Comparing different attitude statements in latent class models of stated preferences for managing an invasive forest pathogen

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Abstract: To better interpret preference data, environmental economists often measure two different types of attitudes: general environmental attitudes, and attitudes specific to an issue. Although methods such as joint latent class modeling can relate these measures to stated preference data, economics literature offers limited guidance on important details, including the relative merits of the two attitude types. This paper analyzes survey data about the management of the invasive, non-native fungus that causes the lethal disease white pine blister rust in high-elevation forests, a problem characterized by long time scales and potentially costly interventions of uncertain efficacy. The paper uses novel techniques for comparing across latent class model specifications to evaluate the relative contribution of general and specific attitude measures to the analysis of contingent valuation data. These demonstrate insights from investigating heterogeneity in respondents' perspectives and superior model performance with specific attitude statements versus with general attitude statements. In addition to the practical content, these results offer novel insight into ongoing debate on the meaning of stated preference valuation measures. (keywords: attitudes; contingent valuation; invasive species; joint latent class model; stated preference; survey methods)

Highlights

- Environmental economists often use attitude data to help understand preferences.
- However, literature offers limited guidance on general versus specific attitudes.
- I analyze preferences for managing an invasive fungus, lethal to nontimber forests.
- Novel techniques help compare specifications of latent class model variables.
- Here, models fit better with specific rather than general environmental attitudes.
1. **Introduction**

People value the environment in different ways and for different reasons. Accordingly, many environmental economists have long been interested in attitude measures and preference heterogeneity. Krutilla (1967 p.779) called for understanding nonmarket values because of the distinct preferences of a particular group he called the "spiritual descendants of John Muir." The National Oceanic and Atmospheric Administration's (NOAA) "blue-ribbon panel" on contingent valuation (CV) (Arrow *et al.* 1993) recommended using measures of attitudes toward the environment not only to help interpret economic data but also to present disaggregated measures of willingness to pay (WTP). Similarly, Arrow *et al.* (1996) urged for cost-benefit analyses to supply information on heterogeneity and the distributional consequences of potential policies. Breffle *et al.* (2011) motivate the model estimated below by pointing to calls for integrating attitude data into economic models that range from McFadden (1986) to more recent papers focused primarily on preference heterogeneity (Ben-Akiva *et al.* 2002; Boxall and Adamowicz 2002; Morikawa *et al.* 2002).

Nonmarket valuation surveys typically elicit information on either one, or both, of two types of attitudes: *general attitudes*, which relate to broad evaluative beliefs or opinions, such as about the environment, and *specific attitudes*, which relate to evaluative beliefs or opinions about the good or issue in question. It is not *a priori* clear whether one attitude type more appropriately complements preference data. The literature offers conflicting examples, and more generally, it offers little explicit discussion of the relative merits of different types of attitude data for improving and understanding economic models. Given the common practice of collecting such data, it is important to examine these relative merits empirically.

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1Abbreviations used below: CV (contingent valuation), JLC (joint latent class model), NEP (new ecological paradigm), RUM (random utility model), WPBR (white pine blister rust), WTP (willingness to pay)
This paper addresses this gap by exploring the relationships among general attitude, specific attitude, and stated preference data from a CV survey about the management of the non-native pathogen that causes the disease white pine blister rust (WPBR) in high-elevation five-needled pine forests. It employs a joint latent class (JLC) model (Morey et al. 2006; Breffle et al. 2011) that links attitude and preference data without assuming any specific relationship between attitudes and preferences except that differences between classes would be similar for both. Because classes estimated by this model correspond to perspectives with commonalities across preference and attitude data, the interpretation of the estimated class segmentation will differ depending on the type of attitude statements used.

The paper demonstrates novel techniques for comparing the relative performance of different sets of attitude data in alternative JLC models. Its main contribution is to compare the relationship between different types of attitude measures and the stated preference data for the empirical application, thereby offering potential insight into the interpretation of the stated preference data and the usefulness of different types of attitude measures in applied environmental economics. Results suggest that although both attitude types have empirical and explanatory merit here, the CV data in this study are substantially more similar to attitudes specifically about the particular issue than to general attitudes about the environment, in the sense that perspectives jointly defined by preferences and the former are more tightly estimated than those jointly defined by preferences and the latter. To the extent they are generalizable, these results offer empirical insight into ongoing debate about the interpretation of stated preference data, specifically, and into the relationships between attitudes and preferences more generally. In addition, the comparison techniques developed below can be generalized to inform
the selection of appropriate covariates in other latent class models, another issue that has received little attention in the literature.

The next section provides background on the relationship between preferences and attitudes and the use of attitudes in nonmarket valuation. Section three introduces the empirical application and data source. Section four presents the conceptual background and general specification of the JLC model, as well as techniques for model comparison. After section five presents empirical results, section six discusses their interpretation and implications.

2. Background: Attitudes, preferences, and nonmarket valuation

This paper focuses on groups of perspectives, in which a perspective refers to a general, unobservable worldview. Though many plausible stories could account for distinct perspectives (e.g., political ideology, socioeconomic status, or genetics), the critical feature is that individuals within a common perspective group share similar attitudes and preferences. Perspectives may or may not be evaluative, and the concept therefore is more general than either attitudes or preferences. Stated preferences describe the tradeoffs people are willing to make; an interest in perspectives as defined here includes analysis of these tradeoffs without precluding the potential merit of understanding other dimensions of people's perspectives, such as their attitudes.

Social psychology defines an attitude as "any belief or opinion that has an evaluative component" (Gray 1999 p.507): attitudes must be about something and that "aboutness" must be evaluative. Attitudes are not directly observable but can be inferred from, for example, one's expressed level of agreement with statements that reflect an attitude, called attitude statements in this paper. Theory typically does not preclude the same attitude fulfilling more than one function, such as the utilitarian function of guiding behavior or the value-expressive function relating to
"…relatively abstract attitudes that people claim as guiding principles behind their more specific attitudes and actions" (Gray 1999 p.507).

In turn, an attitude is more general than a *preference* (e.g., Kahneman *et al.* 1999), which in standard microeconomic theory (e.g., Mas-Colell *et al.* 1995; Varian 2003) is a complete, reflexive, and transitive relation between the elements of a choice set. To have a preference, an individual must have evaluative positions toward the options, which is to say the individual must have attitudes about the elements of a choice set. However, whereas microeconomics asserts that well-behaved preferences must be consistently ordered\(^2\), social psychology allows attitudes to be incomplete or inconsistent. Therefore, a preference consists of a set of attitudes that follow a particular structure; an attitude is necessary but not sufficient for a preference. That is, preferences and attitudes must be similar in content, in the sense that both are evaluative positions over choices, but are different in kind, in the sense that they differ in strictness about their requisite structure. The attitudes statements investigated below are on similar topics to the CV question. Thus, both can be expected to pertain to coherent perspectives as a more general construct. However, because the attitudes statements do not address the tradeoffs that are fundamental to the concept of a preference, the two are different.

