	-0.0257	0.2952	0.4396	4.8035	5.6841	5.6841	2.0665	2.3249

(c) ICLV Model:

	MRS: Quantiles						
	5	10	25	50	75	90	95
Move to Low Cal and accept high time	-4.1219	-2.9709	-1.0826	0.9663	3.0467	4.9405	6.0914
Move to Low Cal and accept Asian	-5.5516	-2.6365	-0.7327	0.1603	1.1009	3.0347	6.0356

of respondents. This is also reflected in the results for the ICLV model (cf. Table 5.8(c)), where the use of the Normal distribution means that means and standard deviation for the marginal rates of substitution cannot be calculated (c.f. Daly et al., 2012b).

5.6 Conclusions

In this paper, we have highlighted the potential benefit of using advanced choice models for studying consumers' food choices. In particular, we have considered the impact that attitudes and underlying preferences can have on the decision making process through the use of a latent variable approach. We began with a simple MNL model, which found that most of the estimates were in line with expectation, and those that were not were found not to be significant. We also estimated a MNL model with variation in sensitivities by age and gender, producing interesting findings, not least in part due to the significant preference differences found between the age groups used.

As a next step, we illustrated how further differences can be accommodated in a latent variable based hybrid model structure which allows us to make use of additional subjective data on attribute rankings and attitudinal questions. Crucially, this model allows us to use such data without risk of measurement error or endogeneity bias. We formulated a model with seven latent variables and showed how this model obtains significant improvements in model fit over the base specification. The latent variables are used to explain both differences in sensitivities in the choice model as well as the responses to attribute ranking questions and attitudinal questions. In this context, a number of interesting socio-demographic interactions were also retrieved.

There is significant scope for future work using such advanced models in a food choice context. Indeed, it is well known that preferences vary extensively across consumers and it is conceivable that a large extent of such heterogeneity relates to underlying convictions, preferences and attitudes. Examples for future areas of application include a focus on topics such as health and diet, ethical food sources, organic food, as well as locally sourced food.

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Chapter 6

Getting the most for your dinner: incorporating attitudinal factors within a multi-agent decision making context

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Abstract

The hypothesis put forward in this paper is that just as with individual choice processes, joint decisions are similarly driven in part by unobserved attitudes. Different possibilities may arise. The attitudes of the different decision makers may all play a role, or the attitudes of one decision maker may be dominant. Similarly, one decision maker may know the attitudes of another decision maker and either try to take them into account, or act against them.

Hence, in addition to socio-economic variables, the decision making structure within a household is likely to have a bearing on the 'household choice'. There are likely to be at least three subgroups of household decision-making structures; a household in which a dictator makes the decisions (akin to the Unitary model); a household wherein the dominance oscillates in accordance with whichever household member maintains the strongest attitude for the specific decision; and finally, for each decision there is a compromise between the household members. In this paper a series of attitudinal questions are asked to both decision makers aimed at determining in which of these categories the household falls. The theoretical part of the paper thus presents a framework for the joint modelling of latent attitudes and decision processes within the context of a multi-agent decision environment.

Keywords: household decisions; joint decisions

6.1 Introduction

Studies which more closely look at 'household' preferences usually employ empirical data wherein each member's preferences are elicited both individually and as a group. The individual preferences are then usually weighted, according to some predetermined rule, in order to gain insight into the joint decision making process. Often this rule will incorporate some socio-economic variables, which results in assigning each member a weight (often referred to as a 'bargaining coefficient') according to their 'status' within the household.

In the last decade or so, there has been increased recognition that the decisions studied may not be made only by the primary income earner, (as is the assumption in many studies) or even that there is a dominant decision maker within the household (c.f. Becker, 1981). These recent studies have focussed on aligning the decision making structure modelled within a household with the real life decision making processes that take place in modern households.

This is achieved through the use of a 'bargaining coefficient', wherein each member of the household who has a 'stake' in the choice, will contribute to the overall decision. This new modelling concept provides the tools needed to attune the estimates and reduce bias/unobserved errors gained from allowing a member of the household to serve as a proxy for all those members concerned.

In Chapter 2, the guiding philosophy behind joint choices was presented. The next section further investigates the concept of the 'bargaining coefficient'. In Section 6.2.1, we describe some of the supplementary questions which were used to approximate a measure of household dominance. Subsequently, Section's 6.2.2 and 6.2.3 outline the model specification used in this context, with a particular emphasis on the specification of the bargaining or weight parameters. This is followed by a discussion of the results in Section 6.2.4, while a concluding discussion is presented in Section 6.3.

6.1.1 The bargaining coefficient

There have been many different ways that people have tried to accomplish the task of representing the household decision making process. The importance of being able to represent this process is the desire to be able to not only predict an individual's choice, but also understand what is important enough to influence his or her choices within the household structure and other group settings.

If we consider Equation 6.1, the household utility function focussing on a two-person context, the deterministic component of utility that household h obtains from choosing alternative i is represented as:

$$V_{hi} = \lambda\left(\beta_1 x_{hi}\right) + (1-\lambda)\left(\beta_2 x_{hi}\right), \tag{6.1}$$

where x_{hi} is a vector of attributes describing alternative i as faced by household h, β_n being a vector of estimated parameters for individuals n, with $n = \{1, 2\}$ (i.e. recognising that we have may have different marginal sensitivities for each household member, with β_1 for person 1 and β_2 for person 2) and λ, the bargaining coefficient, representing the relative distribution of weight between the two household members. In Equation 6.1, we see that if λ takes either the value 0 or 1 this implies that the household decision is made based on the marginal sensitivities of only one member. Consider for example, if $\lambda = 1$ the decision will be based on person 1's preferences only. Whereas if λ falls within the $[0, 1]$ range we can assume that *bargaining* between the two household members has taken place (Beharry-Borg et al., 2009; Browning and Chiappori, 1998; Dosman and Adamowicz, 2006; Vermeulen, 2002).

The bargaining coefficient can take many forms. It can be a random parameter, a function of other criteria (for example, contextual attributes), it can be specific to each attribute within and/or between alternatives, or be constrained to anything the analyst sees fit (Hensher et al., 2008). Empirically, there have been many different specifications used to characterize the bargaining coefficient. We consider some of these studies below.

Random parameter

To allow for the bargaining coefficient to vary across couples and account for any heterogeneity between couples, some studies have chosen to represent λ through the use of a random parameter. In a recent study, de Palma et al. (2011) made use of an experiment to analyse the link between the risky decisions made by couples and the risky decisions made separately by each spouse. First they estimated the degree of risk aversion held by each individual and also the couple together and then they assessed how the risk preferences of the two spouses aggregated when they made risky decisions. They found that the balance of power within the majority of households was fluid; namely they found that it was the male spouse, who initially exhibited more decision-making power, but over the course of the experiment, the female spouse gained more and more power and then ultimately implemented the joint decision. de Palma et al. (2011) supplement these findings with the novel use of some qualitative analysis of the discussions that the couples had, whilst taking part in their experimental tasks. Hence, it would be acceptable to hypothesise that the bargaining coefficient will vary across decisions, and decision-makers, suggesting that the use of a random distribution to estimate λ would lead to more realistic results. A further example of this approach is tested in Beharry-Borg et al. (2009), where they found only 22% of their respondents fell within the range of values reflecting 'bargaining' behaviour, although as shown in Chapter 2 their choice of a Normal distribution ($\lambda \sim N(\mu, \sigma)$) may have led to some misguided results.

Expected measures of influence

The expected value of influence that each individual maintains. This is generally a function of the expected *power use effectiveness* (a function of the resources the individual believe are at their disposal e.g. expertise), *cost* and *benefits of using a power source*. Also, the expected *effectiveness* of the members influence is also taken into consideration. That is, how likely the other member is to comply (Corfman and Lehmann, 1987). Similarly, Dellaert et al. (1998) analyse a conjoint experiment, using a probit model, in which they compare the projected influence parameter based on projected family preference models and the actual family member's preferences.

Based on covariates

Other studies have directly related the measure of influence to covariates, e.g. attitudinal and socio-economic variables (see, for example Arora and Allenby, 1999 and Dosman and Adamowicz, 2006). In these studies the bargaining coefficient can depend on both the characteristics of the household and/or the characteristics of the individuals contained within it.

Much of the past literature on intra-household decisions has concentrated on the bargaining power being directly linked to the relative income of each partner (Bateman and Munro, 2005). There have also been some studies, which focus on how the division of household labour affects decisions. Covariate associations are prevalent in the analysis of households allocation of time doing different activities (see, for example Bradley and Vovsha, 2005, Srinivasan and Bhat, 2005, Zhang et al., 2002 and Zhang et al., 2005).

However, there has been only limited analysis, which considers aspects such as gender ideology, the relative levels of education of each of the household members, employment status and patterns, the production of goods/services within the household or any other factors which may affect a particular household decision (Dosman and Adamowicz, 2006; Katz, 1997; Manski, 2000). According to Adamowicz et al. (2005) understanding the homogeneity of group members (with regard to their objectives, knowledge, task representation, individual preferences and choices) is critical to understanding how groups process information and make decisions.

The present paper makes use of an Integrated Choice and Latent Variable (ICLV) model, allowing us to incorporate supplementary information provided by respondents in attitudinal questions through the use of latent variables (c.f. Ben-Akiva et al., 2002a,b).

6.2 Survey work

Data were collected as part of a wider study to elicit intra-household trade-offs between meal options during early 2011[1]. The respondents used for the survey formed a random sample of Northern Ireland households, and face-to-face interviews were used for preference elicitation. A total of 324 households were interviewed. However, after some extensive data cleaning, only 288 households were included in the present analysis.

6.2.1 Relationship questions

In supplement to the choice task component of the questionnaire, respondents were also presented with questions relating to their feelings and attitudes about their current relationship's dynamics and any dominance featured in this relationship. Characteristics and traits of individuals, families, households and groups has long been investigated in the field of psychology. It is with this knowledge that we integrated personality scale measures into the survey in order to aid the investigation of factors associated with dominant decision makers (see Appendix B.3 for details of all supplementary questions).

