Ecological Economics 138 (2017) 223–237

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Analysis

Can Personality Traits Explain Where and With Whom You Recreate? A Latent-Class Site-Choice Model Informed by Estimates From Mixed-Mode LC Cluster Models With Latent-Personality Traits

Edward R. Morey[a], Mara Thiene[b,*]

[a] Dept of Economics, University of Colorado, Boulder, CO 80309-0256, USA
[b] Dept of Land, Environment, Agriculture and Forestry, University of Padova, Viale dell'Università, 16, 35020 Legnaro, Padova, Italy

A R T I C L E I N F O

Article history:
Received 10 October 2015
Received in revised form 17 February 2017
Accepted 3 March 2017
Available online xxxx

Keywords:
Latent traits
Personality
Sensation seeking
Extroversion
Competitiveness
Mixed-mode latent-class cluster model
Ordinal
Nominal, and cardinal indicators
Latent-class choice model

A B S T R A C T

We test and find that personality traits interact with site characteristics and the ability of a potential companion to determine where, and with whom you recreate. 4605 mountain bikers chose between multiple pairs of hypothetical mountain-bike rides, and, in addition, answered Likert-scale questions on sensation-seeking, competitiveness and extroversion. For each personality trait, a mixed-mode latent-class cluster model was estimated, accounting for that fact that the indicators can have ordinal, cardinal or nominal meaning. Most LC models ignore these distinctions. Our model also allows the scores on questions to be correlated, even after conditioning on class (typically assumed away). Then, a latent-class choice model of trail attributes and companion's ability was estimated using the choice-pair data, with the estimated latent personality-traits as covariates. Three choice classes are identified and the odds of being in each varies by personality: estimated choice probabilities and WTP estimates vary significantly and substantially by class and personality type.

1. Introduction

Preference heterogeneity for a site-specific recreational activity may be over the physical attributes of the site, but also over whether you have a companion and their relative ability. Our hypothesis is people vary in terms of how, and how much they want to be challenged. Site characteristics can make an activity more or less challenging/difficult. If alone you can choose the pace (relaxed to challenging), but if you have a companion you lose control over how the activity will play out, particularly if the companion is of a different ability level, but you can socialize.

This paper simultaneously tackles three research issues. The first one addresses whether personality traits can explain preference heterogeneity for recreational activities. The second and the third research issues deal with econometric features of latent-class (LC) models, which are often used to explore preference heterogeneity. Specifically, the second issue is many estimated latent-class models restrictively assume—often wrongly—that once you condition on class, the different answers used to estimate the model (the scores on the indicator questions—most often answers to Likert-scale questions) are statistically independent. If you assume conditional independence when it does not exist, you get biased parameter estimates (each answer appears more important than it is). The third research issue is scores on indicators vary in terms of their informational content (nominal, ordinal, or cardinal) but many estimated LC models do not take this into account—they restrictively assume all scores have the same informational content, often the wrong one. So, most LC models either ignore information in some of the scores (e.g. assume the scores are simply nominal when they, in fact, have ordinal meaning), or assume information that is not there (e.g. assume the scores have cardinal significance when they do not). We specify and estimate a LC model (specifically a mixed-mode LC cluster model, see Sections 1.2 and 3.1) that allows for dependencies amongst indicators, and, in addition, correctly specifies the scale (nominal, ordinal, cardinal) of the different indicators. Next we discuss how personality traits influence behavior and then present some methodological implications of LC models.

* Corresponding author.
E-mail addresses: edward.morey@Colorado.EDU (E.R. Morey), mara.thiene@unipd.it (M. Thiene).

http://dx.doi.org/10.1016/j.ecolecon.2017.03.038
0921-8009/

1.1. The Influence of Personality Traits on Behavior and Choice

Personality traits tend to be stable over time, situations, and tasks (Fleeson and Noftle, 2008; Funder, 2009). They are also measurable and have a long history of being measured. These two things make them prospective candidates for explaining why I might choose differently from you and why for many individuals their choices show similarities across time, situations, and tasks.

Personality traits, in fact, predict behavior and choice in many situations: choice of drugs (e.g. heroin vs. cocaine), relationship choices, choice of mate, what you study in school and eating habits (Bereczkei et al., 1997; Corulla and Coghill, 1991; Hopwood et al., 2008; Jonason et al., 2012; Mascie-Taylor, 1988; MacNicol et al., 2003), as well as income, job performance, educational achievement and criminal behavior (Almlund et al., 2011). In the *Handbook of the Economics of Education*, Almlund et. al. survey how personality affects choices. While many studies–mostly in other fields have demonstrated that personality traits can explain choices, most economists ignore personality as an explanatory variable.

In our application, we are interested in whether personality traits influence where you recreate and with whom you recreate, or not. Recreational activities involve exertion, the performance of sports-specific skills, risks, thrills, socializing and competition and these aspects of the experience vary by sport, site and companion. It is our hypothesis that variation in preferences over these aspects of recreation vary with personality traits. We test and confirm this hypothesis by modeling and estimating how mountain bikers choose between different rides as a function of site characteristics and companion's ability. Our results cause us to further hypothesize that personality traits can explain choice of sport (running versus golf versus technical climbing), choice of venue and companion(s) given the sport (where to golf, or climb, and with whom) and how often to participate in a specific recreational activity (whether to ski, snowboard, snowmobile, or stay home).

1.1.1. Sports and Personality Traits

Sit and Lindner (2005) find *paratelic* individuals (playful, unconcerned, fun seeking) prefer risky sports while *telic* individuals (serious, goal-directed, achieving) prefer safe sports and endurance activities. More sport-competitive individuals tend to be more telic (Kerr, 1987; Kerr and van Lienden, 1987). More extraverted individuals formally compete more (Kirkcaldy and Furnham, 1991); endurance athletes are more extraverted than non-exercisers and those that exercise more are more extroverted (Egloff and Gruhn, 1996).[1] Extroversion and a tendency to be anxious are both positively correlated with the propensity to exercise, for the latter group to improve mood (Davis et al., 1995). Tolea et al. (2012) finds extroversion positively correlated with muscle strength. Looking ahead, our results contradict some of these findings.

Sensation-seeking involves the desire to seek out new and thrilling sensations and has been associated with high-risk social activities including promiscuous sex, illicit drugs and crime, as well as high-risk sports (Thomson et al., 2013). Thomson et al. identifies a link between a D3 dopamine receptor gene variant and sensation seeking in skiers and snowboarders. Sensation-seeking is positively correlated with physical activity (De Moor et al., 2006; Jack and Ronan, 1998).

