Environ Resource Econ (2007) 37:757–775
DOI 10.1007/s10640-006-9054-7

ORIGINAL PAPER

Relating environmental attitudes and contingent values: how robust are methods for identifying preference heterogeneity?

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Received: 15 December 2005 / Accepted: 17 October 2006 / Published online: 7 December 2006
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Abstract We assess the importance and robustness of cluster analysis and latent class analysis as methods to account for unobserved heterogeneity. We provide a critique and comparison of both methods in the context of measuring environmental attitudes and a contingent valuation study involving endangered species. We find strong evidence of robustness for these methods: group characterization and assignment of individuals to groups are similar between methods, and willingness-to-pay estimates are consistent. In addition, there are significant differences in willingness-to-pay across environmental attitudinal groups, and we find that accounting for unobservable heterogeneity provides a significantly better fitting model.

Keywords Cluster analysis · Contingent valuation · Latent class analysis · New Ecological Paradigm · Unobservable heterogeneity · Willingness-to-pay

Introduction

Economists are increasingly concerned with methods of identifying groups with homogeneous intra-group characteristics, as refining and targeting policy analysis often requires sorting individuals into different groups. We use a unique survey data set containing attitudinal and willingness-to-pay (WTP) responses to investigate the comparative performance of two of the most commonly used techniques for identifying groups with heterogeneous inter-group characteristics and homogeneous intra-group characteristics: cluster analysis (CA) and latent class analysis (LCA). Many behavioral sciences, such as marketing, psychology, and sociology, frequently

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rely on CA and LCA for data analyses. The methods are often applied to attitudinal or more general psychographic data.[1] In economics, applications of CA and LCA are few, especially applications to psychographic data.[2] This scarcity is surprising given the perceived importance of such data for understanding consumers in, for example, marketing. The reason for the scarcity is unclear. There may be the perception that heterogeneity is best accounted for by adding socioeconomic covariates in econometric models where the original economic model assumes all agents are identical. Furthermore, attitudinal and personal value data are sometimes criticized due to a concern that such data are unreliable predictors of behavior.[3] Finally, CA and LCA may be regarded as prone to a great deal of subjectivity in the various steps of statistical analysis. In light of these concerns and criticisms we see a need to examine the potential of CA and LCA to contribute to our knowledge about the heterogeneity of economic agents' attitudes and preferences.

In this paper we address several questions that are pertinent to the continued use and acceptance of CA and LCA techniques within economics. First, are CA and LCA robust in the sense that they yield consistent results? Second, does accounting for unobservable attitudinal heterogeneity add explanatory power? Finally, what insights can be provided regarding a choice between the use of CA or LCA?

We address these questions within the context of a contingent valuation (CV) study designed to estimate WTP for recovery for two endangered species, the peregrine falcon and the shortnose sturgeon. A key feature of the survey is the inclusion of attitudinal questions that comprise the New Ecological Paradigm (NEP) Scale. The NEP scale (originally proposed by Dunlap and Van Liere (1978) and later revised by Dunlap et al. 2000) is designed to measure the strength of environmental attitudes. We apply both CA and LCA to the NEP data in order to identify heterogeneity of environmental attitudes among survey respondents. We use the results to partition respondents into different groups for the purpose of explaining heterogeneity in WTP responses.[4]

Our main findings are the following: We find strong evidence of convergence between CA and LCA. Attitudinal groups identified using CA and LCA are similar in that there is consistency in the way the two methods assign individuals to attitudinal groups. Econometric models of WTP responses are consistent for both methods. Econometric models of WTP responses that include attitudinal group assignments have greater explanatory power than models that use only socioeconomic variables to capture preference heterogeneity. Estimates of WTP for species

[1] Psychographic data includes information on personality traits, personal values, and lifestyle (Wedel and Kamakura 2000).

[2] CA applications include identification of market segments (Baker and Burnham 2001), examination of relationships between farmers' behavioral attitudes and their use of futures contracts (Pennings and Leuthold 2000), and assessment of the convergence of countries' per capita productivity levels (Hobijn and Franses 2000). LCA has been used to identify motivations for wilderness recreation (Boxall and Adamowicz 2002), preference structure in rock climbers (Scarpa and Thiene 2005), preferences regarding fishing characteristics (Morey et al. 2006), and preferences for medical treatments (Thacher et al. 2005).

[3] Interestingly, Baker and Burnham (2001) found that sociodemographic variables performed "little better than flipping a coin" (p. 396), while a model with only cognitive variables performed well for predicting genetically modified organism (GMO) acceptance.

[4] Environmental attitudes can arguably be modeled as either endogenous or exogenous. In this paper we choose to treat attitudes as exogenous; our treatment of environmental attitudes is similar to including environmental group membership as an independent variable.

recovery efforts derived using CA results are consistent with those derived using LCA results, and in both cases stronger pro-environmental attitudes increase the estimates of mean WTP. Finally, CA may be the preferred method when groups are identified based upon a large number of variables or when the time available to learn a new technique is limited. LCA may be the preferred method when the researcher desires more detailed output on predicted behavior and the ability to test the validity of results using a host of commonly used statistical tests.

The next section provides background information on the NEP and describes the data used for the analysis. Section 3 provides an overview of CA and LCA in the context of identifying heterogeneity in environmental attitudes using the NEP. Section 4 evaluates the consistency of results derived using the two methods for identifying attitudinal groups. Section 5 uses the CA and LCA results to investigate the relationship between environmental attitudes and CV estimates. Section 6 discusses the main results and concludes.

Data

The NEP is one of the instruments most commonly used by social scientists to measure environmental attitudes, it has been used for several decades, and the validity of its construction has been repeatedly confirmed.[5] The NEP scale consists of 15 Likert-scale questions from which responses are typically combined into a summated scale, with higher scores indicating stronger pro-environmental attitudes. Table 1 lists the different statements, which are designed to probe five facets of environmental attitudes. The different facets and corresponding statements are the following: reality of limits to growth (1,6,11), anti-anthropocentrism (2,7,12), the fragility of nature's balance (3,8,13), rejection of the idea that humans are exempt from the constraints of nature (4,9,14), and the possibility of an eco-crisis or ecological catastrophe (5,10,15).