Making use of psychology scales, respondents were asked to consider their opinions and attitudes, as member of a partnership and indicate whether they agreed or disagreed with eight statements. The statements were generally based on psychology scales used by Kashima et al. (1995) (see also Markus and Ki-

[1] See also Chapter 3 and Chapter 5 for other applications of this data.

tayama, 1991 and Triandis and Gelfand, 1998). The questions have been grouped into two different categories; one pertaining to measures of "Agency" and the other to measures of "Collectivism".

A person who possesses "Agency" is defined by Depue and Collins (1999) as having a more general motivational disposition that includes dominance, ambition, mastery, efficacy, and achievement. Similarly, Eagly and Wood (1991) state that agency relates to traits such as the inclination to be independent, assertive, and competent and consequently demonstrate characteristics such as dominance during social interactions, elevated levels of activity, and goal achievement. Whereas collectivism, as defined by Kim and Choi (2005): "... emphasizes interdependence, in-group harmony, family security, group-oriented goals, social hierarchies, cooperation, and a low level of competition (Hofstede, 1980; Triandis, 1995)".

The four questions that were used, which related to measures of *agency* were:

(a) "I do things my way regardless of what my partner expects me to do.";

(b) "I feel uneasy when my opinions are different from those of my partner.";

(c) "I stick to my opinions even when my partner doesn't support me."; and

(d) "I base my actions more upon my own judgements than upon the decisions of my partner.".

Responses to these questions are shown in Table 6.1. From the table we can see that the difference between the numbers of males and females stating either "Disagree", "Neither Agree nor Disagree" or "Agree" is marginal. This is especially true for question (a). In the responses to question (b), we find more males stating both "Agree" and also "Disagree" than females, which is a consequence of the higher rate of females stating either "Neither Agree nor Disagree" or "Don't Know" or simply refusing to answer the question. Indeed, for all attitudinal questions relating to both agency and collectivism, more females refused to answer than males and with the exception of questions (a) and (d), more females stated "Don't Know". These results are contrary to previous findings showing a higher prevalence of males stating "Don't Know" in this survey (c.f. Chapters 3 and 5). What is also noticeable, is the high rate of respondents stating "Neither Agree nor Disagree', for all agency related questions we find a minimum of 42% of respondents giving this response. Overall, we find that for those respondents who provided answers that were not neutral, most agreed with statements (a), (c) and (d) and disagreed with statement (b), although the differences are less apparent for statement (a).

Table 6.1: Responses to agency questions.

	Disagree		Neither Agree nor Disagree		Agree		Don't Know		Refused to Answer	
	Count	%	Count	%	Count	%	Count	%	Count	%
(a) *do things my way regardless*										
Male	52	18.06	126	43.75	79	27.43	24	8.33	7	2.43
Female	54	18.75	128	44.44	75	26.04	22	7.64	9	3.13
(b) *feel uneasy when my opinions are different*										
Male	101	35.07	123	42.71	35	12.15	25	8.68	4	1.39
Female	88	30.56	129	44.79	25	8.68	37	12.85	9	3.13
(c) *I stick to my opinions*										
Male	29	10.07	138	47.92	97	33.68	20	6.94	4	1.39
Female	34	11.81	120	41.67	103	35.76	20	6.94	11	3.82
(d) *rely on own judgements*										
Male	23	7.99	147	51.04	88	30.56	25	8.68	5	1.74
Female	29	10.07	126	43.75	101	35.07	20	6.94	12	4.17

The four questions that were used, which related to measures of *collectivism* are:

(e) "I am willing to compromise with my partner when making decisions.";

(f) "I respect and support decisions made by my partner even when they may be wrong.";

(g) "I am prepared to do things for my partner at any time, even though I have to sacrifice my own interests."; and

(h) "I think it is more important to give priority to my partner's interests rather than to my own.".

Responses to the collectivism questions are shown in Table 6.2. In Table 6.2 we see again that the differences between the responses given by males and females are minimal. For question (e), over 40% of males and females agreed with the statement, but this was closely followed by people reporting "Neither Agree nor Disagree" (38% of males and 32% of females). We find similar proportions for the responses to question (f), however with fractionally less people reporting "Agree" than "Neither Agree nor Disagree". For questions (g) and (h), we find the highest proportion of people stating "Neither Agree nor Disagree", with nearly 55% of males reporting "Neither Agree nor Disagree" to question (h).

6.2.2 Measurement equations

Using a similar specification to that used for the cooking indicators in Chapter 5, we make use of an ordered logit specification to model the responses to the agency and collectivism attitudinal questions. However, contrary to Chapter 5, we make use of two ICLV models, each separately including just one latent variable. The first ICLV model includes a latent variable for the questions relating to measures of agency, $\alpha_{A,n}$, and the second ICLV model includes a latent variable for the questions relating to measures of collectivism, $\alpha_{C,n}$. We compare each of these two models with a base MMNL model. Below, we outline the specification for the incorporation of the latent variable $\alpha_{A,n}$ in the first ICLV model. Similar steps can be used to derive the specification for incorporating the latent variable $\alpha_{C,n}$ in the second ICLV model.

Let us assume that we have a latent variable α, which for respondent n takes the value α_n, with:

$$\alpha_n = f\left(z_n, \gamma\right) + \eta_n \tag{6.2}$$

Table 6.2: Responses to collectivism questions.

	Disagree		Neither Agree nor Disagree		Agree		Don't Know		Refused to Answer	
	Count	%	Count	%	Count	%	Count	%	Count	%
(e) *willing to compromise*										
Male	30	10.42	108	37.50	116	40.28	30	10.42	4	1.39
Female	39	13.54	92	31.94	117	40.63	32	11.11	8	2.78
(f) *unconditional support*										
Male	33	11.46	120	41.67	111	38.54	19	6.60	5	1.74
Female	31	10.76	125	43.40	99	34.38	23	7.99	10	3.47
(g) *sacrifice my own interests*										
Male	48	16.67	133	46.18	76	26.39	27	9.38	4	1.39
Female	48	16.67	120	41.67	77	26.74	32	11.11	11	3.82
(h) *give priority to partner*										
Male	61	21.18	158	54.86	43	14.93	20	6.94	6	2.08
Female	69	23.96	135	46.88	51	17.71	21	7.29	12	4.17

where $f(z_n, \gamma)$ represents the deterministic part of α_n, with, z_n being a vector of socio-demographic variables, γ being a vector of estimated parameters and η_n is a random disturbance, which follows a standard Normal distribution across respondents. We use a linear in attributes specification for the deterministic part, and write:

$$\alpha_n = \gamma_\alpha z_n + \eta_n, \tag{6.3}$$

If we consider the probability of observing a given value s, with $s = 1, 2, 3$[2] for the k^{th} indicator relating to agency (with $k = 1, \ldots, 4$) for respondent n:

$$P(I_{k,n}) = \frac{e^{\mu_{k,s} - \zeta_{I_k}\alpha_{A,n}}}{1 + e^{\mu_{k,s} - \zeta_{I_k}\alpha_{A,n}}} - \frac{e^{\mu_{k,s-1} - \zeta_{I_k}\alpha_{A,n}}}{1 + e^{\mu_{k,s-1} - \zeta_{I_k}\alpha_{A,n}}} \tag{6.4}$$

where the estimated effect of the latent variable $\alpha_{A,n}$ on this indicator is given by ζ_{I_k}, and the probability of the actual observed response is then given by:

$$L_{I_{k,n}} = \sum_{s=1}^{S} \mathbb{I}_{\mathrm{s}}^{k,n} \left[\frac{e^{\mu_{k,s} - \zeta_{I_k}\alpha_{A,n}}}{1 + e^{\mu_{k,s} - \zeta_{I_k}\alpha_{A,n}}} - \frac{e^{\mu_{k,s-1} - \zeta_{I_k}\alpha_{A,n}}}{1 + e^{\mu_{k,s-1} - \zeta_{I_k}\alpha_{A,n}}} \right] \tag{6.5}$$

where $\mathbb{I}_1^{k,n} = 1$ if respondent n gives level 1 as the answer to the k^{th} attitudinal question, and zero otherwise. For normalisation, we set $\mu_{k,0} = -\infty$ and $\mu_{k,3} = +\infty$ and estimate the two intermediate values, imposing the constraint that $\mu_{k,s} \geq \mu_{k,s-1}$. Finally, we set $L_{I_n} = \prod_{k=1}^{4} L_{I_{k,n}}$.

6.2.3 Stated choice component

In the stated choice component of the survey, respondents were presented with the choice between three different meal options, described in terms of calories, cooking time, food type and cost. The structure of the interviews was such that each *household head* was asked to complete an individual questionnaire (which included 8 choice tasks) separately and also complete together a *joint* questionnaire. The joint questionnaire also included 8 choice tasks, which for the purposes of comparable analyses were identical in both attributes and order to those completed during the individual interviews. In the choice tasks a *no choice* option was not explicitly included, however if the respondents could not decide, then this was recorded as a "Don't Know" by the interviewer, but if the respondents

[2]Note here, that we consider only three observed levels, as responses "Refused" and "Don't Know" were combined with "Neither Agree nor Disagree" to create a neutral response.

could not *agree* this was recorded as a "Can't Agree" instead.

Recounting the household utility function (c.f. Equation 6.1) focussing on a two-person context, the deterministic component of utility that household h obtains from choosing alternative i is represented as:

$$V_{hi} = \lambda\left(\beta_1 x_{hi}\right) + (1-\lambda)\left(\beta_2 x_{hi}\right) \qquad \forall 1 \leq i \leq 3 \tag{6.6}$$

$$V_{n4} = \delta_{\mathrm{DK}} \mathrm{DK}_{n4} \tag{6.7}$$

$$V_{n5} = \delta_{\mathrm{CA}} \mathrm{CA}_{n5} \tag{6.8}$$

where x_{hi} is a vector of attributes describing alternative i as faced by household h, β_1 and β_2 are vectors of estimated parameters for person 1 and for person 2 respectively and λ the bargaining coefficient, represents the relative distribution of weight between the two household members. Equation 6.6 shows the utility household h will receive if they select any of the first three alternatives, whereas Equation 6.7 shows the utility household h will receive through the selection of the "Don't Know" option (displayed as alternative 4, in this case). Equivalently, Equation 6.8 shows the utility household h will receive from not being able to agree, namely the "Can't Agree" option (alternative 5).