Nonmarket valuation surveys often collect data on general attitudes, specific attitudes, or both (Meyerhoff 2006), but economics does not offer a general theory of attitudes, despite many economists acknowledging their relevance. Most empirical studies provide little, if any, justification of why a particular type of attitude is measured, and literature offers conflicting examples and advice. On the one hand, the NOAA panel (Arrow *et al.* 1993) and others (1997) recommend incorporating general environmental attitudes in economic evaluation. For example,

\(^2\) More flexible concepts of preferences, such as that of bounded rationality, still maintain that preferences are structured and consistent, conditional on circumstances.
the New Ecological Paradigm (NEP) (Dunlap and Van Liere 1978; Dunlap et al. 2000) measures general environmental attitudes with attitude statements such as "The earth has plenty of natural resources if we just learn how to develop them." Kotchen and Reiling (2000) introduced the NEP to the economics literature as a measure of general environmental attitudes, which they and Aldrich et al. (2007) use to identify different groups of respondents with clustering and latent class methods. Similarly, Choi and Fielding (2013) link WTP to protect endangered species to NEP responses in a choice modeling framework, and Videras et al. (2012) use latent class modeling to link respondents' general environmental attitudes, and those of their neighbors, with some pro-environmental behaviors but not others.

On the other hand, some authors (Bamberg et al. 1999; Meyerhoff 2006) suggest that while general attitudes may affect framing of choice, they should have no direct effect on preferences. Supporting this view, Cooper et al. (2004) found no significant relationship between NEP responses and WTP in a CV study about lake water quality improvements. Instead, many environmental economics studies focus on attitudes that are specifically directed toward the management question under investigation (e.g., Langford et al. 2001; Jorgensen et al. 2001; Tapsuwan et al. 2010; Nguyen et al. 2013), whereas a smaller number use both types of attitudes similarly (e.g., Martín-López et al. 2007; García-Llorente et al. 2011). Carson et al. (2001) assert that specific attitudes tend to be "generally better predictors of WTP than self-identification as an environmentalist" (p. 194) and Kealy et al (1990) argue that the specific intentions about specific behaviors measured by CV would be expected to correlate with more specific attitudes. Well-cited studies on the role of "warm glow" in motivating CV responses (Nunes and Schokkaert 2003) and on assessing the scope test for CV (Heberlein et al. 2005) measure specific rather than general attitudes. Finally, two environmental economics latent class studies (Boxall and
Adamowicz 2002; Morey et al. 2006) both rely on measure of attitudes specific to the issues investigated. The implicit assumption seems to be that specific attitudes provide relevant information about preferences because the two are similar, though not identical. However, few if any studies directly compare specific versus general attitudes in economic modeling.

3. Application and Data

For empirical insight, this paper investigates attitude and contingent valuation data from a survey on the public benefits of managing the invasive, non-native pathogen that causes the lethal disease white pine blister rust (WPBR) in high-elevation, five needled-pine forests. These forests cover approximately two million acres of public land in western North America, including several "flagship" National Parks, and are associated with many ecosystem services, including wildlife habitat, watershed regulation, and recreational opportunities (Mattson et al. 1992; Tombback and Kendall 2001; Samman et al. 2003; Petit 2007; Robbins 2010; U.S. Fish and Wildlife Service 2011). They consist of the foxtail pine, Rocky Mountain bristlecone pine, Great Basin bristlecone pine, limber pine, and whitebark pine: species known as containing some of the oldest living organisms on Earth. The non-native fungus Cronartium ribicola, which causes WPBR, was introduced in the early 20th century and has slowly spread across much of these forests' range, leading to mortality at all stages of the trees' lifecycles. This degradation of forest health, which is defined as all four stages of the trees' regeneration cycles occurring simultaneously, thereby threatens the long-run sustainability of these forests (Logan and Powell 2001; Schoettle and Sniezko 2007; Field et al. 2012).

In contrast with conventional invasive species management strategies that first attempt prevention, eradication, and containment and then focus on mitigation of impacts and restoration of degraded areas if needed, the characteristics of the Cronartium ribicola lifecycle mean that the
most viable approach to managing WPBR may be proactive management, which occurs in an
area before it is impacted (Schoettle and Sniezko 2007; Bond et al. 2011; Schoettle et al. 2011).
However, proactive WPBR treatments might prove quite costly in terms of direct expenditures
(Samman et al. 2003; Schwandt 2006; Schoettle and Sniezko 2007; Burns et al. 2008) and may
involve disturbing areas that are not usually subject to forest management of any sort, thereby
reducing the current stream of benefits from the forests in what Bond et al. (2011) call
"management externalities." This management problem is characterized by very long time scales
(of decades to centuries) and potentially costly, proactive intervention of uncertain efficacy. As
such, it shares many characteristics with other pressing issues, such as climate change mitigation.

Previous research (Meldrum et al. 2013; Meldrum et al. 2014) has identified a positive
overall WTP for such proactive management techniques, reflecting general findings of forests
providing significant nonmarket benefits (Kramer et al. 2003; Sills and Abt 2003; Barrio and
Loureiro 2010). However, consistent with other research that finds that attitudes toward forest
health and management vary substantially (McFarlane et al. 2006; Flint et al. 2009; Gelo and
Koch 2012), Meldrum et al. (2013) also found substantial preference heterogeneity, with factor
and cluster analyses suggesting three groups of respondents: those primarily concerned with
nonuse benefits, those also interested in recreational benefits, and those disinterested in the issue.
This paper continues this investigation, seeking a deeper, more rigorous understanding of
perspectives toward this issue.

3.1 Data collection

Data come from an online panel survey of the western US about the management of
WPBR in high-elevation forests (Bond et al. 2011; Meldrum et al. 2011). The survey achieved a
61% response rate in June 2010 with collected demographics suggesting representativeness of
the general population with the exceptions of more white, non-Hispanic respondents and more
with household internet access than expected based on US Census data for the sampled states.

In addition to providing relevant background information and other data collection
sections, this survey asked a dichotomous choice CV question about whether respondents would
be willing to pay a randomly selected one-time cost \( (\text{bid} = \$10, \$25, \$50, \$100, \$250, \$500, \text{or} \ \$1000) \) for a program to manage a randomly selected percentage \( (\text{quantity} = 30\%, \ 50\%, \ \text{or} \ 70\%) \)
of all high-elevation pine forests in the western US for WPBR, with an explicit outcome that "as
a result, these acres will be healthy in 100 years from now." Fewer respondents said "yes" to
each consecutively increasing \( \text{bid} \), with 48\% of respondents answering "yes" overall; more
details have been published elsewhere (Meldrum et al. 2011; Meldrum et al. 2013). The survey
also elicited respondents' level of agreement on a 5-point Likert scale (1 = Strongly Disagree to 5
= Strongly Agree) with the six general attitude statements and seven specific attitude statements
shown in Table I. The general attitude statements are a combination of NEP scale items (Dunlap
et al. 2000) and statements unique to this survey, whereas the specific attitude statements are all
original and pertain to invasive species management, high-elevation forests, or five-needle pines.

