Modelling Differences in Angler Choice Behaviour with Advanced Discrete Choice Models

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Abstract

New Zealand is internationally renowned for having some of the finest and most challenging trout fishing in the world. However, due to continuing development and angling pressure many fishing sites are showing signs of environmental degradation and over fishing. This trend is almost certain to continue into the future given continued population and economic growth. Understanding the determinants of site choice, preference heterogeneity and anglers' substitution patterns is fundamentally important to fishery managers who have the difficult task of maintaining quality angling experiences on a number of fishing sites, managing angling pressure and maintaining license sales.

Recent advances in simulation techniques and computational power have improved the capability of discrete choice models to reveal preference heterogeneity and complex substitution patterns among individuals. This thesis applies and evaluates a number of state-of-the-art discrete choice models to study angler site choice in New Zealand. Recreation specialisation theory is integrated into the analysis to enhance the behavioural representation of the statistical models.

A suite of models is presented throughout the empirical portion of this thesis. These models demonstrate different ways and degrees of explaining preference heterogeneity as well as identifying anglers' substitution patterns. The results show that North Canterbury anglers' preferences vary considerably. Resource disturbances such as riparian margin erosion, reduced water visibility and declines in catch rates can cause significant declines in angler use of affected sites, and at the same time non-proportional increases in the use of unaffected sites. Recreation specialisation is found to be closely related to the types of fishing site conditions, experiences and regulations preferred by anglers. Anglers' preference intensities for fishing site attributes, such as catch rates, vary across different types of fishing sites. This location specific preference heterogeneity is found to be related to specialisation. Overall, the empirical findings indicate that conventional approaches to modelling angler site choice which do not incorporate a strong understanding of angler preference heterogeneity can lead to poorly representative models and suboptimal management and policy outcomes.

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Chapter 1

Introduction

1.1 Background

Individuals' preferences, which are important determinants of their behaviour, are diverse. Such heterogeneity is evident in recreational contexts, including angling, where anglers seek different types of experiences in different settings (e.g., Bryan 1977). In order to optimally manage recreational fishery resources it is important to understand anglers' choice behaviour, their underlying preferences, the nature and extent of preference heterogeneity and their effects upon the resource on which the sport relies.

During the past three decades there has been a rise in the interest, application and econometric advancement in discrete choice models (DCM) (Train 1998; Train 2003). The interest in DCMs in recreation, environmental and natural resource economics has been motivated by the analytical framework's usefulness for revealing preferences, non-market values and forecasting behaviour (Bennett & Blamey 2001; Hanley *et al.* 2003; Scarpa & Alberini 2005). Discrete choice models, which are part of the family of random utility models (RUMs), explain individuals' choice(s) from alternatives using indirect utility functions comprised of observed and unobserved components (McFadden 1974). The observed, or *deterministic* component of utility comprises variables 'observed' by the researcher measuring attributes of the alternatives and decision-maker, plus estimated coefficients, i.e., preference parameters indicating the relative influence of these variables on choice [1]. The unobserved or *stochastic* component of utility contains behavioural influences not explained deterministically (Luce 1959; Marschak 1960). These influences are represented in each alternative's utility function by an error term. Because individuals' levels of unobserved utility are unknown, an assumption must be made regarding their distribution.

[1] Research may also include other variables such as contextual choice influences.

The conventional multinomial logit (MNL) model (McFadden 1974), which uses maximum likelihood estimation, has error terms that are independently and identically distributed (IID) extreme value type 1 (EV1). While MNL is simple to estimate, it is very inflexible because coefficients are estimated as fixed estimates (implying individuals have identical preferences) and the independence from irrelevant alternatives (IIA) property is implied. The IIA property dictates that the ratio of choice probabilities for any pair of alternatives is independent of any other alternative (Luce 1959). As a result, an MNL model cannot capture unexplained taste variation in deterministic utility and predicts very rigid patterns of substitution which may not reflect those exhibited in the data (Ben-Akiva & Lerman 1985). Over time, a number of econometric developments have led to DCMs with considerably more flexibility than MNL.

The evolution in DCMs began with models that relaxed the IID assumption to allow correlation and heteroscedasticity in unobserved utility, e.g., nested logit (McFadden 1978), cross nested logit (CNL) (Vovsha 1997) and heteroscedastic extreme value (HEV) (Bhat 1995). In the mid 1990's interest in the field shifted toward models which incorporated more flexible ways of capturing taste variation in deterministic utility. Latent class multinomial logit (LC-MNL) models started this trend by allowing individuals' tastes to be represented as finite distributions over latent classes (Swait 1994). While LC-MNL can be estimated relatively easily and can incorporate covariates to inform class membership, the model maintains the IID assumption within classes. And so, through the mid 1990's, research was limited to models which *either* relaxed the IID assumption *or* incorporated a limited amount of random preference heterogeneity in deterministic utility. In the late 1990's increases in computer speed and developments in estimation techniques (e.g., Börsh-Saupan & Hajivassiliou 1993) led to the estimation feasibility and breakthrough of the highly flexible mixed logit (ML) model (Train 1998; Train 2003).

Mixed logit refers to a generalised modelling framework which uses simulation-assisted estimation to allow random taste heterogeneity and a full relaxation of IID while maintaining a tractable kernel EV1 error term (Train 2003). The ML framework includes: (i) random parameters [i.e., random parameters logit (RPL)] to allow preference coefficients in observed utility to follow continuous distributions to capture taste heterogeneity over the population (Train 1998); (ii) error components to allow heteroscedaticity and any pattern of correlation between unobserved utilities (Brownstone *et al.* 2000) and (iii) extensions, which allow both random parameters and error components to be decomposed to capture additional understanding of the specific tastes of individuals (Greene *et al.* 2006; Greene & Hensher 2007).

In recent years ML has been applied in a wide range of fields such as transport (e.g., Greene & Hensher 2007), health economics (e.g., Borah 2006), food choices (e.g., Jaeger & Rose 2008), corporate takeovers (e.g, Jones & Hensher 2007), and recreation and natural resource economics (Train 1998; Scarpa & Alberini 2005). Applications have tended to specify *either* random parameters (e.g., Train 1998) *or* error components (e.g., Brownstone & Train 1999). However, given sufficient data quality it is possible to incorporate both simultaneously (e.g., Scarpa *et al.* 2005; Scarpa *et al.* 2007; Campbell *et al.* 2008; Hu *et al.* 2008). In the ML model, including random parameters, error components and extensions, there is a flexible and powerful framework for elucidating preference heterogeneity, substitution patterns and determinants thereof from choice data. The ML framework and its potential further application and enhancement with recreation specialisation theory provide the central focus of this research.

Recreation specialisation (RS), first conceptualised by Bryan (1977) suggests that recreationists' behaviours, preferences and cognitions are related to specialisation. Specialisation is a multidimensional concept measured by indicators of experience, skill and commitment (Bryan 1977; Scott & Shafer 2001). Anglers with low specialisation are expected to prefer fishing with others and higher bag limits (but not place great emphasis on catching large quantities of fish). Due to their limited awareness and involvement anglers with low specialisation are not expected to be very aware of, or concerned with, resource disturbances. Recreation specialisation theory predicts that with increasing experience, skill and commitment individuals' preferences and cognitions undergo a transformation. As anglers specialise they are expected to become particular about the settings in which they fish, emphasise catching more and larger fish, prefer to fish alone or with close peers and prefer regulations which conserve the fish stock. Due to their high level of awareness and involvement, specialised anglers are expected to be relatively more concerned about and averse to resource disturbances. Research has found that specialised anglers place greater value on non-catch related aspects of fishing sites (Oh *et al.* 2005; Oh & Ditton 2006), have a more complex representation of the activity (Ditton *et al.* 1992; Fisher 1997; Miller & Graefe 2000) and ability to describe site attributes with greater specificity (Schreyer & Beaulieu 1986).

Since Bryan's (1977) initial conceptualisation, RS has been given a considerable amount of attention in the leisure studies literature (e.g., Ditton *et al.* 1992; Miller & Graefe 2000; Lee & Scott 2004; Oh & Ditton 2006; Dorow *et al.* 2009). This growing literature has stimulated important measurement and conceptualisation debate which is still largely unresolved (e.g., Scott & Shafer 2001).

1.2 Aims

This thesis is focused on the application of advanced DCMs, namely ML and to a lesser extent LC-MNL, to understand preference heterogeneity and substitution patterns among recreational anglers. Recreational specialisation theory is integrated into some of these models. This linkage provides the opportunity for cross-pollenisation between RS and discrete choice methodology by improving the explanation of angler preference heterogeneity within the context of a DCM, testing RS theory and refining the measurement and conceptualisation of RS. McFadden (2001, p. 12) has suggested such a linkage:

> "What lies ahead for discrete choice analysis? While it has shown itself to be capable of giving good answers to a broad array of policy questions, some possibilities for development of the approach are still to be realised. The potentially important roles of information processing, perception formation and cognitive illusions are just beginning to be explored and behavioural and experimental economics are still in their adolescence. The economic theory of consumers will be enriched by behavioural evidence. I believe that the RUM hypothesis for decision-making, modified to give a much larger role for the role of experience and information in the formation of perceptions and expression of preferences, will be able to explain most economic choice behaviour in the field and in the laboratory".

Advanced DCMs and their linkage with RS are applied and tested in this thesis using the case of New Zealand recreational trout fisheries. New Zealand is internationally regarded as having some of the world's best trout fishing given the country's diverse range of scenic streams, rivers and lakes. Most of these waters contain self-sustaining stocks of large wild trout which are known for being extremely difficult to catch at times (Hill & Marshall 1985). Specialised angling techniques and equipment have been developed, and are used by trout fishers for particular types of waters and conditions (Hill & Marshall 1985). The case study focuses on the North Canterbury region of the South Island which covers a large geographical area and contains a wide variety of fishing sites ranging from large mainstem-braided rivers and small lowland streams to backcountry rivers and lakes (Unwin & Image 2003; Unwin 2009). In the past two decades some of these fishing sites have experienced resource disturbances including: riparian margin erosion, reduced water visibility, loss of trout stocks and invasion by *Didymomosphenia geminata* (Didymo) (e.g., Young & Huryn 1999; Hayes 2002; Davies-Colley *et al.* 2004; Young *et al.* 2005). Didymo is a freshwater diatom which covers river substrates and lake margins causing nuisance to anglers and changes to aesthetics (e.g., Sutherland *et al.* 2007). Angler pressure and congestion is also occurring at greater levels on some waters, reducing trout catchability (Young & Hayes 2004) and the opportunity for angler solitude (Walrond 2001). The influence that these effects have on angler choice behaviour is not well understood.

There is strong evidence that angler activity in North Canterbury is changing. In the past two decades North Canterbury has experienced license sale volatility and large scale redistributions in where anglers are fishing (Unwin & Image 2003; Unwin 2009). This is problematic for fishery managers because it can lead to the overfishing of some fragile waters (e.g., Young & Hayes 2004) and falling revenue which limits managers' ability to manage the fisheries (Abernathy 2006). Resource disturbances have been implicated as possible drivers of the changes in angler activity. However, empirical support is very limited. Given fishing site diversity, angler diversity and the unknown influence of the various kinds of resource disturbances on angler choice behaviour, the case of North Canterbury provides rich grounds for applying flexible DCMs integrated with RS theory to study the determinants of angler site choice.

1.3 Contributions

This research focuses on applying and enhancing flexible DCMs with additional theory to improve behavioural understanding and representation. Through this focus the thesis makes a number of contributions. Broadly, the applied econometric contributions relate to the application of advanced DCMs and evaluation of their performance compared to more conventional approaches on a number of statistical and predictive criteria. Via this approach a number of fishery management issues are addressed:

- How do changes to water visibility, catch rates, angler encounter rates, trout size, bag limit regulations, the quality of riparian margins, and the presence of Didymo influence trout angler choice behaviour? To what extent do anglers' preferences differ?

- What is the nature of anglers' substitution patterns? Are they proportional or non-proportional? Given environmental degradation of lowland streams what is likely to happen to use of other fishing sites?

- Do anglers' preferences for fishing site attributes, e.g., catching an additional trout, differ in intensity on different types of fishing sites?

This thesis also makes a number of contributions to the literature on RS, including the demonstration of a number of approaches for linking RS with DCMs. The motivation is to understand the relevance of RS indicators in determining preference and to test whether individuals' preferences and choice processes are consistent with their levels of specialisation.

Several other smaller scale contributions are made by this thesis. These will be discussed in the appropriate chapters.

1.4 *Outline of the thesis*

The following section outlines the contents of the thesis chapters.

- Chapter 2 begins with a discussion of the underpinnings of random utility theory including sections that deal with particular DCM forms including: MNL, various generalised extreme value (GEV) models, LC-MNL, ML and extended ML. This progression approximately follows chronology and improvements in flexibility. Each model's properties, merits and limitations are discussed. Relevant literature is reviewed.

- Chapter 3 describes the RS concept and theory as well as measurement issues.

- Chapter 4 explains in detail the case of New Zealand recreational trout fisheries including: (i) angler use and its significance, (ii) the different types of fishing sites, (iii) the different kinds of resource disturbances, and (iv) recent trends in angler activity.

- Chapter 5 reports the research design process, including focus groups, experimental design generation, survey construction, piloting and administration. This is followed by descriptive statistics of the data collected.

- Chapter 6 explores extended ML models, which simultaneously specify random parameters plus error components. These models capture both preference heterogeneity for observed fishing site attributes and variance differences in stochastic utility at the alternative level. The error components are independent of the random parameters and fully relax the IID property. The model is further generalised to control for heterogeneity in the random parameter means and heteroscedasticity in the variances of the random parameters as well as error components using anglers' self reported skill levels. The performance of the extended ML models is evaluated against MNL and LC-MNL models using a scenario which simulates environmental degradation to lowland streams.

- Chapter 7 describes different approaches for integrating RS in discrete choice analysis. One approach analyses RS indicators individually. The second approach analyses variables which identify individuals' levels of specialisation. Different models, LC-MNL, MNL, multinomial logit-error component (MNL-EC) and extended ML models, are used to test these different ways of operationalising RS.

- Chapter 8 investigates whether anglers' preference intensities for fishing site attributes differ across backcountry rivers, lowland streams, mainstem-braided rivers and lakes. After reviewing relevant literature and drawing out the management and policy implications, MNL and MNL-EC models are estimated with generic and alternative specific parameters. Auxiliary statistical tests are applied to determine whether the estimated site specific coefficients are statistically different.

- Chapter 9 investigates alternative specific preference heterogeneity among specialised anglers.

- Chapter 10 synthesises the findings, discusses limitations and suggests opportunities for future research.

Chapter 2

Discrete Choice Models

2.1 The behavioral foundation of discrete choice models

Neo-Classical micro-economic consumer theory suggests that individuals are rational decision-makers and when faced with a choice between alternatives, choose the alternative, given a budget constraint and underlying preferences, which maximises utility. Lancaster (1966) broadens this view, suggesting that an alternative's utility can be decomposed into attribute components. Random utility theory (RUT), originated by Thurston (1927) and later developed by Luce (1959) and Marschak (1960), views the decision process from the researcher perspective. In RUT, the decision modelling process is probabilistic, because while the decision-maker has full knowledge of the determinants of choice (i.e., attributes), the researcher does not. Therefore, the researcher, due to incomplete information, cannot perfectly predict individuals' decisions.

Discrete choice models (DCMs) integrate RUT into a framework in which utilities estimated for individuals' alternatives are specified with indirect utility functions composed of observed (*deterministic*) and unobserved (*stochastic*) components[2]. The deterministic component of utility is comprised of attributes of the alternative observed by the researcher (or other influences on choice, e.g., decision maker characteristics or interactions of these variables), plus estimated coefficients. The stochastic component of utility is comprised of: i) unobserved utility, ii) unobserved preference heterogeneity, iii) estimation error and iv) measurement error which arise from the use of proxy variables (Manski 1977)[3]. Stochastic utility is represented by an additive error term. An assumption must be made for the distributional form that the error term takes (Manski 1977). This assumption is extremely

[2] This thesis will interchangeably use the terms deterministic and observed utility as well as the terms stochastic and unobserved utility.
[3] It is for this reason that stochastic utility can more generally be referred to as the *unobserved effects*.

important because it impacts model flexibility and the assumptions made about individuals' tastes and substitution patterns.

Discrete choice models utilise data on individuals' decision outcomes as well as the attributes which comprise the alternatives in individuals' 'choice set(s)'. Variability in attribute levels (i.e., qualities or quantities) across choices and/or alternatives is required to estimate coefficients which are indicative of the relative importance of those attributes to the decision outcome. These parameters are interpreted as individuals' preferences for constituent attributes.

Formally, let the utility (U) of individual angler $i=1,\ldots,N$ for each alternative (j) be a function of a vector of attributes (x) describing the alternative[4]. Vector β represents anglers' preferences, which the analyst wishes to estimate. In this specification the vector β is not individual-specific, as denoted by the absence of subscript i. ε represents the unobserved portion of utility. Each individual's level of unobserved utility for each alternative is treated as random. Formally, let i's utility for alternative j be defined as:

$$U_{ij} = \beta x_{ij} + \varepsilon_{ij} \tag{1.0}$$

The probability (P) of alternative j being chosen by individual i can be expressed as the probability that the utility of alternative j exceeds the utility of all other alternatives q:

$$P_{ij} = Prob\ [U_{ij} > U_{iq}] \qquad \forall q \neq j \tag{1.1}$$

Substituting (1.0) into (1.1) gives:

$$P_{ij} = Prob\ [\beta x_{ij} + \varepsilon_{ij} > \beta x_{iq} + \varepsilon_{iq}] \qquad \forall q \neq j \tag{1.2}$$

Through algebraic manipulation:

[4] Vector x can also include contextual influences and characteristics of the individual.

$$P_{ij} \quad = \; Prob \;\; [\beta x_{ij} - \beta x_{iq} \; > \; \varepsilon_{iq} - \varepsilon_{ij}] \qquad \forall q \neq j \tag{1.3}$$

Equation 1.3 states that the probability that individual *i* chooses alternative *j* is simply the probability that the difference in observed utility $\beta x_{ij} - \beta x_{iq}$ is greater than the difference in unobserved utility $\varepsilon_{iq} - \varepsilon_{ij}$.

2.2 *The multinomial logit model*

The assumption that unobserved utilities for each alternative are independently and identically distributed (IID) extreme value type 1 (EV1) produces the MNL model (McFadden 1974) and allows the unobserved utility difference $\varepsilon_{iq} - \varepsilon_{ij}$ and equation 1.3 to have a closed form solution which can be calculated analytically. In most software and applications the variance σ^2 of each ε_j is set to one. Maximum likelihood procedures are used to estimate β. The probability that the choice outcome y_i is alternative *j* from all alternatives available to the individual can be expressed as the logit formula (Train 2003, pp. 38-41; 78-79):

$$P(y_i = j) = \frac{\exp(\mu\beta \mathrm{x}_{ij})}{\sum_{q=1}^{J} \exp(\mu\beta \mathrm{x}_{iq})} \tag{2}$$

where μ is a scale parameter which is inversely related to the variance of ε (Ben-Akiva & Lerman 1985). For MNL,

$$\mu = \sqrt{\pi^2 / 6\sigma^2}\,, \tag{3}$$

However, the scale parameter cannot be specifically identified in any particular model because of confounding with the vector of utility parameters (Swait & Louviere 1993)[5].

[5] Recent developments in 'scale heterogeneity' multinomial logit (S-MNL) and generalised multinomial logit (G-MNL) models allow one to separate scale from the vector of utility parameters (Fiebig *et al.* 2009).

2.2.1 Multinomial logit model limitations

While the MNL model is the most commonly used DCM, it has three extremely restrictive properties (Train 2003; Hensher *et al.* 2005).

2.2.1.1 Heterogeneity

The MNL model produces parameter estimates which assume that individuals have homogeneous preferences for observed attributes, i.e., vector β represents population means. Two convenient, but limiting, approaches have been used to incorporate systematic (not random) heterogeneity in deterministic utility while maintaining the basic MNL model.

First, individual characteristics or other covariates can be interacted (multiplied) with attribute values. Parameters can then be estimated for each interaction term to reveal the effect that the two variables have in concert upon utility (e.g., Adamowicz *et al.* 1997; Morrison *et al.* 1999; Bauer *et al.* 2004). However, studies have found that significant unobserved heterogeneity remains even after interactions with demographic variables and attributes are specified (Scarpa *et al.* 2005; Hynes *et al.* 2008).

Second, a two step process comprising an exogenous market segmentation technique, such as cluster analysis, can segment individuals into cohorts (e.g., Oh & Ditton 2006). Separate MNL models are estimated for each cohort. This segmentation approach is problematic because it does not reveal a full population preference distribution and secondly because it results in a very large number of preference parameters (depending on the number of cohorts). These parameters cannot be directly compared across cohorts because of differing scale effects (Ben-Akiva & Lerman 1985). In order draw comparisons across models estimated from different samples scale differences must be considered. Approaches which solve the scale difference issue include: comparing ratios of coefficients, e.g., willingness to pay (WTP) estimates, the "nested logit trick" Hensher *et al.* (2008), and the Swait & Louviere (1993) test.

2.2.1.2 Non-correlation and homoscedasticity

The MNL model is based on the assumption that the error terms associated with each alternative have unit variance and are uncorrelated. In other words, the covariance matrix has ones on the diagonal and zeros in all off-diagonal elements. This assumption is unlikely to hold in practice. To illustrate how unobserved utility can be correlated across alternatives consider a scenario where individuals' choices among fishing sites are influenced by scenic attributes not observed by the researcher. Because the salient scenic attributes are unobserved by the researcher their influence becomes embedded in unobserved utility. Consequently, the error terms of the alternatives with common scenic attributes are correlated. However, an MNL model, because of the IID assumption, cannot identify these relationships. Similarly, in a repeated choice situation in which individuals' choices are consistently influenced by the same scenic attributes, error terms become correlated not only across alternatives but also across choice situations. Again, the MNL model cannot identify this pattern of correlation. Correlation in unobserved utilities has important implications when forecasting.

2.2.1.3 Forecasting

The MNL model, as a result of the IID assumption, exhibits the independence from irrelevant alternatives (IIA) property (Luce 1959). The IIA property dictates that the ratio of choice probabilities for any pair of alternatives is independent of any other alternative. Multinomial logit will predict, given the addition, elimination, or qualitative change to a particular alternative that anglers will substitute to other alternatives in a proportional manner (Ben-Akiva & Lerman 1985).

To demonstrate the effect of the IIA property on model forecasts, consider a situation in which:

- Initially, anglers have three fishing sites available. Call these Backcountry River (A), Lowland Stream and Lake (Table 2-1). Each site maintains an equal probability (33.3%) of being chosen (as depicted in column 1).

- A fourth fishing site, Backcountry River (B), which had been closed to anglers because of concerns over the spread of an invasive algae, *Didymo geminata* (Didymo) is reopened.

- The Backcountry River B has scenic characteristics identical to Backcountry River A. However, these scenic attributes are not entered deterministically in the MNL model.

Table 2-1: An example of how the MNL model can bias forecasts

	Pre-reopening	Post-reopening	MNL forecast
Backcountry River B	closed	16.6%	25%
Backcountry River A	33.3%	16.6%	25%
Lowland Stream	33.3%	33.3%	25%
Lake	33.3%	33.3%	25%
	100%	100%	100%

As a result of the reopening Backcountry River B half of the anglers previously fishing Backcountry River A substitute to Backcountry River B. The anglers fishing at the Lake and Lowland Stream do not change their behaviour. Consequently, the Backcountry River A and Backcountry River B now have an equal probability of being chosen (16.6%) while the choice probabilities of the Lowland Stream and Lake alternatives remain unchanged at their previous levels (column 2). Importantly, the relative choice probabilities between alternatives have now changed (i.e., the probability of choosing the Backcountry River A compared to the Lowland Stream has gone from 33.3% / 33.3% =1 to 16.6% / 33.3% = .5). The MNL model predicts a very different outcome by assuming proportionate changes in choice probabilities (i.e., the probability of choosing the Backcountry River A compared the Lowland Stream does not change 33.3% / 33.3% =1; 25% / 25% = 1). The forecast is biased because the similarity in unobserved utilities between the Backcountry River A and B were not identified by the MNL model due to the IID assumption. This simple illustration demonstrates the importance of using models which relax IID to identify important patterns of correlation in unobserved utility. The illustration also raises the importance for researchers to observe as many salient influences on individuals' site choices as possible to reduce the content in the unobserved component of utility. "The consensus is that a good error is a zero error; that is, it is desirable to expand on the systematic term thereby reducing the disturbance term" (Ben-Akiva *et al.* 2002, p. 171). However, capturing all utility systematically is virtually impossible in most choice contexts, not the least angling where "the hefty cost of collecting detailed data for diffuse locations and the presence of characteristics such as aesthetic appeal, secludedness, or fish catch that are hard to measure make unobserved characteristics [utility] an undeniable reality in recreation demand modelling" (Murdock 2006, p. 1-2).

2.2.2 Multinomial logit model applications

Multinomial logit is the basis for many of the more flexible models which maintain an EV1 disturbance, e.g., generalised extreme value (GEV), latent class multinomial logit (LC-MNL) and mixed logit (ML) models. Often studies reporting these more advanced models will report an MNL model for comparison. Therefore, examples of MNL, even in the recreation, environmental and natural resource economics literatures, are numerous - too numerous to cover in detail. Examples of recreational angling site choice studies that have reported MNL include, Bockstael *et al.* (1989); Parsons & Needleman (1992); Feather (1994); Watson *et al.* (1994); McConnell *et al.* (1995); Oh & Ditton (2006) and Dorow *et al.* (2009).

In summary, the limitations of the MNL model are widely recognized in the choice modelling literature and have been from early on (e.g., Williams 1977; Daly & Zachary 1978; McFadden 1978). Over the past thirty years a number of models and extensions to MNL have been developed to improve realism and behavioural understanding. The next sections cover the major developments starting with early innovations which partially relaxed the IID assumption.

2.3 Generalised extreme value models

Generalised extreme value models (GEV) refer to a family of logit models which partially relax the IID assumption, but maintain an EV1 functional form. The various GEV members are differentiated by how they relax the “independence” and/or “identically distributed” part of the IID assumption. There are a large number of GEV variants. The primary models are nested logit (NL), cross-nested logit (CNL), generalised nested logit (GNL) and heteroscedastic extreme value (HEV). The next section provides an overview of these particular GEV models, identifies their strengths, discusses their limitations and briefly refers to relevant applications. Generalised extreme value models are not applied in this thesis and therefore formal specifications are omitted. More in-depth coverage and discussion of GEV models can be found in Train (2003), Hess (2005) and Swait (2006). Ortúzar (2001) provides a review of the historical development of NL models.

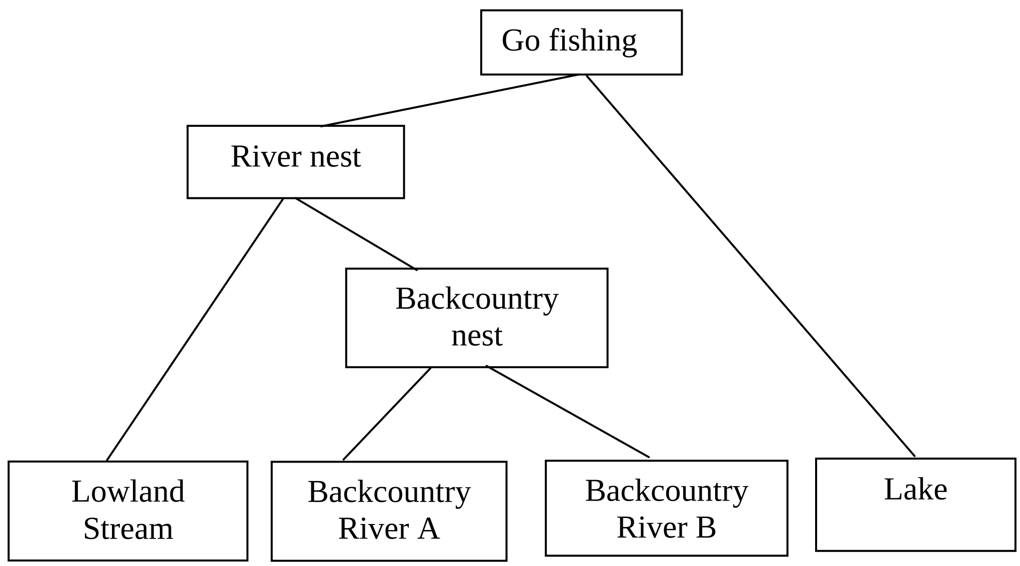
2.3.1 Nested logit

The NL model (Williams 1977; Daly & Zachary 1978; McFadden 1978) partially addresses the problem of correlation in unobserved utilities (Ben-Akiva & Lerman 1985). Correlated error terms imply substitutability, i.e., a high cross elasticity. The NL model partially relaxes the IID assumption by allowing the “nesting” of alternatives thought to share similarities in unobserved utility. Nesting partially relaxes the constant variance assumption and allows covariance in the unobserved utility of alternatives within common nests. Nesting can occur on multiple levels. Nested logit assumes the correlation between alternatives in different nests is zero.

Recall the fishing site choice scenario in section 2.2.1.3 involving four fishing site alternatives named; Backcountry River A, Backcountry River B, Lowland Stream, and Lake. In this scenario, the Backcountry River A and B error terms were correlated due to scenic attributes not captured deterministically.

Figure 2-1 depicts a two level nesting structure which could be used to identify correlation in unobserved utility. The Backcountry River A and B are placed into a 'Backcountry nest' to capture similarity between these two alternatives, e.g., scenic attributes (bottom of Figure 2-1). Further up the nesting structure, all river-based alternatives are nested into a 'River nest' to capture potential similarity on another level, e.g., shared access attributes. The higher level nests include the variance at the lower levels.

Figure 2-1: Example of a nesting structure



Nesting is an arbitrary process which involves empirically testing different tree structures (e.g., Hauber & Parsons 2000)[6]. Various statistical criteria can be used to guide this process. If differences in variance are not present, as identified by non-significant inclusive value (IV) parameters (i.e., the ratio of the scale parameters between nests equals one), then the NL model collapses to an MNL model (Greene 2007).

[6] Hensher (1999) demonstrates how the HEV model can be used as a search engine for identifying the appropriate nesting structure.

2.3.1.1 Limitations

The key feature of NL is that it allows alternatives' unobserved utility variances to differ. While NL allows some correlation within nests, it does not allow correlation between nests. Conventional NL maintains an MNL-like structure for its deterministic component of utility[7]. Therefore, a NL model is limited in its ability to incorporate preference heterogeneity in systematic utility. While the standard NL does not allow for a panel data formulation to control for an individual's persistent unobserved tastes across choice situations an extension, the repeated NL, does (e.g., Morey *et al.* 1993).

2.3.1.2 Applications

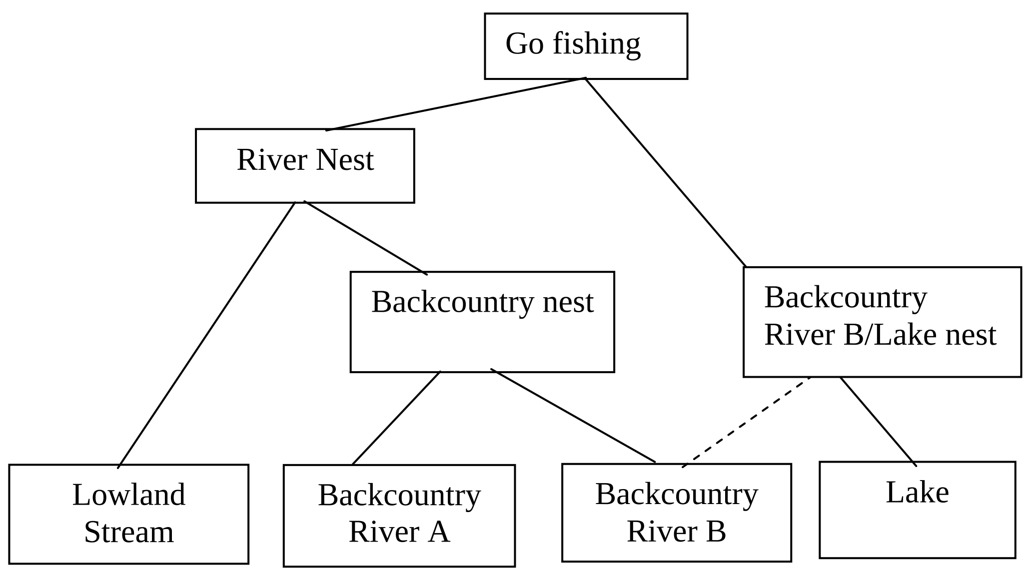
Like MNL, the NL model has numerous applications and still appears in the literature (e.g., Jones & Hensher 2007). Numerous recreation fishing site choice studies have employed NL. For instance, Morey *et al.* (1993) use a repeated NL model to address both Penobscot River anglers' site choice and number of trips per season; Jones & Lupi (1999) employ NL to investigate how a varying range of fishing activities included in the choice set (i.e., the comparative substitutability of fishing sites) affects welfare measures for trout and salmon anglers fishing the Great Lakes and other inland fisheries. Other examples of NL applications in fishing site contexts include, but are not limited to: Morey *et al.* (1991), Hauber & Parsons (2000) and Morey *et al.* (2002). Many of these studies did not report MNL base models to determine to what degree NL specifications and nesting structures improved statistical fit or forecast accuracy. Jones & Hensher (2007) studied corporate takeovers and evaluated the predictive performance of MNL, NL, LC-MNL and ML models. Briefly, these authors find that, "the nested logit model has performed better than basic MNL, but still trails mixed logit and latent class by significant margins" (Jones & Hensher 2007, p. 1215).

[7] The distinction 'conventional' is made because in a few instances research (Hess 2005; Hess *et al.* 2005; Gopinath *et al.* 2005) has estimated hybrid random parameters models with closed form NL (GEV) error structures.

2.3.2 Generalised nested logit

Generalised nested logit (GNL) is an extension to the NL model which allows correlation between alternatives in different nests to be non-zero (e.g., Wen & Koppleman 2001). This provides greater flexibility in the estimation of substitution, or cross-elasticity, between alternative sites compared to NL. This is accomplished by 'cross nesting', i.e., allowing alternatives to appear in more than one nest. Figure 2-2 modifies Figure 2-1 to depict an example of where the Backcountry River B is cross nested, appearing in two separate nests (the Backcountry and Backcountry River B/Lake nests) to allow for additional patterns of correlation.

Figure 2-2: Example of a cross-nesting structure



2.3.2.1 Limitations

Like NL, GNL's deterministic component of utility is analogous to MNL. As a result, GNL is limited in its ability to incorporate random preference heterogeneity in deterministic utility. These limitations were previously described in sections 2.2.1.1 and 2.2.1.2.