The latent variables described above, can now be used as explanatory variables in the utility function, which is rewritten as:

$$V_{hi} = f\left(\beta, x_{hi}, \delta, \lambda, \tau, \alpha_n\right) \tag{6.9}$$

where τ is a vector of parameters that explain the impact of the vector of latent variables α_n on the bargaining coefficient λ.

Our joint model now has two components, a choice model and a measurement model for the attitudinal questions. The likelihood for the observed sequence of choices for household n is given by $L\left(y_n \mid \beta, \delta, \lambda, \tau, \alpha_n\right)$, which is a product of logit probabilities, including the parameters of the base choice model; the parameters β, bargaining coefficient λ, interaction terms τ and the latent variable α. The likelihood for the measurement model for the attitudinal questions is given by $L\left(I_n \mid \zeta_I, \mu, \alpha_n\right)$, which is a function of interaction terms ζ, the threshold parameters μ, and the latent variable. In combination, the log-likelihood function is thus given by:

$$LL\left(\beta, \delta, \lambda, \tau, \gamma, \zeta_I, \mu\right) = \sum_{n=1}^{N} \ln \int_{\eta} L\left(y_n \mid \cdot\right) L\left(I_n \mid \cdot\right) g(\eta)\, \mathrm{d}\eta \tag{6.10}$$

where integration over the random component of α is needed. In addition to the parameters estimated for the standard model, the estimation of this model thus entails the estimation of the vector of interaction terms τ, the parameters of the various measurement equations, and the socio-demographic interaction terms γ.

6.2.4 Results

For the present study, we made use of responses from 288 individuals, giving $6,912$ observations in total, as each member of the household completed the survey both individually and jointly. In all three models, we allow for allow for random heterogeneity in the β parameters, using Normal distributions. All models were coded in Ox 6.2 (Doornik, 2007).

The first column in Table 6.3 shows the estimation results for a MMNL model assuming heterogeneity in both the β and λ parameters. To allow for additional random heterogeneity in the λ parameters we made use of Uniform distributions. The second column in Table 6.3 shows the estimation results for the ICLV model, which included the latent variable relating to measures of agency, $\alpha_{A,n}$. Finally, the third column in Table 6.3 shows the results for the ICLV model, which included a latent variable for the questions relating to measures of collectivism, $\alpha_{C,n}$.

As shown in Table 6.3, we retrieve little differences between the β coefficients in the three models, with the only notable ones being the increased significance of $\sigma_{\beta_{\text{HighTime}}}$ and reduced significance of $\sigma_{\beta_{\text{Italian}}}$ in the MMNL model. Additionally we see the coefficient for $\sigma_{\beta_{\text{Italian}}}$ increase in significance in the ICLV model incorporating the latent variable collectivism. These estimates are in line with previous findings in Chapter 5, although in the model used in Chapter 5, all random heterogeneity was linked to the latent variables only.

When comparing the component of the log-likelihood relating to the choice model, conditional on the other components, we find a significant improvement over the base MMNL model by 23.56 units for the ICLV agency model and 30.39 units for the ICLV collectivism model, for 14 additional parameters each.

Table 6.4 shows the corresponding estimation results for the λ parameters, with λ_a representing the lower bound and λ_s the spread, of the Uniform distribution. Also, $\tau_{\alpha_{\text{P}_1}}$ represents the impact of person 1's latent variable α_{P_1} on the bargaining coefficient λ and $\tau_{\alpha_{\text{P}_2}}$ represents the corresponding impact of person 2's latent variable α_{P_2}. We remember here that as λ tends towards 0 this theoretically gives more weight to person 2's preferences and as λ tends towards 1 gives more weight to person 1's preferences.

What is most noticeable about Table 6.4 is the lack of significant parameters. Considering the MMNL model, we find only the parameters weighting low calo-

Table 6.3: Estimation results for choice model components: β's

	MMNL		ICLV Agency		ICLV Collectivism	
	est.	t-rat.	est.	t-rat.	est.	t-rat.
$\mu_{\beta_{\text{LowCal}}}$	0.4799	9.06	0.4669	9.34	0.4755	9.43
$\sigma_{\beta_{\text{LowCal}}}$	0.7601	10.83	0.7152	-11.50	0.6629	-9.62
$\mu_{\beta_{\text{HighCal}}}$	-0.0929	-1.63	-0.0477	-0.89	-0.1240	-2.22
$\sigma_{\beta_{\text{HighCal}}}$	0.8731	-12.07	0.8245	-12.88	0.9457	-15.58
$\mu_{\beta_{\text{LowTime}}}$	0.1178	2.26	0.1314	2.62	0.1177	2.36
$\sigma_{\beta_{\text{LowTime}}}$	0.6134	6.65	0.6115	-10.76	0.5824	-9.39
$\mu_{\beta_{\text{HighTime}}}$	-0.0865	-1.83	-0.0908	-1.98	-0.0887	-1.91
$\sigma_{\beta_{\text{HighTime}}}$	0.1700	2.07	0.0589	0.69	0.0621	0.64
$\mu_{\beta_{\text{Italian}}}$	-0.2611	-5.59	-0.3006	-6.62	-0.3044	-6.55
$\sigma_{\beta_{\text{Italian}}}$	0.2784	1.60	0.2580	2.99	0.3287	3.39
$\mu_{\beta_{\text{Asian}}}$	-0.5307	-9.91	-0.5686	-11.39	-0.5231	-10.77
$\sigma_{\beta_{\text{Asian}}}$	0.9202	13.79	0.8182	13.71	0.7844	12.92
$\mu_{\beta_{\text{LowCost}}}$	0.3970	5.19	0.3896	5.89	0.3795	5.73
$\sigma_{\beta_{\text{LowCost}}}$	1.6549	22.44	1.5843	25.52	1.7081	25.14
$\mu_{\beta_{\text{HighCost}}}$	-0.1716	-3.41	-0.1467	-3.19	-0.1822	-3.77
$\sigma_{\beta_{\text{HighCost}}}$	0.4984	6.31	0.3193	3.78	0.4743	6.88
δ_{DK}	-3.2585	-25.32	-3.3211	-25.94	-3.3208	-25.88
δ_{CA}	-1.0562	-11.07	-1.1253	-11.89	-1.1260	-11.82
Choice component $\mathcal{LL}$	-7,201.00		-7,177.44		-7,170.61	
Overall $\mathcal{LL}$	-		-9,280.26		-9,308.64	

ries, Asian and low cost have significant lower bounds, with the low cost weight also being the only parameter to have a significant range. For the ICLV model incorporating collectivism latent attitudes we also find a low level of significant parameters, with only $\tau_{\alpha_{\mathrm{P}_2},\lambda_{\mathrm{LowTime}}}$ and $\tau_{\alpha_{\mathrm{P}_2},\lambda_{\mathrm{Italian}}}$ for person 2 and $\tau_{\alpha_{\mathrm{P}_1},\lambda_{\mathrm{Asian}}}$ for person 1 showing significant impacts on the bargaining coefficients. For the ICLV model incorporating agency latent attitudes, only $\tau_{\alpha_{\mathrm{P}_1},\lambda_{\mathrm{LowCost}}}$ is found to be significant. Additionally, we find that for all of the λ distributions, in each of the three models, the mean is not significantly different from 0.5.

We finally turn to the results for the measurement models for the eight attitudinal questions; the four relating to agency are shown in Table 6.5 and the four relating to collectivism are shown in Table 6.6. We can see that the thresholds are all increasing in magnitude, as is required by the model. Additionally, we see positive estimates for the interaction terms in all equations, except for question (b), although this is not significant. This means that a more positive value for the latent variable leads to stronger agreement with the statements. For person 2's agency latent attitude we find significant interactions for being male (negative) and over 50 years old (positive), although these are not significant for person 1. Also, for person 2's collectivism latent attitude we find significant interactions for being male and over 50 years old (both positive), although these are not significant for person 1, who has a significant negative interaction for those under 35 years of age.

6.3 Summary and conclusions

In this paper we have shown, as in Chapter 5 that the use of ICLV models can lead to superior model fit. However, whilst in Chapter 5 this lead to the latent variables explaining both differences in sensitivities in the choice model as well as the responses to attribute ranking questions and attitudinal questions, similar achievements were not as dominant in this current application. Many of the estimated parameters were found to be insignificant and subsequently any conclusions drawn from these should be treated tentatively.

A number of limitations may be acknowledged with regards to the findings in this chapter. Firstly, we assumed a linear specification for the impact of the latent variables on the bargaining coefficient λ. Alternative specifications were trialled, but with exacerbated results. This is not to say that a non-linear specification would not prove useful in other contexts, but as detailed below, given the low statistical power of our model, we chose to remain with a linear specification.