The data we use comes from a previously published study by Kotchen and Reiling (2000), who use the NEP data in the traditional manner of constructing a summated scale in order to test theoretical validity of CV responses. Consistent with attitude–behavior theory, they find that respondents with stronger pro-environmental attitudes are more likely to respond 'yes' to a referendum CV question about protecting an endangered species. Our analysis differs in that we apply CA and LCA to the NEP data and use the results to compare the two methods. We estimate CV values for the purpose of using the NEP (an indicator of environmental attitudes) to compare CA and LCA as methods for identifying heterogeneity of latent attitudes.

The mail survey, conducted in the spring of 1997, was sent to a random sample of 1200 Maine residents. Mailing procedures were conducted in accordance with the Dillman (1978) Total Design Method. After adjusting for undeliverable surveys, the

[5] The predictive, known-group, criterion, content, and construct validity of the NEP have been demonstrated by numerous studies. Results obtained by Ebreo et al. (1999), Blake et al. (1997), and others suggest that the NEP has predictive validity. Examples of studies that demonstrate known-group validity include Edgell and Nowell (1989) and Widegren (1998). Because the NEP has been shown to have predictive and known-group validity, it also has criterion validity. Content validity has been shown by Kempton et al. (1995), and construct validity has been supported by most studies involving the NEP, although especially strong evidence comes from Pierce et al. (1987) and Stern et al. (1995).

Table 1 NEP scale item response frequencies and descriptive statistics[a]

NEP statement		SA	SWA	U	SWD	SD	Mean[b]	StDev
(1) *earthcap*	We are approaching the limit of the number of people the earth can support	27%	32%	23%	11%	8%	3.6	1.2
(2) *modifyenv*	Humans have the right to modify the natural environment to suit their needs	6%	26%	10%	33%	24%	3.4	1.3
(3) *interfere*	When humans interfere with nature it often produces disastrous consequences	42%	39%	8%	8%	3%	4.1	1.0
(4) *ingenuity*	Human ingenuity will insure that we do not make the earth unlivable	12%	25%	28%	21%	13%	3.0	1.2
(5) *abusingenv*	Humans are severely abusing the environment	42%	40%	7%	9%	3%	4.1	1.1
(6) *suffresources*	The earth has plenty of natural resources if we just learn how to develop them	30%	36%	16%	12%	6%	2.3	1.2
(7) *righttoexist*	Plants and animals have as much right as humans to exist	56%	29%	4%	6%	5%	4.2	1.1
(8) *strongbalance*	The balance of nature is strong enough to cope with the impacts of modern industrial nations	1%	10%	20%	33%	35%	3.9	1.0
(9) *lawsofnature*	Despite our special abilities, humans are still subject to the laws of nature	50%	40%	6%	2%	1%	4.4	0.8
(10) *ecolcrisis*	The so-called ‘ecological crisis’ facing human kind has been greatly exaggerated	7%	18%	26%	25%	24%	3.4	1.2
(11) *spaceship*	The earth is like a spaceship with very limited room and resources	25%	33%	16%	19%	7%	3.5	1.3
(12) *humanrule*	Humans were meant to rule over the rest of nature	9%	16%	12%	27%	35%	3.6	1.3
(13) *delicatebalance*	The balance of nature is very delicate and easily upset	39%	39%	10%	10%	3%	4.0	1.1
(14) *controlnature*	Humans will eventually learn enough about how nature works to be able to control it	6%	19%	27%	28%	20%	3.4	1.2
(15) *ecolcatastrophe*	If things continue on their present course, we will soon experience a major ecological catastrophe	23%	31%	27%	14%	6%	3.5	1.2

[a] SA = strongly agree, SWA = somewhat agree, U = unsure, SWD = somewhat disagree, SD = strongly disagree. Frequencies may not sum to 100 due to rounding

[b] Statements are coded such that a higher number indicates stronger pro-environmental attitudes; i.e., odd-numbered statements are coded such that ‘SA’ = 5, ‘SWA’ = 4, ‘U’ = 3, ‘SWD’ = 2, and ‘SD’ = 1, whereas even-numbered statements are coded in reverse

survey response rate was 63%, which is relatively high for a survey of the general population.

The survey was designed to measure environmental attitudes and estimate non-use values for the protection of peregrine falcons and shortnose sturgeons, both endangered species in Maine.[6] In order to avoid potential bias resulting from asking respondents to value more than one species, the sample was split such that one-half received questions about peregrines and the other half received questions about sturgeons. WTP questions were asked in the context of a voter referendum for the establishment of a state-wide fund designated for the purpose of protecting the specified species. The proposed fund was to be instituted through a one-time payment in the form of a tax increase. Of the 629 completed surveys, a useable sample of 563 surveys (272 sturgeon and 291 falcon) remains for the NEP analysis after deleting underage respondents and observations with missing values for one or more NEP statements.

We report descriptive statistics for responses to the NEP statements in Table 1. The response frequencies reflect substantial environmental attitude heterogeneity within the sample. While there appears to be a general consensus about some statements (e.g., 3,5,7,9,13), other statements (e.g., 4 and 10) elicit responses that are more evenly distributed across the various response categories. For instance, the majority of respondents strongly agree with statement 7, ‘‘Plants and animals have as much right as humans to exist,’’ but the responses differ widely regarding statement 10, ‘‘The so-called ‘ecological crisis’ facing human kind has been greatly exaggerated.’’ The strongest pro-environmental attitudes are associated with statement 9, ‘‘Despite our special abilities, humans are still subject to the laws of nature.’’ The weakest pro-environmental attitudes are associated with statement 6, ‘‘The earth has plenty of natural resources if we just learn how to develop them.’’ The general pattern of results reported in Table 1 is similar to that found in other studies using the NEP (e.g., Dunlap et al. 2000; Cooper et al. 2004).