1.1.2. Socializing, Competing and Personality Traits

Social psychology asserts a native desire to seek the company of others; the field offers numerous reasons for wanting a companion. First, and foremost, people get utility from friendship and human contact. This category includes the feelings of security provided by a companion and also the joy of interacting with others, including games and competitive situations. Second, having company during an activity allows you to gauge your own abilities: we use other people to gather information about ourselves—*social comparison* (Festinger, 1954). This innate tendency to compare ourselves to another increases the more similar the other person is in terms of opinions and ability. Comparison is part of our quest to make ourselves feel better.[2] Competing with those who are better and holding your own allows you to identify with them, and competing with lessors and beating them confirms you are not one of them—you have drawn a contrast/distinction between them and you. Both processes can be self-enhancing. Ignoring the costs, when comparing with another person we prefer, on average, to compare ourselves to those who are slightly better; it is a way to improve, but there are potential costs; competing with those slightly better can be threatening (Blanton et al., 1999; Buunk and Gibbons, 2007). This threat is eliminated by recreating alone or by choosing a companion out-of-your-league–termed *self-handicapping*. Some individuals, to protect their egos, purposively handicap their ability (Jones and Berglas, 1978; Shepperd and Taylor, 1999). With biking you can self-handicap by riding hard the day before. Other individuals compare downward—*downward social comparison theory* (Wills, 1981), a way to improve self-esteem is to demonstrate you are better than your companion. The drive to compare is not limited to humans (Gilbert et al., 1995). In mountain biking you only need a technical section to assess relative skill, and only one short, steep climb to assess strength, but a long hard ride to assess endurance. We hypothesize that preference for a companion as a function of their ability (or no companion) will vary with personality traits.

According to *Achievement Goal Theory* you are motivated to demonstrate your competence and achievements, but you have two ways of doing this: by comparing what you do with what others are doing you assess your ability in terms of others and by comparing with your past self in terms of personal improvement (Sit and Lindner, 2005). Whether you prefer to compete with others or with your former self likely depends on your personality.

1.1.3. Personality Traits and Environmental Values

We are not the first to consider the relationship between personality traits and environmental values, but the studies cited below consider the influence of personality on value (use plus non-use) for broad environmental goals and programs, most with a large non-use component, not recreational choice and use values, the topic of this paper.

Psychologists ask whether personality traits affect the probability that you are an environmentalist in preference and advocacy, but they are not much interested in estimating your dollar values for specific policies and programs. Much of this research in psychology has appeared in the *Journal of Environmental Psychology* (e.g., Hirsh, 2010; Milfont and Sibley, 2012). Hirsh (2010) and Hirsh and Dolderman (2007) found that pro-environmental views are associated with *openness* ("One's level of imagination, creativity and openness to ideas") and *agreeableness* ("compassion, empathy and concern for others"), while *consumerism* (the accumulation of market goods) was negatively associated with agreeableness, but (as are pro-environmental views), positively associated with openness. Milfont and Sibley investigate the issue on both an individual level and aggregate country-wide levels. They find, consistent with

[1] Extroverts predominately get their gratification from outside sources, introverts from internal sources (their mental life).

[2] Motives for the drive include self-enhancement, perceptions of relative standing, maintaining a positive self-image and closure (Brickman and Bulman, 1977; Suls et al., 2002). See also Buunk and Gibbons (2007).

Hirsh and Dolderman, that agreeableness, *conscientiousness* (*"carefulness, responsibility and organization"*) and openness are all positively linked to environmental engagement.

There is not much economic literature on the effect of personality traits on environmental values. In a path-breaking paper, Solinõ and Farizo (2014) use choice-experiment data to demonstrate that personality traits influence how individuals choose between different forest-management plans as a function of their environmental benefits relative to their other impacts, finding that individuals with high *open* and *extraverted* scores put more weight on the environmental benefits and those with high scores on *agreeableness* and *neuroticism* (e.g., anxious and nervous) less weight. To test the importance of personality traits they include them in both a random-parameters logit model (parameter means a function of personality traits) and a latent-class model (class-membership probabilities are a function of personality traits). In a second paper, Farizio et al. (2016) use a third technique, latent-factor analysis, to demonstrate that personality traits influence the combination of small and large wind turbines individuals would choose to produce a given amount of electricity—different combinations have different environmental and landscape implication.

While the topic of this paper is how personality traits affect recreational choices, it should be noted that our data and the data in the Farizo, Oglethorpe and Solinõ studies is data from hypothetical-choice experiments. This raises the issue—new to us—of whether individuals have varying preferences over how their preferences are elicited (in actual markets with exogenous prices vs. hypothetical-choice experiments vs. CVM questions vs. real auctions vs. hypothetical auctions) and, if so, whether personality traits can explain some of the variation in preference over how preferences are elicited.[3] In a fascinating paper, Grebitus et al. (2013), investigate by comparing behavior in auctions vs. choice experiments, in both hypothetical and non-hypothetical setting. They find that people make different choices (exhibit different $ values) depending on the elicitation method and estimate the extent the difference depends on their personality. For example, while WTP based on auction data is typically higher than from choice data, the difference is largest for extroverts. They also find that behavior in choice experiments varies more by personality traits than does behavior in auctions. These are aspects of personality on choice that we, and most economists, do not consider.

1.2. Extensions to Latent-Class Modeling: Information Content and Dependence Across Indicators

In our study of hypothetical mountain-bike riders, each respondent was asked multiple questions about sensation-seeking, extroversion and competitiveness—questions that are indicators of personality. The answers were used to estimate three separate latent-class (LC) mixed-mode cluster models, one model for each of these personality traits. For example, the sensation-seeking model divides the respondents into three classes/clusters (sensation-seekers, the cautious and everyone in between). A LC ride-choice model was then estimated with the personality traits as covariates.

Most estimated latent-class models impose restrictions inconsistent with our data—restrictions inconsistent with many data sets or they fail to impose restrictions implied by the data. For example, if the discrete responses to an indicator are ranked in terms of an underlying continuous variable (e.g. weight or extent of agreement) the responses must be ordinal. Examples are (1) skinny, (2) average and (3) overweight; and (1) strongly agree, (2) somewhat agree and (3) disagree. Alternatively, if the discrete responses are not so ranked, the different responses are simply different and their relationships are *nominal*. For example, consider the question I am a… ? With answers plumber, electrician, bricklayer or other. The relationships between the responses are nominal. Cardinal implies ordinal and, in addition, the differences between two numerical responses have meaning. Many indicator questions are Likert-scale questions so the answers must have an ordering (are ordinal) but typically LC cluster models assume there is no ordering, so effectively toss important information in the data. In addition, most LC cluster models assume the answers to the indicator questions are independent once you condition on cluster, which in many applications, including ours, is implausible. The problem is that assuming that indicators are independent conditional on class, when they are not, leads to biased LC parameter estimates and biased estimates of the number of classes (often more than there really are). The latent-class model we estimate imposes neither of these restrictive assumptions and it is more general.[4]

Our two linked latent-class models could be applied to any discrete-choice problem where potentially explanatory data is available in terms of a combination of nominal indicators (e.g. gender), ordinal indicators (e.g. answers to Likert-scale questions) and cardinal indicators (e.g. income). It, for example, could be applied to choice between different policies to reduce global warming as a function of personality traits, income and gender. Many environmental and preservation issues, like global warming and animal preservation, are politically and morally charged. There is been much recent research in political science and psychology that has used Likert-scale and other questions to determine what criteria (justice/fairness, caring for others, loyalty to your community/group, and an ethic of holiness) people use to judge the morality of policies and actions.[5] Think of each of these criteria as a morality trait. You could include in the environmental-choice survey standard questions on each of these five morality traits. You could alternatively, or also, ask questions about political traits (social conservative, fiscal conservative, etc.). The mixed-mode LC cluster model is ideally suited to estimate each respondent's level for a broad mixture of traits, taking account of how the indicators remain correlated, even after conditioning on class. And the estimates of latent traits could then be made covariates in the choice model to assess how the support for different policies varies by morality, political traits and personality traits.