2.3.2.2 Applications

The GNL model [including special cases: the paired combinatorial logit model (Chu 1989; Koppelman & Wen 2000), cross nested logit (CNL) (e.g., Vovsha 1997; Bhat & Guo 2004); the ordered generalised extreme value model (Small 1987) and the product differentiation model (Bresnahan *et al*. 1997) is less common than NL. Hunt *et al.* (2007) provide a recent application of the GNL model (CNL specifically) to a recreation problem involving a revealed preference study of 431 fishing sites. Hunt *et al.* (2007) found: (i) CNL provided an improvement in statistical fit over MNL, but not over NL, (ii) "CNL revealed a much more complex pattern of spatial substitution among fishing sites than either the MNL or NL models" (p. 169), and (iii) no systematic differences in anglers' welfare estimates between CNL and MNL.

2.3.3 Heteroscedastic extreme value

The HEV model (Bhat 1995) does not have a closed form solution and allows the variances of alternatives' errors disturbances to be heteroscedastic. Error heteroscedasticity is translated into differing scale factors for each alternative which affects coefficient estimates in observed utility by either scaling them up or down relative to other alternatives. Each alternative (but not each individual decision maker) is allowed to have a different scale factor. For identification purposes the scale factor of one of the alternatives is set to 1. Heteroscedasticity allows freedom from the IIA property and differential cross elasticities among alternatives. The HEV model, unlike NL and GNL, maintains independence among alternatives' error terms.

2.3.3.1 Limitations

The HEV model does not allow for *any* pattern of correlation between alternatives' ε_j'*s* or across individual's repeated choices. Further, the HEV model, like all conventional GEV variants, maintains the MNL-like structure for the deterministic component of utility[8].

2.3.3.2 Applications

HEV was initially developed and applied by Bhat (1995) to study inter city travel mode choice. Bhat (1995) found the HEV model to be superior to the MNL model in predicting complex substitution patterns in transportation mode choice. Munizaga *et al.* (2000) compared HEV with different model structures (e.g., MNL, NL, multinomial probit) using simulated data with heteroscedasticity between two groups of alternatives. Munizaga *et al.'s* (2000) results showed that in the case of heteroscedasticity across alternatives, the HEV (also MNP and NL) performed better than MNL in policy analysis. Examples of other HEV applications include those in Louviere *et al.* (2000). Searches through the published literature suggest the HEV model has not been applied to study recreation site choice.

2.3.4 Generalised extreme value model summary

Generalised extreme value models relax the IID assumption. While the different GEVs relax the IID assumption in different ways, and to varying degrees, none completely relaxes all aspects of the assumption. All conventional GEV models are limited because they do not allow for the incorporation of random preference heterogeneity in observed utility. Conventional GEV models are essentially MNL models with flexible disturbances.

[8] Again the word conventional is carefully used here because there are exceptions. Hensher (1999) specifies a latent class-HEV model in which preference coefficients are allowed to follow finite mixture distributions to capture taste heterogeneity.

2.4 Latent class multinomial logit choice models

Latent class choice models (Gupta & Chintagunta 1994; Swait 1994) incorporate preference heterogeneity into deterministic utility through a simultaneous estimation process that estimates the joint probability of whether a particular individual chooses an alternative and belongs to a class of individuals who share identical characteristics and preferences. The most common form of latent class choice model is the latent class multinomial logit (LC-MNL) model.

Following Greene (2007), the probability that individual *i*, during choice situation *s*, chooses alternative *j*, is conditioned on their membership of class *C*.

$$P\left(y_{is} = j \mid C\right) = \frac{\exp(\beta_c \mathrm{x}_{ijs})}{\sum_{q=1}^{J_i} \exp(\beta_c x_{ijs})}, \tag{4}$$

where the utility function is described as:

$$U_{ijs} = \beta_c x_{ijs} + \varepsilon_{ijs} \tag{5}$$

Notice that the vector β_c is specified as a class specific vector (denoted by the subscript *c*). The LC-MNL assumes that given class assignment *C*, the choice situations are independent and induces the restrictive IIA property within classes.

Individuals' class memberships are not observed by the analyst but may be (although it is not necessarily) informed by characteristics of the individual such as skill level, level of specialisation, or income. Let H_{ic} represent the prior probability of membership of class *c* for individual *i* taking the form of the MNL.

$$H_{ic} = \frac{\exp(z_i \theta_c)}{\sum_{c=1}^{C} \exp(z_i \theta_c)}, \quad \mathrm{c}=1,\ldots\ldots,\mathrm{C} \quad \theta_C = 0, \tag{6}$$

where z_i represents observable characteristics of the individual which enter the model for class membership. In order to identify the model the *C*th parameter vector is normalised to zero.

This vector is represented by a constant term. The probability that individual *i* chooses alternative *j* is expressed as:

$$P_{ij} = \sum_{c=1}^{C} P_{j|c} \times H_{ic} \tag{7}$$

The LC-MNL estimates coefficients for each pre-specified class *C*. The distribution of coefficients over classes can be visualised as a finite distribution of preference points which captures preference heterogeneity over the population. Increasing the number of classes specified in the model may allow for further differentiation of tastes. However, at some point too much class differentiation causes a loss in statistical fit and interpretation becomes difficult due to the large number of estimated parameters that arise from estimating numerous classes.

2.4.1 Limitations

While LC-MNL relaxes IID between classes, it does not relax IID within classes (e.g., Provencher *et al.* 2002)[9]. Each class maintains its own disturbance with variance equal to one[10]. There are a number of statistical criteria which can be used to identify the optimal number of classes, e.g., Akaike Information Criterion (AIC), corrected AIC (crAIC) (which penalises for extra parameters estimated), or Bayesian Information Criteria (BIC). These criteria are described in Chapter 5. Conventional specification tests such as the likelihood ratio test are not valid (Hynes *et al.* 2008). However, AIC, AICr and BIC have been shown to be inconsistent. For example, Hynes *et al.* (2008) found with the same data set the BIC statistic suggested the existence of six classes, AIC two classes, and crAIC nine! To assist in the class specification decision Scarpa & Thiene (2005) recommend factoring the class

[9] One exception is Hensher *et al.* (1999) where a LC-HEV model is generated to study intercity travel mode choice.

[10] Recently, Magidson & Vermunt (2007) have developed procedures to estimate extended latent class models in the Latent Gold Choice software. This extended specification overcomes the constant scale assumption of LC-MNL. This is important because if the constant scale assumption (across classes) is violated, “the predictions contain additional amounts of error as well as potential bias” (Vermunt & Magidson 2007, p. 1).

specification decision also on: (i) the significance of parameter estimates, and (ii) the meaningfulness of the parameter signs.

Finally, while relatively easy to estimate, LC-MNL is limited because it cannot identify continuous taste distributions. Research by Elrod & Keane (1995) and Allenby & Rossi (1999) suggest that specifying taste distributions over a finite number of points instead of continuously underestimates the extent of heterogeneity.

2.4.2 Applications

A number of recreation-based studies have employed LC-MNL. Boxall & Adamowicz (2002) investigated systematic utility differences among Boundary Water canoeists in Canada using attitudinal measures of motivations to inform the identification of classes. Scarpa & Theine (2005) investigated preference heterogeneity among Italian Alpine Club rock climbers. Provencher *et al.* (2002) investigated serial correlation and preference heterogeneity among Lake Michigan salmon anglers and Provencher & Bishop (2004) used the same case to evaluate the forecasting ability of LC-MNL compared to RPL and MNL. Provencher & Bishop (2004) found no model to be clearly superior to the others. Morey *et al.* (2006) investigated class differences solely on the use of attitudinal responses (no choice data) to questions relating to boat fees, species catch rates and fish consumption advisories. Scarpa *et al.* (2007) investigated the existence of latent classes among Italian hikers in terms of their total demand for days out, using years of experience and socio-economic variables. Hynes *et al.* (2008) used LC-MNL to investigate kayakers' site choices.

2.5 Mixed logit

Mixed logit (ML) (Train 1998; 2003) refers to a generalised modelling framework which maintains an EV1 disturbance, but uses simulated maximum likelihood estimation to allow coefficients to be estimated over a distribution (e.g., normal). For a review of simulation methods see Hajivassiliou & Ruud (1994). There are two general ML specifications, the random parameters specification and the error components specification. The different specifications allow heterogeneity to be expressed in the different components of the model. While research has tended to employ either random parameters or error components, both may be used in concert (e.g., Greene & Hensher 2007).

The ML model initialises with an MNL model. Random parameters are created by simulating (taking draws) around the MNL estimates according to a pre-specified distribution. Procedures can use random draws or smart draws such as Halton or shuffled Halton draws to improve estimation efficiency (Bhat 2003; Train 2003, p. 236). An algorithm[11], guided by the log-likelihood (LL) function, is used in the simulation process to maximise the LL. The model converges when the LL function is maximised. This next section describes the RPL specification and its possible extensions, followed by a section which describes the error component specification and its extension. The final section shows how random parameters can be estimated along with error components.

2.5.1 Random parameters specification

The RPL model is a special case of ML which allows preference coefficients in deterministic utility to be estimated over continuous distributions, representing preference heterogeneity over the population. These taste distributions involve both mean and variance estimates. If variance parameters are insignificant (implying zero taste variation), the RPL model collapses to MNL. There is a great deal of latitude in investigating different distributional forms (e.g., normal, lognormal, triangular). Random parameters logit can be estimated using a panel formulation which allows correlation across individual's choices and relaxes IID. Incorporating variance around parameter means overcomes the restrictive IIA property (Train 1998; 2003).

Drawing directly from Greene (2007), the starting point is to assume the MNL depiction from (2), this time including alternative specific constants (ASCs), α_j, and allowing for multiple choice situations, (s) per individual i. Alternative specific constants measure the mean effect

[11] Newton-Raphson is a commonly used algorithm for this procedure.

of unobserved utility for alternatives and may be included for all choice model forms previously discussed, though they have been withheld up until now for simplicity. One ASC must be normalized for identification purposes. Typically, this normalisation is set to zero. Therefore, up to *J*-1 ASCs may be estimated where *J* is the number of alternatives in individuals' choice sets.

$$P(y_{is} = j) = \frac{\exp(\alpha_{ji} + \beta_{ik}'\mathrm{x}_{jis})}{\sum_{q=1}^{J} \exp(\alpha_{qi} + \beta_{ik}'\mathrm{x}_{qis})} \tag{8}$$

The ML RPL specification takes form by allowing individual parameter estimates β_i in the vector β where:

$$\beta_{ik} = \beta_k + \sigma_k v_{ik} \tag{9}$$

In this formulation β_k is the population mean, v_{ik} is individual specific heterogeneity with mean zero and standard deviation equal to one, and σ_k is the standard deviation of the distribution of β_{ik} around β_k. The analyst observes x and choices, and estimates β_k and σ_k. Specification testing of different distributions, e.g., normal, lognormal, uniform or triangular, determines the appropriate distributional form. Constraints can also be placed on the distribution so that the variance can be a function of the mean. For instance, a triangular distribution can be constrained so that the spread is equal to the mean. This insures that the entire distribution falls on either side of zero (e.g., Greene *et al.* 2006; Greene & Hensher 2007).

The benefit of RPL is that it can capture the entire population taste profile. This is in contrast to MNL and GEV models which can only identify the population mean with a fixed coefficient, or have to rely on interactions to capture systematic taste differences.

Random parameters can identify taste differences in the absence of the interactions. As noted earlier, studies (e.g., Scarpa *et al.* 2005; Hynes *et al.* 2008) have found significant unobserved heterogeneity remains even after interactions with demographic variables and attributes are specified. This suggests that fixed estimate/interaction approaches miss large amounts of important behavioural information.

Train (1998) first introduced RPL using individual level data, in an investigation of damages to recreational trout angling in Montana caused by mining operations[12]. Train (1998) found statistically significant variation in angler preferences and found RPL offered an improvement in statistical fit compared to MNL. Since Train's pioneering study, RPL has been increasingly applied in numerous disciplines such as health economics (e.g., Borah 2006), food choices (e.g., Jaeger & Rose 2008), household choices (e.g, Revelt & Train 1998), corporate takeovers (Jones & Hensher 2007) and transport (e.g., Greene *et al.* 2006). In a recreational angling context, Phaneuf *et al.* (1998) found RPL to significantly improve model performance when investigating individuals' site choices in the Wisconsin Great Lakes Region. Breffle & Morey (2000), in their application to Maine and Eastern Canadian Atlantic salmon anglers, found that RPL explained choices significantly better than MNL and that "restricting preferences to be homogeneous often leads to significantly different mean consumer surplus estimates" (Breffle & Morey 2000, p.2). Provencher & Bishop (2004) investigated the out-of-sample forecasting performance of MNL, LC-MNL and RPL in an application to salmon angling on Lake Michigan. They found that both LC-MNL and RPL revealed statistically significant preference heterogeneity among anglers and improved model fit over MNL. Hunt *et al.* (2005) investigated site choices among moose hunters in Northwest Ontario and Boxall & Adamowicz (2002), site choices among Boundary Water canoeists in Canada. Searches through the published literature suggest that there have been only a small number of RPL applications in recreational fisheries (Train 1998; Phaneuf *et al.* 1998; McConnell &Tseng 1999; Breffle & Morey 2000; Provencher & Bishop 2004; Murdock 2006).

[12] Boyd & Mellman (1980) and Cardell & Dunbar (1980) were actually the first to apply RPL. However, their model used aggregate share data rather than data for each decision-maker. This simplification was required at the time due to computational constraints.

2.5.2 Random parameters plus control for heterogeneity and heteroscedasticity

The random parameter specification can be further extended to control for heterogeneity and heteroscedasticity in the random parameter means and variances, respectively. This feature allows research to incorporate an understanding of both systematic and random preference heterogeneity in deterministic utility. This is accomplished by re-parameterising (i.e., decomposing) random parameter means and variances with covariate data. A small body of research has used this procedure to decompose random parameter means (e.g., Greene *et al.* 2006; Hynes *et al.* 2008) and variances (e.g., Greene *et al.* 2006; Greene & Hensher 2007).

To allow σ_{ik} to be heteroscedastic the specification (x) is extended to:

$$\sigma_{ik} = \sigma_k \exp[\omega_k' hr_i] \tag{10}$$

where ω_k are parameters which capture variance heterogeneity in the random parameters in systematic utility and hr_i are observed variables of the individual (e.g., angler's skill level). Greene & Hensher (2007) use the heteroscedastic random parameter formulation and found that gender has a statistically significant influence on individuals' preferences for in-vehicle travel time and fares.

The means are allowed to be heterogeneous according to observed variables (z_i) of the individual where δ_k are parameters which capture the mean shift. B_{ik} can now be specified as:

$$\beta_{ik} = \beta_k + \delta_k' z_i + \sigma_{ik} v_{ik} \tag{11}$$

Hynes *et al.* (2008), in a kayaking application, control for heterogeneity in means of the random parameters using the individual's self-rated level of kayaking skill. Hynes *et al.* (2008) found preference intensities for water quality and star quality rating of kayaking sites to be related to skill level. Other studies which have decomposed random parameter means outside of environmental and recreation studies include Bhat (1998), Bhat & Zhao (2002) and Greene *et al.* (2006). Searches through the published literature suggest that no studies in the environmental and recreation economics literatures have controlled for heteroscedasticity in random parameters.

2.5.3 Error components

The previous section demonstrated extensions to the RPL model which control for heterogeneity and heteroscedasticity in the random parameters. However, this formulation depends on the selection of random parameter distributions and covariate data (e.g., anglers level of specialisation) to identify preference heterogeneity with residual heterogeneity left in the constant variance EV1 assumption (Greene & Hensher 2007). An RPL model can be further generalised to incorporate error components which accounts for residual unobserved preference heterogeneity not identified by the random parameters. Error components allow unrestricted patterns of inter-alternative correlation and heteroscedastic variances. The estimation procedure for error components is the same as for random parameters. Error components are typically estimated with normal distributions and can be specified for each alternative (alternative specific error components). Parameters are arrived at which maximize the simulated LL. Examples of applications of error components specifications include Brownstone & Train (1999), Herriges & Phaneuf (2002), Greene & Hensher (2007) and Jaeger & Rose (2008).

From Greene (2007), the most basic form of the error components model adapts the MNL model (specification 2) with alternative specific error components (E_{im}) indexed by m=1,……M. E_{im} is normally distributed E_{im} ~ N[0,1]. θ_m is the scale factor for error component *m*, and *s* allows for multiple choice situations. Notice that βs are *not* individual specific.

$$P(y_{is} = j) = \frac{\exp[\alpha_j + \beta x_{ijs} + \theta_j E_{ij}]}{\sum_{q=1}^{J} \exp[\alpha_q + \beta x_{iqs} + \theta_q E_{iq}]} \tag{12}$$

$$U_{ijs} = \beta x_{ijs} + \varepsilon_{ijs} + \theta_j E_{ij} \tag{13}$$

where $j = 1,......J, s = 1,.....S$

Specification 12 is known as a multinomial logit-error component (MNL-EC) model. More elaborate forms of correlation can be handled by nesting and/or cross-nesting error components. This allows multiple alternatives to appear in the same error component, allowing alternatives to appear in more than one nest. An alternative specific MNL-EC specification is analogous to an HEV model. A nested MNL-EC specification is analogous to a NL model. And, a cross-nested MNL-EC specification is analogous to a GNL model. Any pattern of error correlation can be handled by the MNL-ECs within one model by simultaneously specifying alternative specific, nested and cross nested error components. The MNL-EC model, therefore, has the combined flexibility of NL, GNL and HEV.

To further generalize (12) to account for sources of heteroscedasticity in the distribution of ε_j the model becomes:

$$P(y_{is} = j) = \frac{\exp[\alpha_j + \beta x_{ijs} + \theta_j \exp(\gamma'_m he_i) E_{ij}]}{\sum_{q=1}^{J} \exp[\alpha_q + \beta x_{iqs} + \theta_q \exp(\gamma'_m he_i) E_{iq}]} \tag{14}$$

where $\exp(\gamma'_m he_i)$ is heteroscedasticity in the variance of the error terms which is captured by, he_i, characteristics of individual i (e.g., skill level or specialisation).

2.5.3.1 Random parameters with error components

Error components can be estimated in addition to the random parameter specification (8), (e.g., Scarpa *et al.* 2005; Scarpa *et al.* 2007; Campbell *et al.* 2008; Hu *et al.* 2008). This formulation allows account to be taken of: (1) random taste variation in deterministic utility, as well as (2) heteroscedasticity and (3) correlation in unobserved utility. Hess (2005, p. 263) concludes from six different case-studies that if random parameters and error components are not both used there is a "risk of producing biased results, with the findings in relation to the modelled phenomenon, say random taste heterogeneity, being masked by the effects of the unmodelled phenomenon, say correlation between the unobserved part of utility of different alternatives". These effects are so important to differentiate that Hess (2005, p. 263) goes on to say that, "researchers should always strive to jointly allow for random taste heterogeneity and correlated error-terms, with the help of a GEV mixture model, or an appropriately specified MMNL model [A combined random parameters and error component model].

Although some risk of confounding still persists even with such advanced models, this is much reduced when compared to the more basic approaches.”

From Greene (2007), a random parameters error components (RP-EC) model is specified as:

$$P\left(y_{is} = j\right) = \frac{\exp[\alpha_j + \beta_{ik}'\mathrm{x}_{jis} + \sum_{m=1}^{M} d_{jm}\theta_m E_{im}]}{\sum_{q=1}^{J}\exp[\alpha_{qi} + \beta_{ik}'\mathrm{x}_{qis} + \sum_{m=1}^{M} d_{qm}\theta_m E_{im}]}, \tag{15}$$

where E_{im} are individual specific random error terms and, as before, *m* indexes individual error terms. E_{im} is normally distributed E_{im} ~ N[0,1], and θ_m is the scale factor for error component *m*. To allow alternatives to appear in the same nest, d_{jm} is equal to 1 if E_{im} appears in the utility for alternative *j* and 0 otherwise.

Few studies (e.g., Greene & Hensher 2007; Jaeger & Rose 2008) have simultaneously specified random parameters and error components. Herriges & Phaneuf (2002, p. 1077) report, “dramatic increases in the richness of site substitution patterns captured via the inclusion of richer patterns of error correlation”. Hess (2005) suggests that controlling for heterogeneity in observed and unobserved components of utility is important for unconfounding the sources of preference heterogeneity and reducing parameter bias.

2.5.3.2 Random parameters with error components plus control for heterogeneity and heteroscedasticity

To further generalise (15) to account for sources of heteroscedasticity in the distribution of ε_j the model becomes:

$$P\left(y_{is} = j\right) = \frac{\exp[\alpha_j + \beta_{ik}'\mathrm{x}_{jis} + \sum_{m=1}^{M} d_{jm}\theta_m \exp(\gamma'_m he_i)E_{im}]}{\sum_{q=1}^{J}\exp[\alpha_{qi} + \beta_{ik}'\mathrm{x}_{qis} + \sum_{m=1}^{M} d_{qm}\theta_m \exp(\gamma'_m he_i)E_{im}]} \tag{16}$$

where $\exp(\gamma'_m he_i)$ is heteroscedasticity in the variance of the error terms captured by he_i, characteristics of the individual (e.g., skill level or specialisation). The extended RP-EC specification (16) represents the most flexible DCM, according to Greene (2007) by allowing:

- Random parameters to capture taste distributions for observed variables.

- Decomposition of random parameter means and variances with covariates to control for heterogeneity and heteroscedasticity.
- Error components (including alternative specific, nests and cross nests) to capture unobserved heterogeneity not captured by the random parameters and random parameter decomposition terms.
- Decomposition of error components with covariates to control for heteroscedasticity.
- Full relaxation of the IID assumption and fully flexible substitution patterns.

Searches through the published literature suggest only one application of this fully extended ML model. Greene & Hensher (2007) build on Greene *et al.* (2006) to add error components to the RPL specification and determine the extent to which age influences heteroscedasticity in the error components. Studies in the environmental and recreational literatures have not, to this author's knowledge, controlled for heteroscedasticity in random parameters and error components.

2.5.4 Mixed logit limitations

The flexibility of ML comes at a cost. Namely, estimation can be a time consuming process as different numbers of draws, random parameter distributional forms, and error component nesting structures are explored (e.g., Greene & Hensher 2003; Hess 2005). Due to the complex estimation procedures and added number of parameters a number of identification and normalisation issues can arise with ML (Walker *et al.* 2007). In general, these issues arise due to difficulty of identifying a global maximum for the LL function using simulation in situations involving complex model specifications with a large number of random parameters and error components.

The topic of identification and normalisation, though important, has had a limited amount of research (Ben-Akiva & Bolduc 1996; Walker 2001; Chiou & Walker 2007; Walker *et al.*

2007). Typically, research has suggested ensuring identification by verifying parameter stability as the number of draws increases (e.g., Greene & Hensher 2003). This involves systematically testing different numbers of draws. A model is presumed to be identified when: i) it achieves parameter stability, ii) estimated parameters are consistent with prior expectations and iii) and it maximises the LL function. Research has shown, using both synthetic and real data, that ML models achieve better results in terms of (i-iii) when data involves a large number of choice observations and high attribute level variability (Ben-Akiva *et al.* 2001; Munizaga & Alvarez 2005; Cherchi & Ortúzar 2008).

2.6 Multinomial probit

Briefly, MNP allows disturbances to follow normal distributions rather than the EV1 used in logit-based models (Hausman & Wise 1978; Daganzo 1979). Multinomial probit allows heteroscedasticity and non-zero covariances, however the model is difficult to estimate due to the requirement to integrate multiple normal distributions and the use of the GHK[13] simulator to evaluate choice probabilities (see Keane (1994, 1997b) and Swait 2006). The MNP has not seen widespread application, because it is more difficult to program and is less common than ML in software packages.

Like ML, MNP can be estimated with normally distributed attribute weights and/or normally distributed error components. Examples of MNP include Brownstone & Train (1999) who found that the use of a probit GHK simulator requires more estimation time than a ML simulator, that ML and MNP predict similar substitution patterns and that the MNP model obtained a slightly higher simulated LL value than ML. The authors suggest that the LL difference was probably due to simulation variance.

[13] See Hajivassiliou & Ruud (1994) for a description of the GHK simulator.

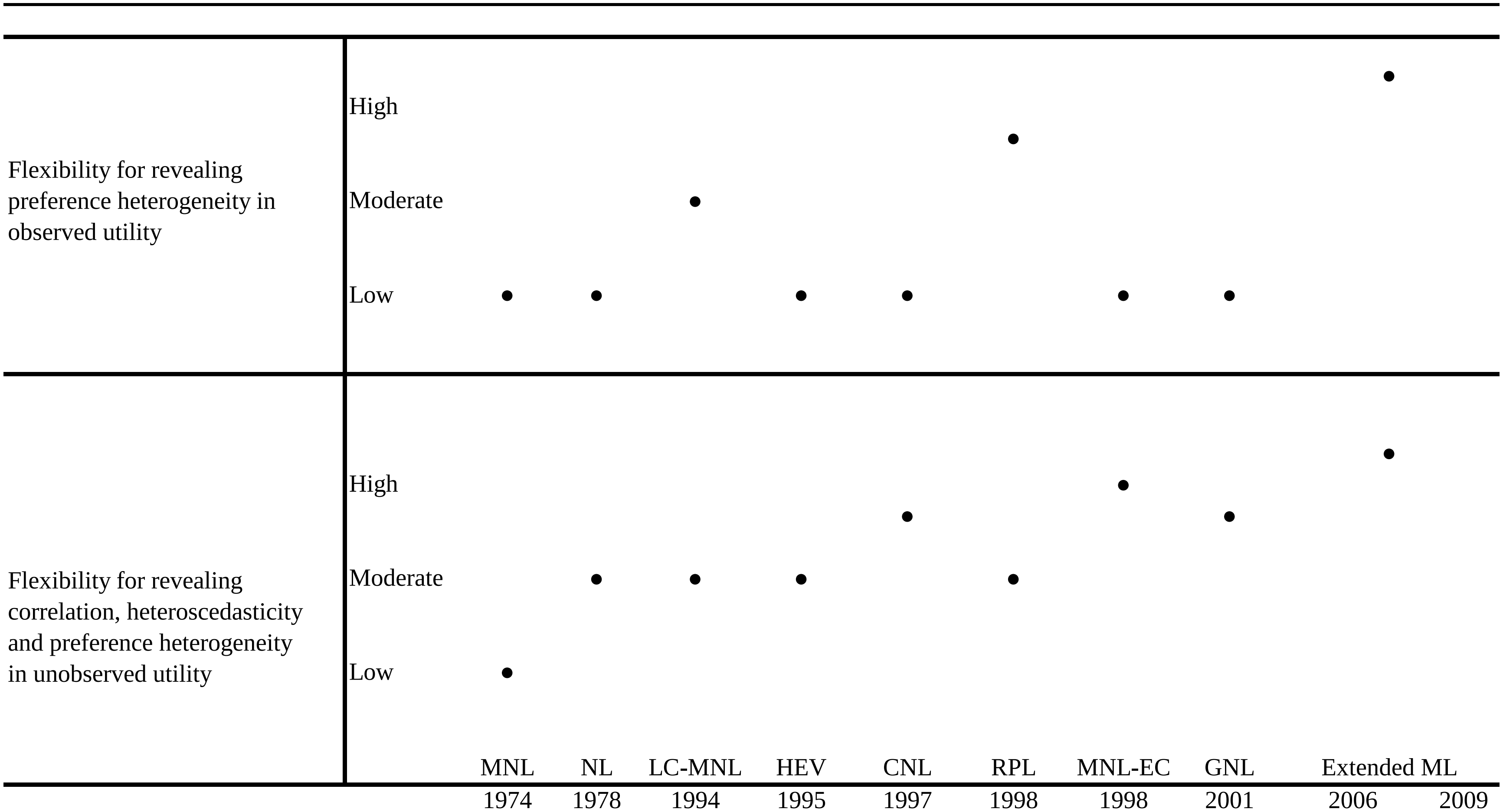
2.7 Discrete choice model summary

Discrete choice models have become popular and powerful tools for studying choice. This chapter provides an overview of the model developments[14] which have occurred since the early 1970s. It shows that the simplicity and convenience of MNL comes at the cost of flexibility in handling preference heterogeneity and maintaining forecast accuracy. Summarising, early econometric developments, including GEV models (McFadden 1978; Williams 1977; Daly & Zachary 1978) and MNP models (Hausman & Wise 1978; Daganzo 1979) focused on relaxing the IID assumption. These models provided only partial solutions to the problems embodied in MNL because they maintained the constraints on how preference heterogeneity could be revealed in observed utility. Latent class multinomial logit addressed this latter problem to a degree, but could not at the same time fully relax the IID assumption (Swait 1994). The ML model and its various extensions provide the advantages of both GEV and LC-MNL models under one framework with added flexibility (Train 2003; Greene & Hensher 2007). While research has tended to employ the RPL specification (e.g., Train 1998; Breffle & Morey 2000; Provencher & Bishop 2004; Hynes *et al.* 2008) error components (Brownstone & Train 1999) can be specified in addition to random parameters to account for residual preference heterogeneity and identify additional patterns of inter-alternative correlation. However, estimating a large number of random parameters and error components may lead to identification problems if data are not of sufficient quality (Munizaga & Alvarez 2005; Cherchi & Ortúzar 2008). Mixed logit extensions can be used to explain the sources of heterogeneity and heteroscedasticity (e.g., Greene & Hensher 2007) embodied in the random parameters and error components. Searches through the published literature suggest that extensions to control for heteroscedasticity have not been explored within the recreation, environmental and natural resource economics literatures. Table 2-2 summarises the chronological development of DCMs which maintain an EV1 disturbance, along with a

[14] There are a large number of DCM variants which, while uncommon, have also appeared in the literature over time such as ML models with GEV disturbances (e.g., Hess 2005; Gopinath 2005) latent class with heteroscedastic extreme value disturbances (Hensher *et al.* 1999) and mixed-probit (e.g., Brownstone & Train 1999). While these were not covered in the review, they serve to illustrate the continued research thrust to push the structural boundaries of DCMs.

comparison of their flexibility. Table 2-3 summarises, compares and contrasts the strengths and limitations of the DCM model forms which will be applied in this thesis.

Table 2-2: Chronology and comparison of flexibility of discrete choice models using an extreme value type 1 disturbance



Note: These dates approximate the first published empirical applications using individual level choice data.

Table 2-3: Summary of the strengths and weaknesses of the different discrete choice models applied in this thesis (adapted from Jones & Hensher 2007)

	MNL	MNL-EC	LC-MNL	RP-EC
Calculation	●Closed form solution	●Partial open, partial closed form solution requires analytical integration and maximum simulated likelihood to estimate model parameters	●Closed form solution	●Partial open, partial closed form solution requires analytical integration and maximum simulated likelihood to estimate model parameters
Estimation difficulty	●Provides one set of globally optimal parameter estimates	●Identificaiton issues due to simulated log likelihood	●Provides one set of globally optimal parameter estimates	●Identification issues due to simulated log likelihood
Expected estimation time	●Minimal	●Moderately time consuming	●Minimal	●Very time consuming
Applications	●Widely used	●Uncommon	●Gaining popularity	●Few applications have used both random parameters and error components simultaneously
Data requirements	●Less demanding data quality requirements	●Demanding data quality requirements	●Less demanding data quality requirements	●Highly demanding data quality requirements
Unobserved Utility "ε"	●Strictly maintains IID	●Overcomes IIA property completely	●Partially relaxes IID	●Random parameters partially relax IID, error components completely relax IID
	● IIA	●Nested error structures capture potential correlation across nests	● IIA within classes	●Overcomes IIA property completely
		●Error components allow for heteroscedastic error terms		●Nested error structures capture potential correlation across nests
		●Decomposition of error components to control for heteroscedasticity		●Error components allow for heteroscedastic error terms ●Decomposition of error components to control for heteroscedasticity
Observed Utility "V"	●Low level of behavioural definition and richness	●Low level of behavioural definition and richness	●Moderate level of behavioural definition and richness	●High level of behavioural definition and richness. Includes additional estimates for random parameters, heterogeneity in means and decompositions in variances (these influences are effectively treated as 'white noise' in basic models).

Chapter 3

Recreation Specialisation

3.1. Introduction

Chapter 2 described discrete choice models (DCMs) and their evolution. It was shown that these statistical methods have become powerful tools for revealing preferences and forecasting angler choice behaviour. To further enhance the behavioural realism and representation of DCMs, research has suggested and demonstrated that additional behavioural theory can be woven into the DCM framework (Walker 2001; Ben-Akiva *et al.* 2002; Hunt 2005; Oh & Ditton 2006; Adamowicz *et al.* 2008; Dorow *et al.* 2009). Hunt (2005, p. 165) recommends:

> "Future researchers should begin to employ more general methods that make much less rigid assumptions about choice behaviour. Researchers should also try to link behavioural theories of anglers to choice modelling approaches. This linkage would further develop an understanding of factors that affect anglers' site choices, participation decisions, site substitutability [and] varying preferences".

This chapter describes the theory of recreation specialisation (RS), which will be incorporated with a number of DCMs in the empirical portion of this thesis to enhance the behavioural representation and explanation of North Canterbury angler site choice.

3.2 Recreation specialisation

Recreation specialisation, first conceptualised by Bryan (1977), was developed as a framework for explaining diversity in recreationists' choice behaviours. Recreation specialisation predicts that anglers' behaviours, including their preferences and cognitions, are systematically related to their level of specialisation. Specialisation is a multidimensional concept consisting of indicators of experience, skill and commitment (Bryan 1977; Scott & Shafer 2001) allowing recreationists to be arranged along a continuum from low to high specialisation (Bryan 1977). Over time, individuals may (but not necessarily) progress to higher levels of specialisation. Progression is generally the exception rather than the rule (Kuentzel & Heberlein 2008).

Recreation specialisation predicts (Bryan 1977) that anglers with low specialisation (that is for example, those who rank angling low in importance relative to their other recreation activities, participate infrequently, have low skill and are not highly committed) are not particular about the type of fishing site (i.e., setting), are relatively unconcerned about resource disturbances or catching a large number of fish, prefer fishing with others and prefer higher bag limits (Bryan 1977; Oh & Ditton 2006). As anglers begin to specialise, catching more fish becomes more important. However, with the most highly specialised anglers catch is believed to be de-emphasised (Bryan 1977). Highly specialised anglers are expected to be relatively more concerned about resource disturbances, particular about the settings in which they fish, emphasise catching larger fish and prefer management regulations which conserve the fish stock. Research has found that specialised anglers have been found to place greater value on non-catch related aspects of fishing sites (Bryan 1977; Oh *et al.* 2005; Oh & Ditton 2006), have a more complex representation of the activity (Ditton *et al.* 1992; Fisher 1997; Miller & Graefe 2004) and ability to describe site attributes with greater specificity (Schreyer & Beaulieu 1986).

In his original study in the intermountain region of Montana, Idaho and Wyoming, Bryan (1977) identified four types of anglers ranging from low to high specialisation: *Occasional Fishers*, *Generalists Fishers*, *Technique Specialist Fishers* and *Technique-setting Specialist Fishers*. From Bryan (1977):

> *Occasional Fishers* - fish infrequently because they are new to the activity and have not established it as a regular part of their leisure, or because it simply has not become a major interest.
>
> *Generalist Fishers* - have established the sport as a regular leisure activity and use a variety of techniques.

> *Technique Specialist Fishers* - specialise in a particular method, largely to the exclusion of other techniques.
>
> *Technique-setting Specialist Fishers* - highly committed anglers who specialise in method and have distinct preferences for specific water types on which to practice the activity.