Although a variety of views were expressed by survey respondents (respondents both strongly agreed and strongly disagreed with all NEP statements), the response frequencies and means indicate that in general the survey respondents agreed with the pro-environmental NEP statements and disagreed with the weak-environmental statements. The average respondent's attitudes fall between undecided and strong pro-environmental.

Measuring environmental attitudes

In this section, we introduce CA and LCA in the context of identifying heterogeneity in environmental attitudes using the NEP. We discuss both methods as they relate to our objective of segmenting individuals into different groups based upon differences in environmental attitudes.[7]

[6] The survey was not designed to address the issue that environmental preferences may change over time. See Le Kama and Schubert (2004).

[7] Factor analysis is another analytical technique sometimes used to segment individuals into groups. Two applications of factor analysis in a CV context are Nunes (2002) and Nunes and Schokkaert (2003).

Cluster analysis

The application of CA techniques to NEP data segments survey respondents into environmental attitudinal groups such that respondents in the same group have similar environmental attitudes, but their attitudes differ from those of respondents in other groups. Although a variety of clustering methods exist and the details of the various methods differ, each method entails the same principal steps. Clustering algorithms are applied either to raw data, standardized data, or proximity coefficients that measure the degree of similarity or dissimilarity between two observations.[8] In the present analysis we use proximity coefficients in the form of Euclidean distances, one of the most commonly used of several proximity coefficients appropriate for use with ordinal data (Romesburg 1984; Aldenderfer and Blashfield 1984).[9] Proximity coefficients are calculated for the ith and jth respondents for all $i = 1, ..., n$ and $j = 1, ..., n$, and are arranged in a symmetric $n \times n$ matrix referred to as a resemblance matrix. Because the Euclidean distances are calculated using responses to NEP statements, the proximity coefficients provide measures of the differences in respondents' expressed environmental attitudes.

We segment survey respondents into different environmental attitudinal groups by applying Ward's minimum variance method to the resemblance matrix.[10] Ward's method (one of the most commonly used clustering methods in the social sciences) is what is referred to as an agglomerative clustering method. This family of clustering algorithms iteratively merges n observations (respondents) into a single cluster in a process of n–1 steps. The various agglomerative algorithms use different criteria to determine which respondents or clusters of respondents are most similar and should thus be merged into a new cluster at each of the n–1 steps. Ward's method uses an error sum of squares criterion to determine which respondents to merge at each stage in the clustering procedure. At each stage the objective is to minimize the increase in the total within-cluster error sum of squares:

$$\min \sum_{m=1}^{g} \mathrm{ESS}_m = \sum_{m=1}^{g} \sum_{i=1}^{n_m} \sum_{k=1}^{p} \left(x_{mi,k} - \frac{1}{n_m} \sum_{i=1}^{n_m} x_{mi,k} \right)^2, \tag{1}$$

where ESS_m denotes the error sum of squares within the mth cluster, $x_{mi,k}$ is the value of the kth NEP variable for the ith individual in the mth cluster, and n_m is the number of individuals in the mth cluster (Aldenderfer and Blashfield 1984; Everitt et al. 2001). The increase in the total within-cluster error sum of squares given in

[8] Standardizing the data is an optional first step that removes arbitrary effects that can occur due to the variables' units of measure, and causes variables to contribute more equally to the proximity coefficients. See Romesburg (1984) for a description of available standardizing functions. Because responses to the NEP statements are measured using a Likert scale, and are thus measured in dimensionless units and contribute equally to the calculation of proximity coeffcients, standardization is an unnecessary step for the present analysis.

[9] The Euclidean distance measure is $d_{ij} = \sqrt{\sum_{k=1}^{n} \left(x_{ik} - x_{jk}\right)^2}$, where d_{ij} = the distance between individuals i and j, and k denotes the kth variable.

[10] Although the choice of a clustering method is relatively arbitrary, the decision depends in part upon the proximity coefficient used, as some algorithms and proximity coeffcients are incompatible. Other considerations and strengths/weaknesses of various algorithms are detailed in Aldenderfer and Blashfield (1984).

equation (1) is proportional to the squared Euclidean distance between the centroids of the merged clusters.[11]

Numerous texts, including Romesburg (1984), Aldenderfer and Blashfield (1984), Johnson and Wichern (1992), and Everitt et al. (2001), provide additional information and details relevant to the various steps and decisions involved in CA. Applications of CA methods usually entail determining the appropriate number of clusters. A variety of texts discuss the many heuristic procedures and more formal tests developed for determining the number of clusters; see for example Everitt et al. (2001) and Aldenderfer and Blashfield (1984). Many software packages contain procedures for conducting CA. Examples include R (Ihaka and Gentleman 1996), CLUSTAN (Wishart 1987), and STATA (StataCorp 2001). We conducted CA using SAS (SAS Institute Inc. 1987).

Latent class analysis

The basic intuition of LCA in the context of the NEP is that response patterns of individuals who share similar environmental attitudes will be highly correlated, but will differ from response patterns of those who have different environmental attitudes. LCA assumes that each individual belongs to one and only one group; however, because class membership cannot be observed, it is treated as if it is probabilistic. LCA typically assumes that answers to a series of questions are independent once class membership has been accounted for; in other words, it is only class membership that causes correlation between an individual's answers.

The estimation goals of LCA are two-fold. The first is to determine the most likely response probabilities given the response pattern of all respondents. We denote this $\pi_{qs|c}$, the probability that an individual in environmental attitudinal group c gives answer s to attitudinal question q; for example, it is the probability that someone in group c answers "strongly agree" to the statement "Humans have the right to modify the natural environment to suit their needs." The second goal is to find the unconditional class probabilities given the response pattern of all individuals. We denote this $\Pr(c)$, the probability that any individual in the sample will belong to environmental group c.

The ln likelihood function for a C-class model for the data in our sample is

$$\ln L = \sum_{i=1}^{N} \ln\left[\sum_{c=1}^{C} \Pr(c) \prod_{q=1}^{Q} \prod_{s=1}^{S} \left(\pi_{qs|c}\right)^{x_{iqs}}\right], \tag{2}$$

where x_{iqs} is a dummy variable that reflects whether individual i chose answer s on question q. The objective is to find the values of $\Pr(c)$ and $\pi_{qs|c}$ that best explain the observed response pattern.