Also, one might postulate that perhaps the use of the chosen agency and col-

Table 6.4: Estimation results for choice model components: λ's

	MMNL		ICLV Agency		ICLV Collectivism	
	est.	t-rat.	est.	t-rat.	est.	t-rat.
$\lambda_{a_{\text{LowCal}}}$	0.6215	2.73	0.5970	2.69	0.4808	1.92
$\lambda_{s_{\text{LowCal}}}$	-0.6068	-1.51	-0.2670	-0.65	-0.3711	-0.87
$\tau_{\alpha_{\text{P}_1},\lambda_{\text{LowCal}}}$	-	-	0.0864	0.76	-0.0574	-0.48
$\tau_{\alpha_{\text{P}_2},\lambda_{\text{LowCal}}}$	-	-	0.1133	1.24	0.0183	0.17
$\lambda_{a_{\text{HighCal}}}$	0.1447	0.72	0.1204	0.55	0.5722	2.66
$\lambda_{s_{\text{HighCal}}}$	0.4785	1.29	0.4702	0.98	0.0608	0.14
$\tau_{\alpha_{\text{P}_1},\lambda_{\text{HighCal}}}$	-	-	0.1119	0.95	0.0842	0.73
$\tau_{\alpha_{\text{P}_2},\lambda_{\text{HighCal}}}$	-	-	0.0313	0.26	-0.1826	-1.42
$\lambda_{a_{\text{LowTime}}}$	0.3431	1.46	0.3526	1.82	0.0791	0.35
$\lambda_{s_{\text{LowTime}}}$	0.0169	0.04	0.1036	0.31	0.4642	1.22
$\tau_{\alpha_{\text{P}_1},\lambda_{\text{LowTime}}}$	-	-	0.1231	1.09	-0.1941	-1.90
$\tau_{\alpha_{\text{P}_2},\lambda_{\text{LowTime}}}$	-	-	-0.0334	-0.32	0.2217	2.10
$\lambda_{a_{\text{Italian}}}$	1.0064	1.80	1.3185	2.34	0.9089	1.78
$\lambda_{s_{\text{Italian}}}$	-1.2844	-1.06	-1.3594	-1.34	-1.6218	-1.52
$\tau_{\alpha_{\text{P}_1},\lambda_{\text{Italian}}}$	-	-	0.1174	0.45	-0.1550	-0.49
$\tau_{\alpha_{\text{P}_2},\lambda_{\text{Italian}}}$	-	-	-0.3619	-1.49	0.6410	2.26
$\lambda_{a_{\text{Asian}}}$	0.4312	2.39	0.8495	4.98	0.6717	4.37
$\lambda_{s_{\text{Asian}}}$	0.2830	0.96	-0.7225	-2.43	-0.4335	-1.55
$\tau_{\alpha_{\text{P}_1},\lambda_{\text{Asian}}}$	-	-	0.0497	0.51	-0.1630	-2.24
$\tau_{\alpha_{\text{P}_2},\lambda_{\text{Asian}}}$	-	-	0.0744	1.13	0.0616	0.60
$\lambda_{a_{\text{LowCost}}}$	0.2846	3.38	0.3166	2.63	0.2475	2.43
$\lambda_{s_{\text{LowCost}}}$	0.5300	3.57	0.3216	1.42	0.3746	1.80
$\tau_{\alpha_{\text{P}_1},\lambda_{\text{LowCost}}}$	-	-	0.1181	2.03	-0.0203	-0.34
$\tau_{\alpha_{\text{P}_2},\lambda_{\text{LowCost}}}$	-	-	0.0320	0.66	0.0676	1.22
$\lambda_{a_{\text{HighCost}}}$	0.1780	0.54	0.4692	1.12	0.7102	2.92
$\lambda_{s_{\text{HighCost}}}$	0.7379	1.22	-0.0289	-0.04	-0.7493	-1.42
$\tau_{\alpha_{\text{P}_1},\lambda_{\text{HighCost}}}$	-	-	0.2872	1.26	-0.1222	-0.88
$\tau_{\alpha_{\text{P}_2},\lambda_{\text{HighCost}}}$	-	-	0.3428	1.60	0.0636	0.45

Table 6.5: Estimation results for structural equation model for latent attitude towards agency and corresponding measurement model estimation results

	Person 1		Person 2	
	est.	t-rat.	est.	t-rat.
$\gamma_{\text{Agency}_{\text{Male}}}$	0.1230	0.89	-0.4177	-2.49
$\gamma_{\text{Agency}_{<35}}$	-0.1157	-0.78	0.1307	0.71
$\gamma_{\text{Agency}_{50+}}$	0.2381	1.60	0.6804	3.33
(a) *do things my way regardless*				
ζ_a	1.1140	5.59	0.8863	4.16
Threshold 1	-1.6696	-7.75	-1.7476	-7.58
Threshold 2	1.3270	6.17	1.1299	5.71
(b) *feel uneasy when my opinions are different*				
ζ_b	-0.2297	-1.44	0.3038	1.93
Threshold 1	-0.7053	-5.43	-0.7806	-5.73
Threshold 2	2.2250	11.06	2.1062	10.77
(c) *I stick to my opinions*				
ζ_c	2.1924	6.05	1.4459	5.24
Threshold 1	-2.7386	-6.53	-3.2207	-8.44
Threshold 2	1.3174	4.02	0.7403	2.78
(d) *rely on own judgements*				
ζ_d	1.8105	6.28	1.2035	5.02
Threshold 1	-2.8296	-7.75	-3.1046	-8.82
Threshold 2	1.2009	4.28	0.9025	3.87

Table 6.6: Estimation results for structural equation model for latent attitude towards collectivism and corresponding measurement model estimation results

	Person 1		Person 2	
	est.	t-rat.	est.	t-rat.
$\gamma_{\text{Collect}_{\text{Male}}}$	-0.1755	-1.00	0.2930	2.02
$\gamma_{\text{Collect}_{<35}}$	-0.5220	-2.34	0.1726	1.00
$\gamma_{\text{Collect}_{50+}}$	0.2769	1.35	0.3544	2.11
(e) *willing to compromise*				
ζ_e	1.0751	4.70	1.5247	5.25
Threshold 1	-2.6731	-8.89	-1.8340	-6.33
Threshold 2	0.3069	1.46	1.2441	4.42
(f) *unconditional support*				
ζ_f	0.6825	3.44	0.9549	4.40
Threshold 1	-2.2909	-9.46	-2.0166	-8.55
Threshold 2	0.4987	3.05	1.0780	5.07
(g) *sacrifice my own interests*				
ζ_g	0.8971	4.61	0.9973	4.41
Threshold 1	-1.9354	-8.13	-0.5018	-7.02
Threshold 2	1.1433	5.58	1.5579	6.57
(h) *give priority to partner*				
ζ_h	0.6946	4.23	1.1223	4.62
Threshold 1	-1.4644	-7.70	-1.0012	-4.72
Threshold 2	1.6250	8.10	2.5574	8.07

lectivism indicators were not sufficiently able to de-tangle the bargaining process taking place within our survey. However, given the findings in Chapter 3, it is more likely that as 65% of people were found to have similar preferences, with an additional 10% found to have similar preferences but with a different measure of scale; this essentially reduced the *bargaining* sample size down to just 25%. In so far as only 25% of households, contained members with differing preferences; who would be in a position to bargain. With such a small proportion of people 'bargaining', it is not surprising that the model struggled to retrieve significant effects. This could also be another reason for the results in Beharry-Borg et al. (2009); who found in their small sample of 45 couples only 22% of their couples fell within the range of values reflecting 'bargaining' behaviour.

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Chapter 7

Summary, conclusions and directions for future research

7.1 Introduction

The research presented in this thesis has been concerned with the enhancement of discrete choice models. Such enhancements have allowed for a better understanding of the behaviour which takes place during the choice process, but have also shown improvements in the explanatory power of discrete choice models. Specifically, the research has explored the role that the different opinions, attitudes and preferences play within different decision making structures.

This chapter provides a summary of the work described in this thesis, documenting the main conclusions, along with potential limitations and suggested avenues for future research.

7.1.1 Intra-household choices

The objective of the first part of the thesis was to examine the effectiveness of different decision making structures within the discrete choice framework. In order to best accomplish this, two different empirical data sets were examined. Having reviewed the literature and conducted a preliminary analysis of the data, it was decided to use the first data set (namely, the Swedish Data) to compare and contrast the existing literature conclusions regarding the model specification and legitimacy of weighting parameters outside the $[0, 1]$ range. The second data set (that is, the Food Data) was then used to supplement other existing literature concerning the ability of a person to correctly act as a proxy for his or her partner when asked to make a decision.

The first paper, focussed on the issue of the representation of heterogeneity in choice models. The data included decisions made by a single person, which affected not only themselves but their partners too. A number of central ideas were put forward in the paper. Firstly, we showed that the weights respondents assign to their partners vary across attributes, although such differences can only be properly retrieved when allowing for heterogeneity in the marginal utility coefficients. Secondly, we showed that there is scope for significant heterogeneity across respondents in their underlying sensitivities as well as the relative weights assigned to themselves and their partners. We also retrieved differences between male and female respondents in both sets of parameters, but noted that such differences were only possible to capture adequately if the random variations were accommodated for simultaneously. Finally, we argued that there is potentially significant scope for confounding between heterogeneity in marginal sensitivities and heterogeneity in bargaining or weight parameters; with the risk of inappropriate assumptions for the distribution of randomly distributed bargaining or weight parameters leading to misguided results and interpretations. These claims were strongly supported by the evidence from the empirical data.

In the second paper we evaluated the literature on the ability of a household member to accurately represent their household through the medium of proxy reporting, finding mixed views. Making use of an empirical data set, which was collected to elicit intra-household trade-offs between meal options, we tested different prediction scenarios. We found that in general, males were more likely to state *"Don't Know"* when asked to provide responses on behalf of their partners. However more importantly, we found that for those males confident in their partners preferences, the level of accuracy was found to be at least as good as their female counterparts. This could have important implications for procedures used to target respondents in household surveys, when there is a need to provide accurate proxy responses.

7.1.2 Integrated choice and latent variable models

The second part of the research was dedicated to extending the current literature on integrated choice and latent variable models. Initially the food data was used to examine a novel application of attribute preference orderings to augment the model information.

In this paper, we highlighted the benefit of using ICLV models in the study of consumers' food choices. Specifically, we looked at the impact attitudes and underlying preferences have on the decision making process. We made use of additional information collected on respondents' attitudes towards cooking and their ranking of the considered attributes. By using an integrated choice and latent variable structure, we avoided the risk of measurement error or endogeneity bias. We highlighted how this model obtains significant improvements in model fit, with the latent variables used to explain both differences in sensitivities in the choice model as well as the responses to attribute ranking questions and attitudinal questions.

In the final paper, we made use of two ICLV models, in a multi-agent decision making context. Again we found a superior model fit. However, when we examined our findings in more detail, we found much insignificance and potentially tentative results. We hypothesised that this could be due to a number of reasons, but primarily a consequence of the respondents in the data having such similar preferences, leading to a failure in the household bargaining model to retrieve significant effects, given that such a small proportion of people fall into the 'bargaining' framework.