Bryan's typology is not canonical, nor mutually exclusive (Bryan 1977; 2001). Rather the key in Bryan's typology is the hierarchy of specialisation with behaviours and preferences tending from the general to the particular (Bryan 1977).

Since Bryan's (1977) initial conceptualisation, RS has received considerable attention in the leisure studies literature, with applications spanning a range of activities including bird watching (Lee & Scott 2004), hunting (Miller & Graefe 2000) and sailing (Kuentzel & Heberlein 1997).

3.3 Measuring recreation specialisation

While it is generally accepted that RS is a multidimensional construct, a key issue in the literature has been determining which dimensions and constituent indicators characterise specialisation (Bryan 1977; Scott & Shafer 2001; McFarlane 2004; Oh & Ditton 2006). Over time, research has experimented with a large number of dimensions and indicators (e.g., Bryan 1977; McFarlane 2004; Oh & Ditton 2006). To clarify, the term *dimensions* refers to the broad characteristic categories which embody the RS essence, e.g., experience, skill and commitment. The term *indicators* refer to proxies of those dimensions. Examples of indicators of the experience dimension are: years fishing, number of days angling per year and the relative importance of angling in one's life compared to other recreation activities (e.g., Bryan 1977; Scott & Shafer 2001; Oh & Ditton 2006).

The proliferation of dimensions and constituent indicators used in research has led to inconsistencies and disputes. For instance, "there remains little agreement about how precisely to characterise and measure the construct" (Scott & Shafer 2001, p. 325-326); "while

Bryan's introduction of the new conceptual framework about 30 years ago stimulated numerous research efforts, conceptualisation and measurement differences remain" (Oh & Ditton 2006, p. 370) and, "the lack of consistent conceptualisation of the dimensions that constitute specialisation and the [indicator] variables used in its measurement have been cited as a limiting factor in the advancement of specialisation research" (McFarlane 2004, p. 311).

Recently, experience[15], skill and commitment dimensions have become generally accepted, or at least commonly used, dimensions in the published literature (e.g., Scott & Shafer 2001; McFarlane 2004; Oh & Ditton 2006). Table 3-1 provides a two-way comparison of the indicator variables used to represent each of these dimensions by studies which have linked RS with discrete choice models (DCMs).

Table 3-1: Comparison of recreation specialisation indicator variables by study and dimension

	Experience/Behavioural	Skill	Commitment
Study/application			
McFarlane (2004) *Vehicle-based camping*	●years of experience. ●number of trips to the study site in the past 10 years ●number of camping trips per year	●self-reported general bush skill	●Principal components analysis found three factor levels from 13 Likert scale questions
Oh & Ditton (2006) *Angling*	●days fished in the last year in saltwater ●days fished in the last year in freshwater	●self-perceived skill level in all fishing activity ●self-perceived skill in saltwater ●subjective constraint of developing fishing skill	●importance of fishing compared to other activities ●member of a fishing club or organisation ●replacement value of fishing equipment

Rules have not been developed for determining the appropriate number of indicators necessary to represent each of the three dimensions. There have been judgement differences about which indicators constitute the various dimensions. For instance, Scott & Shafer (2001) view the indicator *the relative importance of the activity in one's life* as experiential (i.e., behavioural), while Oh & Ditton (2006) view it as an indicator of commitment.

[15] Scott & Shafer (2001) and Oh & Ditton (2006) refer to the experience dimension as the 'behavioral' dimension. To avoid confusion with choice behaviour this thesis adopts the term 'experience'.

Only a small number of studies have used quantitative statistical methods to investigate whether individuals' choice behaviours are consistent with their level of specialisation. The majority of these studies have investigated particular RS dimensions/indicators in isolation. For example McIntyre (1989) investigated commitment and McFarlane *et al.* (1998) investigated experience. Kuentzel & Heberlein (1992) investigated five specialisation dimensions (experience, commitment, media involvement, organisations and hunt style), finding no clear connection on any of these to hunters' site choices. McFarlane (2004) investigated the association between experience, skill and commitment dimensions on site choice of vehicle based campers in Alberta, Canada, using an ordered multinomial logit (MNL) model, finding that campers with more familiarity with campgrounds, higher skill levels, and higher commitment scores, were more likely to choose unmanaged campgrounds.

A few studies have explored the inter-relationship of indicator variables (e.g., Kuentzel & McDonald 1992; Kuentzel & Heberlein 1992; Scott *et al.* 1999; Lee & Scott 2004). For example, Ditton *et al.* (1992) used regression analysis to determine how well variability in the indicator, *participation frequency*, is explained by other indicators of RS. Lee & Scott (2004) used confirmatory factor analysis (CFA) to determine the 'loadings' of particular indicators onto pre-existing RS clusters. It is important to note that these approaches look only at the inter-relationships of indicator variables. They *do not* investigate the relationship between indicator variables and individuals' choice behaviours, preferences or cognitions.

Only two published studies have analysed specialisation and angler site choice according to an overall measure of specialisation by incorporating numerous dimensions/indicators to derive each individual's level of specialisation. Oh & Ditton (2006) used a two step process involving cluster analysis (CA) to create three different specialisation groups (which they termed *advanced*, *intermediate* and *casual*) using a number of indicator variables which were transformed into a small number of factor scores using CFA. Separate MNL models were then used to estimate preferences for each group. In general, Oh & Ditton's (2006, p. 369) findings accorded with theory and "each specialization group showed a notably different pattern of preference". Dorow *et al.* (2009) used an almost identical approach to study heterogeneity of preferences among European eel anglers for regulation changes and the associated welfare changes. They found that different groups of anglers exhibited distinct preferences for catching eels and regulations. However, counter to theoretical expectations, Dorow e*t al.* (2009) found that more specialised eel anglers were more averse to restrictive regulations aimed at conserving the eel stock.

3.4 Summary

This chapter has made the following important points about the RS concept. Anglers can be arranged along a *continuum of* specialisation from low to high. Recreation specialisation theory predicts that anglers vary in their choice behaviour, preferences and cognitions according to their level of specialisation. Anglers with low specialisation are predicted to be relatively less concerned about fishing site setting and resource disturbance, prefer higher bag limits and prefer fishing with others. As anglers begin to specialise, catching more fish is expected to become more important. Highly specialised anglers are particular about the setting they fish, prefer conservation of fish stocks, emphasise the importance of catching larger fish and are concerned with resource disturbance and prefer solitude. Highly specialised anglers have different cognitions including a more complex representation of the activity and ability to describe site attributes with greater specificity. Despite RS's initial purpose as a management and predictive tool few studies have actually tested whether anglers choose sites or maintain preferences according to their level of specialisation. While it is generally accepted that RS is a multidimensional construct the lack of a formalised system for measuring RS has caused inconsistencies and debate. Recent research has conceptualised RS with experience, skill and commitment dimensions. More empiricism is needed to determine the association between particular dimensions and choice behaviour/preferences. Understanding of these deep linkages would inform future measurement and conceptualisation of RS.

Chapter 4

New Zealand Recreational Trout Fisheries

4.1 Introduction

Chapter 1 introduced a recreational fishery management problem which involved a need to understand the link between trout angler activity and resource disturbances in the North Canterbury region of New Zealand. Chapter 2 identified discrete choice models (DCMs) as analytical tools suitable for studying this relationship. Chapter 3 described a theory of recreationist behaviour which can be used to enhance the analysis. This Chapter examines the case of North Canterbury recreational trout fisheries. First, the broader New Zealand context is described. The discussion then focuses in on North Canterbury and includes descriptions of the different types of fishing sites, the various forms of resource disturbances and recent trends in angler activity.

4.2 New Zealand recreational salmonid angling: An overview

New Zealand is internationally renowned for its scenic rivers and lakes, many of which have exceptional water clarity, large wild trout, low angler densities and virtually unrestricted public access (Unwin 2009). Brown trout *Salmo trutta* and rainbow trout *Oncorhynchus mykiss* were introduced in the 1860s (McDowall 1990) and quickly established wild self-sustaining populations in many rivers and lakes. In the 1970s, overseas anglers started visiting New Zealand en mass, triggering the establishment of guiding and lodging services. Combined use of New Zealand recreational salmonid (trout and salmon) fisheries is substantial (Unwin & Image 2003; Unwin 2009). Nationally, full season adult license sales have averaged around 70,000.

In the past two decades there have been three large-scale National Angler Surveys (NAS), sponsored by Fish and Game New Zealand (FGNZ) to estimate national and regional salmonid angling activity according to angler visits to different types of fishing sites and stretches[16]. On the national level, angling effort by residents has been relatively constant with an estimated 1.16 million, 1.11 million and 1.20 million angler days per year (ADPY) spent by residents for the 1994/1995, 2001/2002, and 2007/08 seasons, respectively (Unwin 2009). While overseas anglers are known to make up only a relatively small percentage of total angling effort, (69,100 ± 2,800 ADPY or 5.4% of total angling effort), they represent 12.7% of license sales and a high proportion (≥50%) of total use on some backcountry rivers of the South Island (Unwin 2009).

The total economic value of New Zealand recreational salmonid fisheries is not known. A few studies have estimated individual use values of particular angling rivers. For example, Kerr & Greer (2004) estimated the economic values of the Rangitata River for recreational angling to be between $1.4 and $4.5 million per annum (adjusted to July 2000 levels using the consumers' price index).

4.3 North Canterbury context

North Canterbury comprises part of the eastern South Island. The region is defined by the Southern Alps in the west, the Rakaia River in the south and the Conway River in the north. Extensive plains cover much of North Canterbury from the foothills to the sea. The main city, Christchurch, has a population of 348,435 (Statistics New Zealand 2006). North Canterbury has significant variation in its climate, topography and geology giving rise to a wide range of waters which support trout fisheries. The NAS categorises these different types of fishing sites as mainstem rivers, backcountry rivers, headwaters, lowland rivers, small and large lakes, and reservoirs and canals, according to geographical setting, nature, size and adjacent land use (Unwin & Image 2003; Unwin 2009). These different types of fishing sites are now

[16] This survey does not count the fisheries in the Taupo Conservancy which are administered by the Department of Conservation. The 1994/1995 and 2001/2002 NAS tracked only residential angling activity. The 2007/2008 survey included overseas anglers.

described. Note that because the North Canterbury region does not feature many reservoir or canal fisheries (or receive much angler use on these sites) they are omitted from the following description and subsequently from this research.

4.3.1 Mainstem rivers

Mainstem rivers flow across expansive valleys or plains out to sea. Flow in places is concentrated through a single channel while at other reaches the flow braids out into smaller channels over a shifting substrate of gravel and fine sediment. Agricultural land use adjacent to mainstem rivers is either extensive or intensive, depending on location. Mainstem river trout stocks are often dynamic, dictated by season, temperature, flow patterns, flood events and food supplies. Trout size varies considerably. Mainstem rivers are typically large to very large and have relatively lower water visibility compared to other fishing sites, particularly those in the backcountry. Examples of North Canterbury mainstem rivers include: the Rakaia, Waimakariri, mid to lower Hurunui and mid to lower Waiau (Unwin & Image 2003; Unwin 2009). These mainstem rivers, while supporting trout fisheries, are predominantly used by salmon anglers.

4.3.2 Backcountry rivers

Backcountry rivers flow through a diverse range of landscapes including steep-sided valleys flanked by native beech forests, terraced flats with scrub and matagouri and open plains with tussock grasses. In some cases individual backcountry rivers, in just a short distance (e.g., 20 kilometers), pass through a diverse range of landscapes and environments. Backcountry rivers tend to be small to medium in size and flow over a moderate gradient with substrates comprised of large boulders, stone and gravel. Where there is adjacent agricultural land use, it is extensive rather than intensive. During stable weather periods water visibility is high, ranging upwards of eight meters. Backcountry river trout are on average male, resident, relatively large and become increasingly difficult to capture with angling pressure (Young &

Hayes 2004). Examples of North Canterbury backcountry rivers are the: Hope, Poulter, and North and South Branches of the Hurunui (Unwin & Image 2003; Unwin 2009).

4.3.3 Headwaters

Headwater fishing sites refer to the uppermost sections or tributaries of Backcountry rivers which flow through pristine, remote areas. These fishing sites are typically accessed by helicopter or hiking tracks. Headwaters tend to be small in size and flow over a moderate to steep gradient with substrates comprised of large boulders and stone. During stable weather periods water visibility is exceptionally high. Trout in headwaters are extremely sensitive to angling pressure (Young & Hayes 2004). There are only a few North Canterbury rivers which can be considered truly remote headwater fisheries, e.g., the Esk and the Upper Waiau including its tributaries the Henry and Ada.

4.3.4 Lowland rivers

The most prominent feature of lowland rivers is that they flow through areas with intensive agricultural land use and urban development into mainstem rivers, estuaries, lakes or directly out to sea. Lowland rivers tend to be small to medium sized and flow over a shallow gradient with substrates comprised of loose sediment, mud, gravel and aquatic weed. The flow of lowland rivers is often supplied or supplemented from underground aquifer systems. Lowland rivers typically have areas with grassy banks supported by willows. Like mainstem rivers, trout populations in lowland rivers tend to be dynamic and range in size, though on average they tend to be small to medium sized. Examples of North Canterbury lowland rivers are the: Selwyn, LII, Harts Creek, Kaiapoi, and the South Branch of the Waimakariri (Unwin & Image 2003; Unwin 2009).

4.3.4 Lakes

North Canterbury features many small and a few large lakes. These are predominantly located in inland, high country areas. Agricultural land use adjacent to North Canterbury lakes tends to be extensive dry land grazing, with the exception of Lake Ellesmere which borders an area of intensive agriculture. Trout sizes range considerably, with some lakes (e.g., Lyndon) supporting high numbers of small trout while others (e.g., Hawdon) support low numbers of large trout. A number of North Canterbury lakes receive periodic stocking to supplement the wild trout stocks.

4.4 Angling techniques and equipment

The high water clarity and large average trout size, particularly on backcountry rivers, has given rise to a popular style of fishing known as 'sight-fishing'. When anglers sight-fish they use polarised sunglasses to spot individual trout then typically cast to them using light weight fly-fishing tackle with 'nymphs' or 'dry flies' that imitate natural insects. While sight fishing is most commonly employed on backcountry rivers, the technique is also used on other types of fishing sites (Kent 2006). A range of other techniques are used by anglers, adapted to particular fishing sites and conditions (Hayes & Hill 2005; Kent 2006). For example, anglers employ 'blind casting' techniques on fishing sites with lower water visibility and high trout densities. Instead of casting to individual trout, anglers blind cast either randomly or systematically to cover the water. Techniques and equipment used by fishers on lakes sometimes can be, but are not necessarily, altogether different than those employed on rivers with personal watercraft, downriggers and fish-finding sonar providing examples of techniques not used elsewhere (Kent 2006).

4.5 Resource disturbances

North Canterbury's water resources have come under increasing land and recreational use pressure. As a result, marked environmental and ecological changes have, and are expected to continue to occur. This section provides an overview of the major changes.

4.5.1 Agriculture and the shift toward intensive practices

In the past two decades North Canterbury has experienced a marked increase in intensive horticulture and dairy farming (White 2007). It is well documented that intensive agricultural practices have caused a number of adverse effects to North Canterbury's waters (Cullen *et al.* 2006; Hughey *et al.* 2007). These effects include:

- Diminished or intermittent in-stream flows as a result of water extraction (e.g., Irwell River, Kent 2000) which has reduced trout habitat, spawning areas and trout stocks (Harding *et al.* 1999; Hayes 2002).

- Increased fertiliser application and urine from stock have caused increases in phosphorus and nitrogen levels in the water. This has altered aquatic systems, and caused loss of biodiversity, eutrophication and toxic algal blooms (Young & Huryn 1999).

- Non-point and point source pollution from effluent discharge has degraded water quality and visibility and has led to high bacteria levels (Young *et al.* 2005).

- Unfenced riparian margins and non-bridged stream crossings have led to riparian margin erosion and increases in sediment loads in waterways from stock. This has reduced available trout cover, spawning grounds, water visibility and affected trout feeding behaviour (Young & Huryn 1999; Hayes 2002; Davies-Colley *et al.* 2004).

Degradation to North Canterbury Lowland streams has been rapid with "…73% of [North Canterbury] spring-fed lowland streams in 2005 in poor ecological health – up from 27% in 1999" (Holland 2006 p. 98).

4.5.2 Didymomosphenia geminata

Didymosphenia geminata (Didymo), also known as "rock snot", is a freshwater diatom which was first discovered in New Zealand in 2004. Didymo is easily transferred from one waterway to another and is currently established in approximately 70 South Island river and lake sites. In North Canterbury Didymo is present in the Hurunui, Rakaia and Clarence rivers (www.biosecurity.govt.nz/didymo accessed 2009).

Didymo manifests itself differently depending on season, location, substrate material, flow velocity and water alkalinity (Sutherland *et al.* 2007). During blooms, Didymo forms a thick brown and white mat and stalks which completely cover the substrate. At other times the algae can be latent. Rivers with stable substrates, low alkalinity and moderate flows appear, from empirical evidence, to be those most seriously affected by Didymo (Sutherland *et al.* 2007). Lowland rivers, because of their low flow velocity, fine sediment-based substrate and high nutrient levels, particularly those which are spring-fed, appear to be less susceptible to Didymo (Sutherland *et al.* 2007). The known effects of Didymo on aquatic life, trout size, trout populations and trout feeding habits are still extremely limited.

Direct impacts to anglers of Didymo include aesthetic degradation and nuisance effects by fouling gear (particularly weighted nymph and lure techinques) and creating difficulty landing trout (e.g., Sutherland *et al.* 2007). Biosecurity New Zealand has declared the South Island a "controlled area" for Didymo and while waterways are open to individuals, they are legally obligated to prevent Didymo's spread by thoroughly cleaning personal gear (www.biosecurity.govt.nz). It is unclear what impact Didymo has on angler behaviour (Unwin 2009).

4.5.3 Angler congestion

A recent study by Walrond (2001) on angler use of backcountry rivers in Nelson-Marlborough and Otago indicates that anglers are averse to encounters with other anglers. The study found that the intensity of aversion was related to river accessibility; in general, anglers were less tolerant of encounters on the more inaccessible rivers. Walrond (2001) suggests that the major reason why anglers are sensitive to encounters on backcountry river fisheries is due to the behavioural changes of trout caused by angling pressure. To reduce angler encounter rates FGNZ has piloted a special backcountry licensing system on the Greenstone and Caples Rivers in Otago (Strickland & Hayes 2003; 2004).

4.5.4 Trout catchability

Angling pressure is known to cause changes in trout behaviour. In particular trout become more difficult to catch with additional angling pressure. Young & Hayes (2004) found that after being fished to and/or captured, brown trout in a remote river in Kahurangi National Park would not resume feeding in the open for up to three days, and exhibited signs of reduced catchability. The study also found that on a less remote backcountry river brown trout were less sensitive to angler pressure, emerging sooner to resume feeding after being fished to.

4.6 Regional trends in North Canterbury

In 2007/2008 11,685 full season licenses were sold in North Canterbury and the region received a total of 200.1 ± 8.6 thousand angler days. This constitutes 15.7% of total national use (excluding the Taupo Conservancy). Angling in North Canterbury by overseas visitors constitutes an estimated 2.3% of the total, which is minimal compared with other South Island regions (Unwin 2009). While NAS statistics do not suggest much change in angler activity on the national level, the story is very different on a regional and local level in North Canterbury where angler activity is by far the most volatile out of any of the twelve FGNZ regions (Unwin 2009)

From the 1994/1995 season angling activity in North Canterbury, in terms of total angling effort by New Zealand residents, has fluctuated sharply (Table 4-1)[17]. Total resident angler use fluctuated from 166.7 ± 9.7 thousand angler days in 1994/1995 to 118.0 ± 5.2 and 195.4 ± 8.6 thousand anglers days in the 2001/2002 and 2007/2008 seasons. Angler use of mainstem rivers follows this same pattern, falling from 116.6 ± 8.7 thousand angler days in 1994/1995 to 78.0 ± 4.8 thousand angler in 2001/2002 days, then rebounding to 139.9 ± 7.7 thousand angler days in 2007/2008. A similar, but more drastic pattern occurred in the use of lowland rivers which fell sharply from 30.7 ± 3.5 thousand angler-days in 1994/1995 to 12.3 ± 1.2 thousand angler-days in 2001/2002, slightly rebounding to 16.6 ± 2.7 thousand angler-days in 2007/2008.

A very different pattern in angling effort was observed for use of lakes and backcountry rivers, which steadily rose for the period from 1994/1995 to 2007/2008 (see Table 4-1).

Table 4-1: North Canterbury annual trends in estimated fishing site usage by New Zealand residents
(angler days X 1000 ± 1 SE), 1994/1995 to 2007/2008 (adapted from Unwin 2009)

	1994/1995	2001/2002	2007/2008
Mainstem rivers	116.6 ± 8.7	78.0 ± 4.8	139.9 ± 7.7
Lowland rivers	30.7 ± 3.5	12.3 ± 1.2	16.6 ± 2.7
Small Lake	11.2 ± 1.4	10.4 ± 0.7	15.4 ± 1.8
Large Lake	8.2 ± 1.4	10.2 ± 0.9	15.2 ± 1.7
Backcountry	2.4 ± 0.7	5.0 ± 0.5	7.1 ± 1.0
Headwater	0.3 ± 0.3	1.1 ± 0.3	1.1 ± 0.4
Canal	2.3 ± 1.2	0.0 ± 0.0	0.0 ± 0.0
Reservoir	0.0 ± 0.0	1.0 ± 0.5	0.2 ± 0.1
	166.7 ± 9.7	118.0 ± 5.2	195.4 ± 8.6

Angling in North Canterbury is centred on the unpredictable Chinook salmon fisheries in the region's mainstem rivers, e.g., Rakaia, Waimakariri, Hurunui and Waiau (Unwin & Image 2003; Unwin 2009). Salmon runs are known to dominate the region's angling focus to a

[17] Data for overseas angler use was not collected in the 1994/1995 and 2001/2002 NAS and therefore, the data presented here includes only New Zealand resident anglers. Note: the term resident includes anglers from across all of New Zealand, not just North Canterbury.

greater extent than in any other part of the country (Deans *et al.* 2004, Unwin 1997, 2009). License sales and use of North Canterbury's mainstem rivers (which support those salmon runs) are known to be highly correlated with salmon runs. The salmon run was particularly poor in 2001/2002 and strong in 2007/2008 (Unwin 2009), as were license sales and use of mainstem rivers (Table 4-1). While angler use volatility in North Canterbury is partially explained by the quality of salmon runs, salmon runs alone do not explain why use of lowland rivers, lakes and backcountry rivers have fluctuated at the same time, as these latter types of sites are predominantly, if not entirely, trout fisheries. Resource disturbances, as well as other factors, are more likely causes of changing patterns in use of lowland rivers, lakes and backcountry rivers.

4.7 Summary

This chapter first provided an overview of the history and significance of New Zealand freshwater recreational angling in terms of angler participation and use of fisheries. The particular case of North Canterbury recreational trout fisheries was then described. This description included the different types of fishing sites, the types of angler techniques used at those sites, environmental degradation and other angler effects occurring and, finally, recent trends in angling activity. Data were provided which indicated that the spatial distribution of angler activity in North Canterbury, as well as license sales, has been dynamic. This is problematic for managers. Drops in license sale revenues, even if temporary, impairs Fish & Game's ability to manage the fisheries. Redistribution of angler effort can increase angling pressure at particular sites, which may lead to overfishing, reduced trout catchability and reduced opportunity for angler solitude. In turn, these effects may negatively influence license sales. While there is reason to believe that resource disturbances are underlying causes of the changes in angler activity, it is difficult to draw conclusions from the NAS data and license sale data because trout and salmon angling activity is aggregated. While the quality of salmon runs is known to be strongly related to use of mainstem rivers and license sales, the quality of salmon runs does not immediately explain why use of lowland rivers has declined sharply or why use of lakes and backcountry rivers, which are predominantly or solely trout fisheries, have increased. Resource disturbances occurring on lowland waters caused by intensified land use practices and well as angling pressure are possible drivers. However, the many different kinds of resource disturbances, occurring simultaneously (e.g., reduced water visibility, riparian margin erosion, Didymo and loss of trout stocks), make understanding their individual effects on angler activity extremely difficult. By understanding the individual impacts on anglers fishery managers would be given improved understanding of how to manage particular kinds of sites and attributes of those sites. Similarly, managers could benefit from knowledge of how management regulations, such as bag limits or measures to control angler congestion, influence use of particular kinds of sites. Research of this kind is extremely limited in New Zealand. The North Canterbury context, with its diverse range of fishing sites, changing patterns in angler activity and various forms of resource disturbances occurring at different waters and in different intensities, provides strong motivation for the study of angler site choice.

Chapter 5

Research Design

5.1 Introduction and context

Chapter 4 described a fishery management problem involving changing patterns in angler activity in the North Canterbury region of New Zealand and their possible link to resource disturbances and other effects related to angling pressure. Chapter 2 identified discrete choice models (DCM) as powerful tools for understanding choice behaviour. High quality choice data are essential for estimating DCMs, particularly advanced mixed logit (ML) specifications (Munizaga & Alvarez 2005; Cherchi & Ortúzar 2008), which offer more flexibility for determining substitution patterns compared to simpler model forms (Train 2003). This chapter describes the research and experimental design process used to create a choice experiment which was realistic to anglers, provided sufficient motivation for response, addressed the fishery management problem defined in Chapter 4 and promoted the collection of a large amount of high quality data.

To estimate a choice model, data are needed on individuals' choice responses (the dependent variable), individual characteristics, and attribute levels which comprise the alternatives in individuals' *choice sets* (independent variables). There are two types of choice data: revealed preference (RP), and stated preference (SP). As the terms imply, RP data captures individuals' actual choice responses to actual alternatives in real settings and SP captures individuals' choice responses to alternatives in hypothetical scenarios created by researchers. Both RP and SP techniques have different advantages and disadvantages and it is largely the case-by-case needs and constraints of research which dictate the use of either data paradigm. The following section describes the advantages and disadvantages of RP and SP in the context of North Canterbury freshwater trout angling.

5.2 Revealed versus stated preference

The fundamental advantage of RP data is that it captures actual behavior. As Mark & Swait (2004, p. 564) argue, "the advantage of RP data is that it is based on actual decisions; thus, there is no need to assume that consumers will respond to simulated product markets as they do to actual market situations. This characteristic gives RP data high face validity". The drawbacks of RP data include: difficulty specifying alternatives when a high number of alternatives exist (and as a corollary, the question of which alternatives to include in each individual's choice set), difficulty measuring or obtaining information on attributes and attribute levels of the alternatives and, finally and critically, RP data are often impacted negatively by collinearity as attribute levels can be closely correlated in real life settings (Hensher *et al.* 1999). Careful consideration of the North Canterbury trout angling context validated some of these RP concerns. For example, North Canterbury has: i) a large number of fishing sites (> 100 according to the South Island Sports Fishing Regulations 2008-2009 guidebook, www.fishandgame.org.nz)[18], ii) highly localised and variable weather patterns which cause difficulty in measuring dynamic fishing site conditions (attribute levels), e.g., water visibility (e.g., Hunt 2005) [19], and iii) some North Canterbury fishing sites have very similar attribute levels which are correlated. For example, many backcountry sites have similar water visibility, trout sizes, catch rates and travel distance from Christchurch. Similarities in attribute levels and the shared relationships between attributes would likely cause multi-collinearity problems if RP data were used.

Stated preference, in contrast to RP, can avoid multi-collinearity problems and there is no "measurement" of attribute levels. Stated preference data are also time and cost efficient to collect (Hensher *et al.* 1999), and useful for assessing, ex ante, environmental conditions or management regimes that may not currently exist. While there has been debate whether stated

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[18] McFadden recommends 60 choice observations are needed for each alternative to achieve reliable parameter estimates. Therefore, adequate choice data for the 100+ fishing sites in North Canterbury would require no less than 6000 choice observations (Hensher, Rose & Greene 2005). In North Canterbury, many fishing sites receive less than 60 angler visits per year in practice which prohibits the inclusion of all fishing sites into the study frame (Unwin & Brown 2003).

[19] Two broad approaches have been used to generate attribute measurements in the literature for RP. One approach is to gather data from objective measurements, the other approach is to use perception measurements, that is to ask respondents or expert focus groups what they perceive the attribute levels are. Regardless of whether attribute level measurements were perceived or objective this would be a burdensome and difficult task.

intentions translate into actual behavior, a body of research has shown the SP validity concerns are largely unfounded (e.g., Burke *et al.* 1992; Carson *et al.*, 1994; Adamowicz *et al.* 1998; Hensher *et al.* 1999; Blamey & Bennett 2001; Loureiro *et al.* 2003). Relatively few recreational angling site choice studies have used SP data (Aas *et al.* 2000, Banzhaf *et al.* 2001; Oh & Ditton 2006). Given data availability RP and SP data can be combined to exploit their strengths while minimising existing weaknesses (e.g., Adamowicz *et al.* 1994; Swait 1994; Swait *et al.* 1994).

5.3 Experimental design literature review

Stated preference data are commonly collected in choice experiments (CE) (Louviere & Hensher 1982; Louviere & Woodworth 1983), in which respondents are shown scenarios consisting of alternatives described by attributes with various attribute levels. Variation in attribute levels within and across choice scenarios imposes tradeoffs for individuals and is the key to the revelation of individuals' preferences. An important consideration therefore, is the type of experimental design to use (e.g., Scarpa & Rose 2008). In the past research has most commonly employed either random or orthogonal designs (e.g., Hahn & Shapiro 1966) which maintained attribute level balance. Orthogonality refers to the non-correlation of attribute level configurations. Attribute level balance refers to designs in which particular attribute levels occur a proportionate number of times across alternatives (Huber & Zwerina 1996). Research has questioned the importance of orthogonality and attribute level balance criteria and alternative "efficient" experimental designs which depart from these criteria are now emerging (e.g., Rose & Bliemer 2004; Bliemer & Rose 2005; Ferrini & Scarpa 2007; Scarpa & Rose 2008). These more sophisticated approaches have been shown to reduce standard errors associated with parameter estimates by using information "priors" of individuals' preferences to improve experimental design efficiency (e.g., Ferrini & Scarpa 2007; Scarpa & Rose 2008). The outcome is choice experiments which attain statistically significant parameter estimates with smaller sample sizes, or more reliable parameter estimates given a fixed sample size (Bliemer & Rose 2005).

Bayesian D-efficient designs are one form of efficient experimental design which minimises the D-error, or determinant of the asymptotic variance-covariance (AVC) matrix. The AVC matrix is an approximation of the true variance-covariance matrix (e.g., Ferrini & Scarpa 2007; Rose *et al.* 2008). As the D-error becomes smaller, a design becomes more efficient. Jaeger & Rose (2008) and Rose *et al.* (2008) explain the theory behind, and construction of, Bayesian D-efficient designs. Other types of efficient designs, each based on different criteria for evaluating efficiency, include A, B, S, and C-efficient designs. Scarpa & Rose 2008 compare these different designs and conclude: (i) that D-error type designs are the best option for producing model results that minimise both the standard errors and covariances of the parameter estimates, (ii) C-efficient designs are optimal if the objective is to estimate willingness to pay measures, (iii) S-efficient designs perform best in situations when research is constrained to very small sample sizes, and (iv) B-efficient designs perform relatively poorly and should be avoided.

There are different strategies for generating priors. One strategy uses relevant literature to inform and guide the selection of priors. In the absence of relevant literature, theory can also be used to guide 'guesses' as to what signs the priors take. A better approach is to directly generate priors through administering pilot choice experiment surveys to a representative population of individuals[20].

An important part of the experimental design process is the selection of the alternatives, attributes, attribute levels and ranges and the number of *choice situations* to assign each individual (Hensher *et al.* 2005). Another important question is whether to use qualitative or quantitative attribute measures. Design literature typically advises the use of three to six alternatives (Arentze *et al.* 2003; Caussade *et al.* 2005). However, this is not a strict rule as in particular contexts too few alternatives, attributes and attribute levels may diminish the CE realism and lead to a poor understanding of individual choice. Likewise, too much complexity can lead to cognitive burden and poor data quality. Relevance plays an important role in the cognitive burden of the choice experiment (Cummings & Taylor 1998).

[20] This is because there may be incompatibility when integrating priors from other studies which involve different decision contexts.

5.4 Experimental design generation

In light of the anticipated difficulties with an RP approach, an SP choice experimentation approach was adopted to study North Canterbury anglers' fishing site choices. A CE approach also provided an efficient means for gathering angler-specific data which could be used to identify each angler's level of specialisation (Bryan 1977). The process adopted in this research for *choice set generation*, attribute identification and attribute levels setting included literature review (e.g., Hunt 2005), consultation with Fish and Game New Zealand (FGNZ) and fishery scientists, focus groups and survey pretests.

5.4.1 Alternative, attribute and attribute level specification

The practical motivation behind the research was to address FGNZ management concerns relating to the changes to angler activity documented by the NAS. Therefore, names of the alternatives in the experimental design closely reflected the NAS fishing site categorisation. However, strict adherence to the NAS fishing site categorisation method would have required eight fishing site alternatives, plus a non-fishing alternative. Because canal, reservoir and headwater fishing site categories each comprise less than 1.1% of total usage in North Canterbury (Table 4-1, Chapter 4) they were excluded from this research. Slight modifications were made to the remaining NAS alternative names to improve clarity and ensure that the alternatives were as collectively exhaustive and mutually exclusive as possible; mainstem river was modified to include mainstem-braided river, and lowland river was redefined as lowland stream. Finally, small and large lakes were combined into a single category, Lake. Adding the option to not fish produced the following set of alternatives:

- Mainstem-braided river
- Backcountry river
- Lowland stream
- Lake

- Not fish

A fishing site attribute candidate list was generated from a literature review of: i) recreational angling site choice DCM studies (Chapter 2) and, ii) local literature describing the resource disturbances which are occurring on New Zealand fishing sites (e.g., Young & Huryn 1999; Hayes 2002; Davies-Colley *et al.* 2004). Focus groups comprised of anglers with diverse backgrounds, along with further consultation with FGNZ[21], identified nine salient attributes with regard to the North Canterbury context:

- Cost
- Travel Time
- Angler Encounters
- Water Visibility
- Catch
- Trout Size
- Bag Limit
- Riparian Margin
- Didymo

The research followed Hensher (2004, 2006a, 2006b) by keeping attribute level ranges as wide as possible while at the same time maintaining realism (Cummings & Taylor 1998). Hensher suggests that attribute level range influences parameter estimates and potential mis-specification is more likely to occur when attribute level range is narrow as opposed to wide. Bag limit, riparian margin and Didymo attributes were described with two attribute levels and the remaining attributes were described by three attribute levels. The use of three attribute levels allows non-linear preference effects to be explored (Hensher *et al.* 2005).