In the above maximum likelihood problem, class membership is unknown. The E–M (expectation–maximization) algorithm is a technique that can be used to perform maximum likelihood estimation in the case of incomplete information (Dempster et al. 1977; Arcidiacono and Jones 2003). The basic idea of the E–M algorithm is that one replaces unobserved information with its expected value and

[11] Although Ward's method is similar to the centroid clustering method, the two methods differ in that Ward's method weights the clusters' centroids.

then conducts maximum likelihood estimation as if these expectations were correct. The maximum likelihood estimates can be used to update the original expectations, and the log-likelihood function re-estimated. This iterative process continues until the change in the log-likelihood function becomes sufficiently small. Using these methods, one can estimate the response and class membership probabilities that maximize the log-likelihood function.

Similar use of LCA can be found in Menzel and Scarpa (2005). Standard references to latent class models include Titterington et al. (1985), Bartholomew and Knott (1999), and Wedel and Kamakura (2000). A more detailed explanation of the derivation of this model and how it can be estimated can be found in Morey et al. (2006) and Thacher et al. (2005). Ben-Akiva et al. (2002) provide another example of the application of LCA to discrete choice models. Typically an important part of any latent class modeling procedure is to determine the number of classes and the fit of the model (see Forman (2003) and Eid et al. (2003) for information regarding model fit). A number of software packages now exist that allow estimation of latent class models, including Latent GOLD (Vermunt and Magidson 2000) and Mplus (Muthen and Muthen 2004). The results for this study were estimated using LEM (Vermunt 1997).

Consistency between methods

In this section we assess the convergent and theoretical validity of the CA and LCA applications and the robustness of the results by comparing the CA and LCA results in two ways: the consistency of the assignment of individuals to environmental groups, and the response patterns across groups.[12] Previous studies have used the NEP to identify three groups based on whether respondents have "strong," "moderate," or "weak" pro-environmental attitudes (Kotchen and Reiling 2000; Cooper et al. 2004). We follow the same convention here and assume the existence of three latent groups.[13] Thus, our comparison of CA and LCA is subject to the constraint of having the same number of groups (three in this case).

In distributing respondents to the *strong*, *moderate*, and *weak* attitudinal groups, 65% of respondents were assigned to the same attitudinal groups by CA and LCA.[14] The consistency is especially notable for the *strong* group, but less so for the *moderate* and *weak* groups (see Table 2). As a point of comparison, if group assignments had been random only 33% of respondents would have been assigned to the same group by the two methods. Although 35% of respondents were assigned to different groups by CA and LCA, only one individual was assigned to the *strong* group by CA but the *weak* group by LCA, and no individuals were assigned to *weak* by CA but *strong* by LCA. These results offer evidence of convergent validity, as the two

[12] Convergent validity involves comparing results obtained using two different measures or approaches. Theoretical validity can be addressed by testing whether relationships among the variables meet prior intuitive and theoretical expectations.

[13] For the purpose of the CA and LCA, we use combined data from the falcon and sturgeon surveys. This does not pose any inconsistency in the analysis because the surveys were identical except for the endangered species that was valued.

[14] As discussed in the previous section LCA does not assign individuals to a particular group, but rather provides the probabilities that an individual belongs to each group. In order to compare the CA and LCA results, individuals are assigned to the group for which they have the highest conditional probability.

Table 2 Consistency in group assignments[a]

CA assignment	LCA assignment		
	Strong	Moderate	Weak
Strong	97%	3%	0%
Moderate	23%	70%	6%
Weak	1%	75%	24%

[a] Table entries indicate the percentage of those respondents assigned to group *x* by CA who were assigned to group *y* by LCA. For example, of all the individuals assigned to the *strong* group by CA, LCA assigned 97% of these individuals to the *strong* group and the remaining 3 percent to the *moderate* group

methodologies demonstrate reasonable consistency in the assignment of individuals to environmental groups.

We further examine the consistency of the CA and LCA results by using the Mann-Whitney rank-sum test to assess whether mean respones to the NEP statements differ between methods (Table 3).[15] Results illustrate that for the *strong* groups, mean re-sponses differ for only three statements (*modifyenv*, *strongbalance*, and *delicatebalance*). However, the *moderate* and *weak* groups have statistically different means between methods for 11 and 12 of the NEP statements, respectively. These results reiterate the fact that although the *strong* CA and LCA groups are similar, the *moderate* and *weak* groups are somewhat dissimilar. Results from comparisons of the methods' group assignments and mean NEP responses provide evidence (although not especially strong evidence) of convergent validity.

Tables 4 and 5 report mean responses to the NEP statements for each attitudinal group for CA and LCA, respectively. This same data is illustrated in Fig. 1. The results illustrate how mean responses differ between the *strong*, *moderate*, and *weak* environmental attitudinal groups. As illustrated by the Mann–Whitney rank-sum test results (Tables 4 and 5), the mean responses between the attitudinal groups are statistically different in almost all cases. Exceptions occur for mean responses to the *suffresources* and *controlnature* statements for the *moderate* and *weak* pro-environmental groups derived using CA, and for the *interfere*, *lawsofnature*, and *controlnature* statements for the *moderate* and *weak* groups derived using LCA. The theoretical validity of the CA and LCA applications is supported by the fact that essentially all mean responses are statistically different.

As expected, CA and LCA both yield attitudinal groups for which the *strong* groups have the highest mean responses to each of the NEP statements, the *weak* groups have the lowest mean responses to each NEP statement, and the *moderate* groups have means that fall between those of the *strong* and *weak* groups. This response pattern indicates that the *strong* group has the most pro-environmental attitudes, whereas the *weak* group has the least pro-environmental attitudes. The across-group response pattern therefore provides further evidence of theoretical validity.

There is similarity in the characterization of groups identified using CA and LCA, which indicates consistency in the results and provides further evidence of conver-

[15] Because the NEP data are not normally distributed, it is not appropriate to use the usual *t*-test to determine whether there are statistically significant differences between the groups' mean responses. We therefore make use of the non-parametric Mann–Whitney rank-sum test. Bain and Engelhardt (1992) provide further information regarding this test.