Here, we reiterate an important point made at the start of this thesis. Discrete choice models allow for a high degree of flexibility with regard to the different specifications, which can be employed, but the consequence of this is that they also increase the risk of misspecification and misinterpretation by the researcher. For example, choosing inappropriate distributions to explain either the random taste heterogeneity (as also emphasised in our first paper) or the simple model specification, will have a direct influence on the model results. This can consequently lead to spurious conclusions and potentially misguided policy-decisions. Hence, based on the accumulated empirical evidence, we would agree with the general consensus that the most appropriate form will depend on the specific data. Although, within this thesis we make use of some advanced modelling structures, we do not feel that these techniques should surpass the initial necessary stages needed to gain more knowledge and understanding about the internal behaviour of a data set.

7.2 Potential limitations of the study and avenues for future research

There are a number of potential shortcomings of this research that are acknowledged throughout this thesis. Additionally, a number of important avenues for future research have also been identified in the context of the applied part of this research, especially so but not limited to the integrated choice and latent variable framework. In our third paper, we made use of a novel structure where we utilised information on respondents attribute rankings. There is significant scope for future work investigating the use of other supplementary information, within these advanced models.

In the context of the discussions in the theoretical part of the thesis, there is clearly some scope for further testing. An important aim, would be to establish whether the results produced in this work extend to other datasets and decision scenarios. This applies especially to the findings in our multi-agent models, where there is scope for testing non-linear formulations for the weight parameters. Additionally, an avenue for further work could be to investigate how a respondents knowledge and predictive accuracy for their household, affects joint household decisions, namely, do respondents with higher levels of accuracy, subsequently have higher levels of 'power' within the household decisions?

7.2.1 Other multi-agent decision making structures

Although the focus in this thesis has been on intra-household choices (i.e, considering decision-making structures which include only those members within ones own household), it is important to note that other decision-making structures exist and are well documented in the literature. This next section provides an overview of these other structures, with the hope that the findings and contributions in this thesis could be extended to these other structures.

Interactive Agency Choice Experiments (IACE) Models

Most research so far, has been based on the fact that decisions made are simultaneous. However Brewer and Hensher (2000) has since developed a model, which takes into consideration the fact that decisions are usually acquired after a series of negotiations. Incorporating the sequential nature of a decision process, they make use of Interactive Agency Choice Experiment's (IACE) (Brewer and Hensher, 2000; Hensher et al., 2008; Rose and Hensher, 2004). This alternative approach models endogenous interactions between individual group members through a process of feedback and revision. In their model, Brewer and Hensher (2000) draw on knowledge of game theory.

Neighbourhood Effects

There has been a body of literature (see, for example Brock and Durlauf, 2001, 2002, 2006) that suggests that decisions made by households (and individuals) are influenced exogenously by factors such as their neighbours opinions and attitudes (i.e. social interactions). Social interactions are the interdependencies between individual decisions and the decisions and characteristics of others within a common group. A potential avenue of research, could be to include these endogenous influences on the household within an ICLV structure.

Working as a group

Thorndike (1938) tested the hypothesis (originally conceived by Watson, 1931) that one of the important factors in determining the amount of group superiority (in comparison to the capabilities of individuals attempting simple tasks, such as sentence completion and vocabulary tests) may be the range of possible responses to the task situation. Thorndike (1938) tests the hypothesis that as the range of possible responses is increased, the superiority of 'group' over 'individual' will increase.

The concept that the task *structure* will effect the nature of responses from a group is also discussed by Adamowicz et al. (2005). Their application of this idea, discusses the effects of question structure on the aggregation rule. Adamowicz et al. (2005) suggest that the respondents will adopt similar strategies when making communal decisions to those, which would be used to analyse the task results. For example, in order to apply a 'majority rule' analysis, this would require that the members choose among different alternatives; empirical studies have suggested that when faced with a preference task, groups often apply a majority or plurality rule; also, when faced with an inference task, groups will often apply a 'truth-wins' principle if the members who are correct are able to demonstrate the correctness of their inference (see, for example Laughlin and Ellis, 1986).

Within marketing research, some of the first attempts to model group decisions were carried out by Choffray and Lilien (1976, 1980)[1]. Choffray and Lilien created a range of models which were new to the marketing literature, as their focus was on the interaction mechanism, which mapped the individual choice probabilities into group choice probabilities. This interaction mechanism as proposed by Choffray and Lilien (1976, 1980) was an algebraic function that reflected the nature of how the groups decided. For example, the decision could have been put to a majority vote, or a particular individual could have been elected to make the decision, etc.

7.3 Final word

The theories, deviations and extensions from the more traditional choice model which have been presented in this thesis, have a number of practical applications

[1]Cited in Steckel et al. (1991)

when analysing choices from a variety of applied fields. Therefore, this thesis contributes to the literature concerning decisions which are not made by a single person, but in consultation with other *actors*. It has contributed to recent methodological advances, and supported these using empirical evidence. More specifically, this thesis adds to the growing literature on both integrated choice and latent variable (ICLV) models and multi-agent choices.

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Appendices

Appendix A

Interviewer: At the door

Hello, I'm *(Name)* from MRNI Survey Company and I'm conducting interviews on behalf of Queen's University Belfast about people's preferences for household and food purchases. If you wish to take part in the survey the answers that you provide will be important for decisions regarding future food policy. Any information that you provide will be kept confidential and will not be used for any other purposes. As an incentive for participating you will be entered into a prize draw to win £100 One4all vouchers.

Are you the head of the household, or the partner of the head of the household?

> **If yes: go to 2.**
>
> **If not:** Could I please speak to the head of the household?
>
> > **If yes: go to 1.**
> >
> > **If not present: go to 4.**

1. Hello, I'm *(Name)* from MRNI Survey Company and I'm conducting interviews on behalf of Queen's University Belfast about people's preferences for household and food purchases. If you wish to take part in the survey the answers that you provide will be important for decisions regarding future food policy. Any information that you provide will be kept confidential and will not be used for any other purposes. As an incentive for participating you will be entered into a prize draw to win £100 One4all vouchers. **Go to 2.**

2. Are you and your partner both currently available to take part in a short interview?

> **If no: go to 4.**
>
> **If yes: go to 3.**

3. This interview will help us find out about your attitudes and preferences for household purchases as well as your partner's preferences and attitudes. It will involve answering a few questions individually and then answering some questions jointly. When answering the questions individually, it is important that your partner is not in the room would this be acceptable and are you willing to take part in the interview?

If yes: conduct "household questionnaire".

If no: go to 4.

4. Are you currently available to take part in a short interview?

If no: Thank the person for their time.

If yes: conduct "food questionnaire"[1].

[1] The UKCRC Centre of Excellence for Public Health (NI), were simultaneously collecting a dataset which concentrated on individual food choices only (see Brown, H., Forthcoming. *Preference Survey on Food Choice Behaviour and Obesity.* Ph.D. Thesis. Queen's University Belfast.)

Appendix B

Household questionnaire

B.1 Individual questionnaires - Part I

Note to Interviewer:

This questionnaire is to be answered individually by each member of the household. It is important that whoever answers the questionnaire first is hereafter known as "PERSON 1". Whoever answers the questionnaire second is known as "PERSON 2". These identifiers are necessary when answering the JOINT questionnaire.

If possible it would be ideal if the person not answering the questionnaire cannot hear the answers and/or responses given by their partner.

Interviewer: Thank the respondent for taking the time to complete this questionnaire. Please remind the respondent that it is important for them to complete this questionnaire on their own and not to discuss its contents with their partner.

For each question a "Don't Know" option is provided, but please do not inform the respondent that it is available and only check it, if the respondent does not know an answer.

Person 1

Introduction

To start with, we would like to find out who is usually responsible for buying the food for the household. This relates only to the food that is bought to cook and eat at home, and excludes any food bought in restaurants, cafes etc.

1. Typically who in your household is responsible for buying the food that is bought for you and your partner to cook and eat at home?

   ☐ Always me

   ☐ Usually me

   ☐ Shared (50/50)

   ☐ Usually my partner

   ☐ Always my partner

   ☐ Someone else

2. During a typical week, how many days would you and your partner eat an evening meal together that was prepared and cooked at home?

   ☐ Never

   ☐ 1 – 2 times

   ☐ 3 – 5 times

   ☐ 6 – 7 times

3. During a typical week, how many days do you prepare and cook the evening meal that you and your partner eat together at home?

   ☐ Never

   ☐ 1 – 2 times

   ☐ 3 – 5 times

   ☐ 6 – 7 times

4. During a typical week, how many days would you and your partner, eat the same evening meal (example: both eat lasagne)?

   ☐ Never

   ☐ 1 – 2 times

   ☐ 3 – 5 times

   ☐ 6 – 7 times

Information

In this section we are interested in finding out your preferences for meals. Imagine that each meal option represents a typical evening meal that you would share with your partner in your home. The meal options are described in terms of the number of calories, cooking time, food type and cost.

Each meal option varies in the number of **Calories per portion.**

For the purposes of this research we have classified meals into three different levels depending on the number of calories per portion they contain. The first level contains meals that have less than 400 calories per portion. The second level contains meals that have between 400 and 600 calories per portion. And finally, the third level contains meals that have more than 600 calories per portion.

Interviewer: Ask the respondent if they prefer vegetarian or non-vegetarian meals and show the respondent the corresponding "Calories" show card. Give the respondent time to examine the "Calories" show card.

This show card is intended to illustrate examples of different meals at each of the three **calorie** levels.

Each meal option also varies in the **Length of Time.** This includes the time taken to prepare the ingredients and cook the meal.

Again, for the purposes of this research we have classified meals into three different levels depending on the length of time it takes to prepare and cook. The first level contains meals that take less than 30 minutes. The second level contains meals that take between 31 and 60 minutes. And finally, the third level contains meals that take more than 60 minutes.

Interviewer: Show the respondent the corresponding vegetarian or non-vegetarian "Time" show card. Give the respondent time to examine the "Time" show card.

This show card is intended to illustrate examples of different meals at each of the three **time** levels.

Each meal option also varies by **Food Type.**

Again, for the purposes of this research we have classified meals into three different types. The first of these food types are meals that are typically considered local. The second of these are meals that are typically considered to be Italian. And finally, the third of these are meals that are typically considered to be Asian.