The JLC model estimated below can accommodate multiple similar variables. For
conciseness, however, linear combinations of the attitude statement data, created by factor
analysis, are used for presentation and for re-estimating choice probabilities. Factor analysis
identified two factors each for the general attitude statements and specific attitude statements, as
well as four factors for the full set of attitude statements. Factor scores were named \( \text{ex post} \) by
inspection of dominant factor loadings. The fourth column of Table I shows the factor variables
upon which each statement has a large influence (i.e., factor loading greater than 0.4).
Table I. Levels of agreement and dominant factor loadings for attitude statements.

<table>
<thead>
<tr>
<th>Label</th>
<th>Attitude Statements</th>
<th>Median</th>
<th>Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA1</td>
<td>All environmental issues are important.</td>
<td>4</td>
<td>GF1, CF1, CF2</td>
</tr>
<tr>
<td>GA2</td>
<td>It is important that I pay my fair share for the environment.</td>
<td>3</td>
<td>GF1, CF2</td>
</tr>
<tr>
<td>GA3</td>
<td>The earth has plenty of natural resources if we just learn how to develop them.</td>
<td>4</td>
<td>GF2</td>
</tr>
<tr>
<td>GA4</td>
<td>When humans interfere with nature it often produces disastrous consequences.</td>
<td>3</td>
<td>GF2, CF4</td>
</tr>
<tr>
<td>GA5</td>
<td>Humans have the right to modify the natural environment to suit their needs.</td>
<td>3</td>
<td>none</td>
</tr>
<tr>
<td>GA6</td>
<td>Despite our special abilities humans are still subject to the laws of nature.</td>
<td>4</td>
<td>GF1, GF2, CF1, CF4</td>
</tr>
<tr>
<td>SA1</td>
<td>It is important that high-elevation forests exist for future generations.</td>
<td>5</td>
<td>SF1, CF1</td>
</tr>
<tr>
<td>SA2</td>
<td>It is important that forests I am personally attached to are treated for WPBR.</td>
<td>3</td>
<td>SF1, CF1, CF2</td>
</tr>
<tr>
<td>SA3</td>
<td>It is important that high-elevation forests provide recreation activities, such as camping or hiking.</td>
<td>4</td>
<td>SF2, CF3</td>
</tr>
<tr>
<td>SA4</td>
<td>Tourism related to high-elevation forests is important.</td>
<td>3</td>
<td>SF2, CF3</td>
</tr>
<tr>
<td>SA5</td>
<td>People should not intervene in high-elevation forests.</td>
<td>2</td>
<td>CF1&lt;sup&gt;e&lt;/sup&gt;</td>
</tr>
<tr>
<td>SA6</td>
<td>Protecting five-needled pines from the threat of extinction is important.</td>
<td>4</td>
<td>SF1, CF1</td>
</tr>
<tr>
<td>SA7</td>
<td>Humans have the responsibility to protect ecosystems from pests or diseases that humans introduced.</td>
<td>4</td>
<td>SF1, CF1, CF2</td>
</tr>
</tbody>
</table>

<sup>a</sup>Labeled "GA#" for general attitude statements and "SA#" for specific attitude statements.

<sup>b</sup>Responses range 1 = strongly disagree to 5 = strongly agree

<sup>c</sup>Factors with loading ≥0.4

<sup>d</sup>GF1 = General Factor 1: Protect Nature; GF2 = General Factor 2: Natural Order; SF1 = Specific Factor 1: Protection; SF2 = Specific Factor 2: Recreation; CF1 = Combined Factor 1: Protection; CF2 = Combined Factor 2: Fair Share; CF3 = Combined Factor 3: Recreation; CF4 = Combined Factor 4: Non-interfere

<sup>e</sup>Factor loading is negative (i.e., ≤-0.4)

4. The joint latent class (JLC) model

As reviewed above, the literature provides very little empirical investigation of the relative performance of general versus specific attitudinal statements in helping to understand stated preference data. This paper aims to fill this gap by jointly estimating preference and attitude data with the JLC model proposed by Morey et al. (2006) and analyzed in Breffle et al.
and then comparing the relative performance of model specifications that use different sets of the attitude data. The JLC model jointly estimates separate probability functions for each measured variable (i.e., responses to the CV question and to each attitude statement). Models perform better when they demonstrate better class segmentation: lower variance in estimated probabilities, which signifies greater agreement on estimated preferences or attitudes among members of a given class, and greater independence of these probabilities conditional on class membership, which signifies that class membership more completely captures the systematic similarities in observed data.

4.1 Background: Linking attitudes and preferences with latent class models

According to Henry (1999), latent class models were first developed from latent structure analysis to help link the concept of attitudes to survey data by finding categorical, latent attitudinal variables from dichotomous survey items (Lazarsfeld and Henry 1968; Goodman 1974). Later innovations developed multinomial latent class models that allow class membership probabilities to vary (Gupta and Chintagunta 1994; Kamakura et al. 1994; Bhat 1997). Latent class analysis has long been used to segment both attitudes (e.g., Clogg and Goodman 1984; de Menezes and Bartholomew 1996; Yamaguchi 2000; Eid et al. 2003; Thacher et al. 2005) and market decisions or preferences (DeSarbo and Cron 1988; Kamakura and Russell 1989; Grover and Srinivasan 1989), with both approaches now commonplace in market analysis (Wedel and Kamakura 2000), health economics (e.g., Hole 2008; Øvrum 2011; Sivey 2011), recreation demand (e.g., Scarpa et al. 2007; Hynes et al. 2008; Bujosa et al. 2010), and land management (e.g., Colombo et al. 2009; Hynes et al. 2011; Putten et al. 2011).

The JLC model combines measurements of attitudes and preferences by assuming that both relate to similar perspectives, of which society contains multiple, fairly discrete groups.
According to Provencher and Moore (2006), this model differs from other recent efforts to combine preference and attitude data in assuming that an individual's latent group will affect her answers to questions that measure either attitudes and preferences similarly, therefore jointly estimating the two data types as different forms of the same "primitive preferences." Similarly, Breffle et al. (2011) emphasize the novelty of combining measurements of attitudes and preferences as comparable elicitations of "primitive preferences" in a simultaneous, jointly-estimated model. Note that, because it is not clear that these latent classes pertain to preferences any more than they do to attitudes, this paper uses more generalized language and refers to the estimated latent classes as perspective classes, following the above definition of "perspective."

Breffle et al. (2011) contrast their model with several similar approaches: Swait and Sweeney (2000), Boxall and Adamowicz (2002), and Putten et al. (2011) treat attitude data as exogenous to the choice model by assuming that latent preferences determine attitudes, which then determine preferences in conjunction with sociodemographics and idiosyncratic errors; Owen and Videras (2007) sequentially estimate an attitudinal latent class model and then a choice model essentially weighted by the latent class probabilities; and Patunru et al. (2007) first estimate an attitudinal latent class model then estimate a choice model with respondents deterministically assigned to their highest-probability classes. Moore (2008) finds similar results from estimating her CV data with either the Boxall and Adamowicz (2002) or Morey et al. (2006) model and argues that their subtle differences are negligible versus the importance of including attitudes in valuation at all. Other recent approaches, primarily in the transportation literature, include the simultaneous (Bolduc and Alvarez-Daziano 2010; Daly et al. 2011; Hess and Beharry-Borg 2011) or sequential (Choo and Mokhtarian 2004; Johansson et al. 2006; Temme et al. 2008) estimation of integrated choice and latent variable models, which model the
utility of economic choice as depending on both observed and latent variables about the decision-makers or the alternatives. The JLC model differs from these examples by combining the general developments of latent class modeling with the explicit assumption that preference and attitude data are both manifestations of the same underlying perspectives, yet avoiding imposing any structure on the relationship between the two types of data. The use of the JLC model here does not imply that it is unequivocally superior to all other approaches but rather that it is most appropriate for present purposes, by remaining truly agnostic about the character of perspectives.