Table 3 Attitudinal group mean comparisons: CA versus LCA[a]

NEP statement	Strong	Moderate	Weak
(1) *earthcap*	–0.499	4.682*	1.575
(2) *modifyenv*	2.443*	1.411	4.670*
(3) *interfere*	1.462	3.044*	–1.390*
(4) *ingenuity*	0.624	1.215	1.926*
(5) *abusingenv*	1.162	3.536*	1.685*
(6) *suffresources*	0.253	–0.474	4.263*
(7) *righttoexist*	1.169	4.548*	2.382*
(8) *strongbalance*	1.712*	4.049*	1.712*
(9) *lawsofnature*	–0.588	4.529*	–1.990*
(10) *ecolcrisis*	1.311	3.491*	5.122*
(11) *spaceship*	0.174	3.757*	1.867*
(12) *humanrule*	0.743	2.540*	4.805*
(13) *delicatebalance*	2.611*	4.390*	0.597
(14) *controlnature*	0.696	0.608	0.828
(15) *ecolcatastrophe*	1.541	4.817*	2.868*

[a] Reported numbers are z statistics. The null and alternative hypotheses are as follows. H_0: The distributions of responses to the Likert scale question are equal for CA and LCA. H_A: The distributions are not equal

* Indicates that the null hypothesis is rejected at the 10% level of significance

Table 4 Attitudinal groups' mean NEP responses and comparisons: CA

NEP statement	Group means			Mann–Whitney rank-sum test[a]		
	Strong	Moderate	Weak	Strong–Moderate	Moderate–Weak	Strong–Weak
(1) *earthcap*	4.071	3.785	2.819	–3.284	–8.010	–9.013
(2) *modifyenv*	4.410	3.372	2.594	–9.173	–6.384	–12.322
(3) *interfere*	4.756	3.972	3.650	–9.180	–3.872	–11.860
(4) *ingenuity*	3.558	2.846	2.631	–5.657	–2.135	–6.609
(5) *abusingenv*	4.776	4.024	3.506	–10.023	–5.931	–12.621
(6) *suffresources*	2.635	2.198	2.006	–2.168	–1.177*	–2.859
(7) *righttoexist*	4.846	4.482	3.288	–5.845	–10.344	–12.780
(8) *strongbalance*	4.756	3.842	3.144	–10.435	–7.295	–13.804
(9) *lawsofnature*	4.679	4.421	4.006	–4.705	–5.548	–8.593
(10) *ecolcrisis*	4.455	3.413	2.444	–10.015	–8.546	–13.343
(11) *spaceship*	4.051	3.595	2.806	–5.161	–6.828	–8.816
(12) *humanrule*	4.404	3.676	2.794	–7.034	–6.710	–10.745
(13) *delicatebalance*	4.840	4.036	3.181	–10.806	–8.789	–14.617
(14) *controlnature*	3.929	3.198	3.156	–6.168	–0.421*	–6.098
(15) *ecolcatastrophe*	4.410	3.547	2.575	–9.520	–9.206	–12.741
n	*156*	*247*	*160*			

[a] Reports z statistics

H_0: Distributions of responses are equal for two groups

* Indicates H_0 is rejected at 10% level

gent validity. The *strong* pro-environmental groups have relatively strong pro-environmental attitudes on all questions, although they consistently demonstrate weaker attitudes regarding the sufficiency of the earth's resources (*suffresources*). The *moderate* groups are somewhat environmental on all questions, yet there are

Table 5 Attitudinal groups' mean NEP responses and comparisons: LCA

NEP statement	Group means			Mann–Whitney rank-sum test[a]		
	Strong	Moderate	Weak	Strong–Moderate	Moderate–Weak	Strong–Weak
(1) *earthcap*	4.130	3.398	2.553	–8.360	–3.904	–6.337
(2) *modifyenv*	4.104	3.250	1.914	–8.763	–7.622	–9.162
(3) *interfere*	4.627	3.797	3.671	–11.888	0.632*	–6.317
(4) *ingenuity*	3.459	2.749	2.398	–7.003	–2.592	–4.790
(5) *abusingenv*	4.706	3.819	3.133	–13.519	–3.426	–9.097
(6) *suffresources*	2.574	2.177	1.553	–1.971	–5.505	–4.820
(7) *righttoexist*	4.763	4.156	2.737	–9.124	–6.487	–10.686
(8) *strongbalance*	4.599	3.574	2.933	–13.268	–3.969	–8.992
(9) *lawsofnature*	4.686	4.192	4.151	–9.717	1.044*	–4.758
(10) *ecolcrisis*	4.279	3.130	1.757	–12.355	–8.854	–10.549
(11) *spaceship*	4.041	3.289	2.534	–8.472	–4.129	–6.510
(12) *humanrule*	4.303	3.465	1.925	–9.235	–7.886	–9.898
(13) *delicatebalance*	4.608	3.776	3.038	–12.502	–3.710	–9.102
(14) *controlnature*	3.822	3.146	3.023	–7.063	–0.839*	–3.768
(15) *ecolcatastrophe*	4.280	3.198	2.229	–12.539	–5.964	–8.538
n	*211*	*298*	*54*			