Considerable care was taken to ensure that the attribute levels selected provided realistic choice scenarios (Cummings & Taylor 1998). For example, backcountry rivers typically have

[21] Part of this research has been funded by FGNZ. They were included in the attribute selection process so that the final selection of attributes would address some of their major resource concerns.

much higher water visibility, larger average trout size and are more costly and time consuming to access than other fishing site types. Consequently, the study favoured alternative specific attribute levels which would reflect these differences (Table 5-1). To further maintain realism in the choice tasks, highly unrealistic attribute level combinations were not used; in particular these were scenarios with high cost and low travel times. In addition, the attribute levels for Didymo: "present" and Riparian Margin: "erosion due to stock" were unbalanced, appearing 33% of the time in all fishing site alternative scenarios across the whole of the experimental design to more closely reflect the current status of most North Canterbury fishing sites. Attribute level balance, i.e., Didymo: "present" and Riparian Margin: "erosion due to stock" appearing in 50% of choices, would have been unrealistically high.

Table 5-1: Experimental design attribute levels

	Mainstem-Braided River	Backcountry River	Lowland Stream	Lake
Cost (NZD)	\$30, \$60, \$90	\$60, \$90, \$120	\$20, \$40, \$60	\$60, \$90, \$120
One Way Travel Time (Minutes)	30,60,90	60,90,120	20,40 ,60	60,90,120
Angler Encounters	0,1,2	0,1,2	0,1,2	0,1,2
Water Visibility (Meters)	1,3,5	2,5,8	1,3,5	1,3,5
Angler Catch	1,3,5	1,3,5	1,3,5	1,3,5
Trout Size (lbs)	2, 3.5, 5	3.5, 5, 6.5	2, 3.5, 5	2, 3.5, 5
Bag Limit	0,2	0,1	0,2	0,2
Riparian Margin	Pristine, Erosion due to stock	Pristine, Erosion due to stock	Pristine, Erosion due to stock	Pristine, Erosion due to stock
Didymo	Present, Not Present	Present, Not Present	Present, Not Present	Present, Not Present

Generating and fine tuning the experimental design and internet survey instrument used to deliver the CE to anglers was an iterative process involving four stages.

5.4.1.1 Stage one

During the first stage of the experimental design generation an optimal orthogonal design, which had 108 treatment combinations, was created using Ngene (Choicemetrics 2009). This design was piloted using a hard copy survey instrument with anglers in the Nelson Trout Fisher Club and the Marlborough Angling Club. Respondents (n=52) were asked to complete four choice scenarios each. A multinomial logit model (MNL) was estimated from this sample data. This process provided important feedback pertaining to choice task complexity, realism, the suitability of the tentative alternatives, attributes and attribute levels, and priors which were integrated into more sophisticated experimental design at stage two.

5.4.1.2 Stage two

Stage two of the design process involved the construction of the internet survey instrument using a Bayesian D-efficient design with 96 treatment combinations generated using priors collected at stage one. Internet survey instrumentation was chosen over hard copy format due to advantages relating to cost and time savings (Dillman 2007). The survey consisted of multiple frames informing respondents of the nature of the choice experiment, definitions and examples of the fishing site alternatives, attributes and attribute levels, along with directions and examples for completing the choice scenarios. Each respondent was asked to complete six choice scenarios and a moderate number of questions relating to their angling background to allow identification of their level of specialisation. Andrew Collins of Bullabara and Associates was hired to assist in the construction of the internet survey instrument and its implementation onto a server which was initially trialled with six anglers in personal interview format to resolve any coherency issues. The survey, which was designed to take 15 minutes, was approved by the Lincoln University Human Ethics committee.

5.4.1.3 Stage three

Stage three of the process involved piloting the internet survey instrument in the Central South Island region, the region immediately to the south of North Canterbury, to allow further pretesting of the survey and refinement of the priors. Central South Island region anglers were identified through the FGNZ license holder database. Respondents were asked to complete the full survey, which included six choice scenarios, and were allowed one week to respond. Responses from 62 anglers resulted in 372 choice responses. An MNL model estimated from this data was used to update the priors to further refine the Bayesian D-efficient design.

5.4.1.4 Stage four

Stage four of the process involved administering the finalised internet survey instrument. An improved Bayesian D-efficient design with 96 treatment combinations was blocked into 16 randomised sets of six choice questions to eliminate order bias. This design had a D-error of 0.00886 and was optimised for a main-effects MNL model. While the design could have been optimised for more sophisticated model forms (e.g., random parameters) the approach taken erred on the side of caution given the absence of a strong understanding of extent of taste heterogeneity in the target sample frame[22].The sampling frame included the 6405 anglers with email contacts in the FGNZ database listed for the North Canterbury region[23]. An email from FGNZ invited survey participation and described the nature of the survey, its relevance, and provided a web link to the survey. One reminder email notice was sent one week after the initial invitation. The survey ran for two weeks in April 2008[24]. In order to motivate participation, respondents were eligible for entry into a draw to win their choice of a Sage fly rod or a $1000 gift certificate to a New Zealand based fishing and hunting store.

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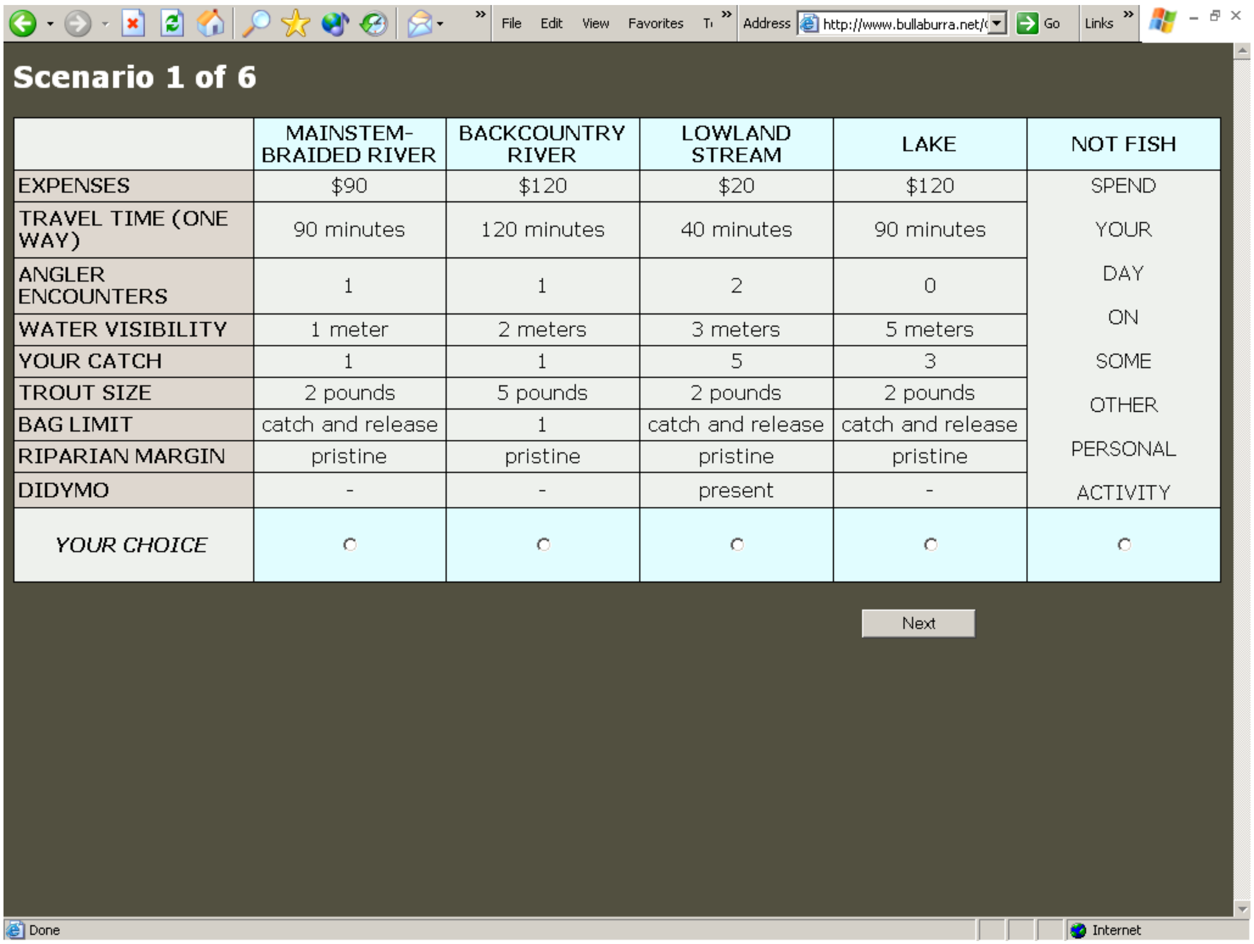
[22] D-efficiency criteria were used instead of C or S efficiency, because the sample size was not constrained and the objective was to produce model results that minimised both the standard errors and covariances of the parameter estimates, rather than estimating willingness to pay measures (Scarpa & Rose 2008).

[23] This list includes anglers who purchased a license in or through the North Canterbury regional office and therefore includes North Canterbury residents, as well as some overseas anglers and residents of other New Zealand regions.

[24] Note: the initial plan was to study the Nelson-Marlborough region. However, because of a relatively small sample frame in Nelson-Marlborough, as a precaution, surveys were run in both the North Canterbury and Nelson-Marlborough regions. Slight modifications were made to alternative names to reflect actual regional differences in fishing site types. In particular the Nelson-Marlborough survey used the names (Mainstem river, Backcountry river, Lowland stream, Braided river, not fish). Attributes, levels and descriptions were the same in both surveys as was the formatting and wording of the survey instruments. The Nelson-Marlborough survey resulted in (n=301) respondents. While this was sufficient to conduct the analysis the larger North Canterbury data set (n=813) was adopted for the analysis here.

Figure 5-1 depicts a screen shot of a choice scenario from the finalised internet survey instrument. Appendix (A) contains the full set of sample screen shots from the internet survey.

Figure 5-1: Example of a choice scenario

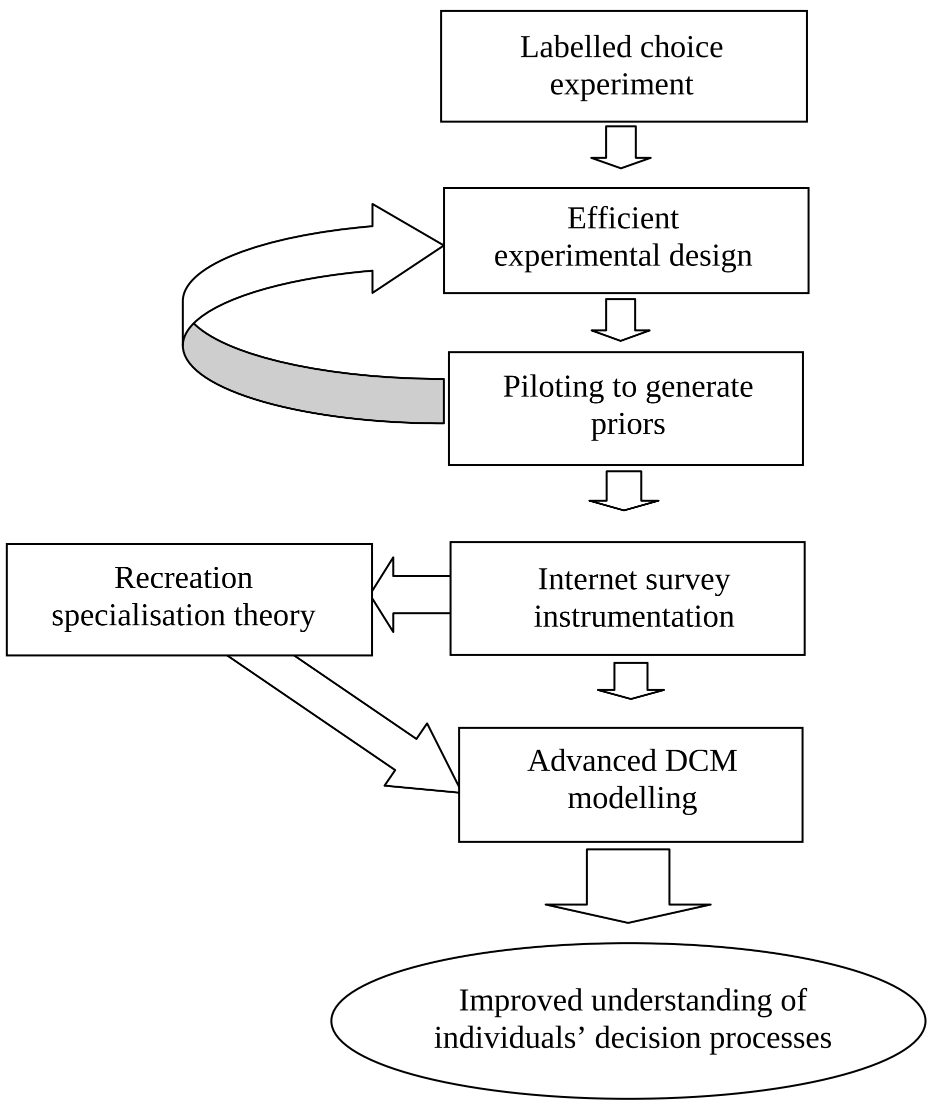


	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
EXPENSES	$90	$120	$20	$120	SPEND YOUR DAY ON SOME OTHER PERSONAL ACTIVITY
TRAVEL TIME (ONE WAY)	90 minutes	120 minutes	40 minutes	90 minutes	
ANGLER ENCOUNTERS	1	1	2	0	
WATER VISIBILITY	1 meter	2 meters	3 meters	5 meters	
YOUR CATCH	1	1	5	3	
TROUT SIZE	2 pounds	5 pounds	2 pounds	2 pounds	
BAG LIMIT	catch and release	1	catch and release	catch and release	
RIPARIAN MARGIN	pristine	pristine	pristine	pristine	
DIDYMO	-	-	present	-	
YOUR CHOICE	○	○	○	○	○

5.5 Conceptual framework of the research design

Figure 5-2 depicts the conceptual framework of the research design (adapted from Jaeger & Rose 2008).

Figure 5-2: Conceptual framework of the research design



5.6 Results

Usable responses were received from 813 of the 6405 individuals in the sample. It is not known how many of the email invitations that were sent were received by the intended recipients, so the actual response rate is unknown, but it is greater than the 12.7% indicated by the figures above. These responses resulted in 4878 completed choice scenarios. Average survey completion time was 14 minutes and 57 seconds. The median respondent:

- Was between 41 and 50 years of age;
- Had 22 years of fishing experience;
- Fished 11-20 days per year;
- Earned $60,000 – $80,000 personal income;
- Fishing was their second most important recreational activity.
- Had intermediate fishing skill.

Only 8% of respondents were internationally based, with 84% living in Canterbury. Ninety five percent of participants were male, 19% belonged to fishing clubs, and 64% used the internet to access fishing-related information. Lakes were the most commonly fished waters, being fished by 76% of survey participants. Lakes were also the water type the anglers fished most often (26% of participants said they fished most often on Lakes). Corresponding figures for other water types were: backcountry rivers (73%, 23%), braided rivers (72%, 22%), mainstem rivers (65%, 19%), and lowland streams (50%, 9%).

5.7 Statistical analysis

Maximum or simulated maximum likelihood estimation is used in the estimation of logit models. Values of coefficients are arrived at which maximize log-likelihood (LL). The higher the LL value (smaller negative number) the better the model fit. The likelihood ratio (LR) statistical test is one means used to test the significance of relative improvements in model fits for nested models. The LR test statistic is $-2(LL_{\text{base model}} - LL_{\text{estimated model}}) \sim \chi^2_{\text{(difference in the number of parameters)}}$. The McFadden R^2 statistic is the most common measure of both overall and relative model fits (Hensher *et al.* 2005). Higher McFadden R^2 values suggest a better overall fit[25]. The Akaike and Bayesian Information Criteria (AIC and BIC) are two additional measures which can be used to compare models with different numbers of parameters. The AIC is a relative measure of improvement in LL with respect to an increase in the number of parameters estimated. AIC = (-2LL + 2k)/n, where k = is the number of parameters and n is the sample size. BIC = (-2LL +k*ln(n))/2. Lower AIC and BIC scores are preferred. Nlogit 4.0 (Econometric Software 2007) was used to conduct all model estimation. In all estimated models presented in the following chapters the attributes Didymo and riparian margin were effects coded. All other attributes were entered as interval-scaled continuous variables (Hensher *et al.* 2005).

[25] McFadden $R^2 = 1-(LL_{\text{estimated model}}/ LL_{\text{base model}})$. It is important to note that the McFadden R^2 statistic is not analogous to the R^2 statistic used in ordinary least squares estimation (Hensher, Rose & Greene 2005 p. 338).

Chapter 6

Taste Heterogeneity and Complex Substitution Patterns

6.1 Introduction

Chapter 2 described extended mixed logit (ML) choice models which incorporate random preference heterogeneity in deterministic utility as well as heteroscedasticity and correlation in unobserved utility. The potential outcome is a single model which is highly descriptive and predictive. Chapter 4 identified a fishery management problem in North Canterbury involving resource disturbances and changes in angler activity. Chapter 5 described the design of the choice experiment to study this problem. This chapter applies extended ML models to explore the link between resource disturbances on lowland streams and angler activity in North Canterbury. This linkage is complicated because of: (i) the numerous forms of resource disturbance, e.g., *Didymomosphenia geminata* (Didymo), riparian margin erosion and declines in water visibility and, (ii) angler preference heterogeneity (e.g., Bryan 1977; Train 1998).

Preference diversity adds complexity to the problem of understanding how fishing site attributes (and changes in the quality thereof) influence angler decisions of whether and where to fish (Train 1998). This is because anglers are known to place different emphasis on catch rates or trout size, ability to take fish home (or otherwise) and resource disturbances (Bryan 1977). The numerous other influences on angler site choice, which are specific to the angler and type of fishing site, but which are difficult to observe from the practitioner's perspective, make unobserved utility a reality (Murdock 2006) and important pieces of information which need to be addressed in the utility construct (Hess 2005). Similarity among alternatives implies substitutability. Depending on the degree of substitutability of alternatives, degradation, or closure to one fishing site may cause anglers to redistribute predominantly to another or, in the case of varying substitutability, exhibit complex substitution patterns.

Redistributions in trout angler activity, particularly to backcountry rivers is problematic because it can lead to angler congestion (e.g., Walrond 2001), overfishing and reduced trout catchability (Young & Hayes 2004). A variety of conditions can lead to reduced fishing license sales and the consequent reduction in revenue is problematic for managers as it reduces their ability to maintain the fisheries, and provide services to anglers (Abernathy 2006). The National Angler Survey (NAS) data along with longitudinal license sale data suggest a complex story of preference heterogeneity, non-proportional substitution patterns and participation opt-out among New Zealand trout anglers (Unwin 2009; Chapter 4).

To improve understanding of angler substitution patterns and the extent to which angler preferences differ for resource disturbances, angler congestion, and regulations, this chapter employs the latent class multinomial logit (LC-MNL) model and ML models to analyse the survey data. The different models are compared with one another and with the multinomial logit (MNL) model on the basis of statistical fit, predictive performance and information revelation.

This chapter is arranged as follows. First outputs from a MNL model, three class LC-MNL model and three different extended ML models with random parameters and error components are described. Then these models are then used to forecast anglers' likely responses to a scenario involving disturbance to riparian margins, water visibility and catch rates at lowland stream fishing sites. Forecasts from the different models are compared. The chapter concludes with a discussion which identifies some management implications from the findings.

6.2 Data analysis

6.2.1 Multinomial logit

Parameter estimates in the MNL model (M1) carry expected signs (Table 6-1). Higher cost and travel time were both evaluated negatively, as were damaged riparian margins and Didymo infestations. The parameter for encounters with other anglers was negative but not significant. Higher water visibility was evaluated positively, as was catching more trout, bigger trout and higher bag limits. The alternative specific constants (ASCs) capture the mean effect of unobserved utility for each fishing site relative to not going fishing. The positive and significant Backcountry ASC indicates that, on average, the unobserved utility anglers receive from backcountry rivers is greater than the utility received by not fishing.

Table 6-1: Summary of the MNL (M1) and LC-MNL (M2) models

	MNL M1		LC-MNL M2					
			Class 1		Class 2		Class 3	
Attributes								
Cost	-0.007	***	-0.007	***	-0.007	***	-0.007	***
Travel time	-0.006	***	-0.007	***	-0.007	***	-0.007	***
Water visibility	0.049	***	0.081	***	0.063	***	-0.005	
Catch	0.111	***	0.274	***	0.075	***	0.003	
Trout size	0.159	***	0.288	***	0.172	***	0.100	***
Bag limit	0.188	***	0.051		0.351	***	0.045	
Riparian margin erosion	-0.412	***	-0.335	***	-0.418	***	-0.730	***
Didymo	-0.273	***	-0.091		-0.329	***	-0.636	***
Encounters	-0.033		-0.227	***	0.081	***	-0.047	
Mainstem-braided ASC	0.128		0.883	*	-0.296		0.925	***
Backcountry ASC	0.603	*	2.170	***	-0.897	***	1.939	***
Lowland ASC	-0.158		0.845	*	-0.592	***	-0.075	
Lake ASC	0.128		0.651		-0.857	***	2.193	***
Constant			-0.367		1.280	***	0.000	
Skill			0.644	***	-0.454	**	0.000	
Class Probability			0.317		0.475		0.208	
Parameters	13		39					
AIC	2.942		2.801					
BIC	2.959		2.852					
LL	-7187.842		-6816.690					
McFadden psuedo-R^2	0.0518		0.1349					

Note: ***, **, * = Significance at 1%, 5%, 10% level

6.2.2 Latent class multinomial logit

The three class LC-MNL model (M2, Table 6-1) incorporates a limited degree of taste variation. Model M2 is preferred over model M1 on AIC, BIC, and the McFadden pseudo-R^2 criteria and reveals different types of anglers according to taste heterogeneity and skill level. Since the LC-MNL M2 and MNL M1 models are not nested, a likelihood ratio (LR) test is not appropriate (e.g., Greene & Hensher 2003). The probabilities of anglers being members of class 1, 2 or 3 are 31.7%, 47.5% and 20.8%, respectively. Both the cost and travel time parameters are fixed across the three classes, because the primary interest of the research is to understand anglers' preferences for fishing site attributes (e.g., catch rates, regulations and resource disturbances).

Skill level is an important determinant of class allocation, with class 1 membership positively associated with more skilled anglers, while class 2 membership was negatively associated with more skilled anglers. The class 3 skill-level parameter was fixed to allow model identification. Noticeably different preference structures are evident between classes. Class 1 anglers have relatively stronger preference intensities for water visibility, catch rate and trout size compared to the other classes. Class 1 anglers view angler encounters negatively, while Class 2 anglers view angler encounters positively. Bag limits are not a significant influence on the choices of class 1 anglers while they are found to be a positive and significant influence for class 2 anglers. Didymo and riparian margin, where statistically significant, are negative influences on anglers fishing site choices, with class 3 anglers most averse to these resource disturbances.

6.2.3 Mixed logit

Coefficients for the observed site attributes in mixed logit models (M3-M5, Table 6-2) were estimated using triangular distributions. Constraints were placed on spread parameters (and hence on heterogeneity) for water visibility, catch, trout size, riparian margin and Didymo parameters so that the spreads would equal the absolute values of the means. Hensher & Greene (2003) show that when the spread parameter is constrained to equal the mean (i.e., $\beta_{jk} = \beta_k + |\beta_k| T_j$ where T_j is a triangular distribution), the density rises linearly to the mean from zero and declines to zero at twice the mean. Therefore, the distribution falls between zero and β_{jk}. This procedure ensures that the distribution with bounded support falls on either side of zero and affords a behaviorally sensible approach where such an outcome is expected *a priori*. Empirically, the triangular distribution is easy to interpret, avoids the problem of long tails associated with drawing from a log-normal distribution and is gaining popularity in the literature (e.g., Hensher & Greene 2003; Hensher *et al.* 2005; Greene *et al.* 2006; Greene & Hensher 2007). Parameter estimates from the LC-MNL model M2 were used to inform the selection of which parameters to constrain and which ones not to. To maintain consistency with model M2 the cost and travel time parameters were estimated as fixed parameters. While fixing the cost and travel time parameters limited understanding of preference heterogeneity for these attributes, this approach was favored because it reduced the model complexity in order to promote identification (Walker *et al.* 2007). As noted before, the primary interest of the research is, specifically, to understand anglers' preferences for attributes directly associated with fishing sites (e.g., catch rates, regulations and resource disturbances). Like M1, models M3-M5 estimate generic parameters for all fishing site alternatives. Note, in Table 6-2 the random coefficients for the observed site attributes are characterised by their *spreads*, while the error components, which were estimated with normal distributions, are characterised by their *standard deviations*. Shuffled Halton draws were specified in preference to regular Halton draws because they provide better coverage of the distribution space when estimating a large number of parameters (Bhat 2003; Train 2003, p. 236). The estimation of M3-M5 was a time consuming process whereby various numbers of draws (r), were specified to determine parameter stability (Chiou & Walker 2007). Parameter stability was achieved when r=750.

Model M3 (Table 6-2) incorporates random parameters plus error components (RP-EC). Model M4 extends model M3 by adding heterogeneity around the error component standard deviations. Model M5 extends model M4 by adding heterogeneity in the means and around the spreads of the random parameters.

Table 6-2: Summary of the RP-EC (M3-M5) models

	RP-EC M3		RP-EC M4		RP-EC M5	
	Mean	Spread	Mean	Spread	Mean	Spread
Attributes						
Cost	-0.006 ***	fixed	-0.005 ***	fixed	-0.010 ***	fixed
Travel time	-0.004 ***	fixed	-0.004 ***	fixed	-0.009 ***	fixed
Water visibility	0.117 ***	0.117 ***	0.118 ***	0.118 ***	0.050 **	0.050 **
Catch	0.227 ***	0.227 ***	0.228 ***	0.228 ***	0.156 ***	0.156 ***
Trout size	0.341 ***	0.341 ***	0.343 ***	0.343 ***	-0.009	0.009
Bag limit	0.212 ***	1.007 ***	0.212 ***	1.003 ***	0.323 ***	1.143 ***
Riparian margin erosion	-0.631 ***	0.631 ***	-0.632 ***	0.632 ***	-0.637 ***	0.637 ***
Didymo	-0.471 ***	0.471 ***	-0.471 ***	0.471 ***	-0.553 ***	0.553 ***
Angler encounters	-0.022	0.684 ***	-0.020	0.692 ***	-0.023	0.906 ***
Mainstem-braided ASC	-1.193 ***		-1.220 ***		0.198	
Backcountry ASC	-1.325 ***		-1.423 ***		0.642 *	
Lowland ASC	-1.431 ***		-1.454 ***		-0.204	
Lake ASC	-1.694 ***		-1.726 ***		0.005	
Heterogeneity in the mean of random parameters						
Water visibility *Skill					0.021	
Catch * Skill					0.012	
Trout size * Skill					0.212 ***	
Bag limit * Skill					-0.096 **	
Riparian margin erosion * Skill					0.021	
Didymo * Skill					0.102 **	
Angler encounters * Skill					-0.033	
Control for heteroscedasticity in the spread of the random parameters						
Water visibility * skill					0.000	
Catch * skill					0.930 ***	
Trout size * skill					2.255 *	
Bag limit * skill					-0.140	
Riparian margin erosion * skill					0.534 ***	
Didymo * skill					0.568 ***	
Angler encounters * skill					-1.038	
Error components		Stdev.		Stdev.		Stdev.
(Mainstem, Lowland) nest		0.848 ***		0.710 ***		0.746 ***
Backcountry		1.313 ***		0.959 ***		0.921 ***
Lake		1.258 ***		1.219 ***		1.050 ***
Control for heteroscedasticity in the standard deviation of the error components						
(Main,Low) * Skill			0.157		0.138	
Backcountry * Skill			0.262 **		0.337 ***	
Lake * Skill			0.018		0.180 **	
Parameters	18		21		35	
AIC	2.764		2.764		2.734	
BIC	2.788		2.792		2.780	
LL	-6749.226		-6745.517		-6657.407	
McFadden psuedo-R^2	0.1435		0.1439		0.1551	

Note: ***, **, * = Significance at 1%, 5%, 10% level

Based on statistical criteria (e.g., AIC, BIC and the McFadden pseudo-R^2) model M3 offers an improvement in fit over the LC-MNL model M2. Similar to model M1, all parameters in model M3 have expected signs and are significant except for angler encounters, which was non-significant. However, the spread parameter for encounters was statistically significant, indicating wide ranging preference heterogeneity among anglers for angler encounters - some anglers view angler encounters very negatively, for others the effect of encounters is innocuous and others view angler encounters positively. This finding was concealed by the MNL model M1.

The ASCs for all fishing site alternatives are statistically significant with a negative sign. This result may seem slightly counter-intuitive, however one must bear in mind that this does not suggest that, all things considered, anglers prefer the not fish option. Instead the negative ASCs suggest that the mean effect of the influences and preference heterogeneity which have not been accounted for systematically have relatively less utility than the not fish option. What is of empirical interest is change in the relative signs in the ASCs from the MNL specification to that of the mixed logit specification in model M3. One plausible explanation for the sign switching is that model M3 systematically explained relatively more of the positive influences on individuals' site choices in deterministic utility, thus leaving content which on average had less utility than the not fish option. Constraints placed on the triangular distributions may have influenced this result. Model M3 specified three error components, although more could have been specified according to Walker *et al.'s* (2007) order condition. One of these error component structures nested the Mainstem-braided river and Lowland stream alternatives (Main, Low). The reasoning behind this decision related to the geographical proximity and commonalities in scenic and environmental features found in many lowland streams and mainstem-braided rivers when contrasted with backcountry rivers and lakes. The two remaining error components captured the standalone unobserved utility variances for the Backcountry river and Lake alternatives. All error components are statistically significant, which shows that there is a substantial amount of preference heterogeneity associated with the fishing site alternatives not accounted for by the random parameters. The relatively large coefficient on the Backcountry river error component, compared to the Lake and Main-Low nested error components indicates that there is more variance in unobserved utility for backcountry rivers.

Model M4 extends model M3 by controlling for error component heteroscedasticity using anglers' self reported skill levels. The Backcountry*skill parameter is positive and statistically significant suggesting that anglers with higher skill level have greater unobserved utility variance than less skilled anglers. The (Main, low)*skill and Lake*skill parameters are positive but not statistically significant, which suggests that a relationship between skill level and unobserved utility variance does not exist for those alternatives. Model M4 offers an improvement in fit over M3 (χ^2=7.418; df =3; p=0.0597).

Model M5 further extends model M4 (χ^2=176.22; df =14; p<0.00001) by adding two additional sources of information: controlling for heteroscedasticity in the spreads of the random parameters and controlling for heterogeneity in the random parameter means, again using anglers' skill levels. Model M5 reveals that as angler skill level increases, preference intensities for catch become stronger, and aversions for Didymo infestation become weaker (i.e., less negative). The negative coefficient on the bag limit*skill parameter suggests that as angler skill level increases preference intensities for the option to take an additional trout home decrease. The heteroscedasticity parameters capture an additional source of angler heterogeneity in the spread estimates of the random parameters. The positive and statistically significant signs for the catch*skill, trout size*skill, Didymo*skill and riparian margin erosion*skill show that as angler skill level increases so too does the variation in preferences for the respectively named attributes. For example, this suggests that there is greater preference heterogeneity among skilled anglers for catch rates, trout size, Didymo infestation and riparian margin erosion, compared to anglers with lower skill level. The ASC in model M5 for backcountry river is positive and statistically significant, which indicates the mean effect of what is not accounted for in systematic utility, is on the average positive. No other ASCs are statistically significant.

6.3 Prediction

The advanced logit models elucidated, to varying degrees, both the extent and some of the source of preference heterogeneity among North Canterbury anglers. To test model performance, so far, this chapter has relied on statistical criteria such as the LR test, McFadden R^2, BIC and AIC. For all cases the more advanced specifications, despite additional parameters, significantly improved model fit, with M5 performing the best.

To further explore the performance of the different DCMs a scenario is simulated and models M1-M5 are used to forecast the change in the probability of anglers choosing each alternative (this effectively reveals direct and cross-elasticities). A scenario is specified which roughly simulates the resource disturbances which have occurred on North Canterbury lowland streams: 50% decrease in water visibility, 50% decrease in catch rate and appearance of riparian margin erosion. For simplicity the scenario assumes that all other fishing sites are unaffected. The status quo scenario sets each fishing site's attribute levels at the averages of attribute levels for that type of site in the experimental design (Table 5-1). It should be noted that the values reported here are based on an un-calibrated stated preference choice model, and do not reflect actual market shares, thus caution should be exercised when interpreting the actual choice probabilities. However, the primary interest here is to investigate the change in behavioural response (captured by the change in choice probabilities) which is forecast by the various models. If non-proportional substitution patterns are present the advanced logit specifications would be expected to reflect these in contrast to model M1 which maintains the independence from irrelevant alternatives (IIA) property. The IIA property dictates that the ratio of choice probabilities for any pair of alternatives is independent of any other alternative (Luce 1959; Ben-Akiva & Lerman 1985).

Table 6-3 presents three columns of data. The first column lists the predicted choice probabilities of anglers choosing each alternative in the status quo scenario. Note, that these probabilities are based on a constants only model (i.e., only ASCs). The second column lists the predicted choice probabilities of anglers choosing each alternative based on the simulated scenario and the full model (ASCs plus all estimated coefficients). The third column calculates the percentage change in choice probabilities from columns one and two. Briefly, given the resource disturbances, model M1 predicts that the probability of anglers selecting the Lowland stream alternative decreases by 48.22% while the probability of selecting the Mainstem-braided river, Backcountry river, Lake and not-fish option increase by 12.90%, 13.36%, 11.76% and 12.47%, respectively. The first point of interest is the precipitous drop in the Lowland stream choice probability. Secondly, as anticipated, the MNL model M1 maintains relatively proportional substitution patterns, which is an artefact of IIA. This is evidenced by the relatively uniform increase in the choice probabilities of the unaffected sites and the not-fish option. The probability changes are not perfectly uniform, as would be expected with IIA, because the status quo does not include the full model with estimated variable coefficients (it just includes ASCs)[26]. This same condition applies for models M2-M5.

The LC-MNL model M2 allowed a limited degree of angler heterogeneity to be revealed as well as a partial relaxation of the IID property (IIA is still maintained within classes). Model M2 predicts a decrease in probability of selecting the Lowland stream alternative of 48.73%, which is almost identical to model M1. However, model M2 predicts non-proportional substitution patterns with choice probabilities increasing for the Mainstem-braided river, Backcountry river, Lake and not-fish options by 15.80%, 11.61%, 10.39%, 18.15% respectively. The non-uniform change in choice probabilities of the unaffected sites and the not-fish option clearly indicate that IIA has been overcome.

The RP-EC model M3 predicts changes in choice probabilities distinctly different to model M1 and model M2. Firstly, model M3 predicts a 62.55% reduction in anglers selecting the Lowland stream alternative, which is noticeably larger than model M1 and model M2. Secondly, model M3 predicts a higher rate of substitution to Mainstem-Braided river alternative. Substitution to the Backcountry river and Lake alternatives are relatively lower but have similar rates (see Table 6-3). Again, the non-uniform change in choice probabilities of the unaffected sites and the not-fish option clearly indicate that IIA has been overcome.

Model M4 which controls for unobserved heterogeneity at the alternative level predicts a pattern of substitution very similar to model M3. Model M5, which controls for heterogeneity in the random parameter means and heteroscedasticity in the random parameter spreads and error component standard deviations, predicts a 52.85% reduction in choice probability for the Lowland stream alternative, and non-proportional substitution patterns tending toward the Mainstem-braided river option.