4.2 JLC model specification

In the JLC model (Morey et al. 2006; Breffle et al. 2011), observations belong to each latent class with some non-zero probability, with each class defined by its perspective. Observations within a class share similar attitudes and preferences, but attitudes and preferences are independent conditional on (perspective) class. Conceptually, latent class mediates between observable data and unobservable constructs of utility and attitudes (Meldrum 2012), and latent classes manifest as a non-structured similarity in evaluative content between the estimated attitudes and preferences. Mathematically, this corresponds to the following likelihood function for observed responses $x_i$ to the CV question, observed responses $y_i$ to attitude statements, and unobserved class $c \in \{1,\ldots,C\}$:

$$L = \prod_i \prod_c \left[ \sum_{l=1}^L \Pr(x_i, y_i|c) \Pr(c) \right]$$

where $\Pr(c)$ is the unconditional probability of belonging to class $c$ and $\Pr(x_i, y_i|c)$ is the probability of observing individual $i$'s responses to attitude statements and the CV question conditional on belonging to class $c$. 
Assuming conditional independence asserts that responses to different attitude statements and the CV question are independent within classes. In other words, class membership is assumed to capture the systematic similarities in observed data across responses. Under this assumption, the likelihood function can be rewritten:

\[
L = \prod_{i} \prod_{c=1}^{k} \left( \Pr(x_i|c) \Pr(y_i|c) \Pr(c) \right)
\]

where \( \Pr(x_i|c) \) is the choice probability, conditional on membership in class \( c \), of observing individual \( i \)'s response \( x_i \) to the CV question; \( \Pr(y_i|c) \) is the attitude probability, conditional on membership in class \( c \), of observing individual \( i \)'s responses \( y_i \) to the attitude statements included in the model; and \( \Pr(c) \) is the membership probability, which conveys the unconditional likelihood that individual \( i \) belongs to class \( c \). Note that in this specification, attitude and preference data are exogenous to each other; neither enters the other's probability function.

Building from the standard RUM, the model assumes that individual \( i \)'s direct utility \( U_{ic} \) from saying "yes" to the CV question, conditional on being in latent class \( c \), is observed with type I generalized extreme value error. Thus, the choice probability \( \Pr(x_i|c) \) is modeled as a binary conditional logit with indirect utility \( V_{ic} \) conditional on latent class:

\[
\Pr(x_i|c) = \frac{\exp(V_{ic})}{1 + \exp(V_{ic})}
\]

\( V_{ic} \) is an assumed linear function of choice attributes and class-specific parameters \( \beta_c \).\(^3\) Mean WTP is calculated at the mean level of included covariates following Hanemann (1989), with

\(^3\) Note that this assumes a symmetric distribution of WTP values. Although authors often use a ln(WTP) model to accommodate a potential long right tail, such a model precludes negative values of WTP, which are a distinct possibility for the specific empirical application studied here. In addition, the latent class approach has the potential to mitigate the long right tail problem, if outlier responses are consistent enough to form a distinct latent class.
standard errors calculated via the delta method. Following Breffle et al. (2011), the attitude probability consists of the probability of each response to attitudes statements:

\[ Pr(\theta \mid c) = \prod \prod (\pi_{qs \mid c}) \]  

(4)

where \( \pi_{qs \mid c} \) is the probability that an individual in class \( c \) chooses level \( s \) in response to attitude statement \( q \) and \( y_{iqs} = 1 \) if individual \( i \) chooses \( s \) in response to \( q \); \( y_{iqs} = 0 \) otherwise\(^4\). Finally, membership probability \( Pr(c) \) is modeled as a simple multinomial logit with no covariates, only a constant, normalized by the sum over the different classes:

\[ Pr(c) = \frac{e^{\eta_c}}{\sum_{d \in C} e^{\eta_d}} \]  

(5)

The joint likelihood means that the choice probability is weighted by product of the attitude probabilities, and each attitude probability is weighted by the product of the other attitude probabilities and the choice probability. Thus, the likelihood of observed CV and attitude statement responses given the class's estimated parameters serves as a weight on the importance of those data upon the estimation of that class's parameters. This relationship links the similar evaluative content of attitudes and preferences without involving further assumption of the functional relationship.

All models were estimated with author-written code built around MATLAB's nonlinear optimization commands. To avoid only locally optimal solutions, an estimation procedure adapted from Bhat (1997) repeats 1000 optimizations, each generated by initializing an expectation-maximization (EM) algorithm (Dempster et al. 1977) with randomly-generated starting probabilities, iterating for two steps, then solving with standard maximum likelihood estimation (Meldrum 2012). The iteration with the lowest absolute value log likelihood was

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\(^4\) Meldrum (2012) models the attitude probability with an ordered logit specification for each attitude statement. Despite the theoretical differences, this alternative specification leads to nearly identical results for this dataset.
selected as optimal. Reported results are not substantively sensitive to the choice of this solution versus those of other iterations.

4.3 Selecting the preferred model

Latent class model estimation requires selecting the appropriate number of classes. The $\chi^2$ distributional assumption of the difference statistic used for a standard likelihood ratio (LR) test is invalid when a full model is restricted by parameters placed at boundary values (Lin and Dayton 1997). Economists typically select the optimal number of classes by subjective discretion over the explanatory usefulness of the modeled results (Wedel and Kamakura 2000; Morey et al. 2006) and over the tradeoff between fit and parsimony, informed by numerous information criterion (Lin and Dayton 1997; Wedel and Kamakura 2000). Commonly calculated information criteria include the Akaike information criterion (AIC) (Akaike 1974), the Bayesian information criterion (BIC) (Schwarz 1978), and the consistent Akaike information criterion (CAIC) (Bozdogan 1987), with lower values signaling a preferred model for a given specification.

Analysts also must determine the best specification, in terms of what variables should be included in the model, a procedure often not detailed in empirical latent class papers. For the JLC model estimated here, this pertains to selecting which type of attitude statements should be included in the attitude probability function. The theoretical background and assumptions of the JLC model suggest three different approaches for comparing model specifications. First, simple comparison of the consistency of the results of estimated models across specifications offers insight into the extent to which estimated groups of perspectives are robust to specification and therefore correspond to meaningful groups in the data.