[a] Reports z statistics

H_0: Distributions of responses are equal for two groups

* Indicates H_0 is rejected at 10% level

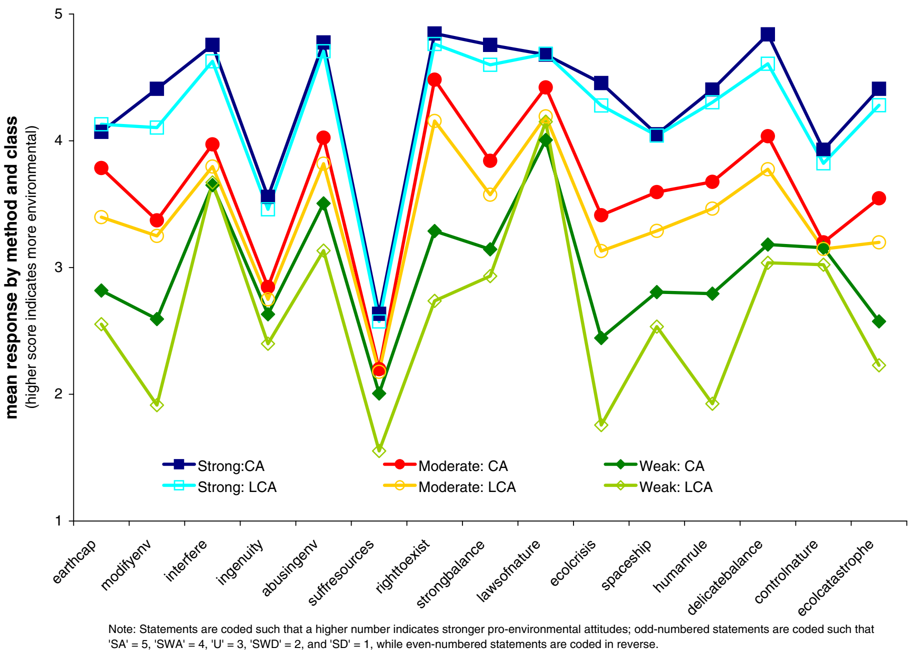

Fig. 1 Mean responses to NEP questions by method and class

some statements for which they are either undecided or appear to not hold a pro-environmental attitude (e.g., *suffresources*, *ingenuity*). The *weak* groups consistently hold seemingly anti-environmental attitudes for statements dealing with limits to growth, although responses on other statements are more mixed. For example, responses to statements associated with the rejection of exemptionalism suggest the presence of uncertainty or somewhat pro-environmental attitudes.

A notable difference between the methods pertains to the size of the different groups (Tables 4 and 5). Although the *moderate* pro-environmental group is consistently the largest, there are substantial differences in group sizes across the techniques. In particular, LCA yields a much smaller *weak* group. Consequently, the LCA *weak* group has weaker pro-environmental attitudes. This difference is most pronounced for the *ecolcrisis* statement and the questions associated with anti-anthropocentrism.

Relationship between attitudes and WTP

We further examine the robustness of CA and LCA by testing whether WTP for endangered species recovery varies across environmental attitudinal groups and between methods. If the attitudinal groups are really different, we would expect WTP to vary by group. Moreover, consistency between CA and LCA should imply that WTP estimates are similar for each group under both analytical methods. In this section we also address the question of whether accounting for unobserved heterogeneity in environmental attitudes provides additional explanatory power in econometric models of WTP responses.[16]

We estimate logit models of dichotomous-choice CV responses, and include the same covariates used in Kotchen and Reiling (2000)—bid amount, previous knowledge about the good, household income, and environmental attitudes as measured by the different methods.[17] Table 6 provides the definitions and descriptive statistics for the variables we use.[18]

Table 7 reports coefficient estimates and significance levels for the falcon and sturgeon surveys. In both attitudinal models and for both data sets, the bid and income variables are significant and have the expected sign. As expected, individuals are less likely to respond 'yes' as the bid amount increases, but are more likely to respond 'yes' as income increases.

All of the attitudinal variables are significant in the sturgeon data set. Under both the CA and LCA methods, the *strong* environmental groups are significantly more likely to agree to the referendum than the *weak* environmental groups. The same holds for the *moderate* environmental groups identified by each method. *Knowledge* is a positive significant explanatory factor at conventional levels for the LCA approach and at the 6% level for the CA approach.

Attitudinal results for the falcon data set are less strong than those of the sturgeon data set. The *strong* environmental group identified by the CA approach is signifi-

[16] For the regression and WTP portions of our analysis we use data from the falcon and sturgeon surveys separately.

[17] While including income as a separate linear term is not utility theoretic, it is common practice and acts as a proxy variable for a number of other socioeconomic attributes (Hanemann and Kanninen 2001).

[18] Observations with missing values for any of the variables included in the regression were deleted. In addition, following the approach taken by Kotchen and Reiling (2000), we exclude individuals exhibiting protest behavior. Estimation was performed using non-linear maximization modules in Python.

Table 6 Descriptive statistics for falcon (n = 203) and sturgeon (n = 198) data sets

Variable	Definition	Falcon		Sturgeon	
		Mean	StDev	Mean	StDev
Bid	Presented bid	$24.57	$11.84	$11.82	$7.96
Income	Household income in 1000s[a]	$41,810	$24,412	$38,750	$24,462
Knowledge	Prior knowledge of species in Maine (1 = yes, 0 = no)	0.46	0.50	0.26	0.44
Age	Age (years)	44.26	14.61	45.02	15.48
Gender	Gender (1 = female, 0 = male)	0.50	0.50	0.50	0.50
HHsize	Number of individuals in household	2.79	1.15	2.62	1.23
CA: Weak	Belongs to weak group identified by CA (1 = yes, 0 = no)	0.25	0.43	0.25	0.44
CA: Moderate	Belongs to moderate group identified by CA (1 = yes, 0 = no)	0.45	0.50	0.43	0.50
CA: Strong	Belongs to strong group identified by CA (1 = yes, 0 = no)	0.30	0.46	0.31	0.46
LCA: Weak	Belongs to weak group identified by LCA (1 = yes, 0 = no)	0.06	0.24	0.09	0.29
LCA: Moderate	Belongs to moderate group identified by LCA (1 = yes, 0 = no)	0.52	0.50	0.51	0.50
LCA: Strong	Belongs to strong group identified by LCA (1 = yes, 0 = no)	0.42	0.50	0.40	0.49

[a] The survey provided a list of income ranges, and respondents were asked to indicate the range that encompassed their household income. We use the median of the indicated income range in our analyses

cantly more likely to agree to the referendum than the *weak* environmental group. The *strong* environmental group identified by the LCA approach and the *moderate* group identified by the CA approach are significantly more likely to agree to the referendum than the *weak* groups at only the 8% and 7% levels, respectively. There is not a significant difference between *moderate* and *weak* groups in the LCA model. *Knowledge* is not a signficantly explanatory factor under either approach.