Section 2 describes the survey and respondents, whereas Section 3 focuses on the models. Results are reported in Section 4, and Section 5 concludes.

2. The Survey and the Respondents

Our population of interest are those riders who take most of the mountain-bike rides—an imprecisely defined group—what we would

[3] For example, the magnitude of the difference between what a person indicates they are WTP when they answer a CVM question and what they actually pay in the market (hypothetical bias) might vary across individuals as a function of observable personality traits. For example, "In a hypothetical environment, a conscientious individual might be more likely to consider how they would behave if the task was real (as individuals in experiments are typically encouraged to do) than would a less conscientious person. If so, then one might expect stronger hypothetical bias for a less conscientious individual than a more conscientious one." (Grebitus et al., 2013). The issue could be viewed as preferences over different ways of framing a question as a function of personality traits.

[4] We have found only one latent-class model that considers the explanatory power of personality traits. Doeven-Eggens et al. (2008) estimate a standard/restrictive, LC cluster model of personal network type that identified three clusters: family-orientated, peer orientated and mixed. The model has no covariates, assumes the indicators are nominal and assumes post-cluster independence. Merz and Roesch (2011) recommend "latent profile analysis" as a way to model and estimate personality heterogeneity and provide an example. LPA assumes the indicator variables are all of the same mode: continuous, which is different from, but not necessarily better than, assuming that are all nominal (the standard assumption). In addition, it also imposes post-conditional independence. Both of these models are special cases of our mixed-mode cluster model.

[5] Broadly speaking, non-Western adults and Western religious conservatives tend to consider all five of these criteria, whereas other Western adults judge on the basis of only fairness/justice and caring (see, for example, Haidt, 2012).

call *serious mountain bikers*. The vast majority of mountain-bike rides are taken by serious riders. Nine-hundred and thirty-seven identical response-solicitation emails were sent out, most to organizational lists of mountain bikers. The solicitation email asked the recipient to complete our online survey and to forward our e-mail to other potential mountain bikers. Our expectation was that the vast majority of our respondents would be serious mountain bikers. No claim is made that the result of this process is a true random sample of serious mountain bikers. The preferences of the respondents approximate the preferences of those who take most of the rides. The survey took place in 2007.

The data includes answers to standard psychological questions (some tweaked toward mountain biking)–see Table 1 and responses to hypothetical choice pairs.[6,7] Fig. 1 (in color) is a snapshot of a choice-pair question from the survey.

2.1. Characterizing Mountain-Bike Rides

Mountain-bike rides vary in terms of six characteristics: trail length, proportion of trail that is singletrack versus doubletrack, total vertical feet of climbing, number of climbs, access fee and the speed of a companion; no companion is a possibility. Single-track is a trail; double-track is, or once was, a two-track dirt road. Morey et al. (2002), found the first five to be significant and important determinants of site choice—they did not consider companion. Table 2 reports the characteristic levels in the design (similar to the 2002 study).

When you ride a trail alone you can choose, within your physical limits, how to ride it—any competitiveness comes from within, but there is no companionship or socializing. If hurt or lost, you are on your own. All is different if you ride with a companion, and, how it differs depends on your relative abilities: you might struggle greatly to maintain contact, or wait at natural stopping points for them to catch up. Or, if evenly matched, sometimes compete and sometimes socialize.

To simplify and avoid the interactive aspects of choice, we present the respondent with choices of trails where the presence (or absence) of a companion and their relative ability is another exogenous aspect of the ride. Consider a gap of 2 min. if both riders ride at their typical pace. This does not imply the gap would always be 2 min., but indicates the second rider would have to struggle to stay with the leader. Depending on your personality, struggling might generate more, or less, utility.

Fifteen versions of the survey were created, each with five choice pairs ("Would you prefer to ride A or B?"). The first pair in each version was a simple hand-created tradeoff (only two characteristics varying); it was included to get the respondent going and to provide data that would be easily understood by non-statisticians. The other 60 pairs were created as follows: first the set of all combinations of ride attributes, W, was identified, then rides that were either impossible (e.g. vertical feet of climbing but zero climbs) or un-rideable (e.g. too steep) were eliminated, leaving a set of W_f different possible rides. Target parameter values for the trail characteristics are from the 2002 study—companion was not in the 2002 study, so for the design parameters on companion were set to zero. Using the specified conditional indirect utility function, along with this set of parameter values, the likelihood function was constructed, along with the associated covariance matrix. The program *SAS choiceff* was used to identify the 120 pairs that would minimize the variation in the parameter estimates around these initial estimates. These 120 rides were randomly paired until all of the choice pairs probabilities were as close to 50 − 50 as possible. The 60 pairs were then randomly allocated between the 15 versions of 4 pairs, one of the simple pairs was added to each version and each respondent was randomly assigned to a version. The average value of the higher of the two choice probabilities is 56.7% with a s.d. of 6%. The different levels of each characteristic appear with close to equal frequency. The only two trail attributes with substantial correlation (36%) are trail length and length of single track; this is because miles of single track must be less than total miles. We are aware the literature on experimental designs has made substantial progress (Scarpa and Rose, 2008) since our design (2007).

There are usable responses from 4605 mountain bikers. While 87% of the respondents are U.S. residents; residents of 49 countries completed the survey.[8] Respondents took twenty-eight thousand rides in the "last 30 days", and a large proportion of these rides included at least one companion. Most respondents do some biking alone: 22% report they usually ride alone, while another 39% report they often do. The mean age of respondents is 37; 86% are male; 80% make $40K or higher, and 32% make $100K or greater. Sixty-five percent report spending between $26 and $100 dollars on fun stuff per week. Most respondents live with a significant other and live in a household with more than one wage-earner. Respondents average 0.6 kids. That most respondents are serious mountain-bikers is illustrated by their gear, their avidity and their skill levels. On average, respondents rode more than six days in the previous thirty and three and a half hours in the previous week and 59% have participated in at least one race.

3. The Models

We estimated three mixed-mode LC cluster models, one for each dimension of personality: competitiveness, sensation-seeking and extroversion. We use the adjective *cluster* to distinguish these three models from a LC *choice* model, not because they are akin to any non-statistical clustering techniques. The modeling details of the LC cluster model are presented only for the competitiveness model.

3.1. A Mixed-Mode Latent-Class Cluster Model of Competitiveness

On the basis of the answers to four Likert-scale questions about competitiveness, plus the number of times the respondent raced in the last year (see Table 1), a mixed-mode LC "cluster" model is estimated.

Assume the population of N mountain bikers consists of C different competitiveness clusters. Each individual belongs to only one of the C clusters, but from the researcher's perspective individual i's cluster is latent/unobserved. Individuals in different clusters are different, or said in the opposite way, individuals who belong to cluster c are more similar to each other than they are to individuals who do not belong to cluster c. Similarity can be in terms of preferences, constraints, beliefs, production, etc. In this first cluster model, similarity is in terms of competitiveness.