The second approach to model comparison focuses on a statistical motivation of the latent class model: to reduce the variance in the error term around estimated probabilities. In a
logit model, error variance cannot be identified separately from the parameters. As Train (2009) explains, the variance of the error term in the logit model for a utility function represented by

\[ U_{t|c}^* = V_{t|c} + \varepsilon_{t|c} \]

is equal to \( \sigma^2 \). To scale this utility to the assumption of variance equal to \( \pi^2/6 \) for the logit model, \( U_{t|c}^* \) is divided by the scale parameter, \( \sigma \), to generate \( U_{t|c} = V_{t|c}/\sigma + \varepsilon_{t|c} \). This means the choice probability of (linear in parameters \( V_{t|c} \)) is actually:

\[
\Pr(X_i|c) = \frac{e^{\beta^*_{c} X_i}}{1 + e^{\beta^*_{c} X_i}} = \frac{1}{1 + e^{\beta^*_{c} X_i}} \]  

(3a)

In other words, each estimated coefficient \( \beta_c \) implicitly includes the scale term \( 1/\sigma_c \), which cannot be identified separately from \( \beta^*_c \). When the ratio of parameters is of more interest than direct interpretation of coefficient estimates, as in calculating WTP, the scale parameter cancels from numerator and denominator. However, although the scale parameter cannot be directly estimated, the relative scale and therefore the relative variance of two different logit equations can be estimated with the ratio of coefficients in the two models that are expected to be the same.

In the choice probability model, although no parameters were constrained across classes or models, constant marginal utility of income across different latent classes is a plausible assumption if mean incomes of classes are similar across classes, an assumption made plausible by not including demographics directly in the probability models and supported by the results described below. Under this assumption, \( \beta^*_{bid} \) is the same for all \( c \) and models, and therefore the ratio of the coefficients \( \beta_{bid} \) on the bid variable across classes or models provides an estimate of the ratio of their scale parameters: \( \frac{\beta_1}{\beta_2} = \left( \frac{\beta^*_1}{\sigma^*_1} \right) / \left( \frac{\beta^*_2}{\sigma^*_2} \right) = \frac{\sigma^*_2}{\sigma^*_1} \). In other words, if \( \beta_1 > \beta_2 \), then \( \sigma^*_2 > \sigma^*_1 \), and the variance of the error term in example model 2 is greater than the variance of the error term in example model 1. If the latent class model has "tightened" the choice estimation,
variance in the errors should go down and, equivalently, the estimated coefficients on the bid variable should go up. In other words, models with larger estimated coefficients on for bid provide relatively better fit of the latent classes.

Finally, the third approach to model comparison considers the likelihood of satisfying the assumption of independence conditional on class. This is analogous to specification testing after a least squares regression, in which an analyst determines whether the assumption of normally distributed, mean-zero errors is reasonably satisfied based on the evidence available. To this end, the full JLC is first estimated as specified in eq. 2 above. Next, observations are weighted by the joint probability of being in each class, based on the optimized parameters. The choice probability is then separately re-estimated, with the attitudes measures that were originally in the attitude probability function now included as choice probability covariates. The explanatory power of the attitudes measures in this re-estimated choice probability is inversely related to the likelihood of the independence conditional on class assumption being satisfied. Thus, in a reversal of typical conventions, evidence of better fit from the re-estimated choice probability model corresponds to worse fit from the original JLC model. Note that this second-stage regression is used only for post-estimation comparison of model specifications.

The fit of the re-estimated choice probability can be evaluated in two ways. First, pseudo-$R^2$ values (McFadden 1974) can be calculated to estimate the improvement in fit for the re-estimated choice probability model that corresponds to the inclusion versus exclusion of the attitudes measures in that model; values at or near zero imply little improved fit and thus little additional explanatory power associated with the attitudes measures. Second, if the parameters on attitude measures in the re-estimated choice probability are significantly different from zero, this signifies a similarity between the attitude and preference data that is not captured by the
latent perspective class. The stronger this significance, and the more parameters that are different from zero, the less likely the conditional independence assumption has been satisfied.

5. Empirical results

This section presents results from a single-class model and three different JLC models. Each JLC model includes a different set of attitude measures in its attitude probability function: general attitude measures only (model 2; six general attitude statements), specific attitude measures only (model 3; seven specific attitude statements), or both types of attitude measures (model 4; thirteen attitude statements). For conciseness, only select parameters are shown.

5.1 Number of classes

Comparison (not shown) of information criteria within each model specification suggest an increasing number of classes as the number of attitude statements included in the attitude probability increases. AIC consistently estimates one more class than BIC and CAIC, but the latter two are more relevant here because they impose a higher penalty for model complexity. For model 1a, a one class model is optimal, suggesting that preference heterogeneity is not observable without attitude statement data. In other words, a model that ignores attitude data appears sufficient if a policy maker only is concerned with aggregate willingness to pay. However, including attitude measures demonstrates distinct grouping of perspectives – in which respondents share similar parameters for choice and attitude probabilities – that are not observable in the preference data alone; three latent classes are estimated for both model 2 and model 3, and four classes are estimated for model 4.

5.2 Results for one-class model

Table II presents the single class model results. Model 1a represents a choice probability equivalent to that used in later joint model estimations, whereas model 1b also includes attitude
factors as covariates to explore the correlation of attitudes with preferences in the pooled model and is similar to the re-estimated choice probabilities shown in Tables III through V. Note that model 1b is based on an assumed relationship between attitudes and preferences, in which the former (partially) determine the latter, that is explicitly avoided with the JLC model structure. In both model 1a and model 1b, the coefficient on quantity is insignificant, a finding consistent with previous analyses (Meldrum et al. 2011; Meldrum et al. 2013), meta-analysis of related stated preference studies (Lindhjem 2007; Barrio and Loureiro 2010), and the expectation of diminishing marginal returns for nonuse values (Rollins and Lyke 1998).

Table II. Conditional logit results for the one-class model 1 (choice probability function only).

<table>
<thead>
<tr>
<th>Model</th>
<th>1a</th>
<th>1b</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantity</td>
<td>-0.11 (0.61)</td>
<td>-0.42 (0.66)</td>
</tr>
<tr>
<td>Bid ($100)</td>
<td>-0.33*** (0.04)</td>
<td>-0.36*** (0.05)</td>
</tr>
<tr>
<td>CF1: Protection</td>
<td>-   (0.18)</td>
<td>0.91*** (0.18)</td>
</tr>
<tr>
<td>CF2: Fair Share</td>
<td>-   (0.14)</td>
<td>0.51*** (0.14)</td>
</tr>
<tr>
<td>CF3: Recreation</td>
<td>-   (0.13)</td>
<td>0.13 (0.13)</td>
</tr>
<tr>
<td>CF4: Non-interfere</td>
<td>-   (0.15)</td>
<td>-0.15 (0.15)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.72* (0.33)</td>
<td>0.91** (0.35)</td>
</tr>
<tr>
<td>WTP ($)</td>
<td>202.06*** (30.11)</td>
<td>197.01*** (29.63)</td>
</tr>
<tr>
<td>LL</td>
<td>294.37</td>
<td>259.79</td>
</tr>
<tr>
<td>AIC</td>
<td>594.7</td>
<td>542.2</td>
</tr>
<tr>
<td>BIC</td>
<td>607.3</td>
<td>571.5</td>
</tr>
<tr>
<td>CAIC</td>
<td>610.3</td>
<td>578.5</td>
</tr>
</tbody>
</table>