We use the models in Table 7 to estimate WTP for each endangered species under each attitudinal measurement method. Table 8 reports the estimated WTP for a representative individual in each group, the 90% confidence intervals around these estimates, and tests of whether WTP differs between the groups and methods.

As expected, WTP is largest in magnitude for the *strong* groups and smallest for the *weak* groups. The 90% confidence intervals show that mean WTP is significantly greater than zero for the *strong* and *moderate* groups but is not significantly greater than zero for the *weak* groups.[19]

We use the method of convolutions to determine whether mean WTP differs significantly between attitudinal groups and between methods.[20] To perform the test we performed 100 replications of the Krinsky–Robb simulation method and calculated the mean WTP for each replication. A distribution of the differences in means

[19] Confidence intervals were calculated using the Krinsky–Robb simulation method (Krinsky and Robb 1986; Park et al. 1991). One thousand random draws were taken from a standard normal distribution, weighted by a Cholesky decomposition of the variance–covariance matrix, and added to the original parameter estimates. This process was replicated 100 times. These new parameter draws were used to calculate the distribution of WTP.

[20] As shown in Poe et al. (1994), comparing confidence intervals between groups is not an appropriate test because it relies on distribtional assumptions about WTP that may not be satisfied.

Table 7 Logit regression for falcon (n = 203) and sturgeon (n = 198) data sets[a]

Variable	Falcon		Sturgeon	
	CA	LCA	CA	LCA
Intercept	–1.14**	–1.04	–0.79	–0.95
Bid	–0.04***	–0.04***	–0.05***	–0.05***
Income	0.02***	0.02***	0.02***	0.01**
Knowledge	0.49	0.45	0.73*	0.77**
CA: Moderate	0.74*	.	1.00***	.
CA: Strong	1.57***	.	1.93***	.
LCA: Moderate	.	0.43	.	1.20**
LCA: Strong	.	1.32*	.	1.69***
Log L	*–119.81*	*–122.19*	*–115.01*	*–120.34*
Restricted Log L	*–139.17*		*–133.17*	
L ratio test	*38.72****	*33.95****	*36.34****	*25.66****

[a] *, **, and *** denote significance at the 10, 5, and 1% levels, respectively

Table 8 WTP by group by method for falcon (n = 203) and sturgeon (n = 198) data sets

Group	Measure	Falcon		Sturgeon	
		CA	LCA	CA	LCA
Strong	WTP[a]	$38.01	$32.48	$40.57	$31.79
	90% CI[b]	[$25.65–$57.00]	[$23.02–$44.63]	[$24.38–$77.18]	[$18.35–$53.69]
Moderate	WTP[a]	$14.34	$7.60	$21.33	$20.52
	90% CI[b]	[$1.08–$24.99]	[(–$7.98)–$17.68]	[$12.54–$35.79]	[$12.33–$33.74]
Weak	WTP[a]	(–$4.59)	(–$0.38)	$1.75	(–$6.46)
	90% CI[b]	[(–$31.58)–$11.67]	[(–$44.92)–$23.62]	[(–$14.62)–$12.76]	[(–$35.17)–$13.96]
Test of differences in means across groups: 90% convolutions test CI[c]					
Strong versus moderate		[$19.53–$28.23]	[$22.48–$26.66]	[$ 6.15–$36.38]	[(–$1.63)–$21.46]
Strong versus weak		[$34.81–$48.42]	[$35.23–$42.20]	[$23.52–$55.49]	[$17.79–$53.02]
Moderate versus weak		[$11.00–$23.87]	[$10.00–$18.66]	[$12.83–$25.58]	[$15.17–$39.31]
Test of differences in means between methods: 90% convolutions test CI[c]					
Strong: CA versus LCA		[$3.44–$8.82]		[(–$11.93)–$30.35]	
Moderate: CA versus LCA		[$5.26–$11.33]		[(–$20.48)–$5.87]	
Weak: CA versus LCA		[(–$6.05)–$ 5.87]		[(–$2.52)–$23.25]	

[a] Calculated for representative individual in the group using parameter estimates

[b] Calculated using the Krinsky–Robb approach based on 100 replications of 1000 random draws

[c] A confidence interval that excludes 0 shows that WTP differs significantly between groups or methods

was then calculated. We report the 90% confidence intervals for this difference in means. A confidence interval that excludes 0 signifies that the difference in mean WTP between the two groups is significantly different from zero. See Poe et al. (1994 and 2005) for additional explanation of this method. The "Test of differences in means across groups" section in Table 8 shows that with one exception (the *strong* and *moderate* LCA groups in the sturgeon data set) the *strong* environmental groups have a significantly higher mean WTP than the *moderate* and *weak* environmental groups, and the *moderate* environmental groups have a significantly higher mean WTP than the *weak* environmental groups. This provides strong evidence that groups with stronger pro-environmental attitudes have significantly higher WTP, and additional evidence of CA and LCA theoretical validity.

Another question of interest is whether WTP significantly differs between groups identified by CA and those identified by LCA. For example, is there a significant difference in the mean WTP of the CA *strong* group and the LCA *strong* group? In the sturgeon data set for each attitudinal group, there are no significant differences in the mean WTP estimated using the two methods (see section "Test of differences in means between methods" of Table 8). The results are not as strong in the falcon data set: only for the *weak* group do the mean WTP not differ between the two methods. Thus, for the sturgeon data set we find strong evidence that CA and LCA are identifying groups with the same mean WTP (and thus evidence of convergent validity), but this result generally does not hold for the falcon data set.

To test whether attitudinal data adds useful information beyond what is already captured through demographic data, we run comparison models for both sets of data: a full model that includes both demographics and attitudinal variables and a restricted model that excludes the attitudinal variables. Because we wish to assess the additional explanatory value provided by attitudinal data, we account for as much demographic heterogeneity as possible by adding gender, age, and household size to the models presented in Table 7. The likelihood ratio tests reported in Table 9 show that the restricted models, which exclude the attitudinal variables, consistently provide a significantly worse fit. Demographics do not fully capture the same information as attitudinal data.