The researcher observes $(\mathbf{x}_i, \mathbf{z}_i)$ for each sampled individual, where both $\mathbf{x}_i$ and $\mathbf{z}_i$ are vectors of random-variables. Each element

[6] The questions on extroversion/introversion are from the Jung-Myers-Briggs inventories, the competitiveness questions are from the "Revised Competitiveness Index (CI-R)" (at http://www.rollins.edu/psychology/houston/research.html) and the sensation-seeking questions are from Hugh Stephens' Sensation-seeking Scale (at http://www.ithaca.edu/faculty/stephens/sss.html). Since creating and implementing our survey, our understanding of personality traits and their measurement has progressed. If we were to do another survey that included measures of personality traits, we would ask many of the same exact questions asked in some of the articles we cite, making our results more comparable.

[7] One can see the survey as the respondents saw it at http://www.colorado.edu/economics/morey/static/index.html.

[8] A static version of the survey with summary statistics can be found at http://www.colorado.edu/economics/morey/static/index.html.

Table 1
Likert-scale questions on competitiveness, sensation-seeking, and extroversion.

How strongly do you agree or disagree with the following statement?[a],[b]		
Pcomp1	Comp1	Competition destroys friendships (1%, 9%, 25%, 32%, 32%)
Pcomp2	Comp2	Games with no clear cut winners or losers are boring (3%, 7%, 15%, 21%, 53%)
Pcomp3	Comp3	I enjoy competing with others (26%, 46%, 15%, 9%, 3%)
Compete	Comp4	Mountain bike rides are an opportunity to compete with others (10%, 32%, 26%, 20%, 12%)
race_ord	Comp5	Number of races done in the last 12 months (1 = never raced, 2 = 1 race, 3 = 2–3 races, 4 = 4–5 races, 5 = 6 or more races) (62%, 8%, 11%, 5%, 14%)
Punpred	Sensation1	Unpredictability is what makes life enjoyable (28%, 49%, 15%, 6%, 1%)
Pfright	Sensation2	I like to do things that are a little frightening (32%, 51%, 10%, 6%, 1%)
Pexplor	Sensation3	I like exploring new trails even if I get lost (48%, 39%, 6%, 5%, 1%)
Pnoplan	Sensation4	I rarely spend much time on the details of planning ahead (9%, 23%, 17%, 35%, 15%)
fast_des	Sensation5	If you had to choose between a fast, smooth descent with little risk of falling or a descent at the limits of your technical ability, which would you choose? (0 = Smooth, fast, and little risk of falling; 1 = at my limit of my ability) (45%, 55%)
lov_speed	Sensation6	To what extent do you agree with the statement "I love to go fast on my mountain bike." (52%, 32%, 10%, 5%)
worry_cr	Sensation7	To what extent do you agree with the statement, "I worry about crashes or injuries." (15%, 43%, 20%, 16%, 6%)
frighte	Sensation8	To what extent do you agree with the statement "Riding alone frightens me." (2%, 14%, 15%, 24%, 44%)
Pfriend	Extroversion1	One only needs a few dependable friends (16%, 35%, 21%, 17%, 11%)
Pgoodf	Extroversion2	I have a wide circle of good friends (22%, 33%, 19%, 20%, 6%)
Pavoid	Extroversion3	I try to avoid arguments and confrontations (23%, 41%, 18%, 14%, 4%)
enj_frie	Extroversion4	Mountain bike rides are an opportunity to be with and enjoy my friends (50%, 31%, 13%, 4%, 1%)
soc_ride	Extroversion5	How often do you socialize off the bike (parties, dinner, talk on the phone, have coffee or drinks, etc.) with your mountain-bike partners? (0 = never;1 = occasionally; every few months; 2 = a moderate amount; 1–2 a month; 3 = quite often, on average 1 a week) (6%, 31%, 31%, 32%)

[a] Each question is scored: 1 = definitely agree, 2 = somewhat,agree, 3 = neither agree nor disagree, 4 = somewhat, disagree, 5 = definitely disagree.
[b] Probabilities of responses to scores are reported in parenthesis.

of $\mathbf{x}_i$ is an *indicator* for individual *i*. Each of the five competitiveness questions in Table 1 indicates an aspect of the individual's competitiveness. $\mathbf{z}_i$, a vector of covariates, is defined below.

We estimate Pr(c), the probability of belonging to cluster c. Indicators can be discrete or continuous and nominal, ordinal, or cardinal. All of the competitiveness indicators (questions) have a finite and small number of response categories, S, so are discrete random-variables, each with five response categories, so $S = 5$. Discrete indicators can vary in terms of the type of mathematical *scale* on which they are measured. Most LC cluster models, but not this one, assume the discrete indicators are all nominal, so ignore the information conveyed by any ordinality or cardinality in any of the indicators.

Let Q, $q = 1, 2, \ldots, Q$ denote the number of indicators, here $Q = 5$ —there are five competitiveness questions. For discrete indicators, one estimates either the probability that an individual in cluster c has

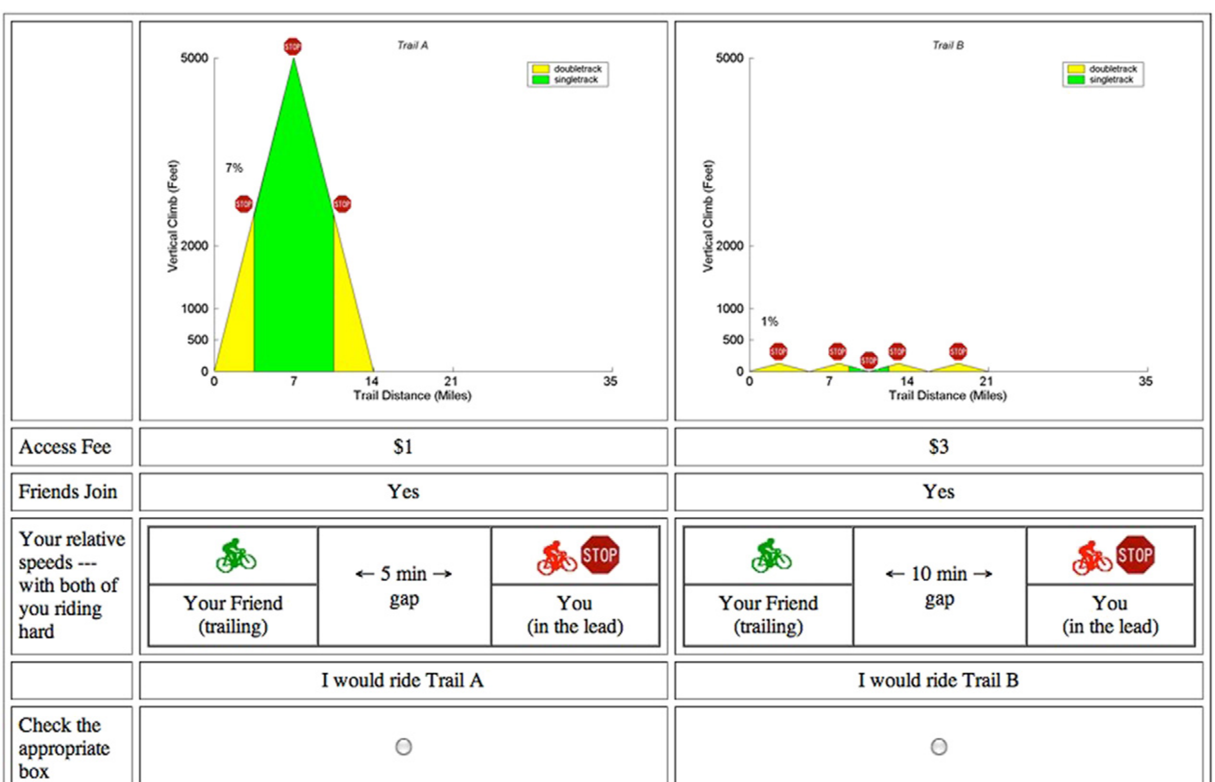

Fig. 1. An example of a choice pair. (the color version is online: the lighter tone (yellow) is doubletrack).