[26] Nlogit's (4.0) simulation feature imposes that the base scenario uses a constants only model.

Table 6-3: Scenario analysis: Lowland stream degradation

	Status quo (constants only)	**Post-scenario**	
MNL M1	Choice probability	Choice probability	% change in choice probability
Lowland	20.96%	10.85%	-48.22%
Mainstem-braided	21.81%	24.63%	12.90%
Backcountry	30.62%	34.71%	13.36%
Lake	17.01%	19.02%	11.76%
Not Fish	9.60%	10.80%	12.47%
Total	100.00%	100.00%	
LC-MNL M2			
Lowland	21.42%	10.98%	-48.73%
Mainstem-braided	23.11%	26.76%	15.80%
Backcountry	30.21%	33.72%	11.61%
Lake	16.86%	18.61%	10.39%
Not Fish	8.41%	9.93%	18.15%
Total	100.00%	100.00%	
RP-EC M3			
Lowland	21.01%	7.87%	-62.55%
Mainstem-braided	21.81%	26.71%	22.44%
Backcountry	30.64%	34.93%	14.01%
Lake	17.28%	19.60%	13.42%
Not Fish	9.25%	10.89%	17.66%
Total	100.00%	100.00%	
RP-EC M4			
Lowland	21.31%	7.96%	-62.64%
Mainstem-braided	22.12%	27.13%	22.68%
Backcountry	29.74%	34.04%	14.45%
Lake	17.43%	19.80%	13.61%
Not Fish	9.40%	11.07%	17.71%
Total	100.00%	100.00%	
RP-EC M5			
Lowland	21.10%	9.95%	-52.85%
Mainstem-braided	21.73%	25.85%	18.94%
Backcountry	30.24%	33.86%	11.97%
Lake	17.51%	19.60%	11.92%
Not Fish	9.42%	10.74%	14.04%
Total	100.00%	100.00%	

6.4 Discussion & management implications

This chapter contributes to the literature by applying advanced ML models which: (i) reveal both the extent and source of heterogeneity among individuals in observed and unobserved utility according to anglers' skill levels and, (ii) are able to identify complex substitution patterns (Greene *et al.* 2006; Greene & Hensher 2007).

Background data collected on trout anglers suggests that the majority of anglers fishing North Canterbury use multiple types of sites and methods while fewer anglers tend to target one type of fishing site to the exclusion of others. On the whole this indicates a relatively flexible population likely to be willing to transfer activity between locations according to conditions. Although some anglers have strong preferences for particular waters the advanced logit models (M3-M5) indicate that anglers on the whole are indeed willing to transfer their fishing effort to alternative sites and that this pattern of substitution is non-proportional. The implication is that loss of some waters has the potential to significantly increase angler pressure on other waters.

The role of respondent heterogeneity is apparent. Both the LC-MNL and ML models indicate that there are distinct differences in tastes between anglers. These taste heterogeneities are consistent with other recent discrete choice recreation studies (Train 1998; Breffle & Morey 2000). It was clear from this research that while the LC-MNL model was able to identify finite preference differences between anglers the ML models provided a richer understanding of preference heterogeneity by revealing population preference profiles over a continuous distribution.

In the past researchers believed that ML was limited in its capacity to reveal sources of heterogeneity. For instance, "while these procedures [mixed logit] incorporate and account for heterogeneity, they are not well-suited to explaining the sources of heterogeneity" (Boxall & Adamowicz 2002, p. 422) and "although the random parameters approach is useful to assess the extent of preference heterogeneity, the typical absence of an explanation for the source of preference heterogeneity limits the usefulness of the approach for managers (i.e., one typically assesses the extent and not the causes of the variability in preferences)" (Hunt 2005, p. 160). Extensions to the ML model adopted here overcome these limitations.

ML extensions identified that some preference heterogeneity, both in the random parameters and error components, could be explained by angler skill level. Bryan (1977) hypothesised that skill level is one of the key indicators of specialisation. Though this chapter investigates only one of the constituent dimensions of specialisation, skill level, the models M2 and M5 are consistent with Bryan's (1977) hypotheses. For model M2, members of class 1 fit the mould of highly specialised anglers; these anglers are more likely to be highly skilled, are averse to encounters with others, are not concerned with bag limits and prefer to catch larger trout. The positive signs on the trout size and water visibility parameters and negative signs on the encounters and bag limits parameters for class 1 anglers are consistent with Bryan's conjecture that specialised anglers have strong positive preferences for larger size fish, and are more negatively affected by environmental degradation. Class 2 anglers fit the mould of anglers with relatively low specialisation. The contrast between the two latent classes emphasises the need for fisheries managers to understand and account for angler heterogeneity in managing freshwater fisheries. Model M5 revealed similar findings - as anglers increase in skill, preference intensities for trout size increase and for bag limits decrease. Further, anglers become less averse to Didymo infestation. This latter finding, which was also identified by model M2, is in contrast to what specialisation theory suggests, i.e., anglers become more sensitive to resource disturbance with increasing specialisation. Research on ecological effects of Didymo on invertebrate density, dynamics and trout stocks and so forth, are limited at this point in time, because Didymo is such a recent phenomenon (Sutherland *et al.* 2007). However, there have been some anecdotal reports from anglers suggesting that trout stocks (in some cases) may actually benefit from Didymo infestation due to higher invertebrate densities. If this is true then perhaps more highly skilled anglers are more astute about these collateral benefits and as a result have less of an aversion to Didymo. Finally, the finding that more highly skilled anglers have greater variance in unobserved utility is consistent with Bryan's hypothesis that specialised anglers have more complex representations of the activity (Ditton *et al.* 1992; Fisher 1997; Miller & Graefe 2000). Complex representations entail a larger number and variation in attributes (grounded in both positive and negative utility) that enter anglers' decision processes. This ultimately will cause greater variance in unobserved utility. The question arises as to why the interactions for each site were not significant? A plausible reason is that North Canterbury backcountry rivers and lakes (lakes are predominantly located in the interior backcountry areas), compared to mainstem and lowland waters, tend to have far more variation in scenery, native vegetation, nuisance sand flies and accessibility. The increased likelihood that these kinds of unobserved effects enter the decision processes of more skilled anglers may explain, at least partly, why variance increases with skill for just these particular fishing sites. Chapter 7 deals more thoroughly with this issue.

While the models reported here systematically explained some of the random heterogeneity captured in the ML models using angler skill level, it may be possible to gain a better understanding of preference heterogeneity by incorporating a larger number of specialisation indicator variables or aggregate measures of specialisation (Bryan 1977). This is the focus of the next chapter.

Chapter 7

Recreation Specialisation and Angler Site Choice

7.1 Introduction

The extended mixed logit (ML) models developed in Chapter 6 outperformed the multinomial logit (MNL) and latent class-multinomial logit (LC-MNL) models to a considerable degree in terms of providing better fits, unrestricted substitution patterns and greater revelation of preference heterogeneity among anglers. Chapter 6 demonstrated the capability of extensions to ML which control for heteroscedasticity in both random parameters and error components. The purpose of this chapter is to build from the ML models developed in Chapter 6 by using multidimensional measures of recreation specialisation (RS) to provide a theoretically-based explanation of the nature of preference heterogeneity and heteroscedasticity among North Canterbury anglers (Bryan 1977). In general, linking RS with discrete choice models (DCMs) is a relatively unexplored avenue. This gap in the literature provides scope for investigating different approaches for integrating RS in discrete choice analysis.

7.2 Recreation specialisation

Chapter 3 described the RS concept. Briefly, RS is a multidimensional concept measured by indicators of experience, skill and commitment (Scott & Shafer 2001; McFarlane 2004; Oh & Ditton 2006). Recreation specialisation predicts that anglers with low specialisation (e.g., those who rank angling low in importance relative to their other recreation activities, participate infrequently, have low skill and are not highly committed), like being able to take fish home, prefer fishing with others, are not particular about where they fish, and are relatively unconcerned about resource disturbances and catching lots of fish. Highly specialised anglers, on the other hand, are predicted to have a different set of preferences and cognitions. Specialised anglers are expected to prefer to fish alone or with close peers, be very particular about the setting in which they fish, emphasise catching larger and more fish, prefer catch-and-release type regulations which conserve the fish stock and be relatively more concerned about resource disturbances. Highly specialised anglers have been found to place greater value on non-catch related aspects of fishing sites (Bryan 1977; Oh *et al.* 2005; Oh & Ditton 2006), have a more complex representation of the activity (Ditton *et al.* 1992; Fisher 1997; Miller & Graefe 2000) and have the ability to describe site attributes with greater specificity (Schreyer & Beaulieu 1986).

Despite the high level of attention given toward the RS concept (at the time of writing Bryan's (1977) paper had been cited 358 times according to google.scholar), review of the published literature revealed that only two studies have integrated the RS concept with DCM to test whether anglers' choice behaviours (i.e., preferences) are consistent with their levels of specialisation. Oh & Ditton (2006) used specialisation to study heterogeneity of preferences for red drum angling regulations. Dorow *et al.* (2009) studied heterogeneity of preferences among European eel anglers. Both studies used very similar two-step processes to integrate RS into discrete choice analysis. In step one, Oh & Ditton (2006) and Dorrow *et al.* (2009) used cluster analysis (CA)[27] to identify specialisation groups according to a number of indicators. Each study used unlabelled choice experiments and identified three separate cohorts which they termed *advanced*, *intermediate* and *casual*. Separate MNL models were then used to estimate preferences for each cohort. While this approach is one way to integrate RS into discrete choice analysis, it results in multiple models[28]. These models and their parameters can be cumbersome to interpret and compare due to scale issues (Ben-Akiva & Lerman 1985). This chapter describes and applies two alternative approaches for integrating

[27] In confirmatory factor analysis variability among individuals' indicator variables are explained and modelled as linear combinations involving a fewer number of factor scores, plus error terms. CFA allows research to determine if the loadings of indicator variables conform to pre-established theory (e.g., McFarlane 2004; Oh & Ditton 2006).The CA approach 'clusters' individuals based on shared similarities and dissimilarities using indicator variables (Chipman & Helfrich 1988; McIntyre & Pigram 1992; McFarlane 1994,1996; Scott & Thigpen 2003; Dorow *et al*. 2009). Statistical criteria are used to assist in the determination of the number of latent 'cohorts'.

[28] The reason why multiple models must be estimated is because cohorts are not interval scaled. This means that the difference in specialisation between groups is not necessarily proportional. Therefore cohort variables cannot be interacted with attributes or included in a LC-MNL model without dummy or effects coding. Dummy or effects coding each specialisation cohort and interacting these variables also results in a very large number of parameters.

RS into discrete choice analysis which avoid scale issues and the requirement to employ multiple models.

7.2.1 Analysing individual recreation specialisation indicators: An empirical approach

An alternative approach to Oh & Ditton (2006) and Dorrow *et al.* (2009) for integrating RS is to analyse RS indicators individually (e.g., McIntyre 1989; Kuentzel & Heberlein 1992; Boxall & Watson 1998; McFarlane 2004). Treating RS indicators individually has some advantages. First, it provides understanding of the particular relationships of each dimension/indicator with individuals' choice behaviours. Some dimensions/indicators may have weak, strong or different relationships to individuals' preferences altogether. Second, treating dimensions/indicators individually in analysis avoids the problem of having to indentify individual's aggregate level of specialisation.

In the context of a DCM the empirical approach compared to a theoretical approach (which will be described shortly) has some disadvantages. First, it results in a large number of estimated parameters – this number is dependent upon the number of indicators and the ways in which the indicators enter the model. Second, incorporating a large number of indicators could lead to interpretation and identification issues in the extended ML model, as well as high estimation time outlays from specification testing.

To avoid identification issues and high estimation time outlays from specification testing, conventional DCMs can be used. One approach uses an LC-MNL model to segment anglers into latent classes according to taste differences and specialisation indicators. Alternatively, an MNL model could be used with specialisation indicators 'interacted' with site attributes. Fixed parameters could then be estimated for each interaction term. These interaction parameters would determine the relationship between the indicators and individuals' preferences (e.g., Adamowicz *et al.* 1997; Morrison *et al.* 1999; Bauer *et al.* 2004). However, individual RS indicators are likely to be correlated, which makes estimating a number of interactions problematic. This is because if the interaction variables are correlated model estimation procedures have difficultly teasing apart the separate influences. Consequently, the standard errors on the estimates increase significantly which negatively impacts parameter statistical significance. While analysing a suite of indicators empirically is one option for integrating RS in discrete choice analysis, the essence of RS theory suggests that anglers can be arranged along a "continuum" of specialisation (Bryan 1977, p. 31). A continuum implies that each individual maintains an identifiable level of specialisation.

7.3 Analysing recreation specialisation: a theoretical approach

The literature reveals two broad approaches which have been used to identify individuals' specialisation: clustering approaches and the simple aggregation method (SAM). The issues with CA or combined CFA/CA approaches were previously described. The SAM uses a system in which for each individual, the sum of all indicator scores identifies their level of specialisation (e.g., Wellman *et al.* 1982; Donnelly *et al.* 1986; Williams & Huffman 1986; Virden & Schreyer 1988; Miller & Graefe 2000; Valentine 2003). The SAM affords a convenient alternative to CA approaches for identifying individuals' specialisation and has a number of advantages. It is computationally convenient and potentially identifies a high number of specialisation levels consistent with the RS concept as a "continuum" and a "process" (Bryan 1977; Scott & Shafer 2001) [29]. The SAM allows individuals on the 'specialisation extremes' (i.e., non-specialised and extremely specialised individuals) to be identified whereas CA may misidentify these individuals by bundling them with specialisation cohorts (e.g., Oh & Ditton 2006; Dorrow *et al.* 2009). Identifying specialisation level with one variable is much more parsimonious than the CA approaches and improves the feasibility of employing the flexible extended ML models with specialisation as an independent variable (which is the main objective of this chapter).

[29] Research which has used CA has commonly specified four or fewer levels. For instance, Oh & Ditton (2006) and Dorow *et al.* (2009) identified three levels of specialisation which they termed *casual, intermediate* and *advanced.* This low level of RS differentiation may oversimplify and limit the analysis between specialisation and preference.

7.4 Chapter Outline

Incorporating RS with DCMs provides the opportunity to better understand the determinants of angler preferences, test RS theory and make measurement and conceptualisation contributions toward the RS concept. In view of gaps in the literature and the limitations of using CA approaches for integrating RS into discrete choice analysis this chapter explores alternative approaches. The chapter is arranged as follows. First, the RS indicator variables and coding system used in the analysis are discussed. Next, outputs from five different models are reported. The first two models (LC-MNL and MNL) investigate RS indicators empirically. The following MNL, multinomial logit-error component (MNL-EC), and random parameters-error component (RP-EC) models incorporate RS using the SAM. The findings from the different approaches are described and the chapter concludes with a discussion on the implications of incorporating RS within DCMs.

7.5 Measuring recreation specialisation among New Zealand trout anglers

The internet survey which was used to obtain the choice experiment data (Chapter 4) included a number of RS indicator variable questions. These questions were designed to include experience, skill, and commitment dimensions of the specialisation construct (as described in chapter 3). The indicators: (i) number of days per year angling (*daysyear*), (ii) years angling (*yearsfish*), and (iii) the importance ranking of fishing compared to other activities in one's life (*rankfish*), covered the experience dimension. The indicators: (iv) skill level (*skill*), and (v) the importance of improving skill level, covered the skill dimension. The indicators: (vi) the importance of trout fishing in one's life (*impfish*), and (vii) angling club membership (*clubmemb*) covered the commitment dimension (Scott & Shafer 2001; McFarlane 2004; Oh & Ditton 2006)[30]. Finally, respondents were asked their age and income levels. Table 7-1 describes the RS indicator variables and coding system.

[30] Note: the dimensions which indicator variables belong to rests largely on interpretation. The objective in this research was not to formalise a system for allocating indicators to various dimensions. Instead the focus is on determining the effect that individual indicators and groupings thereof have on preferences.

Table 7-1: Specialisation indicator variables including age and income

Variable Name	Variable Description	Coding	
rankfish	In comparison to other recreational activities you participate in how does trout angling rank in importance?	0 = 3rd or lower 1 = 2nd 2 = 1st	
daysyear	How many days per year do you typically go trout fishing?	0 = 1-10 1 = 11-20 2 = 21≤	
yearsfish	How many years have you been trout fishing?	An integer	
skill	Relative to other New Zealand trout anglers what best reflects your angling skill level?	0 = Novice 1 = Intermediate 2 = Advanced	
impskill	How important is improving your level of angling skill and knowledge	0 = Not important 1 = Moderately important 2 = Highly important	
impfish	How important is trout fishing in your life?	0 = Not important 1 = Moderately important 2 = Highly important	
clubmemb	Are you a member of an angling club?	0 = No 1 = Yes	
income	What is your annual personal income?	0 = Under $20,000 1 = $20,000 - $40,000 2 = $40,001 - $60,000 3 = $60,001 - $80,000 4 = $80,001 - $100,000	5 = $100,001 - $120,000 6 = $120,001 - $140,000 7 = $140,001 - $160,000 8 = Over $160,000 I would rather not say
age	What is your age?	0 = 18-30 1 = 31-40 2 = 41-50 3 = 51-60	4 = 61-70 5 = 71-80 6 = Over 80 years of age I would rather not say

7.6 Empirical approaches for integrating recreation specialisation in analysis

7.6.1 A latent class multinomial logit model

A three class LC-MNL model (equation 4, Chapter 2) (M6) was estimated with all site attributes plus the seven RS indicator variables, as well as age and income (Table 7-2)[31]. Like model M2, the cost and travel time parameters were fixed across the three classes. The probability that anglers belong to class 1, 2 or 3 is .303, .427 and .225 respectively. Using the specialisation construct (Bryan 1977) the specialisation of the three classes can be evaluated by comparing attribute coefficients for each class and using indicator variable coefficients to identify the characteristics of individuals in each class. If the empirical LC-MNL approach is useful then both site attribute coefficients and indicator variables should display systematic relationships according to RS theory. Class expectations are:

- One class of anglers (highly specialised) should show greater positive preferences for improved water visibility, catch rates and trout size, indifference or negative utility from increasing bag limits, and greater aversion to encounters with other anglers and resource disturbances. These individuals would be expected to fish more often, have more experience, view angling as highly important in their life and compared to other recreation activities, have high skill, place greater importance on improving skill level and be likely to be members of angling clubs.

- A second class of anglers (low specialisation), compared to the other classes would be expected to show relatively less preference intensity for improved water visibility, catch rates and trout size, higher positive utility from increasing bag limits and angling encounters, and be less averse to resource disturbances. These individuals would be expected to fish less often, have less experience, view angling as not important in their life and compared to other recreation activities, have low skill, place less importance on improving skill level and not be members of angling clubs.

[31] The MNL model M1 (described in Chapter 5) reappears in Table 7-2 to provide a base of comparison.

- The third class should fall in between the other two classes in terms of preference intensities.

The preference structures of the three classes in M6 for site attributes resemble those found in the LC-MNL model M2 (as discussed in Chapter 6). While preference heterogeneity is evident, comparison of the classes, according to RS theory, does not provide clear evidence of specialisation. Instead the findings are mixed. For instance, while class 1 anglers show stronger tastes for higher water visibility, larger trout, restrictive bag limits and angling alone (suggesting specialisation), they were found to have less aversion to riparian margin erosion than members of other classes as well as no statistically significant preference for Didymo.

The RS indicator parameters provide additional evidence that members of class 1 are more specialised, however, the evidence is not compelling. Class 1 anglers tend to have higher skill (*skill*) and place greater importance on improving skill (*impskill*) – suggesting high specialisation. Class 2 anglers, who appear least specialised, are more likely to rank angling as not very important in their lives' (*impfish*) and low in importance compared to their other recreation activities (*rankfish*) - suggesting lower specialisation. However, contrary to expectations of highly specialised anglers, class 1 anglers do not rank angling high in terms of overall importance in their lives (*impfish*) or relative importance compared to other recreation activities (*rankfish*) and they tend to fish less (*daysyear*) and have fewer years experience (*yearsfish*). Finally, class 1 and 2 anglers are almost equally likely to be members of angling clubs. Age and income did not play a role in determining class membership.

Finally, class 1 anglers' alternative specific constants (ASCs) for all fishing sites (except Lake) are statistically significant and positive suggesting that class 1 anglers' unobserved utility (on average) for these respective alternatives are greater than the utility received from the option to not fish. Nearly the opposite was found of class 2 anglers. Unobserved utility for Class 2 anglers at all sites (except mainstem-braided rivers) is less than the utility received from the option to not fish. These findings suggest that all things remaining equal class 2 anglers are more likely to choose not to go fishing.

Table 7-2: Summary of the LC-MNL (M6) model which incorporates individual specialisation indicator variables

	MNL M1		LC-MNL M6					
			Class 1		Class 2		Class 3	
Attributes								
Cost	-0.007	***	-0.007	***	-0.007	***	-0.007	***
Travel time	-0.006	***	-0.007	***	-0.007	***	-0.007	***
Water visibility	0.049	***	0.078	***	0.067	***	-0.003	
Catch	0.111	***	0.295	***	0.078	***	-0.001	
Trout size	0.159	***	0.298	***	0.160	***	0.129	***
Bag limit	0.188	***	0.008		0.366	***	0.081	**
Riparian margin erosion	-0.412	***	-0.330	***	-0.407	***	-0.737	***
Didymo	-0.273	***	-0.082		-0.301	***	-0.664	***
Encounters	-0.033		-0.209	***	0.086	***		
Mainstem-braided ASC	0.128		1.207	**	-0.303		0.841	***
Backcountry ASC	0.603	*	2.424	***	-0.843	***	1.904	***
Lowland ASC	-0.158		1.139	**	-0.614	***	0.020	
Lake ASC	0.128		0.887		-0.835	***	2.079	***
Constant			-0.557		2.222	***		
Rank			-0.192		-0.511	**		
Daysyear			-0.371	*	0.077			
Yearsfish			-0.028	***	-0.022	**		
Skill			1.115	***	0.223			
Impskill			0.464	*	-0.159			
Impfish			0.163		-0.603	**		
Clubmemb			0.653	*	0.614	*		
Income			0.000		-0.001			
Age			0.003		0.002			
Class Probability			0.303		0.472		0.225	
Parameters	13		55					
AIC	2.942		2.792					
BIC	2.959		2.865					
LL	-7187.842		-6780.402					
McFadden psuedo-R^2	0.0518		0.1395					

Note: ***, **, * = Significance at 1%, 5%, 10% level

7.6.2 A multinomial logit model

The second approach for analysing individual RS indicators empirically incorporates a MNL model (equation 2, Chapter 2) with RS indicators interacted with alternative site attributes (Table 7-3). Because estimating interactions for all RS indicators and site attributes would have resulted in 63 interaction terms, only four RS indicators (*daysyear, skill, impfish,* *rankfish*) were included in the analysis. These indicators were carefully selected to represent each of the three respective RS dimensions: experience, skill and commitment (Scott & Shafer 2001; McFarlane 2004; Oh & Ditton 2006)[32]. The cost and travel time site attributes were not interacted. The estimated interaction effects identify the relationship between RS indicators and individuals' preferences for site attributes.

The estimated site attribute parameters in model (M7) follow those reported in model M1 with a few notable exceptions – while the water visibility, catch and trout size parameters were significant in model M1 they are not significant in model M7. This is because the interaction terms in model M7 have explained much of the choice information associated with these attributes.

Ten out of the 28 interaction terms are significant. The positive sign on the *water visibility * skill* interaction term suggests that anglers with higher skill have stronger preferences for improved water visibility. Similarly, anglers with higher skill have stronger preferences for catching larger trout. Anglers who rank fishing as highly important in their lives also have stronger preferences for improved water visibility, catching more trout and restrictive bag limits. Anglers who rank fishing high in relative importance to their other recreation activities have stronger preferences for improved catch rates and catching larger trout but also stronger aversion to Didymo. Anglers who fish more often prefer higher bag limits – this was the only significant interaction found for the RS indicator *daysyear*. No other statistically significant relationships were found. Part of the reason why only 10 of the 28 interaction terms were significant may be partly due to correlation among the indicator variables (hence interaction terms). Appendix B presents a table showing the calculated correlations among individual RS indicator variables.

[32] Note: Scott & Shafer (2001) suggest that the relative importance indicator i.e., *rankfish* belongs in the behaviour dimension while Oh & Ditton (2006) suggest that this respective indicator is of the commitment dimension.

Table 7-3: Summary of the MNL (M7) model which includes interactions of individual specialisation indicator variables

	MNL M1		MNL M7				
Attributes	Mean		Mean		*Interactions*		
Cost	-0.007	***	-0.008	***	Water visibility * Daysyear	-0.012	
Travel time	-0.006	***	-0.006	***	Water visibility * Rankfish	-0.002	
Water visibility	0.049	***	-0.008		Water visibility * Skill	0.024	*
Catch	0.111	***	0.020		Water visibility * Impfish	0.043	***
Trout size	0.159	***	-0.001		Catch * Daysyear	-0.006	
Bag limit	0.188	***	0.451	***	Catch * Rankfish	0.027	*
Riparian margin erosion	-0.412	***	-0.380	***	Catch * Skill	0.010	
Didymo	-0.273	***	-0.226	***	Catch * Impfish	0.054	***
Encounters	-0.033		0.085		Trout size * Daysyear	-0.010	
					Trout size * Rankfish	0.080	***
Mainstem-braided ASC	0.128		0.231		Trout size * Skill	0.050	***
Backcountry ASC	0.603	*	0.706	**	Trout size * Impfish	0.030	
Lowland ASC	-0.158		-0.080		Bag limit * Daysyear	0.075	***
Lake ASC	0.128		0.225		Bag limit * Rankfish	-0.022	
					Bag limit * Skill	-0.053	
					Bag limit * Impfish	-0.234	***
					Riparian margin erosion * Daysyear	0.015	
					Riparian margin erosion * Rankfish	-0.050	
					Riparian margin erosion * Skill	0.025	
					Riparian margin erosion * Impfish	-0.034	
					Didymo * Daysyear	0.011	
					Didymo * Rankfish	-0.106	***
					Didymo * Skill	0.053	
					Didymo * Impfish	-0.020	
					Encounters * Daysyear	0.031	
					Encounters * Rankfish	-0.082	**
					Encounters * Skill	-0.032	
					Encounters * Impfish	-0.036	
Parameters	13		41				
AIC	2.942		2.898				
BIC	2.959		2.898				
LL	-7187.842		-7053.579				
McFadden psuedo-R^2	0.0518		0.0695				

Note: ***, **, * = Significance at 1%, 5%, 10% level

7.7 Theoretical approaches for integrating recreation specialisation in analysis

While models M6 and M7 treated RS indictors individually, models M8-M10 analyse variables which identify individuals' levels of specialisation via the SAM. Extensive specification testing was conducted using different SAM measures which incorporated different numbers of indicator variables from Table 7-1. Contrary to intuition, SAM measures which incorporated all seven indicators did not result in the best model fit, as judged by the McFadden pseudo-R^2, AIC and BIC statistics. While not every possible combination of indicators was tested, it was found that a SAM measure which incorporated just three of the seven RS indicators (*rankfish, skill* and *impfish*) yielded the best model fits out of those tested. Importantly, *rankfish*, *skill* and *impfish* cover each of the three constituent dimensions of specialisation according to Scott & Shafer (2001). Therefore, the SAM measure, which simply summed the three indicators for each individual, without weighting, was both parsimonious and theoretically sound.

7.7.1 A multinomial logit model

The MNL model M8 (equation 2, Chapter 2) interacts the SAM-derived RS variable with all site attributes except cost and travel time (Table 7-4). All model M8 interaction terms are statistically significant except for the *riparian margin erosion*RS* interaction term. The positive signs on the *water visibility*RS, catch*RS* and *trout size*RS* interaction terms provide evidence that anglers with higher specialisation have stronger preferences for high water visibility, catching more trout and bigger trout. The negative signs on the *bag limit*RS*, *Didymo*RS* and *encounters*RS* interaction terms provide evidence that anglers with higher specialisation prefer restricting bag limits and show greater aversion to Didymo and angler encounters. These results closely follow theoretical expectations (Bryan 1977).

Briefly, the estimated parameters for water visibility, catch and trout size while significant in model M1 are no longer significant in model M8. This is because the RS interaction terms have explained much of the choice information associated with these respective attributes. There are two notable differences between models M1 and M8. First, the M8 angler encounters coefficient becomes significant. This suggests that once specialisation is controlled for, anglers prefer to encounter other anglers. Secondly, the M8 bag limit coefficient increases substantially in magnitude suggesting that once specialisation is controlled for, anglers prefer to be able to keep more fish.

7.7.2 A multinomial logit-error component model

Model M9 (equation 14, Chapter 2) generalises model M8 by adding error components to capture unobserved utility variance differences (heteroscedasticity) at the alternative level. These error components are decomposed with the SAM-derived RS variables. Similar to the models M3-M5 in Chapter 6, alternative specific error structures were estimated for the Backcountry river and Lake alternatives while the Mainstem-braided and Lowland alternatives were nested. Other nesting structures could have been applied, however to maintain consistency with Chapter 6, models M9 and M10 maintained a similar structure to models M3-M5. Parameter stability in model M9 was achieved with 500 shuffled Halton draws (Bhat 2003; Train 2003; Chiou & Walker 2007).

The estimated coefficients for the site attributes are similar to those in model M8 with the exception that the Backcountry river ASC is no longer significant. All error components are statistically significant, indicating that there is substantial amount of heterogeneity in unobserved utility at the alternative level. The larger coefficient on the Lake error component indicates there is comparatively greater variance in unobserved utility for the Lake alternative compared to the other sites.

In model M9 all interaction terms are statistically significant - the *riparian margin erosion*RS* interaction term is now found to be statistically significant. The negative sign on this interaction term suggests that more highly specialised anglers are more averse to riparian margin erosion, following theoretical expectations (Bryan 1977). All other interaction terms follow those described in model M8. The positive sign on the *Backcountry river*RS* coefficient suggests that as specialisation increases so too does heteroscedasticity in unobserved utility for backcountry sites.

Table 7-4: Summary of the MNL (M8), MNL-EC (M9), and RP-EC (M10) models which include SAM-derived RS variables

	MNL M1	MNL M8	MNL-EC M9	RP-EC M10	
	Mean	Mean	Mean	Mean	Spread
Attributes					
Cost	-0.007 ***	-0.007 ***	-0.008 ***	-0.010 ***	fixed
Travel time	-0.006 ***	-0.006 ***	-0.007 ***	-0.009 ***	fixed
Water visibility	0.049 ***	-0.001	0.022	-0.002	0.002
Catch	0.111 ***	0.017	0.022	-0.083 ***	0.083 ***
Trout size	0.159 ***	-0.014	0.030	0.079 ***	0.079 ***
Bag limit	0.188 ***	0.442 ***	0.446 ***	0.446 ***	1.202 ***
Riparian margin erosion	-0.412 ***	-0.363 ***	-0.414 ***	-0.511 ***	0.511 ***
Didymo	-0.273 ***	-0.188 ***	-0.246 ***	-0.415 ***	0.415 ***
Angler encounters	-0.033	0.107 **	0.099 *	0.040	0.024
Mainstem-braided ASC	0.128	0.230	0.083	0.208	
Backcountry ASC	0.603 *	0.699 **	0.372	0.577 *	
Lowland ASC	-0.158	-0.073	-0.264	-0.182	
Lake asc	0.128	0.223	-0.160	-0.013	
Interactions/Heterogeneity around the random parameter means					
Water visibility *RS		0.016 ***	0.012 **	0.022 ***	
Catch * RS		0.029 ***	0.034 ***	0.068 ***	
Trout size * RS		0.053 ***	0.053 ***	0.053 ***	
Bag limit * RS		-0.077 ***	-0.072 ***	-0.071 ***	
Riparian margin erosion * RS		-0.019	-0.025 **	-0.035 *	
Didymo * RS		-0.031 **	-0.029 ***	-0.011	
Encounters * RS		-0.045 ***	-0.042 ***	-0.030 *	
Heterogeneity around the spread of random parameters					
Water visibility * RS				0.873	
Catch * RS				0.449 ***	
Trout size * RS				0.396 ***	
Bag limit * RS				-0.073	
Riparian margin erosion * RS				0.240 ***	
Didymo * RS				0.279 ***	
Encounters * RS				0.691 *	
Error components			Stdev.		Stdev.
(Main, Low)			0.757 ***		0.878 ***
Backcountry			0.937 ***		0.889 ***
Lake			1.090 ***		1.098 ***
Heterogeneity around the standard deviations of the error components					
(Main,Low) * RS			0.038	-0.014	
Backcountry * RS			0.069 *	0.120 ***	
Lake * RS			0.016	0.050	
Parameters	13	20	26	35	
AIC	2.942	2.898	2.778	2.717	
BIC	2.959	2.924	2.813	2.763	
LL	-7187.842	-7074.840	-6775.125	-6615.957	
McFadden psuedo-R^2	0.0518	0.0667	0.1402	0.1604	

Note: ***, **, * = Significance at 1%, 5%, 10% level

Recreation Specialisation (RS) variable

7.7.3 A random parameters-error component model

The success of the MNL-EC model M9 motivated the estimation of a model which adds random parameters and decompositions of the random parameter means and spreads. The RP-EC model formulation M10 is similar to M5 which was applied in Chapter 5. Like model M5, model M10 was estimated using triangular distributions and 750 shuffled Halton draws (Bhat 2003; Train 2003; Chiou & Walker 2007). The site attributes were estimated as generic across all sites for parsimony. Constraints were placed on spread parameters for the water visibility, catch, trout size, riparian margin and didymo parameters so that the spreads would equal the mean values of the distributions. The bag limit and angler encounter parameters were not constrained. Cost and travel time parameters were estimated as fixed parameters. Model M10 specifies the same error component structure as M3-M5, and M9. Whereas model M5 investigated the relationship between skill level and preference, model M10 use the multidimensional SAM-derived RS variable.

The decompositions of the random parameter means are similar to the interaction effects in models M8 and M9. Specifically, model M10 finds that anglers with higher specialisation have stronger preference intensities for higher water visibility, catching more trout, catching bigger trout and forrestrictive bag limits. Likewise, these anglers also have stronger aversions to riparian margin erosion and angler encounters.

The heterogeneity around the spreads of the random parameters captures additional sources of angler heterogeneity. The positive and statistically significant signs for *catch*RS, troutsize*RS, Didymo*RS, riparian margin erosion*RS* and *encounters*RS* indicate that specialised anglers' preferences differ to a greater extent than do anglers with low specialisation.

Like model M9, all model M10 error components are statistically significant. The statistically significant *Backcountry river*RS* variable suggests that specialised anglers exhibit more variability in their preferences for unobserved utility at backcountry rivers.