Standard errors shown in parentheses; asterisks designate parameter significance: * p<0.05; ** p<0.01; *** p<0.001. Dependent variable is response to CV question (yes=1).
The coefficient on bid is negative and precise, following expectations from utility theory and also meaning that the scale parameter, an implicit component of that coefficient, is precisely estimated. Mean WTP for the average size treatment is $202, with a standard error of $30. Small differences between this estimate and that presented in Meldrum et al. (2013) can be attributed to the omission of sampling probability weights and demographic data here for simplicity, because both of those considerations lowered the latter WTP estimates. Including attitudes as covariates in model 1b improves model fit, as demonstrated both by likelihood ratio tests and by the greater magnitude of the coefficient on the bid coefficient. CF1: Protection and CF2: Fair Share attitude factors are strongly correlated with CV response in the multivariate model, whereas CF3: Recreation and CF4: Non-interfere attitude factors do not. This suggests that the data contain more nuanced information about perspectives than is directly observed from the CV data alone.

5.3 Results for three-class models with only one type of attitude statement each

To investigate, Tables III and IV show results of models 2 (general attitude statements only) and 3 (specific attitude statements only), respectively. In each table, Panel 1 presents select results from estimating the original JLC model: class share size, choice probability parameters, and information criteria. Panel 2 presents important post-estimation results: mean WTP as estimated from the original choice probability; results relevant for comparing model specifications (specifically, coefficients on attitude measures in the re-estimated choice probability\(^5\) and pseudo \(R^2\) for the re-estimated choice with or without the attitude statements included); and mean factor scores and a key demographic variable, by class.

Both models segment the classes similarly in terms of share size and mean WTP. Each includes a small, first class with a WTP not significantly different from zero, a larger, second class with a

---

\(^5\) bid and quantity are included in the model but not shown; they are statistically indistinguishable from the same in the original choice probability model. Their omission from display emphasizes that the re-estimated choice probability is only to be used for post-estimation comparison of model specifications, not for inference.
WTP similar to that estimated with the one-class model 1, and a third class with a WTP approximately twice as high as the middle group. Thus, the similar results across differing specifications suggests that the set of three different perspectives corresponds to meaningful differentiation across observations.

Table III. Select results for model 2 (using general attitude statements only), with three classes.

<table>
<thead>
<tr>
<th>Panel 1: Select joint latent class model results</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shares</td>
<td>14.3%</td>
<td>51.5%</td>
<td>34.3%</td>
</tr>
<tr>
<td>Choice Probability(^a) Parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quantity</td>
<td>0.02</td>
<td>-0.12</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(2.06)</td>
<td>(0.91)</td>
<td>(0.91)</td>
</tr>
<tr>
<td>Bid ($100)</td>
<td>-1.59***</td>
<td>-0.49***</td>
<td>-0.20**</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.09)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.18</td>
<td>1.19*</td>
<td>0.72</td>
</tr>
<tr>
<td></td>
<td>(1.08)</td>
<td>(0.48)</td>
<td>(0.50)</td>
</tr>
<tr>
<td>LL</td>
<td>3995.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>8158.3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>8509.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAIC</td>
<td>8593.6</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel 2: Select post-estimation results</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>WTP ($)</td>
<td>-10.51</td>
<td>230.73***</td>
<td>361.33***</td>
</tr>
<tr>
<td></td>
<td>(26.32)</td>
<td>(35.00)</td>
<td>(85.05)</td>
</tr>
<tr>
<td>Re-estimated Choice Probability(^a) Parameters(^b)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GF1: Protect Nature</td>
<td>0.22</td>
<td>0.62*</td>
<td>0.79***</td>
</tr>
<tr>
<td></td>
<td>(1.26)</td>
<td>(0.29)</td>
<td>(0.21)</td>
</tr>
<tr>
<td>GF2: Natural Order</td>
<td>-0.25</td>
<td>-0.21</td>
<td>-0.21</td>
</tr>
<tr>
<td></td>
<td>(1.59)</td>
<td>(0.31)</td>
<td>(0.19)</td>
</tr>
<tr>
<td>pseudo-R(^2)(^c)</td>
<td>0.050</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean by Class(^d)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CF1: Protection</td>
<td>-0.46</td>
<td>0.03</td>
<td>0.14</td>
</tr>
<tr>
<td>CF2: Fair Share</td>
<td>-0.60</td>
<td>-0.05</td>
<td>0.33</td>
</tr>
<tr>
<td>CF3: Recreation</td>
<td>-0.24</td>
<td>-0.03</td>
<td>0.15</td>
</tr>
<tr>
<td>CF4: Non-interfere</td>
<td>-0.21</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>Income (imputed from categories)</td>
<td>$65,415</td>
<td>$67,016</td>
<td>$58,797</td>
</tr>
</tbody>
</table>

Standard errors shown in parentheses; asterisks designate parameter significance: \(^*\) p<0.05; \(^**\) p<0.01; \(^***\) p<0.001.
\(^a\)Dependent variable is response to CV question (yes=1). \(^b\)Re-estimated coefficients for Quantity and Bid are statistically indistinguishable from original coefficients, by class and model. \(^c\)pseudo-R\(^2\) value compares re-estimated choice probability model with and without attitude factors included. \(^d\)Mean factor scores and demographics for each class, weighted by each respondents’ probability of belonging to each class.
However, further comparison suggests that model 3 fits the data better than model 2. One approach to comparison proposed above uses bid estimates as an indicator of the scale factor (i.e., the inverse of error variance) under the assumption of constant marginal utility of income. Here, this assumption is supported by the similarity in income across classes for model 2 (Kruskal Wallis p=0.122) and model 3 (Kruskal Wallis p=0.634). For model 3, the magnitude of

**Table IV. Select results for model 3 (using specific attitude statements only), with three classes.**

<table>
<thead>
<tr>
<th>Shares</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>23.2%</td>
<td>32.6%</td>
<td>44.2%</td>
<td></td>
</tr>
</tbody>
</table>

**Panel 1: Select joint latent class model results**

<table>
<thead>
<tr>
<th>Choice Probability&lt;sup&gt;a&lt;/sup&gt; Parameters</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantity</td>
<td>-0.93</td>
<td>0.97</td>
<td>-1.19</td>
</tr>
<tr>
<td>(0.92)</td>
<td>(0.90)</td>
<td>(0.88)</td>
<td></td>
</tr>
<tr>
<td>Bid ($100)</td>
<td>-0.46**</td>
<td>-0.47***</td>
<td>-0.31***</td>
</tr>
<tr>
<td>(0.16)</td>
<td>(0.09)</td>
<td>(0.06)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.45</td>
<td>0.66</td>
<td>1.87***</td>
</tr>
<tr>
<td>(0.52)</td>
<td>(0.49)</td>
<td>(0.50)</td>
<td></td>
</tr>
</tbody>
</table>