Table 2
Characteristic levels.

Characteristic	Levels
Trail length (miles)	7, 14, 21, 35
Miles of singletrack	0, 3.5, 7, 14, 21, and 35
Vertical ft. of climbing	0, 500, 1000, 2000 and 5000
Number of climbs	0, 1, 2 and 4
Access fee	\$1, \$3, \$5, \$8 and \$20
Time gap (min. behind to ahead)	solo, −10, −5, −2 0 (same ability), +2, +5 and +10

category s for indicator q or, more generally, the probability of each possible response pattern.[9]

Answers to Likert-scale questions have an ordering, e.g., "strongly agree," "somewhat agree," "neither agree nor disagree," "somewhat disagree," and "strongly disagree," so each of these indicators is a discrete, ordinal random-variable.

Indicators can also include measures of how much was produced or whether an action was taken, such as how many times you have raced, making them cardinal indicators. Since our race question allowed only five response categories (never, 1, 2 or 3, 4 or 5, and 6 or more), this indicator is also treated as a discrete, ordinal random-variable.[10]

The vector $\mathbf{z}_i$ is a vector of U *covariates*. A covariate is not a variable on which one wants to group respondents—those are indicators—rather covariates are variables that influence the probability that individual i belongs to cluster c. Like indicators, covariates can be discrete or continuous.

The goal is to specify and estimate the joint density function of $\mathbf{x}_i$, conditional on $\mathbf{z}_i$, $f(\mathbf{x}_i|\mathbf{z}_i)$, with a specification that parsimoniously explains and predicts the number of clusters, how they differ in terms of the levels of the Q indicators and allocates each individual to a specific cluster with high probability as a function of their covariates and indicators. Put simply, the goal is to accurately characterize the discrete variation in competitiveness. One could estimate C but this is not warranted in this application: our goal is to estimate a most and a least competitiveness-cluster to see if behavior can be explained in terms of the two extremes on this dimension of personality, so C is set to 3.

Assume the following, quite general, LC cluster specification (Vermunt and Magidson, 2005)

$$f(\mathbf{x}_i\,|\mathbf{z}_i\,) = \sum_{c=1}^{3}\left[\prod_{h=1}^{H} f(\mathbf{x}_{hi}\,|c\,)\Pr(c\,|\mathbf{z}_i\,)\right] \quad (1)$$

where $\Pr(c|\mathbf{z}_i)$ is the probability individual i belongs to cluster c conditional on their covariates. Eq. (1) separates the Q indicators into H mutually distinct subsets, where the vector $\mathbf{x}_{hi}$ denotes the observed levels of the indicators in set h. Conditional on c, indicators in set h are assumed statistically independent of indicators in the other sets, but the indicators in h are allowed to be mutually dependent. $f(\mathbf{x}_{hi}|c)$ denotes the joint density for the $\mathbf{x}_{hi}$, conditional on cluster. Eq. (1) is called a *mixed-mode LC cluster model* because it allows for a mixture of indicators with different scales (Everitt, 1988; Moustaki, 1996; Moustaki and Papageorgiou, 2004; Vermunt and Magidson, 2002).

Here, we are not interested in explaining why an individual has the personality he has, so have no need for covariates, so Eq. (1) simplifies to

$$f(\mathbf{x}_i) = \sum_{c=1}^{C}\left[\prod_{h=1}^{H} f(\mathbf{x}_{hi}\,|c\,)\Pr(c)\right] \quad (2)$$

The $\Pr(c)$ are parameters to estimate subject to the restrictions $0 \le Pr(c) \le 1$ and $\sum_{c=1}^{3}\Pr(c) = 1$.

In contrast to the above model, the standard and basic, LC cluster model assumes once you condition on cluster all of the indicators are statistically independent; so Eq. (2) is replaced by its special case, $f(\mathbf{x}_i) = \sum_{c=1}^{C}\left[\prod_{q=1}^{Q} f(x_{qi}\,|c\,)\Pr(c)\right]$, where x_{qi} is a scalar, and has its own independent density. Restrictively assuming that, conditional on cluster, each indicator is independent is a strong, and typically questionable, assumption. Consider the Likert-scale statement "I enjoy competing" and the question "Number of races done in the last year". It is reasonable to expect the answers to these two questions would remain correlated (and, looking ahead to the estimates, they remain, as expected, correlated). Assuming indicators are independent when they are not produces inconsistent parameter estimates.

If all the indicators are discrete, independent random-variables that can only take a finite, and small, number of **nominal** values, $f(x_{qi}|c)$ is simply the probability of observing x_{qi} conditional on belonging to cluster c; that is, if $x_{qi} = s$ (individual i choose response s to question q), $f(x_{qi}|c)$ becomes $\pi_{sq}|c$, a number rather than a function, where $\pi_{sq}|c$ is the probability an individual chooses level s of indicator q, conditional on being a member of cluster c. All indicators that take only one of a small number of values can be parameterized as multinomial distributed in that the multinomial admits nominal indicators and can admit, when appropriate, ordinal indicators and dependencies amongst indicators.

Turning to the $\pi_{sq}|c$, consider **first** the case of local independence, and only *nominal* indicator categories. In which case each $\pi_{sq}|c$ is a multinomial where the response probability—the probability of indicator q taking category s for individual i, conditional on belonging to cluster c is

$$\pi_{sq}\,|c\, = \frac{e^{R_{sq|c}}}{\sum_{s'=1}^{S_q} e^{R_{s'q|c}}} \quad (3)$$

where S_q is the number of response categories for indicator q. $R_{sq|c}$ can be viewed as the *relevance* of response category s for indicator q for an individual in cluster c: response categories that are more *relevant* are more likely to be selected. $R_{sq|c}$ has two parameters:

$$R_{sq|c}\, = \mu_{sq} + \alpha_{sq|c} \quad (4)$$

The first parameter, μ_{sq}, is independent of cluster; the second shifts with cluster, $\alpha_{sq|c}$. (If, for example, indicator 1 has five categories and there are three clusters, there are five μ_{s1} parameters and fifteen $\alpha_{s1|c}$ parameters.)

If the response categories of indicator q have a natural ordering—are *ordinal*—as are ours

$$\alpha_{sq|c}\, = (ord_{sq})\alpha_{q|c} \quad (5)$$

where ord_{sq} is a specified numerical value used to represent response category s for indicator q; ord_{sq} is restricted to be increasing in s. We assume response categories are represented with 1 for "definitely agree" and 5 for "definitely disagree" with unit differences; ord_{sq} for "neither agree nor disagree" is 3 for all q. So, $\alpha_{1q|c}\, = 1 \times \alpha_{q|c}$, $\alpha_{2q|c} = 2 \times \alpha_{q|c}\,, \ldots, \alpha_{5q|c} = 5 \times \alpha_{q|c}$.