The majority of the estimated random parameter means (and spreads) are statistically significant. The random parameter means for water visibility and encounters are not significant. One random parameter mean estimate stands out - the catch parameter, which is statistically significant, but negative. This result was counterintuitive. Extensive specification testing and literature review was conducted to determine the cause of the sign change on the catch parameter. Greene *et al.* (2006), pp. 87-88 note that,

"the introduction of interaction terms [e.g., RS], …., designed to uncover variance heterogeneity can no longer guarantee that the parameter distribution will be limited to one side of zero, despite constraints imposed on the underlying distribution" and "a significant, non-zero value for [ω_k, i.e., the variance heterogeneity parameter][33] may allow for parameter estimates of either sign, given that the parameter estimate is no longer solely dependent on the draw, η (conditional or otherwise) from [a known empirical distribution (e.g., triangular)], but also upon the additional information imparted through $\sigma_k \exp[\omega_k' hr_i]$. As such, even if all draws from [the triangular distribution] are constrained to one side of zero, the addition of $\sigma_k \exp[\omega_k' hr_i]$ within the estimate of marginal utility for attribute *k*, $[\hat{\beta}_k = [\bar{\beta}_k \upsilon_k + \sigma_k \times \sigma_k \exp[\omega_k' hr_i] \times \eta]$ allows for the possibility that some random parameter estimates will not be of the desired sign. Although we do not show it here, this same issue exists when decomposing the mean of random parameter distributions to uncover sources of heterogeneity. Whilst the literature has identified the need to employ distributions that dictate the sign of random parameters, research on the impact of accommodating heterogeneity around the mean of random parameter distributions and variance heterogeneity appears to be absent (see Hensher 2004)".

The unexpected sign on the catch parameter is unlikely to bear any consequence on model forecasts as much of the utility residing in the catch attribute is explained by the decomposition parameters.

7.8 Comparison of model fits

Table 7-5 compares the fits between models M1, M7, M8, M9 and M10 based on AIC, BIC and a likelihood ratio (LR) test. These statistical criteria are described at the end of Chapter 4. Model M6 cannot be compared directly with models M1, M7, M8, M9 and M10 because it is not nested with these models (e.g., Greene & Hensher 2003) There is overwhelming

[33] Note: the notation used in this thesis is slightly different than that of Greene, Hensher & Rose (2006). For consistency, the thesis notation (pp. 30-31) is maintained and substituted into the quotation.

evidence, based on all statistical criteria that going from model M1 to M7, from M1 to M8, from M8 to M9 and from M9 to M10 produces better fits.

Table 7-5: Comparison of model fits of models (M1) and (M7-M10)

	Form	Interactions	LL	Parameters	AIC	BIC	Likelihood Ratio Test
M1	MNL	None	-7187.842	13	2.942	2.959	
M7	MNL	(daysyear, skill, impfish, rankfish)	-7053.579	41	2.898	2.898	M7 vs M1 ($\chi 2$=269; df =28; p<0.0001)
M8	MNL	SAM	-7074.840	20	2.898	2.924	M8 vs M1 ($\chi 2$=226; df =7; p<0.0001)
M9	MNL-EC	SAM	-6775.125	26	2.778	2.813	M9 vs M8 ($\chi 2$=599; df =6; p<0.0001)
M10	RP-EC	SAM	-6615.957	35	2.717	2.763	M10 vs M9 ($\chi 2$=318; df =9; p<0.0001)

There is a very large improvement in going from model M8 to M9. This is due to two reasons. First, the panel formulation allows the six choices made by each individual to be correlated. Second, the error components were able to identify a substantial amount of preference heterogeneity resident in unobserved utility not identified by the fixed site attribute coefficients or interaction terms in M8.

7.9 Discussion

While the models developed in Chapter 6 focus primarily on understanding the *extent* of preference heterogeneity, this chapter focused primarily on developing the understanding of the *source* of heterogeneity using RS theory (Bryan 1977; Scott & Shafer 2001). From a fishery management perspective it is important to understand how various types of anglers are affected by resource disturbances, regulations or policies, particularly from the perspective of maintaining a license sales base and sustainable use of fisheries. From the perspective of modelling behaviour, explaining as much variability as possible (deterministically) is important because it reduces the information embodied in the stochastic disturbance term and leads to forecasts with greater certainty (Hensher *et al.* 2005).

Despite 30 years of support in the leisure studies literature, few studies have linked the RS concept with an analytical framework to investigate whether individuals' choice behaviours (including preferences and cognitions) accord with their level of specialisation (e.g., McFarlane 2004; Oh & Ditton 2006; Dorow *et al.* 2009). This gap in the literature provided motivation for exploring a number of different methods for integrating RS with DCMs.

The first approach analysed RS indicators empirically. This resulted in a very large number of estimated parameters. To handle this problem, LC-MNL and MNL models were used because they could be estimated relatively quickly and avoided potential identification issues with ML. In general, the three class LC-MNL model (M6) did not reveal clear specialisation differences among latent classes. While a two class model provided stronger evidence of specialisation, it resulted in a poorer overall model fit and so it was not reported. The result from the three class model corroborates Oh & Ditton (2006, p. 375) who found the LC-MNL model "did not provide coherent results for specialisation [indicator] variables"[34].

The MNL model (M7) incorporating RS indicator interactions provided a slightly better understanding of the relationship between specialisation indicators and preference for site attributes. Most of the statistically significant interactions followed theoretical expectations, however a large number were insignificant. In particular, frequency of participation was found only to be weakly related to individuals' preferences for site attributes. This demonstrates that individual indicators (and dimensions) have different relationships to, and ability to explain preferences (Scott & Shafer 2001). While it was beyond the scope of this chapter, the more rigorous and extensive empirical investigation of additional RS indicators would provide important insight which could contribute to the measurement and conceptualisation debate[35] involving which indicators best represent specialisation and in turn predict behaviour (e.g., Scott & Shafer 2001). Correlation among RS indicators is an issue which limits the number of indicators which can be incorporated into the analysis.

The SAM approach avoided estimation of multiple models or employing an extremely large number of effects coded variables as well as correlation issues. While basic and relatively *ad hoc*, the SAM generated RS variables provided parsimonious, easily interpreted and intuitive

[34] Note: this model is only mentioned in passing and is not formally reported in Oh & Ditton (2006).
[35] E.g., "There remains little agreement about how precisely to characterise and measure the construct" (Scott & Shafer 2001, p. 325-326).

results, which accorded with theoretical expectations. Significant relationships were found between RS and *all* observed attributes in model M9 and *most* observed attributes in models M8 and M9.

While the MNL model M8 was successful in showing how preference intensities for observed site attributes are related to specialisation, an important motivation of this chapter was to develop the flexible ML models from Chapter 6 to incorporate RS. It was shown that preferences for observed site attributes (catching more trout, larger trout, riparian margin erosion, Didymo, encounters with anglers) and unobserved components of utility (for the Backcountry river alternative in particular) increase with specialisation. In practice this suggests that managing recreational fishing resources for highly specialised anglers is relatively more complicated than it is for anglers with low specialisation; highly specialised anglers are likely to require a larger number of management regimes to cover their greater range of tastes. An important question is why specialised anglers' preferences differ more? Heteroscedasticity in observed site attributes and unobserved effects are two separate issues. The following two paragraphs address each one.

Greater variance for *observed site attributes* among specialised anglers may be the result of different forms (not levels) of specialisation (Kuentzel & Heberlein 2006). For example, some anglers might be backcountry river specialists and specifically focus on using light fly tackle and 'sight fishing' for trout which are typically large, few and far between, and difficult to catch (Young & Hayes 2004). These types of specialists are more likely to be intolerant of angler encounters, prefer high water visibility, and place greater emphasis on catching large trout (Walrond 2001; Young & Hayes 2004). Other anglers may be mainstem-braided river specialists and specifically focus on using heavy-duty gear and blind fishing techniques to target sea run trout. When fishing sea run trout in the lower reaches and mouths of mainstem-braided rivers low water visibility is advantageous and angler densities are often high due to joint salmon angling. Mainstem-braided river specialists are likely to be more tolerant of angler encounters (because many of these fishers will be targeting salmon and because of the expectation of a high number of angler encounters), prefer low water visibility and place greater emphasis on higher catch rates. These examples demonstrate how disparities in preferences can emerge and be maintained by specialised anglers. This is in contrast to beginner or occasional anglers, who are generally not concerned with fishing site setting and are far more interested in catching a fish or two and being able to take those fish home (Bryan 1977). This illustration also raises the question of whether preference parameters for observed site attributes should be estimated as alternative specific (as opposed to generic) to account for site specific tastes. This issue is investigated in Chapter 8.

The reason why specialised anglers have greater variance in the unobserved utility for backcountry rivers is not exactly clear. This is because there is no way to determine what is in the unobserved component of utility. Before offering a few possible causes it is helpful to clarify the nature of this problem. From Chapter 2, the unobserved effects contain: i) unobserved utility, plus ii) unobserved preference heterogeneity, iii) estimation error and, iv) measurement error (Manski 1977). The ASCs measure the mean of the unobserved effects (for J-1 alternatives). In essence the error components capture the variance around the mean of the ASCs. The decompositions of these error variances determine whether variance increases or decreases according to covariates. This chapter found that for the Backcountry river alternative, error variance increases according to specialisation. It is not likely that this variance phenomenon is related to (iii) and (iv). This is because all alternatives included the same generic parameter estimates and so estimation or measurement error would be equal across alternatives. Therefore, the variance phenomenon is more likely related to differences in: (i) specialised anglers' unobserved utilities (unobserved attributes) and, (ii) unobserved preference heterogeneity related to those unobserved attributes. As noted in chapter 6, Backcountry rivers tend to have more variation, in scenery, native vegetation, nuisance sand flies and accessibility compared with other fishing sites. The greater number and variation in unobserved influences of backcountry rivers, along with specialised anglers' awareness of these, is likely the reason why variance increases with specialisation (Schreyer & Beaulieu 1986).

Additional research is needed to understand the nature of specialisation and heteroscedastcity, particularly for unobserved utility. This relationship is important because the variance of unobserved utility is linked to the scale term (Ben-Akiva & Lerman 1985; Swait 1993). The scale term either scales up or down coefficients in the observed portion of utility. Almost all of past DCM research has treated this scale term as a constant (all individuals have scale homogeneity) except for Breffle & Morey (2000) and Fiebig *et al.* (2009). If alternatives' unobserved components of utility are heteroscedastic, yet the scale term is treated as a constant, coefficients in the observed portion of utility become biased for particular individuals. New research is focusing on relaxing the constant scale assumption through its random parameterisation (Fiebig *et al.* 2009). However, instead of treating the scale term as a random distribution across individuals it may be possible to add deeper insight by segmenting the scale term according to specialisation heterogeneity. This may be the key to further improving the understanding and prediction of choice behaviour within the DCM framework.

Chapter 8

Alternative-specific Preference Heterogeneity

8.1 Introduction

Past recreational angling site choice literature (e.g., Train 1998; Morey *et al.* 2002) and Chapters 6 and 7 of this thesis, have made the assumption that anglers' marginal (dis)utilities for observed fishing site attributes do not vary from site to site. In other words, anglers have been assumed to receive the same utility from catching a trout in a backcountry river as they do in a lake, and so forth. This assumption is embodied in generic, rather than alternative specific, coefficient estimates for observed attributes in each alternative's utility function[36]. While a generic specification produces a relatively parsimonious model it may fail to capture the presence of alternative specific preference heterogeneity (ASPH). Failure to address ASPH may overlook relevant behavioural information which has important management and policy implications. This chapter investigates this issue.

Recreation site choice research employing discrete choice models (DCMs) (e.g., Hunt *et al.* 2005; Hanley *et al.* 2003) is now commonly estimating coefficients in observed utility using continuous (e.g., Train 1998) or finite mixture distributions (Boxall & Adamowicz 2002; Provencher & Bishop 2004) to account for heterogeneity. Repeatedly, research (including Chapters 5 and 6 of this thesis) has found anglers to exhibit a significant amount of random preference heterogeneity even after coefficients are decomposed with angler characteristics (e.g., level of specialisation, Chapter 7). While it is econometrically parsimonious to capture preference heterogeneity for observed site attributes for all fishing sites with a single generic variance parameter, a significant portion of this 'randomness' may be systematically related to a deeper source of taste variation - ASPH. That is, the random taste variation identified by generic random terms may be caused by the site-specific tastes that anglers have for particular

[36] Alternative specific constants (ASCs) capture utility differences across alternatives. However, ASCs only identify the mean utility of <u>unobserved</u> attributes.

attributes, according to fishing site context. One can visualise ASPH as a set of finite preference points distributed over the population of alternatives. If not accounted for, ASPH may be misinterpreted as random heterogeneity across individuals in a generic coefficient.

Understanding ASPH for observed site choice attributes has important management implications. For instance, anglers may view encounters negatively on some fishing sites (e.g., backcountry rivers, Walrond 2001), but non-negatively on lakes, where fishing pressure has less of an impact on trout catchability (Young & Hayes 2004), and where trout densities are higher. Similarly, anglers' preference intensities for catching trout may differ according to fishing site type and location. In North Canterbury, trout in backcountry rivers are known to be almost entirely wild, whereas in lakes a significant portion originate from artificial stocking practices (e.g., Lake Lyndon). In a generic random parameters specification this alternative specific heterogeneity may be misinterpreted or confounded with taste heterogeneity between individuals. Enacting a strategy to control congestion or calculate natural resource damage assessments (NRDA) on all fishing sites based on information from a generic congestion coefficient in the presence of ASPH (even though disturbance around the mean is accounted for) may lead to a suboptimal outcome.

Alternative specific preference heterogeneity has important implications for policy and conducting NRDA. For instance, Train (1998) and Morey *et al.* (2002) used DCMs to inform the State of Montana about damages to trout streams caused by the mining operations of the Atlantic Richfield Co. (ARCO). Their purpose was to estimate the compensation needed to make anglers just as well off as before the damage occurred to trout stocks at particular fishing sites. In each case, the research collected choice and alternative data from a number of fishing sites spread over a large geographical area. Following standard practice, Train (1998) and Morey *et al.* (2002) specified generic parameters to estimate anglers' marginal utility for trout stocks. These generic coefficients assume that anglers' marginal utilities for additional trout stocks (and catch rates) are identical across different fishing sites. While Train's (1998) single generic random parameter for trout stock found significant taste heterogeneity, this apparently 'random' heterogeneity may have been caused by systematic differences in anglers tastes for trout stocks at the different fishing sites. If trout stock values for the damaged site were systematically related to outlying tails of the distribution then substituting in the generic coefficient value for the affected site could bias the level of damage assessment either up or down for a specific site.

Choice research outside of recreation studies has explored the significance of context, space and site specific tastes. Jaeger & Rose (2008) found context is an important influence on food choice. Campbell *et al.* (2009) found spatial differences in individuals' willingness to pay for landscape improvements in Ireland. Greene *et al.* (2006) and Green & Hensher (2007) specify alternative specific parameters for common attributes such as in-vehicle travel time and egress time for public and private modes of transportation and found marginal utility differences across alternatives. This chapter contributes to this literature by investigating whether anglers' marginal (dis)utilities for observed site attributes differ across fishing sites. New Zealand recreational trout fisheries provide an example of a recreation context where recreationists choose from fishing sites which have a number of similar attributes, but differ markedly in their natural characteristics. It is contended that important information which could improve resource management, policy and NRDA is lost when the influence of observed attributes is assumed to be invariant across sites.

To investigate whether New Zealand anglers exhibit ASPH for observed fishing site attributes, models are estimated with both alternative specific and generic parameter specifications for site attributes. These models are compared on the basis of various statistical criteria and the Delta Method test (Klein 1953; Casella & Berger 1990) is used to evaluate whether site-specific parameters are significantly different from one another.

In order to test the ASPH hypothesis a multinomial logit (MNL) model (M11) was estimated with alternative specific parameters for observed site attributes (Table 8-1). Cost and travel time parameters were estimated as generic. Initially, model M11 was estimated with alternative specific coefficients for all observed site attributes (except for cost and travel time). However, none of the alternative specific coefficients for the encounters variable were significant. Therefore, encounters were consolidated into a single generic coefficient. The

MNL (M1) model which is reproduced in Table 8-1 with generic coefficients is described in Chapter 6.

All M11 parameter estimates carry expected signs. Higher cost and travel time were both evaluated negatively, as were all site specific coefficients for damaged riparian margins and Didymo infestation. Likewise, for all sites better water visibility was evaluated positively, as were catching more trout, bigger trout and increased bag limits. The ASCs indicate the mean effect of all unobserved influences on anglers' choice for each fishing site alternative, relative to the not fish option. The positive and significant ASC for the Lake alternative indicates that, *ceteris paribus*, what has been left out of the model for the Lake alternative has higher utility than not going fishing. The remaining ASCs are not significant.

While statistical tests are necessary for confirmation, at this point comparison of the alternative specific coefficients strongly suggests ASPH (Table 8-1). For instance, according to M11:

- Higher water visibility on mainstem-braided rivers and backcountry rivers is relatively more important to anglers than higher water visibility on lowland streams and lakes.

- Anglers gain more utility from catching additional trout, larger trout and taking them home from a backcountry river compared to all other sites.

- Anglers are most averse to riparian margin erosion on backcountry rivers, however, there does not appear to be much difference between aversion to erosion to riparian margins on any of the river-based alternatives.

- Anglers are relatively more averse to Didymo infestation on mainstem-braided and backcountry rivers than they are to Didymo infestation on lowland streams and lakes.

Table 8-1: Summary of the MNL (M11) and MNL-EC (M12) models which account for alternative specific preference heterogeneity

	MNL (M1)		MNL (M11)		MNL-EC (M12)	
Attributes						
Cost	-0.007	***	-0.0061	***	-0.0072	***
Travel time	-0.006	***	-0.0049	***	-0.0065	***
Water visibility Generic	0.049	***				
Water visibility Mainstem			0.0806	***	0.1139	***
Water visibility Backcountry			0.0681	***	0.0856	***
Water visibility Lowland			0.0523	**	0.0644	**
Water visibility Lake			0.0427	*	0.0510	*
Catch Generic	0.111	***				
Catch Mainstem			0.1221	***	0.1568	***
Catch Backcountry			0.1904	***	0.2354	***
Catch Lowland			0.1223	***	0.1411	***
Catch Lake			0.0710	***	0.0926	***
Trout size Generic	0.159	***				
Trout size Mainstem			0.2253	***	0.2824	***
Trout size Backcountry			0.2632	***	0.3494	***
Trout size Lowland			0.1398	***	0.1727	***
Trout size Lake			0.1012	***	0.1303	***
Bag limit Generic	0.188	***				
Bag limit Mainstem			0.1907	***	0.2303	***
Bag limit Backcountry			0.2759	***	0.3420	***
Bag limit Lowland			0.1481	***	0.1727	***
Bag limit Lake			0.1733	***	0.2248	***
Riparian Margin Generic	-0.412	***				
Riparian Margin Mainstem			-0.4632	***	-0.5534	***
Riparian Margin Backcountry			-0.4767	***	-0.6112	***
Riparian Margin Lowland			-0.4484	***	-0.5304	***
Riparian Margin Lake			-0.3754	***	-0.4708	***
Didymo Generic	-0.273	***				
Didymo Mainstem			-0.3795	***	-0.4498	***
Didymo Backcountry			-0.3614	***	-0.4465	***
Didymo Lowland			-0.2231	***	-0.2856	***
Didymo Lake			-0.2376	***	-0.2819	***
Encounters Generic	-0.033		-0.0361		-0.0416	
Mainstem ASC	0.128		-0.3580		-0.1154	
Backcountry ASC	0.603	*	-0.4541		-0.4140	
Lowland ASC	-0.158		-0.1188		0.3422	
Lake ASC	0.128		0.4368	*	0.8595	*
Error components						
Mainstem-braided					1.0000	
Backcountry					1.2850	***
Lowland					0.7329	***
Lake					1.0315	***
Not fish					1.5452	***
Parameters	13		31		36	
AIC	2.942		2.942		2.769	
BIC	2.959		2.983		2.816	
LL	-7187.842		-7170.878		-6744.067	
McFadden R^2	0.0518		0.0541		0.1441	

Note: ***, **, * = Significance at 1%, 5%, 10% level

The MNL M11 McFadden R^2 statistic is relatively poor (0.0541) suggesting that much of the variability in individuals' site choices, despite taking account of ASPH for observed fishing site attributes, has not been explained. Section 8.3 applies additional statistical tests to determine whether the observed alternative specific coefficients are statistically different from one another.

To investigate ASPH further, error components are added to M11 to produce M12 (Brownstone *et al.* 2000). The multinomial logit-error component (MNL-EC) model M12 specification not only permits the variances around the means of the unobserved effects to be heteroscedastic, it also allows for correlation over individuals' repeated choices (Train 2003). Model M12 was estimated with five alternative specific error structures, one for each alternative to capture alternative specific variance heterogeneity around the mean of unobserved utility for each alternative, including the 'not fish' option. According to Walker *et al.'s* (2007) equality condition the alternative specific error component with the smallest variance was normalised to promote model identification[37]. As recommended by Walker *et al.'s* (2007) the error component with the smallest variance was identified by first estimating the model without normalisation imposed. This procedure identified the Mainstem-braided river error component as having the smallest variance. Next, the same model was re-estimated with the Mainstem-braided error structure normalised to one. Whereas previous models in Chapters 6 and 7 required 750 shuffled Halton draws to reach parameter stability, the MNL-EC model M12 reached parameter stability with 500 draws. This is because M12 has fewer random parameters.

All alternative specific coefficients for observed site attributes in M12 maintain the same pattern as in M11. The observed site attribute coefficients in M12 have the appearance of being larger, however, this is only due to a scale effect (see Ben-Akiva & Morikawa 1990). The four estimated error components (Backcountry, Lowland, Lake and 'not fish') are statistically significant. A statistical test could not be conducted on the Mainstem-braided error component because of the normalisation imposed. The 'not fish' error component is

[37] The validity and method for carrying out this procedure via Nlogit 4.0 was confirmed via correspondence with William Greene.

largest, suggesting that there is relatively more unobserved utility variance for the 'not fish' option compared to the fishing site options. Out of the fishing site options the Backcountry river error component is largest and the Lowland stream smallest which gives an indication of the relative differences in unobserved utility variance. Section 8.3 applies tests to provide statistical support to this conclusion. The addition of the five alternative specific error terms, plus panel specification, produced a marked improvement in model fit.

8.2 Generic versus site-specific parameters

Table 8-2 compares the fits between models M1, M11, and M12 based on AIC, BIC and a likelihood ratio (LR) test. These statistical criteria are described in section 5.7 of Chapter 5. The evidence is mixed as to whether adding additional parameters going from specification M1 to M11 produces a better fitting model. The AIC statistic does not change, the BIC statistics grows larger suggesting that M11 is not a better fitting model, whereas the LR test suggests the opposite.

The evidence is strong that the MNL-EC model M12 is a better fitting model than M1 according to AIC, BIC and the LR test. Likewise, evaluations of the same statistical criteria indicate that M12 is a better fitting model than M11.

Table 8-2: Comparison of model fits (M1, M11, and M12)

	Form	Site-specific	LL	Parameters	AIC	BIC	Likelihood Ratio Test (Specific vs Generic)
M1	MNL	No	-7187.842	13	2.942	2.959	
M11	MNL	Yes	-7170.878	31	2.942	2.983	M11 vs M1 ($\chi2$=33.928; df =18; p<0.012)
M12	MNL-EC	Yes	-6744.067	36	2.769	2.816	M12 vs M1 ($\chi2$=887.55; df =23; p<0.000)
							M12 vs M11 ($\chi2$=853.62; df =5; p<0.000)

8.3 *Marginal rates of substitution*

Marginal rates of substitution (MRS) are estimated to test for differences in preferences for the same attribute at different sites. Each MRS equals one in the absence of ASPH. An MRS significantly different from one is indicative of the existence of ASPH. Because MRS is a ratio of two estimated parameters confidence intervals must take account of variances for both, as well as their covariance. The Delta method (Klein 1953; Casella and Berger 1990), which is based on a Taylor's series expansion of a function of parameters, is used to derive confidence intervals for MRS and to test the significance of differences from unity.

Only Backcountry river coefficients are compared, though further tests could have been applied to draw out relationships between other alternative specific coefficients. That is the MRS numerator always assumes an alternative specific Backcountry coefficient, e.g., water visibility, and the denominator interchanges the respective coefficient for other alternatives. Table 8-3 reports the results for the Delta tests applied to both M11 and M12 models.

The columns highlighted in gray in Table 8-3 report the p-values. One minus the p-value is the probability that MRS is statistically different from one. For model M11 statistically significant differences, at the 10% level (p-value ≤ .10), are found between:

- Catching an additional trout at a backcountry river and all other fishing site alternatives.

- Catching larger trout size at a backcountry river compared to for lakes and lowland streams.

- Didymo infestation on backcountry rivers and lowland streams.

Model M12 improves upon model M11 by finding additional significant differences in anglers' MRS for:

- Riparian margin erosion on backcountry rivers compared to lakes;

- Didymo infestation on backcountry rivers compared to lakes.

Further, with a few exceptions, model M12 produces smaller p-values than model M11 for the MRS test statistic (see columns highlighted in grey in Table 8-3).

Table 8-3: Marginal rates of substitution for observed site attributes for the MNL (M11) and MNL-EC (M12) models

	M11				M12			
Coefficients	MRS	Sd(MRS)	Z (MRS=1)	p (Z)	MRS	Sd(MRS)	Z (MRS=1)	p (Z)
Water visibility Backcountry (/)								
Water visibility Lake	1.59	0.99	-0.60	0.55	1.68	1.07	-0.63	0.53
Water visibility Lowland	1.30	0.62	-0.49	0.63	1.33	0.58	-0.57	0.57
Water visibility Mainstem-braided	0.84	0.28	0.55	0.58	0.75	0.23	1.06	0.29
Catch Backcountry (/)								
Catch Lake	2.68	1.01	-1.67	0.09	2.54	0.89	-1.73	0.08
Catch Lowland	1.56	0.33	-1.68	0.09	1.67	0.37	-1.83	0.07
Catch Mainstem-braided	1.56	0.33	-1.70	0.09	1.50	0.31	-1.64	0.10
Trout size Backcountry (/)								
Trout size Lake	2.60	0.93	-1.71	0.09	2.68	0.92	-1.82	0.07
Trout size Lowland	1.88	0.46	-1.91	0.06	2.02	0.46	-2.22	0.03
Trout size Mainstem-braided	1.17	0.20	-0.85	0.40	1.24	0.20	-1.16	0.24
Bag limit Backcountry (/)								
Bag limit Lake	1.59	0.44	-1.36	0.17	1.52	0.48	-1.09	0.28
Bag limit Lowland	1.86	0.56	-1.54	0.12	1.98	0.68	-1.44	0.15
Bag limit Mainstem-braided	1.45	0.34	-1.31	0.19	1.49	0.42	-1.16	0.25
Riparian margin erosion Backcountry (/)								
Riparian margin erosion Lake	1.27	0.18	-1.46	0.14	1.30	0.17	-1.80	0.07
Riparian margin erosion Lowland	1.06	0.13	-0.47	0.64	1.15	0.13	-1.14	0.25
Riparian margin erosion Mainstem-braided	1.03	0.12	-0.25	0.81	1.10	0.13	-0.83	0.41
Didymo Backcountry (/)								
Didymo Lake	1.52	0.34	-1.51	0.13	1.58	0.34	-1.70	0.09
Didymo Lowland	1.62	0.32	-1.94	0.05	1.56	0.28	-1.99	0.05
Didymo Mainstem-braided	0.95	0.13	0.35	0.72	0.99	0.13	0.05	0.96

The Delta Method statistical test can also be applied to investigate whether the error component estimates in model M12 are statistically different for one another, that is, whether the ratios of individual error component variances are statistically different from one. Briefly, the p-values reported in the last column of Table 8-4 indicate that there is strong statistical evidence that all four estimated error components (Backcountry river, Lowland stream, Lake and ‘not fish’) are different from one another.

Table 8-4: Marginal rates of substitution for error components from the MNL-EC (M12) model

Coefficients	MRS	Sd(MRS)	Z (MRS=1)	p (Z)
Backcountry river error component (/)				
Not Fish error component	0.83	0.08	2.12	0.03
Lake error component	1.25	0.12	1.99	0.05
Lowland stream error component	1.75	0.26	2.93	0.00
Lowland stream error component (/)				
Not Fish error component	0.47	0.07	7.69	0.00
Lake error component	0.71	0.11	2.57	0.01
Lake error component (/)				
Not Fish error component	0.67	0.07	4.86	0.00

8.4 Discussion

Recent choice research in fields outside of recreational angling has addressed context, spatial influences and the alternative specific marginal utilities for common attributes across alternatives. This chapter contributes to this literature by investigating ASPH for fishing site attributes. Fundamental and key to this investigation was the use of a labelled choice experiment (Louviere & Hensher 1982; Louviere & Woodworth 1983) and underlying experimental design (e.g., Rose *et al.* 2008; Scarpa & Rose 2008), to allow variation in attribute levels within and across alternatives.

When several statistical tests, which assessed the standard errors around the MRS, were applied less than half of the Backcountry river alternative specific coefficients were found to be statistically different from the respective alternative specific coefficients. While tests did not confirm that anglers have ASPH for all attributes, some important discoveries were made. For instance, according to model M12 it was found that anglers value catching an additional trout in a backcountry river 2.54 times more than they do in a lake; increasing trout size is (2.68, 2.02, 1.24) times more valuable to anglers in a backcountry river than on a lake, lowland stream and mainstem-braided river, respectively. Riparian margin erosion is a larger concern on backcountry rivers then it is on lakes (1.30 times more) and Didymo infestation on backcountry and mainstem-braided rivers concerns anglers more than its presence on lowland streams and lakes.

The finding that the addition of error components in model M12 produced more reliable estimates of individuals' preference parameters in observed utility is evidenced by an increase in the number of statistically significant MRS test statistics and generally lower p-values. This empirical finding corroborates past research (e.g., Hess 2005) which suggests that models which maintain the IID assumption confound observed and unobserved utility and can bias parameter estimates in observed utility.

Why do anglers exhibit ASPH? One hypothesis is that in practice common fishing site attributes are actually not so common. For instance, Didymo infestation in backcountry and mainstem-braided rivers is typically thicker and more persistent than on lowland streams and lakes (e.g., Sutherland *et al.* 2007). Backcountry river brown trout are typically resident, male, older on average and harder to catch than their counterparts in the other fishing sites (Jellyman & Graynoth 1994; Young & Hayes 2004) such as lakes where a significant portion of the trout stocks originate from exogenous stocking. Similar differences occur with the riparian margin attribute and the ecological and environmental effects of erosion across the different fishing sites. The survey instrument did not describe these plausible natural attribute differences. It could be hypothesised that more specialised anglers would be aware of nuances and have developed preferences related to these nuances in so called "common" site attributes. The next chapter investigates this issue.

While tests were not conducted to determine the extent to which heterogeneity in a generically specified random coefficient (as in Chapters 5 and 6) is caused by ASPH, the models presented here depict how ASPH can be interpreted as a distribution of preference points over a population of alternatives. To provide further differentiation further analysis could be conducted to estimate random alternative specific parameters instead of relying on fixed estimates. However, estimating separate random parameters for the large number of alternative specific coefficients is computationally burdensome (Train 2003). Past recreational angling site choice research has assumed that individuals' preferences for observed site attributes are not specific at the alternative level (e.g., Train 1998; Provencher & Bishop 2004). In conclusion, the significant differences in alternative specific site attributes in the models in this chapter reveal an important layer of behavioural information not addressed previously and raise further questions related to underlying assumptions and complexity of modelling recreation demand across a number of characteristically different sites.

Chapter 9

Recreation Specialisation and Alternative-specific Preference Heterogeneity

9.1 Introduction

The models developed in Chapter 6 found wide-ranging preference heterogeneity among North Canterbury anglers according to the random parameters which assumed a generic specification. When the investigation went further and deeper it was found that some of this heterogeneity embodied by the random generic terms was explained by angler specialisation and a phenomenon termed alternative specific preference heterogeneity (ASPH). This short chapter ties these concepts together to investigate ASPH among specialised anglers. It is hypothesised that specialised anglers maintain definite forms of ASPH because specialised anglers are known to have refined setting preferences, as well as more experience with and awareness of which types of conditions (i.e., attribute qualities) constitute favourable angling experiences on different waters (Bryan 1977). A multinomial logit error component (MNL-EC) model is used to investigate this hypothesis.

There are two motivations for this chapter and the application of the MNL-EC model. First, to deepen the understanding of site specific tastes among specialised anglers. Second, to generate a choice model that: (i) is relatively computationally convenient, (ii) avoids complex stochastic representations of taste heterogeneity in deterministic utility, and (iii) allows heteroscedasticity and correlation in unobserved utility. This type of model specification follows the philosophy of Louviere & Swait (forthcoming, p. 5) who state that,

> "One should first focus on strong specification of the mean or systematic utility (by which we specifically don't mean complex stochastic representations of taste heterogeneity), then specify the stochastic utility variance (i.e., the diagonal or the error covariance), thirdly focus on the off-diagonals of the covariance matrix, and

then finally loop back and put the icing on the cake with considerations like taste heterogeneity".

9.2 A multinomial logit-error component model

In the spirit of Louviere & Swait (forthcoming) the MNL-EC model M13 (equation 12, Chapter 2) specifies:

1) Alternative specific parameters for all site attributes except cost and travel time (to develop a strong specification of systematic utility).

2) Five alternative-specific error components (to specify the stochastic utility variance). The Mainstem-braided river error component is fixed to promote identification (Walker *et al.* 2007).

3) Two additional error components. One nests the Lowland stream and Mainstem-braided river alternatives together. The second nests the Backcountry river and Lake alternatives together. These nests allow additional patterns of correlation (i.e., off-diagonals in the covariance matrix).

4) Interaction effects for all alternative site attributes except for cost and travel time with specialisation variables generated via the simple additive method (SAM) in Chapter 7 (to allow taste heterogeneity without the use of random parameters).

While this specification results in a large number of estimated coefficients, only six of these parameters require simulation (i.e., the error components). Model M13 (Table 9-1) was estimated with 500 shuffled Halton draws (Bhat 2003; Train 2003; Chiou & Walker 2007).

It is evident that a number of site attribute parameters lose their statistical significance compared to the MNL model M1 (described in section 6.2 of Chapter 6). This is because some (or much) of the information has now been identified by the interactions with the variables which identify individuals' specialisation. Almost all interactions follow *a priori* expectations (Bryan 1977). As an overview, it is apparent that for some attributes specialisation is a strong determinant of ASPH on all fishing site alternatives. For other attributes, specialisation is only found to have a relationship with one of the four fishing site alternatives. Specifically, improved water visibility is only found to be a statistically significant driver of specialised anglers' site choice of backcountry rivers. This was expected given that sight fishing, a technique employed by skilled anglers on backcountry rivers, requires high water clarity. On the other hand, techniques employed on mainstem-braided rivers and lowland streams do not rely on sight-fishing to the extent that they do on backcountry rivers. Specialised anglers have stronger preferences for catching more trout on all fishing sites than less specialised anglers. A similar finding occurs with trout size - however, the relatively large trout size Backcountry interaction term suggests that specialised anglers are particularly concerned with catching bigger trout on backcountry rivers. However, this assertion is speculative and needs additional statistical support to be validated. Specialised anglers are found to have stronger preferences for restrictive bag limits on all fishing sites compared to less specialised anglers. Finally, model M13 finds that specialised anglers are particularly more concerned with riparian margin erosion on lakes, Didymo on backcountry rivers as well as angler encounters on backcountry rivers compared to less specialised anglers. The latter two results were expected *a priori*. This is because blooms of Didymo are known to be thicker and more prolific in backcountry rivers compared to lowland streams and lakes (Sutherland *et al.* 2007), and reduced trout catch-ability (as a result of angler pressure) is more of an issue in backcountry rivers (particularly those that are remote, Young & Hayes 2004).