Interviewer: Show the respondent the corresponding vegetarian or non-vegetarian "Food Type" show card. Give the respondent time to examine the "Food Type" show card.

This show card is intended to illustrate examples of different meals in each of the three **Food Types.**

The meal options also have different **Costs.** This is the total cost for all of the ingredients needed to produce a typical evening meal which would feed you and your partner.

For the purposes of this research, we have set three cost levels. These are £5, £10 and £15.

Choices

In the following questions you will be asked to choose between three options. Each option represents a typical evening meal that you and your partner would share in your home. As described earlier each meal option varies in the number of calories, cooking time, food type and cost.

We would like you to indicate the meal option that you would prefer most and the meal option that you would prefer least out of the three.

We would also like you to indicate the meal option that you think your partner would prefer most and the meal option that you think your partner would prefer least out of the three.

When making your choice please consider all of the features of each option. There are no right or wrong answers. It is very important that you do not consult with your partner when reaching your decisions.

To demonstrate what we would like you to do, please consider this example:

Interviewer: Show the respondent the "EXAMPLE CHOICE TASK" card and explain the following:
In this example there are three meal options to choose from and each varies in the number of calories, cooking time, food type and cost. What we would like you to tell us is the meal options that you would most and least prefer as well as the meal options that you think your partner would most and least prefer. Do you understand what you have to do?

Interviewer: If the respondent understands what they have to do, proceed to the choice tasks. If the respondent does not understand, please explain the example to them again.

Show the respondent the "CHOICE TASK 1" and explain:
Imagine that the evening meals that you and your partner could share were restricted to only these three options:

		Option A	Option B	Option C	Don't Know
Me	Which of the meal options you would prefer most?				
	Which of the meal options you would prefer least?				
My Partner	Which of the meal options do you think your partner would prefer most?				
	Which of the meal options do you think your partner would prefer least?				

*** REPEATED FOR 8 CHOICE TASKS IN TOTAL ***

5. Thinking about the choices you made, would you say that you ignored any of the following features?

	Yes	No	Don't Know
Calorie Content			
Time Spent to Prepare/Cook			
Food Type			
Cost			

6. How easy/difficult did you think it was to make the choices:

	Very Difficult	Difficult	Neither Difficult nor Easy	Easy	Very Easy	Don't Know
You would prefer?						
Your partner would prefer?						

FOR INTERVIEWER ONLY:

7. Please record whether the respondent was alone:

   ☐ Yes

   ☐ No

8. Please record the respondent's gender:

   ☐ Male

   ☐ Female

Please remind the respondent that it is important for them to complete this questionnaire on <u>their own</u> and not to discuss it's contents with their partner. Thank the respondent for taking the time to complete this questionnaire and finish their FIRST interview.

Now begin the FIRST individual interview with their partner.

Person 2

Introduction

To start with, we would like to find out who is usually responsible for buying the food for the household. This relates only to the food that is bought to cook and eat at home, and excludes any food bought in restaurants, cafes etc.

9. Typically who in your household is responsible for buying the food that is bought for you and your partner to cook and eat at home?

   ☐ Always me

   ☐ Usually me

   ☐ Shared (50/50)

   ☐ Usually my partner

   ☐ Always my partner

   ☐ Someone else

10. During a typical week, how many days would you and your partner eat an evening meal together that was prepared and cooked at home?

    ☐ Never

    ☐ 1 – 2 times

    ☐ 3 – 5 times

    ☐ 6 – 7 times

11. During a typical week, how many days do you prepare and cook the evening meal that you and your partner eat together at home?

    ☐ Never

    ☐ 1 – 2 times

    ☐ 3 – 5 times

    ☐ 6 – 7 times

12. During a typical week, how many days would you and your partner, eat the same evening meal (example: both eat lasagne)?

    ☐ Never

    ☐ 1 – 2 times

    ☐ 3 – 5 times

    ☐ 6 – 7 times

Information

In this section we are interested in finding out your preferences for meals. Imagine that each meal option represents a typical evening meal that you would share with your partner in your home. The meal options are described in terms of the number of calories, cooking time, food type and cost.

Each meal option varies in the number of **Calories per portion.**

For the purposes of this research we have classified meals into three different levels depending on the number of calories per portion they contain. The first level contains meals that have less than 400 calories per portion. The second level contains meals that have between 400 and 600 calories per portion. And finally, the third level contains meals that have more than 600 calories per portion.

Interviewer: Ask the respondent if they prefer vegetarian or non-vegetarian meals and show the respondent the corresponding “Calories” show card. Give the respondent time to examine the “Calories” show card.

This show card is intended to illustrate examples of different meals at each of the three **calorie** levels.

Each meal option also varies in the **Length of Time.** This includes the time taken to prepare the ingredients and cook the meal.

Again, for the purposes of this research we have classified meals into three different levels depending on the length of time it takes to prepare and cook. The first level contains meals that take less than 30 minutes. The second level contains meals that take between 31 and 60 minutes. And finally, the third level contains meals that take more than 60 minutes.

Interviewer: Show the respondent the corresponding vegetarian or non-vegetarian “Time” show card. Give the respondent time to examine the “Time” show card.

This show card is intended to illustrate examples of different meals at each of the three **time** levels.

Each meal option also varies by **Food Type.**

Again, for the purposes of this research we have classified meals into three different types. The first of these food types are meals that are typically considered local. The second of these are meals that are typically considered to be Italian. And finally, the third of these are meals that are typically considered to be Asian.

Interviewer: Show the respondent the corresponding vegetarian or non-vegetarian "Food Type" show card. Give the respondent time to examine the "Food Type" show card.

This show card is intended to illustrate examples of different meals in each of the three **Food Types.**

The meal options also have different **Costs.** This is the total cost for all of the ingredients needed to produce a typical evening meal which would feed you and your partner.

For the purposes of this research, we have set three cost levels. These are £5, £10 and £15.

Choices

In the following questions you will be asked to choose between three options. Each option represents a typical evening meal that you and your partner would share in your home. As described earlier each meal option varies in the number of calories, cooking time, food type and cost.

We would like you to indicate the meal option that you would prefer most and the meal option that you would prefer least out of the three.

We would also like you to indicate the meal option that you think your partner would prefer most and the meal option that you think your partner would prefer least out of the three.

When making your choice please consider all of the features of each option. There are no right or wrong answers. It is very important that you do not consult with your partner when reaching your decisions.

To demonstrate what we would like you to do, please consider this example:

Interviewer: Show the respondent the "EXAMPLE CHOICE TASK" card and explain the following:
In this example there are three meal options to choose from and each varies in the number of calories, cooking time, food type and cost. What we would like you to tell us is the meal options that you would most and least prefer as well as the meal options that you think your partner would most and least prefer. Do you understand what you have to do?

Interviewer: If the respondent understands what they have to do, proceed to the choice tasks. If the respondent does not understand, please explain the example to them again.

Show the respondent the "CHOICE TASK 1" and explain:
Imagine that the evening meals that you and your partner could share were restricted to only these three options:

<table>
<tr><th></th><th></th><th>Option A</th><th>Option B</th><th>Option C</th><th>Don't Know</th></tr>
<tr><td rowspan="2">Me</td><td>Which of the meal options you would prefer most?</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Which of the meal options you would prefer least?</td><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="6"></td></tr>
<tr><td rowspan="2">My Partner</td><td>Which of the meal options do you think your partner would prefer most?</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Which of the meal options do you think your partner would prefer least?</td><td></td><td></td><td></td><td></td></tr>
</table>

*** REPEATED FOR 8 CHOICE TASKS IN TOTAL ***

13. Thinking about the choices you made, would you say that you ignored any of the following features?

	Yes	No	Don't Know
Calorie Content			
Time Spent to Prepare/Cook			
Food Type			
Cost			

14. How easy/difficult did you think it was to make the choices:

	Very Difficult	Difficult	Neither Difficult nor Easy	Easy	Very Easy	Don't Know
You would prefer?						
Your partner would prefer?						

FOR INTERVIEWER ONLY:

15. Please record whether the respondent was alone:

- ☐ Yes
- ☐ No

16. Please record the respondent's gender:

- ☐ Male
- ☐ Female

Please remind the respondent that it is important for them to complete this questionnaire on <u>their own</u> and not to discuss it's contents with their partner. Thank the respondent for taking the time to complete this questionnaire and finish their FIRST interview.

Now begin the JOINT interview with BOTH MEMBERS of the household together.

B.2 Joint questionnaire

Interviewer: This questionnaire is to be answered by BOTH MEMBERS of the household together.

> **Note to Interviewer:**
> "Person 1" in the questionnaire refers to the member of the household that completed the questionnaire first and "Person 2" in the questionnaire refers to the member of the household that completed the questionnaire second.

Thank the respondents for taking the time to complete this questionnaire. Please remind them that it is important that both members of the household complete this questionnaire together and it is not just completed by only one member.

Also, remind them that all of the information provided will not be used for any other purposes than this research and will remain confidential at all times.

For each question a "Don't Know" option is provided, but please do not inform the respondent that it is available and only check it, if the respondents do not know an answer.

Introduction

To start with, we would like to find out who is usually responsible for buying the food for the household. This relates only to the food that is bought to cook and eat at home, and excludes any food bought in restaurants, cafes etc.

17. Typically who in your household is responsible for buying the food that is bought to cook and eat at home?

    ☐ Always PERSON 1

    ☐ Usually PERSON 1

    ☐ Shared (50/50)

    ☐ Usually PERSON 2

    ☐ Always PERSON 2

    ☐ Someone else

18. Typically who in your household is responsible for preparing the food that is cooked and eaten at home?

    ☐ Always PERSON 1

    ☐ Usually PERSON 1

    ☐ Shared (50/50)

    ☐ Usually PERSON 2

    ☐ Always PERSON 2

    ☐ Someone else

Choices

Similar to what you were asked to do in the individual questionnaires; in the following questions you will be asked to choose between three options. Each option represents a typical evening meal that you and your partner would share in your home. Again there are three meal options and each varies in the number of calories, cooking time, food type and cost.