Given that the models yield similar results, an obvious question of interest is whether the logit model using CA or LCA is preferred. Although information criteria such as the Akaike (AIC) or Bayesian (BIC) information criteria are commonly used for this purpose, these measures cannot test whether the models are statistically different. For this reason we use the Vuong test (Vuong 1989) to test the null hypothesis that the two models are equally close to the true specification.[21] We do not find a significant difference between the two models, and thus cannot conclude that there are statistical reasons for choosing one model over the other.

Discussion

We apply CA and LCA to NEP data in order to identify environmental attitude heterogeneity. Results stemming from CA and LCA are similar; there is consistency in the assignment of individuals to attitudinal groups, as well as consistency in the characterization of the identified groups. Moreover, we find that environmental attitudes are strong and significant predictors of CV responses, regardless of the

[21] The Vuong test statistic is

$$\frac{1}{\sqrt{n}}\frac{\mathrm{Log}L_{\mathrm{LCA}}-\mathrm{Log}L_{\mathrm{LCA}}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[\mathrm{Log}L_{\mathrm{LCA}}(i)-\mathrm{Log}L_{\mathrm{CA}}(i)\right]^2-\left[\frac{1}{n}\left(\mathrm{Log}L_{\mathrm{LCA}}-\mathrm{Log}L_{\mathrm{CA}}\right)\right]}}\sim N(0,1),$$

where i is an individual in the sample.

Table 9 Comparison of observable heterogeneity model with models that also include attitudinal controls for falcon (n = 203) and sturgeon (n = 198) data sets[a]

Model	Falcon		Sturgeon	
	Log L	L ratio test	Log L	L ratio test
Observable heterogeneity[b]	–126.50	.	–121.17	.
Observable heterogeneity + CA variables	–119.71***	13.59	–112.43***	17.47
Observable heterogeneity + LCA variables	–122.09**	8.82	–116.81**	8.71

[a] *, **, and *** denote significance at the 10, 5, and 1% levels, respectively

[b] Includes income category, gender, age, household size, knowledge, bid, and intercept as explanatory variables

method used to identify attitudes. Both methods show that WTP increases with the strength of pro-environmental attitudes. In all cases but one, we find significant differences in WTP between the attitudinal groups. We also find that in four of the six cases there were not significant differences in the mean WTP derived from the two grouping methods. Furthermore, we find that models that include attitudinal data have a significantly better fit than a model that includes solely socio-demographic variables. We thereby provide evidence that including unobservable attitudinal heterogeneity provides greater explanation of individuals' preferences and choices.

Given the consistency across the classification techniques, an important question is the following: What insights might be provided regarding which method, CA or LCA, is most appropriate for incorporating environmental attitudes into CV studies? Both methods have strengths and weaknesses. The primary limitation of LCA is that, depending on the data, the number of parameters that must be estimated increases very quickly. This is the case with the NEP data. Since there are five response categories for each of 15 questions and three classes, one must estimate four of the levels for each question and each class and two of the class probabilities, translating into 182 parameters. In some applications this may limit the number of groups that can be estimated. While techniques are available for reducing the number of variables to be estimated, these techniques require expertise on the part of researchers. Nevertheless, LCA has solid statistical tests for determining the fit of the model and indicative tests for determining the appropriate number of groups.[22] Additionally, the outputs of predicted response probabilities, conditional probabilities, and unconditional probabilities can be useful for economic analysis.

CA has the advantages that it is available in numerous software packages, and it is not as complex as LCA and therefore does not require as much time to learn. Additionally, CA is not limited in the number of groups that can be estimated. A disadvantage of CA is the need to make somewhat arbitrary decisions between competing options and methods at various stages of the clustering process. Although

[22] For example, the Pearson and Read–Cressie statistics, both measures of how well the observed and expected frequencies of responses compare, can be used to statistically determine whether the number of groups fits the data (Forman 2003). In the case of sparse data, these statistics can be bootstrapped (Eid et al. 2003). Once the set of models that fit the data is determined, information criteria such as the AIC, CAIC, AIC_C, and BIC (which assess the fit of the model with a penalty imposed for the number of parameters) can be used to choose between the models (Akaike 1974; Bozdogan 1987; Hurvich and Tsai 1989; Schwarz 1978). The use of information criteria can be subjective if the criteria yield different results.

guidelines and considerations for the various decision points exist, there are no definitive rules. Thus, although CA is relatively easy to implement in comparison with LCA, its appropriate use requires in-depth knowledge and experience. Another weakness of the CA procedure is that the Euclidean distance between two individuals is calculated using the differences between the values of their NEP responses rather than on the actual values of the responses. Thus, the same Euclidean distance will result under the following two scenarios: (1) individual i responds 1 and j responds 3, and (2) individual i responds 3 and individual j responds 5. For this reason LCA may be considered superior, as LCA segments individuals based upon an overall response pattern.

Because CA and LCA have different strengths and weaknesses, the desired method for capturing attitudinal heterogeneity may depend on particular research goals and/or data availability. Fully addressing the question of whether CA or LCA is more appropriate for incorporating environmental attitudes into CV studies will require analysis of the techniques applied to other data sets.

In conclusion, this paper compares two methods for incorporating unobservable heterogeneity in valuation studies and finds the results are generally convergent—the methods identified similar attitudinal groups, assigned individuals to groups with reasonable consistency, and WTP did not vary significantly between methods, but did vary significantly between groups. A model that excluded attitudinal variables illustrated that socioeconomic variables did not fully capture preference heterogeneity. Future research should examine whether similar results are obtained when CA and LCA are applied to NEP responses within the context of other CV studies. If similar results are obtained, this would corroborate that the NEP is a valuable tool for measuring environmental preference heterogeneity, and that CA and LCA are capable of identifying heterogeneous preference groups. Future research might also strive to determine whether analyzing NEP responses using CA and LCA analysis provides superior results to the more common approach of capturing environmental attitudes.

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