Like in model M11 and M12 (Chapter 8) the positive and significant alternative specific coefficient for the Lake alternative indicates that, *ceteris paribus*, what has been left out of the model for the Lake alternative has higher utility than to 'not fish'. The remaining ASCs are not significant.

Table 9-1: Summary of the MNL-EC (M13) model specified with alternative specific parameters and recreation specialisation variable interactions

			MNL-EC M13				
	Mean						
Attributes			*Interactions with RS*		*Error components*		
Water visibility Mainstem-braided	0.084		0.010		Mainstem-braided	1.000	
Water visibility Backcountry	0.001		0.025	***	Backcountry	1.062	***
Water visibility Lowland	0.105	**	-0.013		Lowland	0.589	***
Water visibility Lake	0.046		0.001		Lake	0.947	***
Catch Mainstem-braided	0.017		0.043	***	Not fish	1.385	***
Catch Backcountry	0.092		0.042	***	(Mainb, Low)	0.192	
Catch Lowland	0.007		0.042	***	(Back, Lake)	0.669	***
Catch Lake	0.014		0.034	**			
Trout size Mainstem-braided	0.136	**	0.045	***			
Trout size Backcountry	0.124	*	0.064	***	*ASCs*		
Trout size Lowland	0.029		0.047	***	Mainstem-braided ASC	-0.137	
Trout size Lake	0.030		0.051	***	Backcountry ASC	-0.328	
Bag limit Mainstem-braided	0.445	***	-0.066	***	Lowland river ASC	0.329	
Bag limit Backcountry	0.759	***	-0.115	**	Lake ASC	0.804	*
Bag limit Lowland	0.365	***	-0.061	**			
Bag limit Lake	0.464	***	-0.073	***	Cost	-0.008	***
Riparian Margin Mainstem-braided	-0.448	***	-0.036		Travel time	-0.006	***
Riparian Margin Backcountry	-0.587	***	-0.009				
Riparian Margin Lowland	-0.494	***	-0.013				
Riparian Margin Lake	-0.268	**	-0.062	*			
Didymo Mainstem-braided	-0.349	***	-0.036				
Didymo Backcountry	-0.274	**	-0.053	**			
Didymo Lowland	-0.225	**	-0.019		Parameters	68	
Didymo Lake	-0.293	***	0.000		AIC	2.750	
Encounters Mainstem-braided	0.093		-0.047		BIC	2.840	
Encounters Backcountry	0.215	*	-0.083	***	LL	-6663.709	
Encounters Lowland	0.060		-0.037		McFadden psuedo-R^2	0.1543	
Encounters Lake	0.015		-0.003				

Note: ***, **, * = Significance at 1%, 5%, 10% level

Recreation specialisation (RS) variable

Five of the six estimated error components are statistically significant (a statistical test was not applied to the alternative specific Mainstem-braided error component because of its normalisation). The ‘not fish’ error component variance is largest suggesting that there is relatively more unobserved utility variance for the ‘not fish’ option compared to the fishing site options. Out of the fishing site options the Backcountry river error component is largest and the Lowland stream is smallest, which gives an indication of the relative differences in unobserved utility variance. The error component nest (Back, Lake) is significant, suggesting additional patterns of correlation between the Backcountry and Lowland alternatives not identified by the alternative specific structures. The (Mainb, low) error nest was insignificant.

The overall fit of model M13 (Table 9-2) is relatively strong compared to alternative specific models M11 and M12 which were reported in Chapter 8. According to the McFadden pseudo-R^2 and AIC test statistics Model M13 performs better than both M11 and M12. However, according the BIC test statistics (which penalises more for additional parameters) model M12 outperforms both models M11 and M13.

Table 9-2: Comparision of model fits (M11, M12, and M13)

	Form	Site-specific	Interactions	LL	Parameters	AIC	BIC	Likelihood Ratio Test
M11	MNL	Yes	No	-7170.878	31	2.942	2.983	
M12	MNL-EC	Yes	No	-6744.067	36	2.769	2.816	
M13	MNL-EC	Yes	RS	-6663.709	68	2.750	2.840	M13 vs M11 ($\chi 2$=854; df =37; p<0.0001)
								M13 vs M12 ($\chi 2$=161; df =32; p<0.0001)

9.3 Discussion

This brief chapter sought to explain angler preference heterogeneity systematically with fixed parameters as opposed to relying on a stochastic treatment and determine whether specialised anglers exhibit different forms of ASPH. While the MNL-EC model, specified with alternative specific parameters with RS interactions, resulted in a very large number of parameters, a very fine level of detail was achieved. It is contended that this information is more beneficial to fishery managers then a purely random treatment of heterogeneity with a generic parameter. It has been noted in this thesis that managing angler congestion has become a highly topical issue for Fish and Game New Zealand (FGNZ). Managers are typically concerned with managing particular waters for particular kinds of anglers. While models in Chapters 6 through 8 did not provide clear evidence of where and who to manage congestion for, model M13 identified that managing angler encounter rates is only an issue on backcountry rivers for a limited number of specialised individuals.

"The consensus is that a good error is a zero error; that is, it is desirable to expand on the systematic term thereby reducing the disturbance term" (Ben-Akiva *et al.* 2002, p.171). Despite building up a strong deterministic component of utility by incorporating site specific parameters and specialisation interactions, a significant amount of information remained in unobserved utility. The error components were instrumental in identifying variance differences as well as inter-alternative correlation. While random parameters could have been added, they were largely obviated by the use of error components which were able to identify unobserved taste heterogeneity at the alternative level.

This chapter concludes the empirical investigation of North Canterbury angler site choice. It demonstrates an alternative to a random parameter treatment of heterogeneity where observed heterogeneity is explained by a large number of fixed coefficients and the residual unobserved heterogeneity is explained by a small number of error components. This type of specification is relatively easy to estimate, allows for complex substitution patterns, and produces a high level of detail regarding angler preferences.

Chapter 10

Summary, Conclusions and Directions for Future Research

This chapter summarises, reflects on and draws conclusions from the research embodied in this thesis. Important findings, challenges and avenues for future research are discussed.

10.1 Research objectives and design

The North Canterbury region constituted a particularly challenging and important region to study because of its diverse range of fishing sites, large angler base, unique resource disturbance problems and volatile angler activity patterns. The core objective of this thesis was to develop a strong understanding of preference heterogeneity and substitution patterns. This was accomplished by using a framework of stated preference choice experimentation, advanced discrete choice modelling and applied recreation specialisation (RS) theory.

The close working relationship developed with anglers during the design of the study was critical to enabling development of a stated preference study design that was realistic to anglers (Cummings & Taylor 1998), could be applied over the internet, provided sufficient motivation for anglers to participate, and allowed revelation of their underlying preferences. Modelling the decisions regularly faced by anglers, with large numbers of alternatives and many salient attributes that vary across sites, is a complex statistical task requiring a large amount of high quality data (Munizaga & Alvarez 2005; Cherchi & Ortúzar 2008). The series of survey pilots was essential to identifying appropriate alternatives, attributes, attribute levels and generating priors to continually improve the efficiency of the experimental design. Internet application, while incurring substantial setup costs, allowed a large amount of data to be collected relatively quickly and cheaply.

The progression in the choice modelling literature was closely followed. At the beginning of the PhD (2006), extensions to mixed logit (ML) were being developed (Greene *et al.* 2006; Greene & Hensher 2007). It was on this new frontier that the research was focused. The main objective was to capture within one model a strong understanding of taste variation for observed site attributes as well as correlation and heteroscedasticity in the unobserved utilities for different sites. Then, develop these models further by weaving in RS theory to explain heterogeneity and heteroscedasticity in the random parameters and error components. The target of this integrated approach (e.g., Walker 2001; Adamowicz *et al.* 2008) was to develop models which revealed both random and systematic heterogeneity, as well as were highly capable of identifying individuals' substitution patterns. Over the course of the data analysis hundreds of extended ML models were estimated, though only a handful of these are reported in the thesis. This process led to a number of important findings, challenges, and an evolution in understanding of where and how to account for heterogeneity.

At the beginning of the choice analysis it was evident that the conventional MNL model specified without interactions or site-specific attributes performed poorly. This was anticipated given the model's highly restrictive assumptions, the difficult North Canterbury context, the large number of alternatives included in the design and the diverse group of anglers. When more flexible modelling procedures were applied (Chapter 6) wide-ranging taste heterogeneity was evident. The research found that even after random parameters were employed there was still a substantial amount of unexplained preference heterogeneity. Error components were instrumental in accounting for this residual preference heterogeneity, which differed across alternatives. The extended ML models clearly outperformed the more basic MNL and LC-MNL models in terms of fitting the data better and revealing heterogeneity and substitution patterns. Chapter 6 made a contribution by evaluating the performance of these extended ML models which have not appeared in the recreation or environmental economics literatures. The models were shown to reveal important behavioural insights, such as the relationship between heteroscedasticity and skill level. To achieve greater explanatory power, as well as provide a theoretical basis for evaluating the model parameters, the research then integrated multidimensional measures of RS which included measurements of anglers' skill levels.

Despite 30 years of support in the literature only two studies had used both RS and DCM to investigate angler site choice (Oh & Ditton 2006; Dorow *et al.* 2009). Both of these studies used very similar procedures involving cluster analysis (CA) to identify a small number of specialisation cohorts, relatively simple unlabelled experimental designs and estimation of separate conventional MNL models for each cohort. The purpose of Chapter 7 was to demonstrate other more straightforward approaches for operationalising RS as well as more sophisticated modelling procedures which could avoid the use of multiple models and ensuing scale issues. While the empirical approach did not necessarily lead to a parsimonious model (or the best way to ultimately operationalise specialisation), it was shown to be useful for providing a means for evaluating the relative contribution of individual indicators towards explaining preference. Due to the absence of a rigorous theoretical model of specialisation, and the limitations imposed by CA approaches, the simple aggregation method (SAM) for identifying each individual's level of specialisation was adopted (e.g., Wellman *et al.* 1982; Donnelly *et al.* 1986; Williams & Huffman 1986; Virden & Schreyer 1988; Miller & Graefe 2000; Valentine 2003). The SAM proved to be convenient, parsimonious and very effective. The major advantage of the SAM is that RS could be integrated with the extended ML models without having to use an extremely large number of parameters or multiple models. Using the SAM-derived RS variables, *all* of the estimated interaction parameters in multinomial logit-error component (MNL-EC) model M9 were statistically significant and followed theoretical expectations. These same results were replicated in the fully extended ML model M10 which, in addition, controlled for heteroscedasticity finding that preference heterogeneity in both observed site attributes and unobserved utility increases (becomes more diverse) with specialisation. In general, the integration of RS into the analysis, particularly with the SAM-derived RS variables, led to significantly better fitting models and new and improved insights into anglers' choice processes.

It is important to note that the use of extended ML models did not come without a cost. Namely the random parameters methods for revealing heterogeneity in deterministic utility were extremely time-consuming because of the requirements for specification testing with different distributional forms for each of the attributes. Exploring the extensions to control for heterogeneity and heteroscedasticity in the random parameters with a large number of covariates increased the specification testing time considerably. It was found that only a relatively small number of individual specialisation indicator variables could be used to decompose each random parameter. When the number of covariates increased to beyond three, statistical significance was generally lost, due to some correlation among the specialisation indicator variables. This problem, along with the large number of parameters which would have resulted, prohibited the investigation of individual RS indicators within the random parameters specification.

Despite the integration of RS with the extended ML models to explain the sources of heterogeneity, there remained a significant amount of unexplained taste variation in the random parameters. This remaining unexplained heterogeneity, as well as the high estimation outlays encountered with a random parameter treatment, motivated investigation of other potential sources of preference heterogeneity. Personal observation, literature review and discussions with experts led to a hypothesis that anglers have site specific tastes not only for factors unseen, but also for those observed. For example, catching a trout or seeing another angler had different marginal utilities according to the fishing site alternative (e.g., mainstem-braided river versus a backcountry river). This led to the hypothesis of alternative specific preference heterogeneity (ASPH), which was subsequently tested and found to be an important layer of choice influence. The array of alternative specific parameters, for any one particular attribute, could be viewed as a finite preference distribution across sites (not individuals). While generic random parameters embody this distribution, the important alternative specific information is not made explicit. This finding, specification and treatment of heterogeneity, is important because it can improve managers' understanding of which sites and attributes of those sites are relatively most important to manage in order to maximise angler welfare. For example, improving catch rates, maintaining Didymo free environments or restoring riparian margins. It was argued in Chapter 8 that failure to account for ASPH could bias natural resource damage assessments (e.g., Train 1998; Morey *et al.* 2002) either up or down.

The findings in Chapters 7 and 8 motivated the research to take one final step to investigate the relationship between ASPH and specialisation. Evidence was found that site-specific preferences are strongly linked with specialisation. Chapter 9 demonstrated that it was possible to explain a large amount of choice variability systematically with site specific parameters interacted with specialisation variables instead of relying on stochastic representations using a generic parameter specification. Explaining heterogeneity systematically in this new way is advantageous because it reduces model identification issues and produces a richer, more definitive, understanding of the nature of preference heterogeneity. The knowledge derived from estimating a large number of models in this study suggest that is highly important to develop a strong understanding of heterogeneity in systematic utility. A sound approach is to first explain as much choice variability as possible deterministically, then, after ASPH and RS have been explored, focus on building in random taste heterogeneity. Error components should then be used to identify residual unobserved preference heterogeneity, as well as correlation among alternatives.

10.2 Avenues for future research

The research embodied in this thesis leads to a large number of possibilities for further exploration of the RS concept with DCMs. One potential avenue could investigate preference heterogeneity among different kinds (not levels) of specialisation. Bryan's (1977) initial conceptualisation of RS suggested that as anglers specialise their setting preferences become more particular, tending toward spring-creek fishing sites which have demanding yet predictable conditions. Recent specialisation research suggests that the single trajectory view (i.e., specialists tending toward just one type of site) is too narrow and that specialisation occurs over numerous pathways (Kuentzel & Heberlein 2006). Over the course of this research numerous forms of setting-specialisation became apparent. For example, there was evidence of anglers who specialised solely in fishing backcountry rivers - to the exclusion of other types of waters. Similarly there was evidence of lake, lowland and mainstem-braided river setting-specialisation. It can be hypothesised that setting specialists, due to focusing of their efforts on different types of fishing sites, will develop, over time, more specific tastes. If sites have strong characteristic differences it is likely that, viewed as a whole, specialised anglers' preferences will diverge. While this research did not differentiate between kinds of setting-specialisation, the finding that specialists (when bundled together) showed increasing preference heterogeneity as identified by model M10 in Chapter 7 supports this hypothesis.

There a number of ways in which the multiple specialisation trajectory hypothesis can be explored. One simple way could use the existing data and segment anglers according to where they most prefer to fish in practice. Separate models, which account for specialisation (e.g., model M9 in Chapter 7), could be estimated for each group. A better approach builds in important design considerations, recognising setting-specialists, by definition, tend to choose one type of site, or not go fishing. Therefore, a design which includes a number of different types of fishing site alternatives is inefficient. To improve efficiency, research could employ designs which pivot off each respondent's current behaviour or knowledge base (e.g., Hensher 2004; Layton & Hensher 2008; Rose *et al.* 2008). For example, backcountry river-setting specialists could be administered a design which only includes backcountry rivers, but offers different conditions on backcountry river alternatives, and the option to not fish. Models could then be estimated which investigated backcountry-specialists' fishing site choice(s). This type of research design would provide a better understanding of site specific tastes of specialised individuals and also greater understanding of the nature and source of heteroscedasticity in unobserved utility, which is highly important given its relationship to the scale term.

Another potential avenue for future research is to utilise emerging development in 'scale heterogeneity' multinomial logit (S-MNL) and generalised multinomial logit (G-MNL) models to account for differences in scale across respondents according to specialisation (Bryan 1977). The G-MNL and S-MNL models (Fiebig *et al.* 2009) allow coefficients in deterministic utility to be scaled up or down for individuals according to their individual level of variance in unobserved utility, reflecting that some individuals exhibit very random behaviour while others behave more predictably. Currently, the applications in Fiebig *et al.* (2009) assume that scale follows a random (lognormal) distribution, and their attempts to parameterise scale distributions with observed covariates and measures of task complexity were unsuccessful. The authors state that, "clearly more work is needed in this topic" (Fiebig *et al* (2009, p. 24). With the statistically significant relationships found in this thesis between RS and heteroscedasticity in the unobserved utility, it seems highly likely that SAM-derived RS measures can be used to identify scale heterogeneity. Segmenting the scale term via RS could result in the next substantial breakthrough in terms of understanding and predicting choice behaviour within the DCM framework.

Other avenues for advancing and testing the DCM - RS framework developed in this thesis include: utilising revealed preference (RP) data (or better yet, combining RP with stated preference (SP) data, (e.g., Von Haefen & Phaneuf 2008), and (ii) extending the framework to other recreational activities, such as hunting.

10.3 Conclusions

This thesis has made a number of significant contributions to the literature by: (i) developing, demonstrating and evaluating a number extended ML models; (ii) integrating these models with RS theory; (iii) identifying the importance of exploring alternative specific (rather than assuming generic) preference parameters in a model of recreation site choice, and finally, (iv) demonstrating that ASPH is strongly related to RS. The application of the internet survey instrument, as well as the labelled (alternative-specific) Bayesian D-efficient experimental design, constitute new, innovative steps forward in recreation and environmental demand modelling. Finally, much of the work developed in this thesis, and the practices adopted, have relevance to a broad audience concerned with modelling choice behaviour, and are not restricted to the recreational angling case explored here.

Clearly, individuals' choice behaviours are complex and heterogeneous, making deterministic explanation of all influences on choice impossible in practice. Whether research accounts for heterogeneity in deterministic utility with purely stochastic representations using random parameters or drills down deeper to understand the underlying sources of heterogeneity is an important decision which is dictated by the experimental design and/or data quality and data availability. Such possibilities should, however, be carefully considered prior to data collection. Regardless, it is important to evaluate the entire utility construct (i.e., elements in both observed and unobserved components of utility). The findings from this research are clear. Methods which oversimplify anglers’ choice processes risk generating poorly representative models which will likely lead to suboptimal management and policy outcomes.

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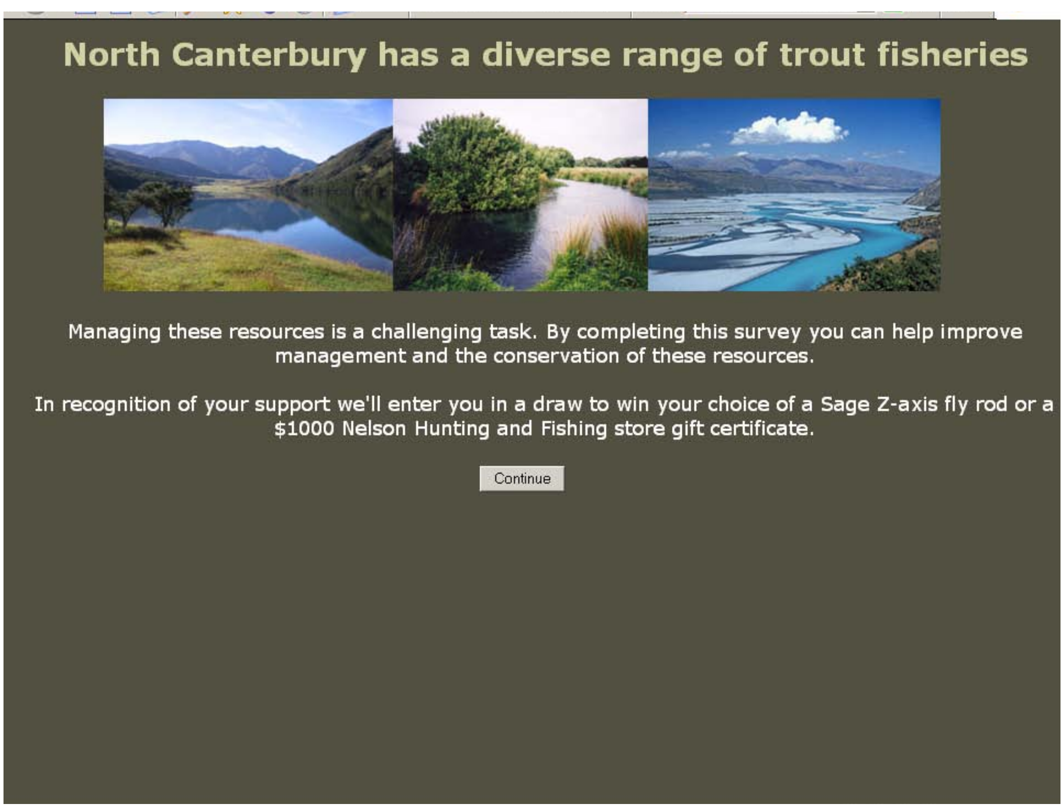
Appendix A: Screen shots of the internet survey



Fishery Site Choice Game:

The objective of the fishery site choice game is to help us understand your angling preferences. You will be presented with some hypothetical descriptions of rivers where you could go fishing. You will also be given the option to not fish. All you have to do is evaluate the options and indicate to us the action you would take imagining that you are making a 'real life decision'.

Continue

This survey is designed to be fun and interesting. You will be asked to:

1. Take part in a "fishing site choice game".

2. Provide some information about your angling background.

Continue

Consent Form

This research is being conducted by:
Stephen Beville (PhD Candidate)
Environment Society & Design Division
PO Box 84 Lincoln University, Lincoln 7647
Phone (03) 325 3838 ext 8746

This research is supervised by:
Geoff Kerr (Associate Professor)
Environment Society & Design Division
PO Box 84 Lincoln University, Lincoln 7647
Phone (03) 325 2811

Please be assured that your identity is strictly confidential and will not be made public under any circumstance. To ensure anonymity and confidentiality participant names will not be recorded in the data used by the researcher. Consent forms and identifying information will be kept separately from the data both during and after the study. Fish and Game will have access to the data and consent forms. This research has been reviewed and approved by the Lincoln University Human Ethics Committee.

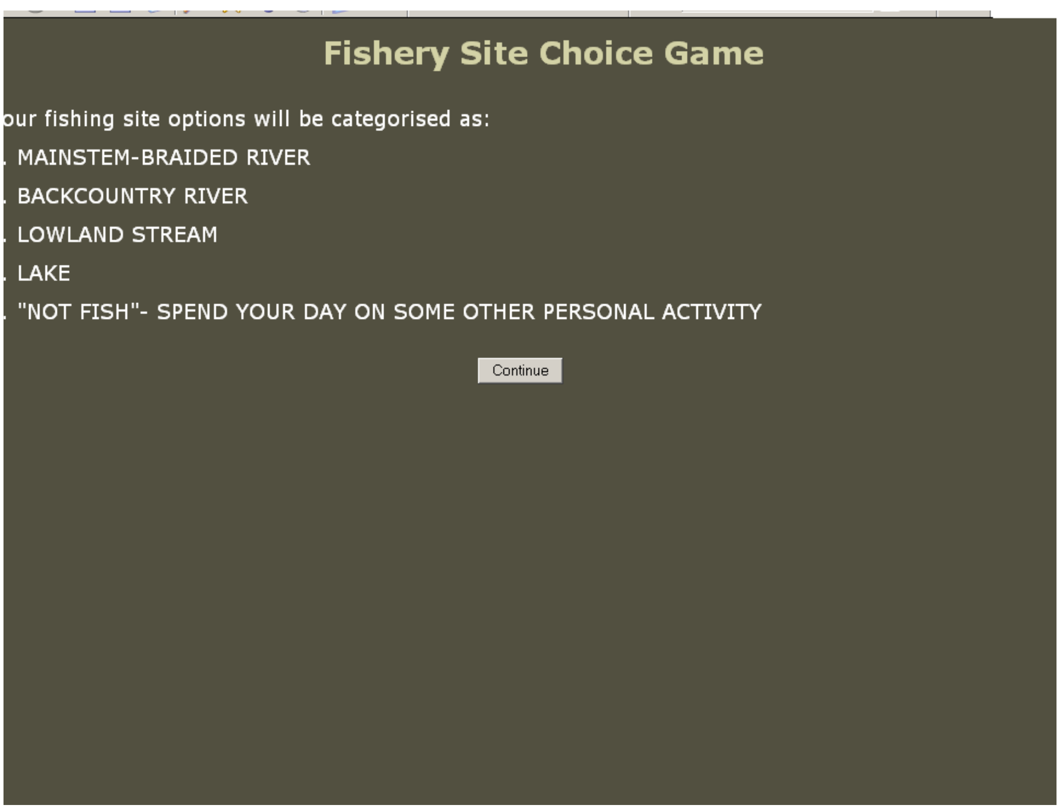
I have read and understood the description of the survey and the nature of the research that it will be used for. On this basis, I consent to the publication of the results of the project with the understanding that complete anonymity will be maintained.

I understand that I may withdraw any information provided in the survey within 21 days of completion.

I understand that I will be entered in a prize draw as recognition of my contribution to this research. I acknowledge that I am over the age of 18.

Accept
Decline

Continue



Fishery Site Choice Game

our fishing site options will be categorised as:

. MAINSTEM-BRAIDED RIVER

. BACKCOUNTRY RIVER

. LOWLAND STREAM

. LAKE

. "NOT FISH"- SPEND YOUR DAY ON SOME OTHER PERSONAL ACTIVITY

Continue

Examples of the fishery site choices

MAINSTEM-BRAIDED RIVER

BACKCOUNTRY RIVER

LOWLAND STREAM

LAKE

Continue

Rivers and lakes in North Canterbury which would be examples of the fishery site choice categories

MAINSTEM-BRAIDED RIVER

Rakaia River

Waimakariri River

Lower Hurunui River

BACKCOUNTRY RIVER

Hope River

Doubtful River

Broken River

LOWLAND STREAM

Harts Creek

South Branch of Waimakariri

Selwyn River (below Coes Ford)

LAKE

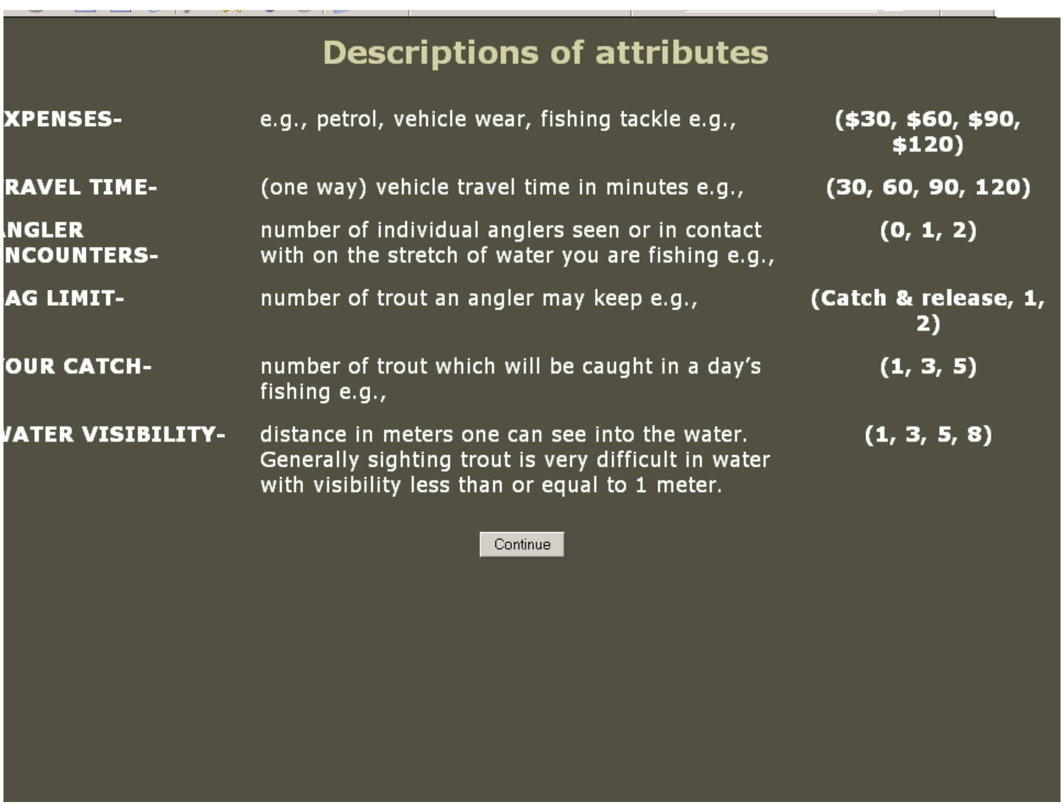
Lake Selfe

Lake Taylor

Lake Coleridge

Continue


Each fishery site option will be described by nine attributes:
XPENSES
RAVEL TIME
NGLER ENCOUNTERS
ATER VISIBILITY
OUR CATCH
ROUT SIZE
AG LIMIT
IPARIAN MARGIN
IDYMO
Continue


Descriptions of attributes
XPENSES-
e.g., petrol, vehicle wear, fishing tackle e.g.,
($30, $60, $90, $120)
RAVEL TIME-
(one way) vehicle travel time in minutes e.g.,
(30, 60, 90, 120)
NGLER NCOUNTERS-
number of individual anglers seen or in contact with on the stretch of water you are fishing e.g.,
(0, 1, 2)
AG LIMIT-
number of trout an angler may keep e.g.,
(Catch & release, 1, 2)
OUR CATCH-
number of trout which will be caught in a day's fishing e.g.,
(1, 3, 5)
ATER VISIBILITY-
distance in meters one can see into the water. Generally sighting trout is very difficult in water with visibility less than or equal to 1 meter.
(1, 3, 5, 8)
Continue

Descriptions of attributes

RIPARIAN MARGIN - environmental condition of the margin of land running along the waterway.

(Example of riparian margin with <u>erosion due to stock</u>)

(Example of riparian margin in <u>pristine condition</u>)

Continue

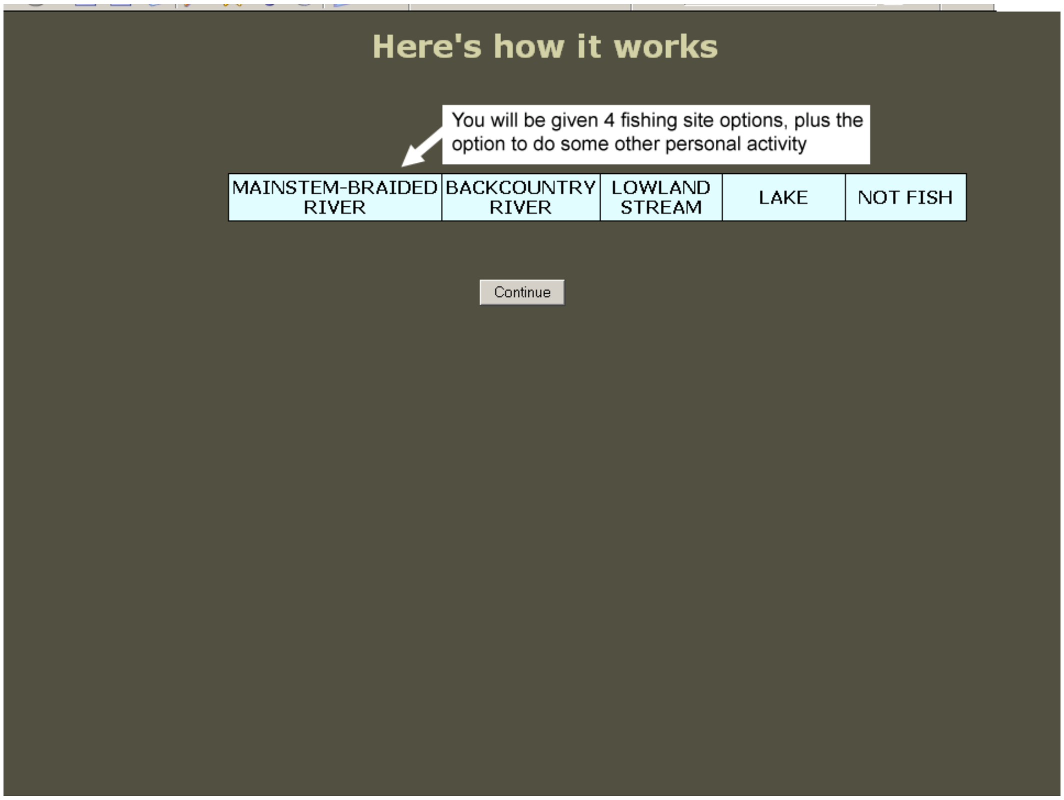
Descriptions of attributes

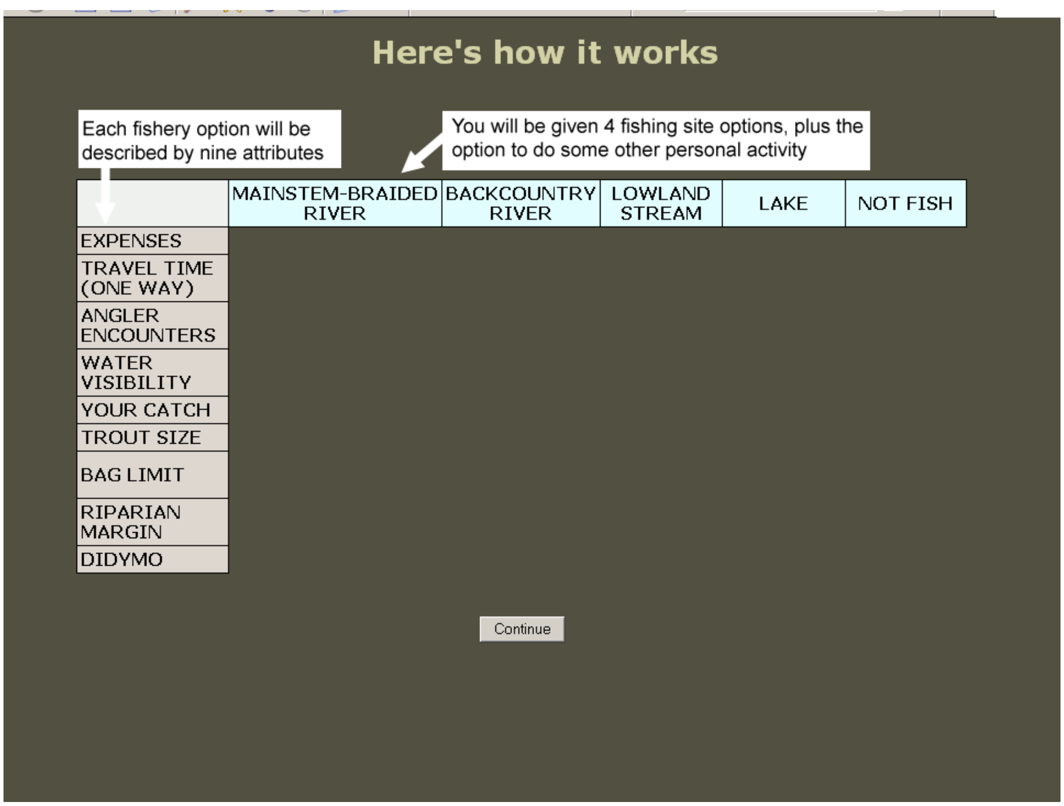
DIDYMO - an invasive algae first detected in New Zealand in 2004 can form thick brown mats on rocks in rivers and lakes. Anglers fishing Didymo-infested waters are urged by Biosecurity New Zealand to thoroughly clean fishing apparel and equipment before visiting other waterways.