We would like you to now consider these options together and jointly indicate your preferences for the meals that are offered to you both. Please indicate the meal option that you would both prefer most and the meal option that you would both prefer least out of the three.

When making your choice please consider all of the features of each option. There are no right or wrong answers.

To demonstrate what we would like you to do, please consider this example:
Interviewer: Show the respondent the "EXAMPLE CHOICE TASK" card and explain the following:
In this example there are three meal options to choose from and each varies in the number of calories, cooking time, food type and cost. What we would like you to tell us is the meal options that you would both most and least prefer. Do you understand what you have to do?

Interviewer: If the respondents understand what they have to do, proceed to the choice tasks. If they do not understand what they have to do, please explain the example to them again.

Interviewer: If the respondents do not know which meal options to choose, please indicate this by checking the "Don't Know" box. However, if the respondents could not agree which meal options to choose, please indicate this by checking the "Can't Agree" box.

FOR INTERVIEWER ONLY:

19. Please record the choice task block:

    - ☐ A
    - ☐ B
    - ☐ C

Show the respondents "CHOICE TASK 1" and explain:
Imagine that the evening meals that you and your partner could share were restricted to only these three options:

	Option A	Option B	Option C	Don't Know
Which of the meal options do you both prefer most?				
Which of the meal options do you both prefer least?				

*** REPEATED FOR 8 CHOICE TASKS IN TOTAL ***

20. Thinking about the choices you made, would you say that you ignored any of the following features?

	Yes	No	Don't Know
Calorie Content			
Time Spent to Prepare/Cook			
Food Type			
Cost			

21. How easy/difficult did you think it was to make your choices?

    - ☐ Very Difficult
    - ☐ Difficult
    - ☐ Neither Difficult nor Easy
    - ☐ Easy
    - ☐ Very Easy
    - ☐ Don't Know

22. Thinking about your preferences, who would you say cares more for the following things:

	Person 1	We Care The Same	Person 2	Don't Know	We Can't Agree
Who cares the most about calories?					
Who cares the most about time spent cooking?					
Who cares the most about food type?					
Who cares the most about cost?					

23. Thinking about the choices you have made, please indicate the extent to which you agree or disagree with each of the following statements:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Don't Know
The meal options we were presented with were realistic.						
We were able to fully understand the tasks we were faced with.						
We were able to make choices as in a real world scenario.						

Socio-economic Questions

Finally, just a few questions about the both of you, which will once again be treated confidentially.

24. What is your relationship status?

    ☐ Married / Civil Partnership

    ☐ Cohabiting

    ☐ Other *(Please Specify)* ....

25. How long have you lived together?

26. Please tick the age band that is applicable to you:

	PERSON 1	PERSON 2
Less than 18		
18-24		
25-34		
35-50		
51-59		
60-64		
65-75		
75+		

27. Which of the following categories best describes your annual income (whether from employment, state benefits, investment or any other source) before the deduction of tax?

PER WEEK	PER YEAR	PERSON 1	PERSON 2
Less than £150	Less than £7,800		
£150 - £299	£7,800 - £15,599		
£300 - £449	£15,600 - £23,399		
£450 - £599	£23,400 - £31,199		
£600 - £899	£31,200 - £46,799		
£900 - £1,199	£46,800 - £62,399		
£1,200 - £1,499	£62,400 - £77,999		
£1,500 - £2,249	£78,000 - £116,999		
£2,250 and over	£117,000 and over		

28. Which of the following categories best describes your employment status?

	PERSON 1	PERSON 2
In full-time employment		
In part-time employment		
Self-employed		
Unemployed		
Retired		
Student		
Otherwise not working		

29. What is your highest education obtained?

	PERSON 1	PERSON 2
No qualifications		
CSE/GCSE/O Levels		
A Level/Baccalaureate		
Vocational Qualification		
Degree		
Postgraduate Degree		

Interviewer: Thank the respondents again for their time and finish the joint interview.

Now begin the SECOND individual interview with PERSON 1.

B.3 Individual questionnaires - Part II

Person 1

Preferences & Attitudes

In the following section we are interested in finding out about **your** personal preferences and attitudes for food purchases and decisions.

30. Thinking about your preferences, which of these four features would you say is...

	Calorie Content	Time Spent to Prepare/Cook	Food Type	Cost	Don't Know
The most important to you?					
The least important to you?					
The most important to your partner?					
The least important to your partner?					

31. Thinking about your preferences for the number of calories a typical evening meal should contain, which of the three levels would you...

	Less than 400 calories per portion	Between 400 and 600 calories per portion	Over 600 calories per portion	Don't Know
Most prefer your evening meal to contain?				
Least prefer your evening meal to contain?				

32. Thinking about your preferences for the length of time a typical evening meal should take to prepare and cook, which of the three levels would you. . .

	Less than 30 minutes	Between 31 and 60 minutes	Over 60 minutes	Don't Know
Most prefer your evening meal to take?				
Least prefer your evening meal to take?				

33. Thinking about preferences for food types, which of the three groups would. . .

	Local	Italian	Asian	Don't Know
You most prefer your typical evening meal to be?				
You least prefer your typical evening meal to be?				
Your partner most prefer their typical evening meal to be?				
Your partner least prefer their typical evening meal to be?				

34. Below are statements about your attitudes towards food, please indicate the extent to which you agree or disagree with each of the following statements:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Don't Know
Cooking is not much fun.						
Compared with other daily decisions, my food choices are not very important.						
I enjoy cooking for others and myself.						

35. To what extent do you agree with the following statements?

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Don't Know
I have a good understanding of my partner's preferences for food.						
I have a good understanding of my partner's preferences for the number of calories a typical meal should include.						
I have a good understanding of my partner's preferences for the length of time that a typical meal should take to prepare and cook.						
I have a good understanding of my partner's preferences for the amount of money that should be spent on a typical meal.						

Attitudes

In the following section we are interested in finding out about your personal preferences and attitudes for household purchases and decisions in general.

36. Below are statements about how you consider your opinions and attitudes, as member of a partnership. Please indicate whether you agree or disagree with each of the following statements:

	Disagree	Neither Agree nor Disagree	Agree	Don't Know	Refused
I am willing to compromise with my partner when making decisions.					
I do things my way regardless of what my partner expects me to do.					
I respect and support decisions made by my partner even when they may be wrong.					
I am prepared to do things for my partner at any time, even though I have to sacrifice my own interests.					
I feel uneasy when my opinions are different from those of my partner.					
I think it is more important to give priority to my partner's interests rather than to my own.					
I stick to my opinions even when my partner doesn't support me.					
I base my actions more upon my own judgements than upon the decisions of my partner.					

37. Finally we would like to ask you about what you thought of the questionnaire, please indicate the extent to which you agree or disagree with each of the following statements:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Don't Know
We thought that the questionnaire was too long.						
We thought that the questionnaire was interesting.						
We thought that the questionnaire was educational.						

FOR INTERVIEWER ONLY:

38. Please record whether the respondent was alone:

- ☐ Yes
- ☐ No

39. Please record the respondent's gender:

- ☐ Male
- ☐ Female

Thank the respondent for taking the time to complete this questionnaire and finish their SECOND interview.

Now begin the SECOND individual interview with their partner.

Person 2

Preferences & Attitudes

In the following section we are interested in finding out about **your** personal preferences and attitudes for food purchases and decisions.

40. Thinking about your preferences, which of these four features would you say is...

	Calorie Content	Time Spent to Prepare/Cook	Food Type	Cost	Don't Know
The most important to you?					
The least important to you?					
The most important to your partner?					
The least important to your partner?					

41. Thinking about your preferences for the number of calories a typical evening meal should contain, which of the three levels would you...

	Less than 400 calories per portion	Between 400 and 600 calories per portion	Over 600 calories per portion	Don't Know
Most prefer your evening meal to contain?				
Least prefer your evening meal to contain?				

42. Thinking about your preferences for the length of time a typical evening meal should take to prepare and cook, which of the three levels would you...

	Less than 30 minutes	Between 31 and 60 minutes	Over 60 minutes	Don't Know
Most prefer your evening meal to take?				
Least prefer your evening meal to take?				

43. Thinking about preferences for food types, which of the three groups would...

	Local	Italian	Asian	Don't Know
You most prefer your typical evening meal to be?				
You least prefer your typical evening meal to be?				
Your partner most prefer their typical evening meal to be?				
Your partner least prefer their typical evening meal to be?				

44. Below are statements about your attitudes towards food, please indicate the extent to which you agree or disagree with each of the following statements:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Don't Know
Cooking is not much fun.						
Compared with other daily decisions, my food choices are not very important.						
I enjoy cooking for others and myself.						

45. To what extent do you agree with the following statements?

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Don't Know
I have a good understanding of my partner's preferences for food.						
I have a good understanding of my partner's preferences for the number of calories a typical meal should include.						
I have a good understanding of my partner's preferences for the length of time that a typical meal should take to prepare and cook.						
I have a good understanding of my partner's preferences for the amount of money that should be spent on a typical meal.						

Attitudes

In the following section we are interested in finding out about your personal preferences and attitudes for household purchases and decisions in general.

46. Below are statements about how you consider your opinions and attitudes, as member of a partnership. Please indicate whether you agree or disagree with each of the following statements:

	Disagree	Neither Agree nor Disagree	Agree	Don't Know	Refused
I am willing to compromise with my partner when making decisions.					
I do things my way regardless of what my partner expects me to do.					
I respect and support decisions made by my partner even when they may be wrong.					
I am prepared to do things for my partner at any time, even though I have to sacrifice my own interests.					
I feel uneasy when my opinions are different from those of my partner.					
I think it is more important to give priority to my partner's interests rather than to my own.					
I stick to my opinions even when my partner doesn't support me.					
I base my actions more upon my own judgements than upon the decisions of my partner.					

47. Finally we would like to ask you about what you thought of the questionnaire, please indicate the extent to which you agree or disagree with each of the following statements:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Don't Know
We thought that the questionnaire was too long.						
We thought that the questionnaire was interesting.						
We thought that the questionnaire was educational.						