[9] For jointly-distributed continuous indicators, one estimates the parameters in their joint-density function.
[10] In contrast, for an indicator such as the cost of your mountain bike, you might reasonably assume cost is normally distributed.

This ordinality restriction is called the *adjacent-category* restriction or the *adjacent-category ordinal logit model* (Agresti, 2002; Agresti et al., 2000; Goodman, 1979; Vermunt and Magidson, 2005). Its use is, unfortunately, non-existent in recreational choice and environmental valuation. The restriction is appropriate and useful if you believe there is an underlying continuous variable with the discrete response moving up (or down) the scale as the continuous variable passes successive thresholds, as is the case with our five indicators, where s increases as it passes decreasing thresholds of agreeableness. This specification correctly reduces the number of parameters that need to be estimated. This adjacent-category restriction needs to be carefully interpreted.[11]

3.1.1. Relaxing Local Independence With Ordinal Random-Variables

For sets of indicators that are dependent—after conditioning on cluster—the multinomial can be generalized, Eqs. (3), (4) and (5) to accommodate this (Hagenaars, 1988; Qu et al., 1996). Vermunt and Magidson (2005) do this by specifying mutually distinct subsets of indicators and estimating the relevance of every possible combination of responses to the indicators in each subset. For example, if the first two indicators ($q = 1,2$) are discrete, as in this case, and you suspect they are statistically dependent, but independent of all the other indicators, and if $S_1 = 5$ and $S_2 = 5$, there are 25 different response combinations for these two discrete random-variables. The joint density of $(x_{1i}, x_{2i}|c)$, the two-indicator subset,is a multinomial with 25 alternatives. For this example, let $R_{s'1s''2s|c}$ denote the joint relevance of response category s' to indicator 1 and response category s'' to indicator 2, conditional on belonging to cluster c . $R_{s'1s''2|c}$ can be parameterized as

$$R_{s'1s''2|c} = (\mu_{s'1} + \alpha_{s'1|c}) + (\mu_{s''2} + \alpha_{s''2|c}) + \gamma_{(s'1)(s''2)}$$
$$s' = 1,2,..,5 \quad s'' = 1,2,..,5 \tag{6}$$

where the parameter $\gamma_{(s'1)(s''2)}$ is picking up the dependence of a response of category s'' to indicator 2 on response category s' to indicator 1. (For example and looking ahead, the parameter $\gamma_{(51)(32)}$ would indicate the dependence of a category 3 response to indicator 2 on a category 5 response to indicator 1.) Given $S_1 = 5$ and $S_2 = 5$ there are ten $\gamma_{(s'1)(s''2)}$. (Note $\gamma_{s'1s''2} = \gamma_{s''2s'1}$). More generally, let $\mathbf{s}_{q\in h}$ be a specific vector of responses to the indicators in set h.[12] The joint relevance of this vector of responses to the indicators in set h is

$$R_{\mathbf{s}_{\mathbf{q}\in h}|c} = \sum_{q\in h,}\sum_{s\in\mathbf{s}_{\mathbf{q}\in h}} [\mu_{sq} + \alpha_{sq|c}] + \sum_{\substack{q,q'\in h\\ q<q'}}\sum_{\substack{s,s'\in\mathbf{s}_{\mathbf{q}\in h}\\ s<s'}} \gamma_{(sq)(s'q')} \tag{7}$$

The $\gamma_{(sq)(s'q')}$ parameters capture the local dependence between response s to indicator q and response s' to indicator q'. If the $\gamma_{(sq)(s'q')}$ are all zero, all of the indicators in h are locally independent and $R_{\mathbf{s}_h|c} = \sum_{q\in h}\sum_{s\in\mathbf{s}_h} [\mu_{sq} + \alpha_{sq|c}] = \sum_{q\in h} R_{qs|c}$. Our personal experience is that if multiple indicators measure similar constructs, one often rejects the null hypothesis of local independence. And, imposing independence often leads the researcher to choose too many clusters (Vermunt and Magidson, 2005).

[11] Relevance need not be monotonic, but as $\alpha_{q|c}$ increases in absolute value, it becomes more likely that relevance will be monotonic (either increasing or decreasing) in s for that cluster.

[12] For example, if there are three indicators in h, one $\mathbf{s}_h$ is $\mathbf{s}_h \equiv (2,4,1,)$ indicating a category 2 response for indicator 1, a category 4 response of indicator 2, and a category 1 response for indicator 3.

Since, in our competitiveness cluster model, all the indicators are discrete and **ordinal**, $\alpha_{sq|c}$ and $\gamma_{(sq)(s'q')}$ in Eq. (7) are parameterized as

$$\alpha_{sq|c} = (ord_{sq})\alpha_{q|c} \tag{8}$$

and

$$\gamma_{(sq)(s'q')} = \gamma_{qq'}(ord_{sq})(ord_{s'q'}) \tag{9}$$

The ln-likelihood function is then

$$\ln L = \sum_{i=1}^{N=4605} \ln\left[\sum_{c=1}^{3}\left[\prod_{h=1}^{H} f(\mathbf{x}_{hi}\,|c\,)\Pr(c)\right]\right]$$
$$= \sum_{i=1}^{N=4605} \ln\left[\sum_{c=1}^{3}\left[\Pr(c)\prod_{h=1}^{H}(\pi_{\mathbf{s}_{h_i}}\,|c\,)\right]\right] \tag{10}$$

where $\pi_{\mathbf{s}_{h_i}}|c$ is the probability, conditional on c, of observing the individual's response pattern to the indicators in set h. The maximum-likelihood parameters are obtained by maximizing ln$L$ with respect to the parameters: the three $P(c)$, the twenty-five μ_{sq} (one for each of the five response levels for each of the five indicators), the fifteen $\alpha_{q|c}$(one for each indicator for each of the three clusters), and a $\gamma_{qq'}$ for each pair of indicators (questions) assumed dependent. Estimation is with the statistical software Latent Gold (Vermunt and Magidson, 2005).

We chose which indicators to assume dependent (which $\gamma_{(sq)(s'q')}$ to not restrict to zero) based on how much the ln-likelihood function would increase if a pair-wise dependency is allowed. Since all of our indicators are assumed ordinal, adding an additional pair-wise dependency adds a single parameter, $\gamma_{qq'}$. The final model includes a specific dependency parameter only if its inclusion significantly increased, based on a likelihood-ratio test, the explanatory power of the model.

The estimated competitiveness LC cluster model is reported in the results section. There is no need here to present the LC cluster models of sensations seeking or extroversion/introversion: the theory is the same as for the competitiveness model.

3.2. A Latent-Class Model of Ride Choice With Competitiveness, Sensation-Seeking and Extroversion Covariates

3.2.1. The Ride Choice

Unlike the estimated LC cluster models, this model is quite standard. Assume rider i's utility if they do ride j and belong to behavioral class c_b is

$$U_{ij|c_b} = V_{ij|c_b} + \varepsilon_{ij|c_b} \tag{11}$$

where $\varepsilon_{ij|c_b}$ is a draw from an Extreme-value distribution. The term *ride* denotes a trail/companion combination. The notation $|c_b$ denotes conditional on belonging to behavioral class c_b. We assume three classes, $c_b = 1,2,3$.[13] The probability of rider i choosing ride A given they belong to c_b and given the choice pair A, B is, therefore

$$P_{iA|c_b} = \frac{e^{V_{iA|c_b}}}{e^{V_{iA|c_b}} + e^{V_{iB|c_b}}} \tag{12}$$

[13] Models with additional behavioral classes were estimated but did not add in terms of significance or interest.