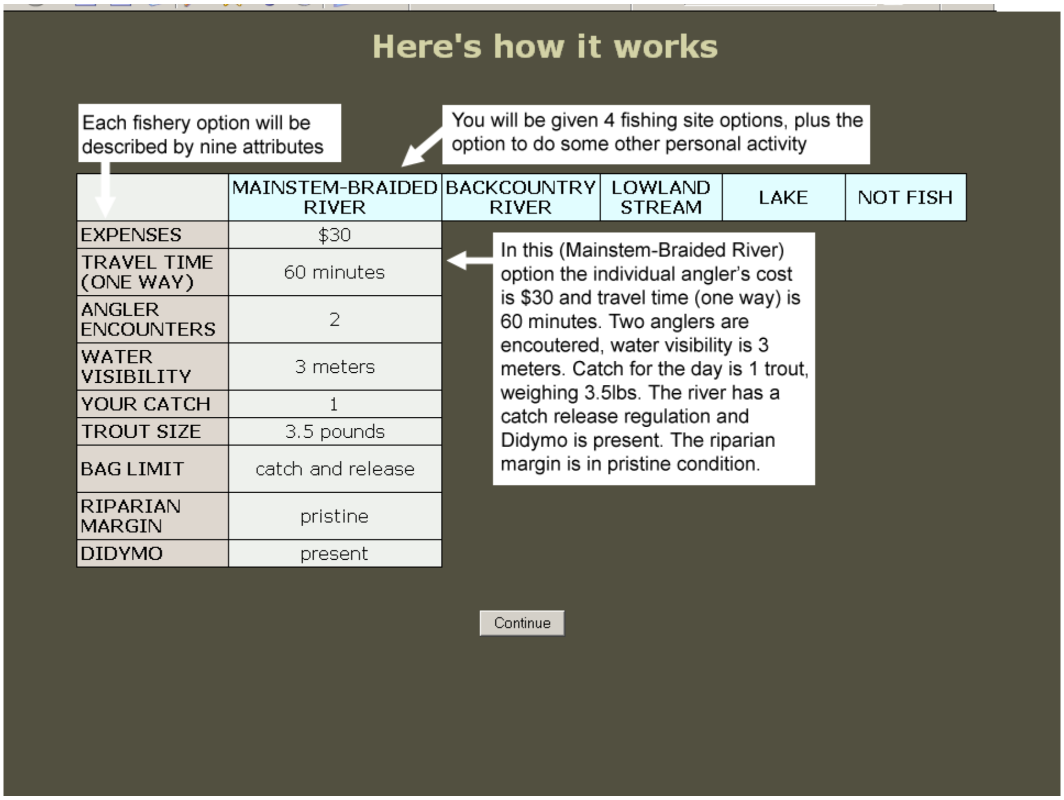
Example of Didymo

Example of Didymo

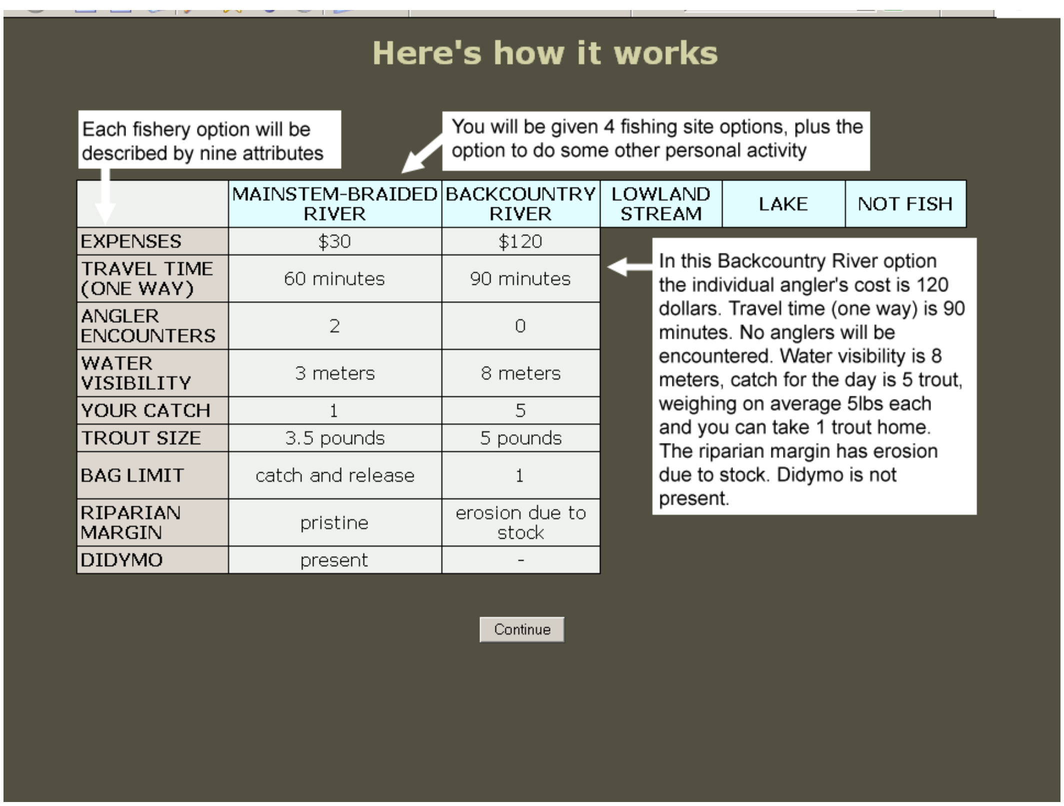
Continue


Here's how it works
You will be given 4 fishing site options, plus the option to do some other personal activity
MAINSTEM-BRAIDED RIVER
BACKCOUNTRY RIVER
LOWLAND STREAM
LAKE
NOT FISH
Continue


Here's how it works
Each fishery option will be described by nine attributes
You will be given 4 fishing site options, plus the option to do some other personal activity
MAINSTEM-BRAIDED RIVER
BACKCOUNTRY RIVER
LOWLAND STREAM
LAKE
NOT FISH
EXPENSES
TRAVEL TIME (ONE WAY)
ANGLER ENCOUNTERS
WATER VISIBILITY
YOUR CATCH
TROUT SIZE
BAG LIMIT
RIPARIAN MARGIN
DIDYMO
Continue



	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
EXPENSES	$30				
TRAVEL TIME (ONE WAY)	60 minutes				
ANGLER ENCOUNTERS	2				
WATER VISIBILITY	3 meters				
YOUR CATCH	1				
TROUT SIZE	3.5 pounds				
BAG LIMIT	catch and release				
RIPARIAN MARGIN	pristine				
DIDYMO	present				



	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
EXPENSES	$30	$120			
TRAVEL TIME (ONE WAY)	60 minutes	90 minutes			
ANGLER ENCOUNTERS	2	0			
WATER VISIBILITY	3 meters	8 meters			
YOUR CATCH	1	5			
TROUT SIZE	3.5 pounds	5 pounds			
BAG LIMIT	catch and release	1			
RIPARIAN MARGIN	pristine	erosion due to stock			
DIDYMO	present	-			

Here's how it works

Each fishery option will be described by nine attributes

You will be given 4 fishing site options, plus the option to do some other personal activity

	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
EXPENSES	$30	$120	$20	$90	SPEND YOUR DAY ON SOME OTHER PERSONAL ACTIVITY
TRAVEL TIME (ONE WAY)	60 minutes	90 minutes	60 minutes	90 minutes	
ANGLER ENCOUNTERS	2	0	1	2	
WATER VISIBILITY	3 meters	8 meters	1 meter	5 meters	
YOUR CATCH	1	5	3	5	
TROUT SIZE	3.5 pounds	5 pounds	2 pounds	5 pounds	
BAG LIMIT	catch and release	1	catch and release	catch and release	
RIPARIAN MARGIN	pristine	erosion due to stock	pristine	pristine	
DIDYMO	present	-	-	present	

All five options are now shown

Continue

Directions:

This portion of the survey is designed to be fun and interesting. You will be presented with 6 different hypothetical fishing site choice game scenarios similar to the one shown on the previous screen (the fishing site option descriptions will change from scenario to scenario). Each scenario will include the option to 'not fish' i.e., spend your day on some other activity.

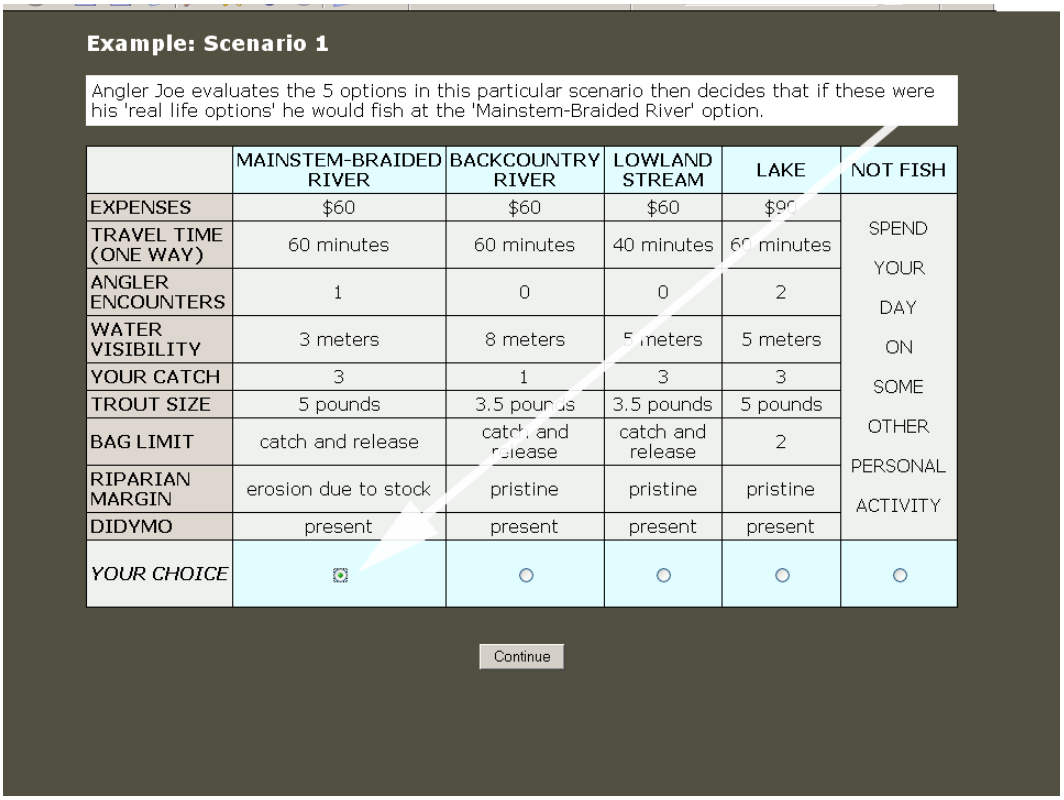
For each of the 6 scenarios assume that you have a free day, the weather has been settled and the forecast is for more fine weather. Next, carefully consider the options described. Then, as accurately as possible, identify the option you yourself would choose in a 'real life' situation. Click on your chosen option.

The objective of the fishery site choice game is to help managers understand your preferences. Therefore, in each scenario, always indicate your most preferred fishing site option. If you would not fish at any of the fishing sites be sure to choose the 'not fish' option.

*Some of the fishing site descriptions may not reflect your personal experience of the actual fishing sites in the region- for this exercise try to imagine that the conditions and options described are the actual fishing sites available to you.

Before starting please have a look at two example scenarios.

Continue

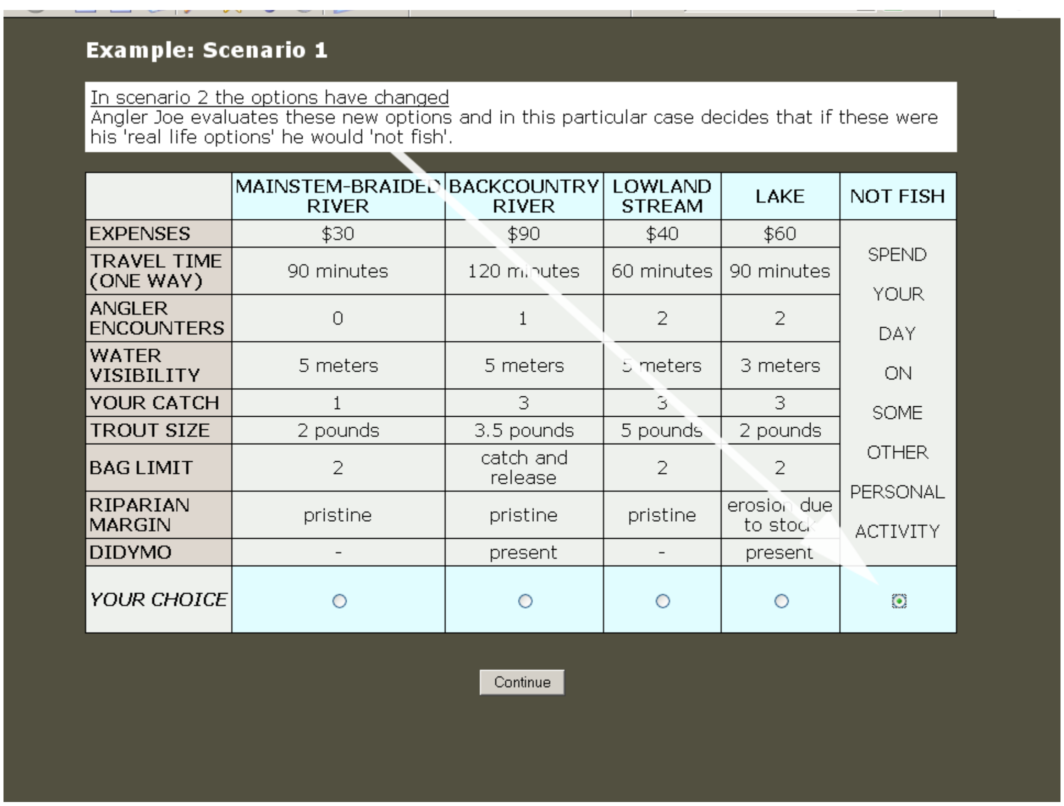


Example: Scenario 1

Angler Joe evaluates the 5 options in this particular scenario then decides that if these were his 'real life options' he would fish at the 'Mainstem-Braided River' option.

	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
EXPENSES	$60	$60	$60	$90	SPEND YOUR DAY ON SOME OTHER PERSONAL ACTIVITY
TRAVEL TIME (ONE WAY)	60 minutes	60 minutes	40 minutes	60 minutes	
ANGLER ENCOUNTERS	1	0	0	2	
WATER VISIBILITY	3 meters	8 meters	5 meters	5 meters	
YOUR CATCH	3	1	3	3	
TROUT SIZE	5 pounds	3.5 pounds	3.5 pounds	5 pounds	
BAG LIMIT	catch and release	catch and release	catch and release	2	
RIPARIAN MARGIN	erosion due to stock	pristine	pristine	pristine	
DIDYMO	present	present	present	present	
YOUR CHOICE	◉	○	○	○	○

Continue

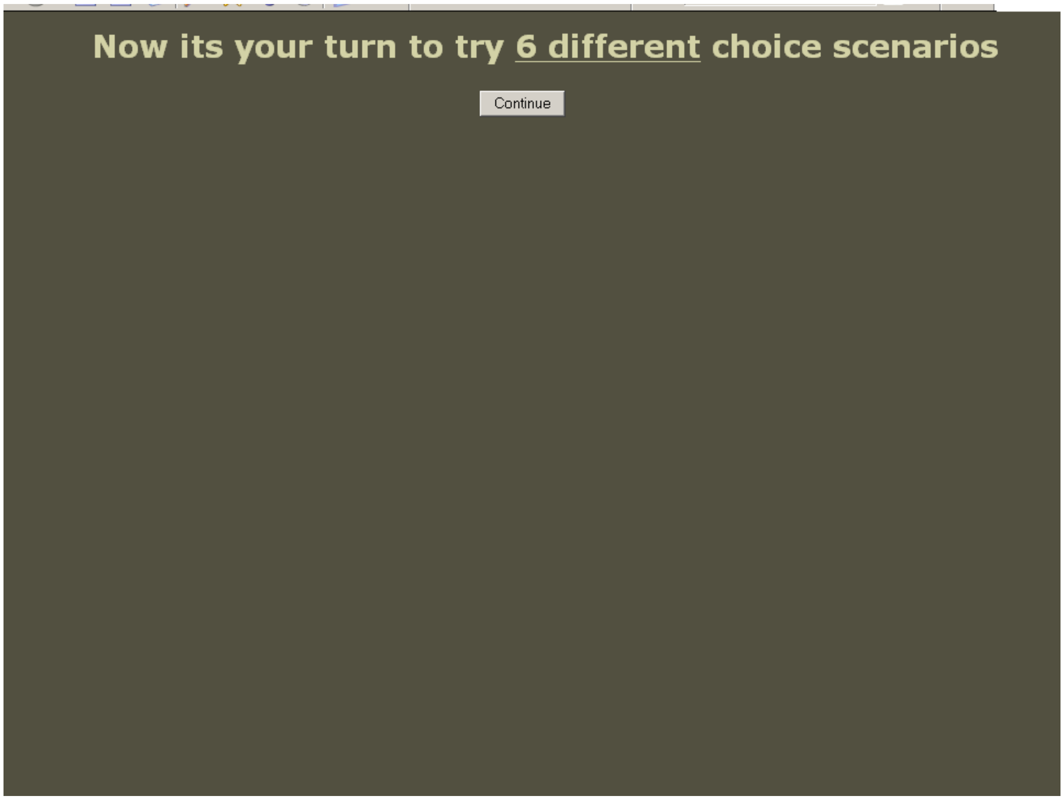


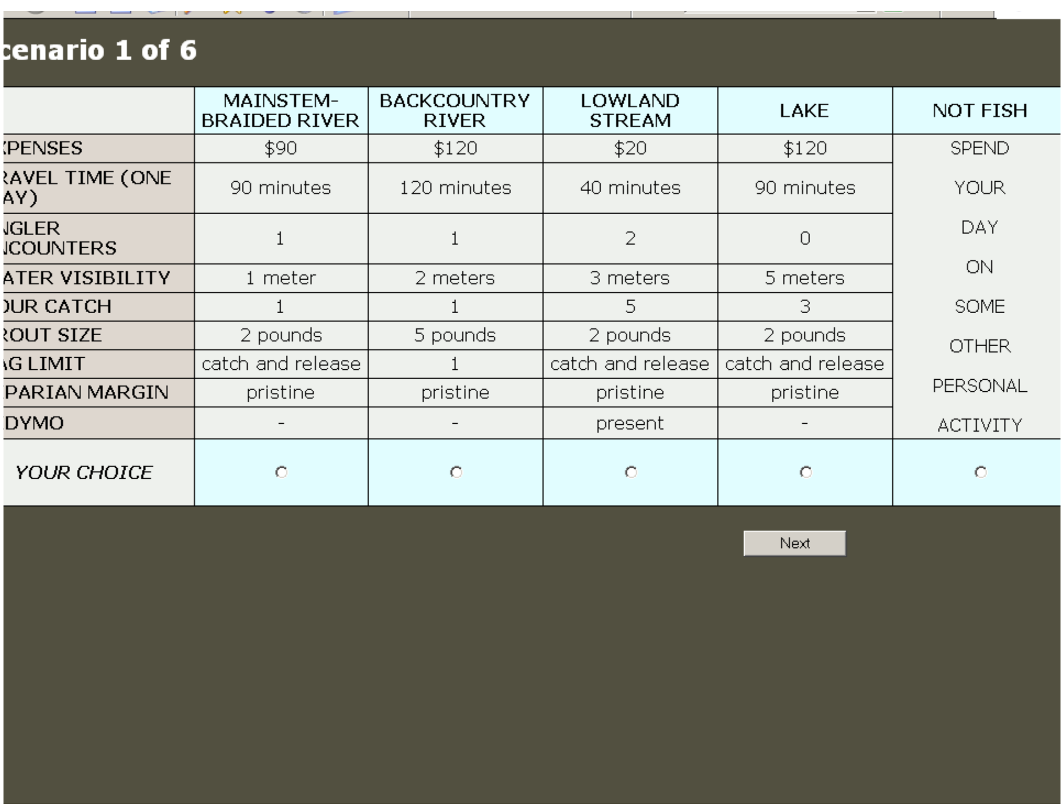
Example: Scenario 1

In scenario 2 the options have changed
Angler Joe evaluates these new options and in this particular case decides that if these were his 'real life options' he would 'not fish'.

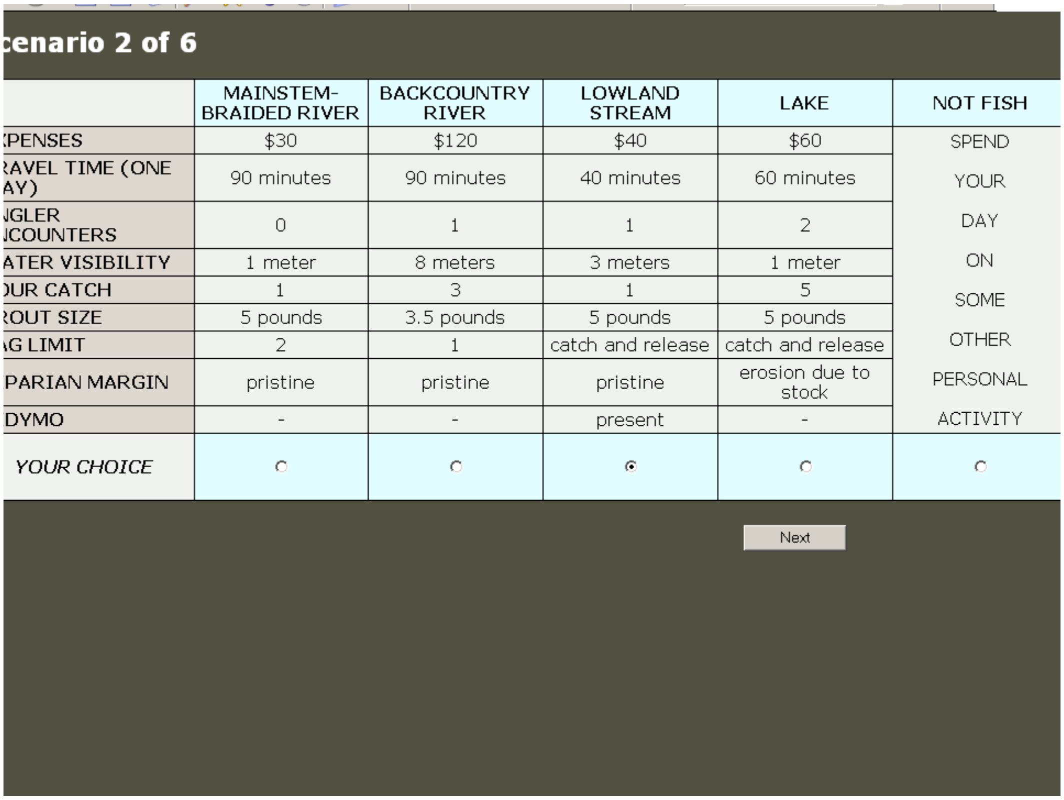
	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
EXPENSES	$30	$90	$40	$60	SPEND YOUR DAY ON SOME OTHER PERSONAL ACTIVITY
TRAVEL TIME (ONE WAY)	90 minutes	120 minutes	60 minutes	90 minutes	
ANGLER ENCOUNTERS	0	1	2	2	
WATER VISIBILITY	5 meters	5 meters	5 meters	3 meters	
YOUR CATCH	1	3	3	3	
TROUT SIZE	2 pounds	3.5 pounds	5 pounds	2 pounds	
BAG LIMIT	2	catch and release	2	2	
RIPARIAN MARGIN	pristine	pristine	pristine	erosion due to stock	
DIDYMO	-	present	-	present	
YOUR CHOICE	○	○	○	○	◉

Continue





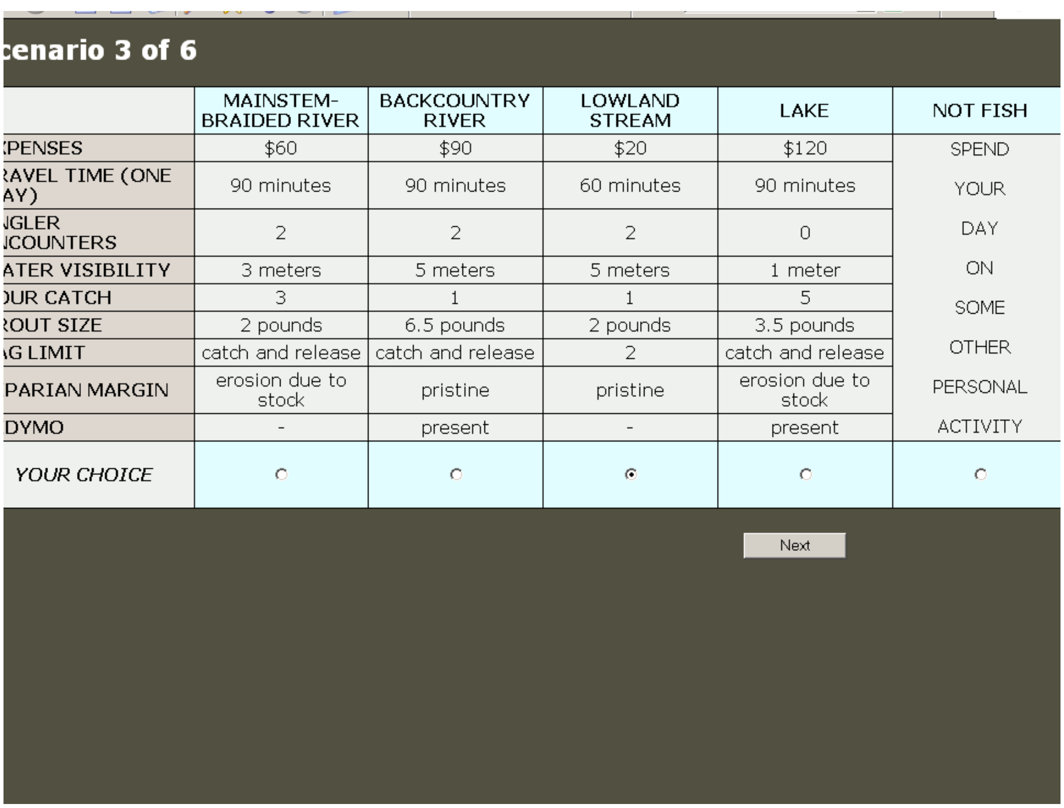
	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
PENSES	$90	$120	$20	$120	SPEND YOUR DAY ON SOME OTHER PERSONAL ACTIVITY
AVEL TIME (ONE AY)	90 minutes	120 minutes	40 minutes	90 minutes	
GLER COUNTERS	1	1	2	0	
ATER VISIBILITY	1 meter	2 meters	3 meters	5 meters	
UR CATCH	1	1	5	3	
OUT SIZE	2 pounds	5 pounds	2 pounds	2 pounds	
G LIMIT	catch and release	1	catch and release	catch and release	
PARIAN MARGIN	pristine	pristine	pristine	pristine	
DYMO	-	-	present	-	
YOUR CHOICE	○	○	○	○	○



cenario 2 of 6

	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
ƐPENSES	$30	$120	$40	$60	SPEND
ƦAVEL TIME (ONE AY)	90 minutes	90 minutes	40 minutes	60 minutes	YOUR
NGLER NCOUNTERS	0	1	1	2	DAY
ATER VISIBILITY	1 meter	8 meters	3 meters	1 meter	ON
OUR CATCH	1	3	1	5	
ROUT SIZE	5 pounds	3.5 pounds	5 pounds	5 pounds	SOME
AG LIMIT	2	1	catch and release	catch and release	OTHER
PARIAN MARGIN	pristine	pristine	pristine	erosion due to stock	PERSONAL
DYMO	-	-	present	-	ACTIVITY
YOUR CHOICE					

Next



cenario 3 of 6

	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
ƐPENSES	$60	$90	$20	$120	SPEND
ƦAVEL TIME (ONE AY)	90 minutes	90 minutes	60 minutes	90 minutes	YOUR
NGLER NCOUNTERS	2	2	2	0	DAY
ATER VISIBILITY	3 meters	5 meters	5 meters	1 meter	ON
OUR CATCH	3	1	1	5	
ROUT SIZE	2 pounds	6.5 pounds	2 pounds	3.5 pounds	SOME
AG LIMIT	catch and release	catch and release	2	catch and release	OTHER
PARIAN MARGIN	erosion due to stock	pristine	pristine	erosion due to stock	PERSONAL
DYMO	-	present	-	present	ACTIVITY
YOUR CHOICE					

Next

cenario 4 of 6

	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
PENSES	$30	$90	$60	$90	SPEND YOUR DAY ON SOME OTHER PERSONAL ACTIVITY
RAVEL TIME (ONE AY)	60 minutes	90 minutes	40 minutes	60 minutes	
NGLER NCOUNTERS	2	0	0	2	
ATER VISIBILITY	3 meters	2 meters	1 meter	3 meters	
OUR CATCH	3	3	5	1	
ROUT SIZE	3.5 pounds	6.5 pounds	5 pounds	5 pounds	
AG LIMIT	2	1	2	2	
PARIAN MARGIN	erosion due to stock	erosion due to stock	erosion due to stock	pristine	
DYMO	present	present	present	-	
YOUR CHOICE	○	◉	○	○	○

Next

cenario 5 of 6

	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
PENSES	$30	$90	$40	$90	SPEND YOUR DAY ON SOME OTHER PERSONAL ACTIVITY
RAVEL TIME (ONE AY)	90 minutes	60 minutes	60 minutes	120 minutes	
NGLER NCOUNTERS	1	0	0	1	
ATER VISIBILITY	1 meter	2 meters	1 meter	3 meters	
OUR CATCH	1	5	5	3	
ROUT SIZE	5 pounds	6.5 pounds	3.5 pounds	2 pounds	
AG LIMIT	catch and release	catch and release	catch and release	2	
PARIAN MARGIN	pristine	pristine	erosion due to stock	pristine	
DYMO	-	present	-	-	
YOUR CHOICE	○	○	◉	○	○

Next

cenario 6 of 6

	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
PENSES	$90	$90	$40	$60	SPEND YOUR DAY ON SOME OTHER PERSONAL ACTIVITY
RAVEL TIME (ONE AY)	90 minutes	60 minutes	20 minutes	120 minutes	
NGLER NCOUNTERS	1	2	0	2	
ATER VISIBILITY	3 meters	5 meters	5 meters	1 meter	
UR CATCH	1	5	1	5	
ROUT SIZE	2 pounds	5 pounds	5 pounds	2 pounds	
G LIMIT	2	catch and release	2	catch and release	
PARIAN MARGIN	pristine	pristine	pristine	pristine	
DYMO	-	present	present	-	
YOUR CHOICE	○	◉	○	○	○

Next

Just a few more questions

How many years have you been trout fishing?

10

How many days per year do you typically go trout fishing?

- ○ 1-5
- ○ 6-10
- ◉ 11-20
- ○ 21-30
- ○ 31-40
- ○ 41-50
- ○ 51-60
- ○ 61-70
- ○ 71-80
- ○ 81-90
- ○ 91-100
- ○ 101+

Over the past few years has your interest in trout fishing:

- ◉ gone up?
- ○ gone down?
- ○ stayed the same?

Over the past few years has the amount of time you've spent trout fishing:

- ◉ gone up?
- ○ gone down?
- ○ stayed the same?

Continue

How important to you is improving your level of angling skill and knowledge?
- Not important
- Moderately important
- Highly important

How important is trout fishing in your life?
- Not important
- Moderately important
- Highly important

In comparison to other recreational activities you participate in how does trout angling rank in importance?
- 1st
- 2nd
- 3rd or lower

Do you use internet trout fishing resources (websites/forums)?
- Yes
- No

Are you a member of an angling club?
- Yes
- No

Continue

Relative to other New Zealand trout anglers what percentile best reflects your angling skill level?
- Novice
- Intermediate
- Advanced

What are your preferred method(s) to catch trout?
- Fly only
- (Spinner or bait)
- Both Fly and (spinner or bait)

What species do you fish for?
- Trout only
- Trout and Salmon
- Trout and other saltwater species
- Trout, Salmon and other saltwater species

Indicate all of the fishery types you regularly fish or have interest in fishing (if just one, select that one only):
- Mainstem rivers
- Backcountry rivers
- Lowland streams
- Braided rivers
- Lakes

Continue

Which of the following do you fish most often?
- Mainstem rivers
- Backcountry rivers
- Lowland streams
- Braided rivers
- Lakes

Where do you live?
- Nelson-Marlborough region
- West Coast
- North Canterbury
- Central South Island
- Otago
- Southland
- North Island New Zealand
- Internationally

What is your gender?
- Male
- Female

What is your age?
- 18-30
- 31-40
- 41-50
- 51-60
- 61-70
- 71-80
- Over 80 years of age
- I would rather not say

What is your annual personal income?

What is your age?
- 18-30
- 31-40
- 41-50
- 51-60
- 61-70
- 71-80
- Over 80 years of age
- I would rather not say

What is your annual personal income?
- Under $20,000
- $20,000 - $40,000
- $40,001 - $60,000
- $60,001 - $80,000
- $80,001 - $100,000
- $100,001 - $120,000
- $120,001 - $140,000
- $140,001 - $160,000
- Over $160,000
- I would rather not say

What is your marital status?
- Single
- Have partner but not married
- Married
- I would rather not say

How many children do you have?

0

Continue

In recognition of your help you are eligible for a draw to win your choice of either a Sage Z-axis fly rod (your choice of model) or a gift certificate to Nelson Hunting and Fishing worth $1000. If you would like to enter the draw please provide us with your email address.

Your email address:

The winner of the draw will be notified by July of 2008.

Continue

Appendix B: Correlations among individual specialisation indicator variables

	rankfish	daysyear	yeasrsfish	skill	impskill	impfish	clubmemb	income	age
rankfish	1.000								
daysyear	0.459	1.000							
yeasrsfish	0.156	0.157	1.000						
skill	0.425	0.422	0.492	1.000					
impskill	0.313	0.286	-0.127	0.087	1.000				
impfish	0.610	0.433	0.191	0.439	0.381	1.000			
clubmemb	0.179	0.238	0.062	0.178	0.213	0.203	1.000		
income	0.016	-0.085	0.048	0.100	0.029	0.050	0.046	1.000	
age	0.125	0.040	0.590	0.217	-0.121	0.070	0.062	0.061	1.000