FOR INTERVIEWER ONLY:

48. Please record whether the respondent was alone:

    ☐ Yes

    ☐ No

49. Please record the respondent's gender:

    ☐ Male

    ☐ Female

Thank the respondent for taking the time to complete this questionnaire and finish their SECOND interview.

FOR INTERVIEWER ONLY:

50. For the joint interview who predominantly answered the questions?

 - ☐ Always PERSON 1
 - ☐ Usually PERSON 1
 - ☐ Shared (50/50)
 - ☐ Usually PERSON 2
 - ☐ Always PERSON 2

51. Please record you interviewer ID number:

Appendix C

Choice Cards

Example Choice Task Card

Figure C.1 shows the "EXAMPLE CHOICE TASK" card, which was used to demonstrate to the respondents what they needed to do during the choice tasks.

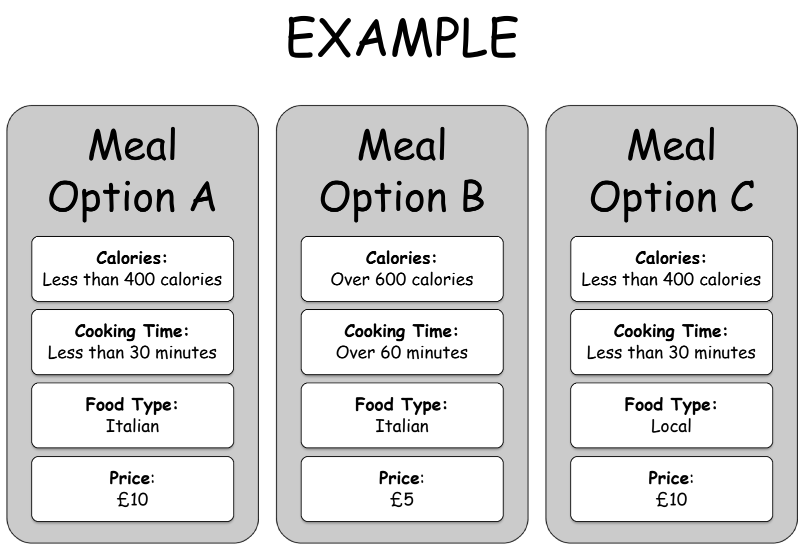

Figure C.1: Example Choice Task

Choice Task Cards

There were three block designs used in the survey. The blocks were randomised across respondents. Section C shows the cards used in Block A, Section C shows the cards used in Block B and Section C shows the cards used in Block C.

Block A

Choice Card 1

	Meal Option A	Meal Option B	Meal Option C
Calories:	Over 600 calories	Less than 400 calories	Less than 400 calories
Cooking Time:	Over 60 minutes	31 - 60 minutes	Less than 30 minutes
Food Type:	Local	Asian	Local
Price:	£5	£15	£10

Choice Card 2

	Meal Option A	Meal Option B	Meal Option C
Calories:	Less than 400 calories	Over 600 calories	400 - 600 calories
Cooking Time:	31 - 60 minutes	Less than 30 minutes	Over 60 minutes
Food Type:	Local	Asian	Italian
Price:	£5	£10	£15

Choice Card 3

	Meal Option A	Meal Option B	Meal Option C
Calories:	Less than 400 calories	Over 600 calories	400 - 600 calories
Cooking Time:	Over 60 minutes	31 - 60 minutes	Less than 30 minutes
Food Type:	Asian	Local	Local
Price:	£15	£5	£10

Choice Card 4

	Meal Option A	Meal Option B	Meal Option C
Calories:	400 - 600 calories	400 - 600 calories	400 - 600 calories
Cooking Time:	Less than 30 minutes	Over 60 minutes	31 - 60 minutes
Food Type:	Local	Asian	Italian
Price:	£15	£15	£5

Choice Card 5

	Meal Option A	Meal Option B	Meal Option C
Calories:	Less than 400 calories	Over 600 calories	Over 600 calories
Cooking Time:	Less than 30 minutes	Over 60 minutes	31 - 60 minutes
Food Type:	Italian	Italian	Asian
Price:	£10	£5	£15

Choice Card 6

	Meal Option A	Meal Option B	Meal Option C
Calories:	Over 600 calories	Less than 400 calories	Over 600 calories
Cooking Time:	31 - 60 minutes	31 - 60 minutes	Less than 30 minutes
Food Type:	Local	Italian	Asian
Price:	£10	£10	£10

Choice Card 7

	Meal Option A	Meal Option B	Meal Option C
Calories:	Over 600 calories	400 - 600 calories	Less than 400 calories
Cooking Time:	31 - 60 minutes	Less than 30 minutes	Over 60 minutes
Food Type:	Asian	Local	Italian
Price:	£5	£15	£10

Choice Card 8

	Meal Option A	Meal Option B	Meal Option C
Calories:	Less than 400 calories	400 - 600 calories	Over 600 calories
Cooking Time:	31 - 60 minutes	31 - 60 minutes	Over 60 minutes
Food Type:	Italian	Local	Asian
Price:	£10	£5	£15

Figure C.2: Block A – Choice Cards 1 to 8

Block B

Choice Card 1

	Meal Option A	Meal Option B	Meal Option C
Calories:	Over 600 calories	Less than 400 calories	400 - 600 calories
Cooking Time:	Less than 30 minutes	Over 60 minutes	Over 60 minutes
Food Type:	Italian	Local	Asian
Price:	£15	£5	£5

Choice Card 2

	Meal Option A	Meal Option B	Meal Option C
Calories:	Over 600 calories	400 - 600 calories	Less than 400 calories
Cooking Time:	Over 60 minutes	31 - 60 minutes	Less than 30 minutes
Food Type:	Local	Italian	Asian
Price:	£10	£15	£5

Choice Card 3

	Meal Option A	Meal Option B	Meal Option C
Calories:	400 - 600 calories	400 - 600 calories	Over 600 calories
Cooking Time:	Less than 30 minutes	Over 60 minutes	31 - 60 minutes
Food Type:	Asian	Asian	Local
Price:	£10	£15	£5

Choice Card 4

	Meal Option A	Meal Option B	Meal Option C
Calories:	400 - 600 calories	Over 600 calories	Less than 400 calories
Cooking Time:	Less than 30 minutes	Over 60 minutes	Less than 30 minutes
Food Type:	Italian	Asian	Local
Price:	£15	£5	£15

Choice Card 5

	Meal Option A	Meal Option B	Meal Option C
Calories:	Over 600 calories	Less than 400 calories	400 - 600 calories
Cooking Time:	31 - 60 minutes	Less than 30 minutes	Over 60 minutes
Food Type:	Asian	Italian	Local
Price:	£5	£10	£15

Choice Card 6

	Meal Option A	Meal Option B	Meal Option C
Calories:	Less than 400 calories	Less than 400 calories	Over 600 calories
Cooking Time:	Over 60 minutes	Over 60 minutes	Less than 30 minutes
Food Type:	Asian	Local	Italian
Price:	£5	£10	£15

Choice Card 7

	Meal Option A	Meal Option B	Meal Option C
Calories:	Over 600 calories	Less than 400 calories	400 - 600 calories
Cooking Time:	31 - 60 minutes	Less than 30 minutes	Over 60 minutes
Food Type:	Asian	Italian	Italian
Price:	£15	£5	£10

Choice Card 8

	Meal Option A	Meal Option B	Meal Option C
Calories:	Less than 400 calories	Over 600 calories	Less than 400 calories
Cooking Time:	Over 60 minutes	Less than 30 minutes	31 - 60 minutes
Food Type:	Asian	Italian	Local
Price:	£10	£10	£5

Figure C.3: Block B – Choice Cards 1 to 8

Block C

Choice Card 1

	Meal Option A	Meal Option B	Meal Option C
Calories:	400 - 600 calories	Over 600 calories	Less than 400 calories
Cooking Time:	Less than 30 minutes	Over 60 minutes	31 - 60 minutes
Food Type:	Italian	Local	Asian
Price:	£5	£15	£10

Choice Card 2

	Meal Option A	Meal Option B	Meal Option C
Calories:	400 - 600 calories	400 - 600 calories	400 - 600 calories
Cooking Time:	Over 60 minutes	Less than 30 minutes	31 - 60 minutes
Food Type:	Asian	Italian	Local
Price:	£15	£5	£15

Choice Card 3

	Meal Option A	Meal Option B	Meal Option C
Calories:	400 - 600 calories	Over 600 calories	Less than 400 calories
Cooking Time:	Over 60 minutes	31 - 60 minutes	Less than 30 minutes
Food Type:	Italian	Italian	Italian
Price:	£5	£15	£10

Choice Card 4

	Meal Option A	Meal Option B	Meal Option C
Calories:	Less than 400 calories	Over 600 calories	400 - 600 calories
Cooking Time:	31 - 60 minutes	31 - 60 minutes	31 - 60 minutes
Food Type:	Italian	Local	Asian
Price:	£15	£10	£5

Choice Card 5

	Meal Option A	Meal Option B	Meal Option C
Calories:	Over 600 calories	400 - 600 calories	Less than 400 calories
Cooking Time:	Less than 30 minutes	31 - 60 minutes	Over 60 minutes
Food Type:	Local	Asian	Italian
Price:	£10	£5	£10

Choice Card 6

	Meal Option A	Meal Option B	Meal Option C
Calories:	Less than 400 calories	400 - 600 calories	Over 600 calories
Cooking Time:	31 - 60 minutes	Less than 30 minutes	Over 60 minutes
Food Type:	Local	Asian	Local
Price:	£5	£10	£15

Choice Card 7

	Meal Option A	Meal Option B	Meal Option C
Calories:	400 - 600 calories	Less than 400 calories	Over 600 calories
Cooking Time:	Over 60 minutes	Less than 30 minutes	31 - 60 minutes
Food Type:	Italian	Asian	Italian
Price:	£10	£15	£5

Choice Card 8

	Meal Option A	Meal Option B	Meal Option C
Calories:	400 - 600 calories	Less than 400 calories	Over 600 calories
Cooking Time:	Less than 30 minutes	Over 60 minutes	Less than 30 minutes
Food Type:	Local	Local	Asian
Price:	£15	£10	£5

Figure C.4: Block C – Choice Cards 1 to 8