This model, being a standard LC choice model, restrictively assumes $i's$ choices are independent after conditioning on class.

The deterministic component of utility, $V_{ij|c_b}$, is assumed a function of the following trail and companion characteristics:

$trail_j =$ miles of trail on ride j, $single_j$ = fraction of the trail that is singletrack, $grade_j$ = average grade on the climbs (expressed as a %), and $climbs_j$ = number of climbs.

$expend_i =$ weekly expenditures by rider i on entertainment (in \$) and fee_j = fee charged (in \$).

$D_{li} = 1$ if i spends on himself for entertainment less than \$25 a week, and zero otherwise. $D_{mi} = 1$ if i spends on himself for entertainment between \$25 and \$100 a week and zero otherwise. And $D_{hi} = 1$ if i spends on himself for entertainment more than \$100 a week and zero otherwise.

$solo_j = 1$ if i is alone on ride j and zero otherwise; $backX_j = 1$, if there is a companion and at normal effort levels i would be X minutes behind at each wait point, zero otherwise (X is 10, 5, or 2); and $frontX_j = 1$, if there is a companion and at normal effort levels i would be X minutes ahead at each wait point, zero otherwise.

The intent is to estimate and predict ride choice, by behavioral class. Specifically assume

$$\begin{aligned} V_{ij}|c_b = &(\beta_{el|c_b} D_{li} + \beta_{em|c_b} D_{mi} + \beta_{eh|c_b} D_{hi})(expend_i - fee_j) \\ &+ \beta_{s|c_b}(single_j) + \beta_{t|c_b}(trail_j) + \beta_{c|c_b}(climbs_j) + \beta_{g|c_b}(grade_j) \\ &+ \beta_{solo|c_b}(solo_j) \\ &+ \beta_{b10|c_b}(back10_j) + \beta_{b5|c_b}(back5_j) + \beta_{b2|c_b}(back2_j) \\ &+ \beta_{f2|c_b}(front2_j) + \beta_{f5|c_b}(front5_j) + \beta_{f10|c_b}(front10_j) \end{aligned} \quad (13)$$

with the restriction $climbs_j = 0 \Longleftrightarrow grade_j = 0$.

The first line of Eq. (13) is the utility rider i gets from non-biking entertainment, conditional on choosing ride j and belonging to c_b. It depends on the rider's budget for entertainment minus the fee for ride j, and the rider's marginal utility from expenditures on entertainment. $\beta_{el|c_b}$ is, for example, the marginal utility of expenditures for those who spend less than \$25 a week and belong to c_b (the subscripts l, m and h denote low, medium and high budgets for entertainment). There are step-income effects, a simple way to incorporate the common observation that willingness-to-pay is a function of available income. Income effects are allowed to vary by class.

The next line in Eq. (13) represents, conditional on class, the baseline utility from the site's characteristics, independent of whether the rider has a companion. The last three lines determine how the utility of the ride is affected by the presence of a companion and the companion's ability. If one is riding alone ($solo_j = 1$ implying $frontX_j = backX_j = 0\ \forall\ X$), the expected utility from the ride shifts from the baseline by $\beta_{solo|c_b}$. If the rider has a companion ($solo_j = 0$), and utility shifts from the baseline by

$$\begin{aligned} V_{companion_{j|c_b}} = &\beta_{b10|c_b}(back10_j) + \beta_{b5|c_b}(back5_j) + \beta_{b2|c_b}(back2_j) \\ &+ \beta_{f2|c_b}(front2_j) + \beta_{f5|c_b}(front5_j) + \beta_{f10|c_b}(front10_j) \end{aligned} \quad (14)$$

This expression is zero if the companion is of your ability ($frontX_j = backX_j = 0\ \forall\ X$), the default. So, if a companion of your ability is preferred to riding alone $\beta_{solo|c_b} < 0$; if a companion of your ability is preferred to a companion of a different ability, $V_{companion_{j|c_b}} < 0$. The specification allows for companion effects to vary by class.

3.2.2. The Personality Covariates

Now consider the three dimensions of personality as possible probabilistic determinants of the class memberships. Let $HComp_i = 1$ (zero otherwise) if the rider's probability of being in the highly competitiveness cluster2 is ≥80% given their answers to the five competitiveness questions. In contrast, rider i is non-competitive ($NComp_i = 1$) if their probability of being in the non-competitive cluster3 is ≥80%). Using the 80% cutoff, if rider i is sensation-seeking, $SensSeek_i = 1$ (zero otherwise) and if the rider is cautious, $Caus_i = 1$. If rider i is an extrovert, $Extro_i = 1$ (zero otherwise) and if the rider is an introvert, $Introv_i = 1$.

Denote the probability rider i belongs to c_b given their likely personality,

$$\begin{aligned} &\Pr(c_b{:}\ HComp_i, NComp_i, SensSeek_i, Caus_i, Introv_i, Extrov_i) \\ &= \exp(\varphi_{c_b} + \lambda_{HC|c_b} HComp_i + \lambda_{NC|c_b} NComp_i + \lambda_{SS|c_b} SensSeek_i \\ &\quad + \lambda_{CS|c_b} Caus_i + \lambda_{I|c_b} Introv_i + \lambda_{E|c_b} Extrov_i) \\ &\quad \div \sum_{n=1}^{3} [\exp(\varphi_{c_n} + \lambda_{HC|c_n} HComp_i + \lambda_{NC|c_n} NComp_i \\ &\quad + \lambda_{SS|c_n} SensSeek_i + \lambda_{CS|c_n} Caus_i \\ &\quad + \lambda_{I|c_n} Introv_i + \lambda_{E|c_n} Extrov_i)] \end{aligned} \quad (15)$$

where n in the denominator indexes the three behavioral classes. In words, the rider's personality traits enter into the choice model as covariates that influences the rider's class-membership probabilities.

The ln-likelihood function for choices of the A/B alternatives is

$$\begin{aligned} \ln L = &\sum_{i=1}^{4583} \sum_{k=1}^{m_i} \sum_{c_b = 1}^{3} \Pr(c_b{:}\ HComp_i, \ldots, Extrov_i) \\ &* \left[s_{iA_k}(\ln P_{iA_k|c_b}) + (1 - s_{iA_k})(1 - \ln P_{iA_k|c_b}) \right] \end{aligned} \quad (16)$$

where m_i is the number of choice pairs answered by rider i ($m_i \le 5$), and $s_{iA_k} = 1$ if rider i selects alternative A in pair k and zero otherwise. 22,685 choice pairs were answered. The maximum likelihood $\boldsymbol{\beta}$ (Eq. (13)) and $\boldsymbol{\lambda}$ (Eq. (15)) estimates are those that maximize Eq. (16).

4. Results and Discussion

We first describe results from the three estimated mixed-mode cluster models, followed by those of the ride choice model.