LL 4122.81  
AIC 8437.62  
BIC 8839.10  
CAIC 8935.10

**Panel 2: Select post-estimation results**

<table>
<thead>
<tr>
<th>WTP ($)</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>-194.89</td>
<td>242.78***</td>
<td>410.97***</td>
<td></td>
</tr>
<tr>
<td>(121.36)</td>
<td>(45.13)</td>
<td>(58.01)</td>
<td></td>
</tr>
</tbody>
</table>

Re-estimated Choice Probability<sup>a</sup> Parameters<sup>b</sup>

<table>
<thead>
<tr>
<th>SF1: Protection</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1.19*</td>
<td>-0.48</td>
<td>0.60</td>
<td></td>
</tr>
<tr>
<td>(0.59)</td>
<td>(0.60)</td>
<td>(0.52)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>SF2: Recreation</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.20</td>
<td>-0.31</td>
<td>-0.08</td>
<td></td>
</tr>
<tr>
<td>(0.43)</td>
<td>(0.32)</td>
<td>(0.21)</td>
<td></td>
</tr>
</tbody>
</table>

pseudo-R<sup>2</sup><sup>c</sup> 0.017

Mean by Class<sup>d</sup>

<table>
<thead>
<tr>
<th>CF1: Protection</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.81</td>
<td>-0.09</td>
<td>0.49</td>
<td></td>
</tr>
<tr>
<td>CF2: Fair Share</td>
<td>-0.69</td>
<td>-0.05</td>
<td>0.39</td>
</tr>
<tr>
<td>CF3: Recreation</td>
<td>-0.52</td>
<td>-0.08</td>
<td>0.33</td>
</tr>
<tr>
<td>CF4: Non-interfere</td>
<td>0.10</td>
<td>0.04</td>
<td>-0.08</td>
</tr>
</tbody>
</table>

Income (imputed from categories) $67,102 $66,190 $60,694

Standard errors shown in parentheses; asterisks designate parameter significance: * p<0.05; ** p<0.01; *** p<0.001.
<sup>a</sup>Dependent variable is response to CV question (yes=1). <sup>b</sup>Re-estimated coefficients for Quantity and Bid are statistically indistinguishable from original coefficients, by class and model. <sup>c</sup>pseudo-R2 value compares re-estimated choice probability model with and without attitude factors included. <sup>d</sup>Mean factor scores and demographics for each class, weighted by each respondents’ probability of belonging to each class.
the class 1 and class 2 coefficients on *bid* are larger than that in model 1a, and the class 3 *bid*
coefficient is very similar to that in model 1a, suggesting similar or lower error variance for each
class versus model 1a. In contrast, for model 2, although classes 1 and 2 (representing 66% of the
sample) have a larger magnitude *bid* coefficient than model 1a, class 3 has a smaller magnitude
*bid* coefficient, suggesting an increase a variance for class 3 and thus a smaller net improvement
in fit. This suggests that although both model 2 and 3 improve fit over model 1a, model 3 shows
a greater improvement.

Additional model comparison focuses on the re-estimated choice probability parameters
and pseudo-\(R^2\) values, in which typical conventions are reversed because significant coefficients
and higher pseudo-\(R^2\) values suggest greater explanatory power from the re-estimated choice
probability, which in turn signifies a worse JLC model fit because it corresponds to weaker
adherence to the assumption of independence conditional on class. Under this test, model 3 again
outperforms model 2. Model 2 has a substantially higher pseudo-\(R^2\) value than does model 3,
with the latter suggesting that including the attitude factors in the choice probability re-
estimation for model 3 provides very limited additional explanatory power over the original
choice probability. Similarly, class 2 and 3 of model 2 both have significant coefficients for GF1:
Protect Nature, whereas model 3 has only one, weakly significant (\(p=0.045\)) coefficient for either
attitude factor.

Finally, both models 2 and 3 lead to significant differences in attitude scores across
perspective classes (ANOVA for factor scores across classes within each model, \(p<0.003\) for all
factor scores except CF4: Non-interfere, for which \(p=0.029\) for model 2 and \(p=0.056\) for model
3). Mean scores follow the expected pattern in relation to the economic preferences (i.e., WTP):
class 2 attitude scores and WTP are close to sample averages; class 1 is not willing to pay and
has more negative attitudes toward protection, paying one's "fair share" for the environment, and the importance of recreation; and class 3 shows the inverse.

5.4 Results for four-class model with both types of attitude statements

Table V uses an analogous format to present results from model 4, which uses both specific and general attitude statements in the attitude probability function. This model results in a class breakdown reminiscent to that from models 2 and 3, with the smaller class that is not willing to pay seemingly divided into two groups of roughly equal size (classes 1 and 2), one of which demonstrates a strong negative response to quantity; it is plausible that those who do not believe these forests should be protected would favor smaller treatment programs. Also consistent with the other models, a large proportion of the sample (class 3; 37%) is willing to pay a fairly precisely estimated average of $229. As with the second class from models 2 and 3, this class's mean attitude factor scores deviate little from sample averages. Model 4 class 4, on the other hand, not only expresses the large WTP of nearly $500 per respondent but also demonstrates more positive attitudes toward the importance of both protection and recreation versus average.

Model 4 performs relatively well in the proposed latent class model selection criteria, although not as strongly as model 3. Income again does not vary across classes (Kruskal Wallis p=0.818), and class 4 demonstrates slightly larger error variance (smaller magnitude bid coefficient) for the choice probability function than model 1a does, whereas classes 2 and 3 have substantially tighter variance; bid is too imprecise to tell for class 1. The pseudo-$R^2$ is between that of model 2 and model 3, and the lack of significant parameters in the re-estimated choice probability suggests close adherence to the conditional independence assumption.
Table V. Select results for model 4 (using both types of attitude statements), with four classes.

<table>
<thead>
<tr>
<th></th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shares</td>
<td>10.7%</td>
<td>15.7%</td>
<td>37.2%</td>
<td>36.4%</td>
</tr>
<tr>
<td>Panel 1: Select joint latent class model results</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Choice Probability(^a) Parameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quantity</td>
<td>0.44</td>
<td>-5.04***</td>
<td>-0.06</td>
<td>-0.26</td>
</tr>
<tr>
<td></td>
<td>(0.94)</td>
<td>(0.94)</td>
<td>(0.91)</td>
<td>(0.90)</td>
</tr>
<tr>
<td>Bid ($100)</td>
<td>-0.21</td>
<td>-2.22**</td>
<td>-0.48***</td>
<td>-0.29*</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.75)</td>
<td>(0.10)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.07</td>
<td>2.39***</td>
<td>1.13*</td>
<td>1.53**</td>
</tr>
<tr>
<td></td>
<td>(0.73)</td>
<td>(0.64)</td>
<td>(0.50)</td>
<td>(0.58)</td>
</tr>
<tr>
<td>LL</td>
<td>7556.26</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>15560.53</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>16497.32</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAIC</td>
<td>16721.32</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel 2: Select post-estimation results</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTP ($)</td>
<td>-410.61</td>
<td>-0.44</td>
<td>229.40***</td>
<td>481.87***</td>
</tr>
<tr>
<td></td>
<td>(640.00)</td>
<td>(25.61)</td>
<td>(45.11)</td>
<td>(142.49)</td>
</tr>
<tr>
<td>Re-estimated Choice Probability(^a) Parameters(^b)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CF1: Protection</td>
<td>0.04</td>
<td>-0.07</td>
<td>-0.32</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>(0.49)</td>
<td>(1.14)</td>
<td>(0.50)</td>
<td>(0.55)</td>
</tr>
<tr>
<td>CF2: Fair Share</td>
<td>0.51</td>
<td>1.02</td>
<td>-0.75</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>(0.46)</td>
<td>(1.13)</td>
<td>(0.41)</td>
<td>(0.34)</td>
</tr>
<tr>
<td>CF3: Recreation</td>
<td>0.20</td>
<td>-0.81</td>
<td>-0.08</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.54)</td>
<td>(0.94)</td>
<td>(0.30)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>CF4: Non-interfere</td>
<td>-0.33</td>
<td>-0.87</td>
<td>-0.58*</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>(0.46)</td>
<td>(1.05)</td>
<td>(0.37)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>pseudo R(^2)(^c)</td>
<td>0.032</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean by Class(^d)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CF1: Protection</td>
<td>-0.92</td>
<td>-0.59</td>
<td>0.04</td>
<td>0.48</td>
</tr>
<tr>
<td>CF2: Fair Share</td>
<td>-0.58</td>
<td>-0.64</td>
<td>-0.11</td>
<td>0.56</td>
</tr>
<tr>
<td>CF3: Recreation</td>
<td>-0.93</td>
<td>-0.25</td>
<td>0.04</td>
<td>0.34</td>
</tr>
<tr>
<td>CF4: Non-interfere</td>
<td>0.25</td>
<td>-0.07</td>
<td>0.06</td>
<td>-0.10</td>
</tr>
<tr>
<td>Income (imputed from categories)</td>
<td>$68,660</td>
<td>$67,833</td>
<td>$65,224</td>
<td>$59,650</td>
</tr>
</tbody>
</table>

Standard errors shown in parentheses; asterisks designate parameter significance: * p<0.05; ** p<0.01; *** p<0.001.
\(^a\)Dependent variable is response to CV question (yes=1). \(^b\)Re-estimated coefficients for Quantity and Bid are statistically indistinguishable from original coefficients, by class and model. \(^c\)pseudo-R2 value compares re-estimated choice probability model with and without attitude factors included. \(^d\)Mean factor scores and demographics for each class, weighted by each respondents’ probability of belonging to each class.

6. Discussion and conclusion

These results consistently demonstrate heterogeneity in perspectives that is similar to that found previously with less robust clustering methods (Meldrum et al. 2013). Approximately 40%
of the sample is well represented by the aggregated average WTP of about $200 for the
management of WPBR in high-elevation forests, and a simple weighted average across classes
recreates similar average WTP estimates of $216 for model 3 and $217 for model 4. Like any
aggregate measure, such mean willingness to pay estimates provide a compromise value that
reflects a central estimate for the population, but they hide the richness of perspectives within,
such as the 35-45% of the sample with an estimated more than $400 benefit from management,
which appears to be linked to both use and nonuse values. The converse is also obscured: about
25% of respondents would receive no significant benefits from the management, and a costly
program would lead to a loss of welfare for those respondents.

Such variation suggests potential feedbacks between management options and the
benefits of that management that are not demonstrated in the homogeneous preference model
before they were not represented in the CV choice question underlying that model. For example,
management that successfully protects the forests but precludes recreation in them may undercut
the benefits to the 35% of the sample that values it most highly. However, acknowledgment of
such heterogeneity, and the relationship of attitudes to preferences, does not invalidate standard,
aggregate measures of WTP any more than, for example, acknowledgment of minority votes
invalidates majority rule in a democracy; standard measures of WTP describe a representative
perspective important for making decisions in a diverse society. The implications of the results
of analyzing heterogeneity depend in part on a policymaker's decision rule, although many argue
this is outside the scope of economic analysis: in this case, majority rule would argue for
accommodating the strong majority perspective of substantial support for the management,
whereas Pareto optimality would forbid management without compensatory distributions to the
minority perspective associated with no significant benefits from the proposed management.
Regardless of decision rules, however, a policymaker might be interested in a richer description of the perspectives held by society, and jointly modeling attitude and preference data can offer insight into such richness.

Results also offer insight into the roles of different types of attitude measures in these models. Relying on specific attitude measurements instead of general attitude measurements, model 3 strongly outperforms model 2 in both approaches to model comparison. This means that perspectives defined by CV data and specific attitude data are more sharply defined than perspectives defined by CV data and general attitude data. In other words, in this dataset, the CV responses are more similar to attitudes specifically about the management of WPBR in high-elevation forests than to more general environmental attitudes.

Although this result may sound intuitive and obvious to many economists, it is not uncommon to have commentators question the validity of stated preferences methods on the grounds of their potential relationship to general environmental attitudes. Indeed, these results offer an empirical example that can inform the ongoing debate about the usefulness and meaning of contingent valuation results (e.g., Carson 2012; Kling et al. 2012; Hausman 2012; Haab et al. 2013). In particular, closer coherence to specific attitudes runs counter to a proposed "contribution model" of stated preferences (Kahneman and Knetsch 1992; Spash 2006), in which "the spirit of donation, rather than benefit acquisition, is the primary motivation underlying a positive WTP response" (Ryan and Spash 2011 p.675). If WTP is motivated by an intention to contribute to general environmental causes rather than to the specific issue addressed by the survey, as suggested by the contribution model, it is not clear why preferences would align more closely with specific attitudes than general environmental attitudes. The latter would presumably correspond more closely to the "spirit of donation" and the former would relate more closely to
the benefits associated with the specific proposed program being asked about; the contribution model predicts that general attitudes would be at least as, if not more, closely related to stated preferences than specific attitudes are, which is the opposite of the empirical results above.

Finally, to the extent they are generalizable, these empirical results offer practical advice about the type of attitudes analysts should collect in surveys. The coherence of perspectives estimated with the specific attitudes and preference data here suggests that the evaluative content of these attitudes is similar to that of the preferences. In this case, specific attitudes proved most useful for improving the fit of preference estimation. In contrast, if analysts are more interested in using attitude statements to capture information that is different in content from that conveyed by economic choice data, then the evidence above suggests that general attitudes would be more appropriate. Of course, if survey space allows, collecting and analyzing both types of attitude measures appears useful.

In summary, these results demonstrate widespread, though far from unanimous, support for managing WPBR in high-elevation forests, support that appears motivated primarily – but not exclusively – by an interest in the forests' nonuse benefits. Although accommodating preference heterogeneity does not change the aggregated WTP results, the JLC model provides useful information not available from the estimation of preference data alone, such as the facts that many respondents care strongly about the recreation and tourism opportunities associated with high-elevation forests, and indeed those who feel that way tend to be willing to pay far more to protect these forests than other respondents. In addition, these results suggest differing explanatory roles for measures of different types of attitude, where specific attitudes appear to have more similar content to stated preferences than general attitudes do, with potential implications for the design and interpretation of nonmarket valuation survey research.
Acknowledgments

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