4.1. The Estimated Mixed-Mode LC Cluster Model of Competitiveness

Based on *p-values*, all of the estimated parameters are significant. For those parameters that vary by cluster, the $\alpha_{q|c}$, they differ significantly by cluster. The predicted membership probabilities for the three competitiveness clusters are 62%, 20% and 18% (Table 3).

In terms of estimated dependencies, five of the $\gamma_{qq'}$ dependence parameters are significantly different from zero: $\gamma_{15} > 0$, $\gamma_{25} < 0$, $\gamma_{35} < 0$, $\gamma_{45} < 0$ and $\gamma_{12} > 0$ (specific values by request). They indicate that the first four competitive questions ($q = 1, 2, 3, 4$) are each correlated with how often the rider raced in the last 12 months ($q = 5$), and, in addition, the first two competitiveness questions are correlated. So, since the other four indicators are each correlated with indicator 5, all of the indicators are jointly dependent (there is only one h and all five indicators are in this set). So $\prod_{h=1}^{H} f(\mathbf{x}_{hi}|c) = f(\mathbf{x}_i|c) = f(x_{1i}, x_{2i}, x_{3i}, x_{4i}, x_{5i}|c)$, and the null hypothesis that the levels of the indicators are independent after conditioning on cluster is completely rejected.

In words, the combined answers to 5, 2, 3 and 4 have decreased relevance (compared to assuming them independent). For example, the answers to the statement, "I enjoy competing with others" and the "Number of races in the last twelve months" do not have as much

Table 3
Latent-class cluster model of competitiveness.

Estimated probabilities for each level of each question, by cluster[a]			
	Comp CL1	Comp CL2	Comp CL3
		Highly competitive	Not competitive
Cluster size	62%	20%	18%
Competition			
Comp1	"Competition destroys friendship"		
1[b]	1%	0%	4%
2	8%	0%	21%
3	28%	5%	40%
4	37%	25%	26%
5	27%	69%	9%
Mean	3.81	4.63	3.16
Comp2	"'Games with no winners …boring"		
1	3%	6%	0%
2	7%	11%	2%
3	15%	20%	7%
4	22%	22%	17%
5	52%	41%	73%
Mean	4.13	3.80	4.61
Comp3	"I enjoy competing with others"		
1	17%	76%	3%
2	59%	23%	29%
3	17%	1%	26%
4	6%	0%	29%
5	1%	0%	13%
Mean	2.15	1.24	3.20
Comp4	"rides …opportunity to compete …"		
1	5%	33%	0%
2	33%	53%	4%
3	33%	12%	15%
4	22%	2%	35%
5	7%	0%	45%
Mean	2.93	1.84	4.21
Comp5			
Never raced	64%	52%	69%
1 race	8%	8%	7%
2–3 races	10%	13%	9%
4–5 races	5%	7%	4%
6 or more	13%	20%	11%
Mean	0.96	1.35	0.82

[a] For each class, for each question, response categories sum to one.
[b] 1 = Definitely agree, 2 = somewhat agree, 3 = neither agree nor disagree, 4 = somewhat disagree, 5 = definitely disagree.

combined relevance as they would if the questions were independent, and this decrease in relevance increases the more you have raced and the less you agree with "I enjoy competing with others." Since $\gamma_{12} > 0$, the more you disagree with "Competition destroys friendships" and the more you disagree with "Games with no clear cut winners or losers are boring," the more relevant are these two questions in determining the composition of your clusters. The answers to questions 1 and 5 also have increased relevance the more you race and the less you agree with "Competition destroys friendships".

The main (the μ_{sq} and the $\alpha_{q|c}$) are difficult to directly interpret, so we turn to the estimated $\pi_{sq}|c$, the probability a rider chooses response category s to question q, conditional on being a member of cluster c (Table 3). Before examining the estimated $\pi_{sq}|c$, it is reasonable to ask what was gained by allowing the responses to the competitiveness questions to be post-conditioning dependent. Three things were gained: the model with dependence statistically dominates the model with independence, the estimated $\pi_{sq}|c$ are quite different if independence is incorrectly assumed, and we have a map of the correlations.

Starting with the average response-levels by cluster for each indicator, the means in Table 3, competitiveness cluster2 is the highly competitive cluster and cluster3 the not competitive. In explanation, cluster2 is: i) least likely to agree that "Competition destroys friendships" (cluster3 most likely); ii) most likely to agree that "Games with no clear cut winners or losers are boring" (cluster3 the least likely); iii) most likely to agree that "Competing is enjoyable" (cluster3 least likely); iv) more likely to agree that "Mountain bike rides are an opportunity to compete with others" (cluster3 least likely); v) more likely to race (cluster3 least likely). As expected, the majority of respondents are in cluster1 (62%), not extreme in terms of competitiveness.

That cluster2 is the cluster of highly competitive bikers is also apparent from the estimated $\pi_{sq}|c$ in Table 3. For example, the estimated probability a rider in cluster2 answers "completely disagree" that "Competition destroys friendships" is 69%, for those in cluster3 it is only 9% (most in cluster3 thought competitive has a negative effect on friendships). The estimated probability a rider is in cluster c given that they chose response s to indicator q, $\pi_{c|sq}$, also demonstrate that cluster2 is the competitive cluster and cluster3 is the least competitive cluster. For example, the probability of being in cluster2 given you "definitely agree" with "Rides… opportunity to compete…" is 76% whereas for cluster3 it is 3%. The probability rider i is in cluster c conditional on their answers the competitiveness questions, $\Pr(c : \mathbf{x}_i)$, assigns most individuals to a competitiveness cluster with high certainty.

4.2. The Estimated Mixed-Mode LC Cluster Model of Sensation-Seeking

There are eight Likert-scale questions about sensation-seeking—see Table 1. Three clusters are assumed. Based on *p-values*, all of the parameters are significant. And for those parameters that vary by cluster, the $\alpha_{q|c}$, they differ significantly by cluster. The estimated cluster-membership probabilities for the three sensation clusters are 58%, 28% and 14% (Table 4). Most riders are assigned with high certainty to a cluster.

Five of the $\gamma_{qq'}$ parameters, the correlation parameters, are significantly different from zero: $\gamma_{16} < 0$, $\gamma_{56} < 0$, $\gamma_{57} > 0$, $\gamma_{38} < 0$ and $\gamma_{78} > 0$. So, for this aspect of personality,

$$\prod_{h=1}^{3} f(\mathbf{x}_{hi}\,|c) = f_2(x_{2i}\,|c)f_4(x_{4i}\,|c)f(x_{1i},x_{3i},x_{5i},x_{6i},x_{7i},x_{8i}\,|c)$$

So, there are three independent subsets of sensation-seeking indicators "Liking to do things that are a little frightening" –Indicator 1– and "I rarely spend much time on the details of planning ahead" -Indicator 4- are both independent of all of the other indicators; Indicators 1, 3 plus 5–8 form a third correlated subset. Within $f(x_{1i},x_{3i},x_{5i},x_{6i},x_{7i},x_{8i}|c)$, the joint responses to questions 1, 3, 5, 6 and 8 have less relevance in determining the cluster-membership probabilities than they would if the answers to these questions were all independent, and the joint responses to questions 5, 7 and 8 have more relevance: only questions 5, 7 and 8 ask specifically about bad things that might happen on a ride. As in the case of competitiveness, the model with dependences dominates a model that imposes independence, and the estimated $\pi_{sq}|c$ are numerically quite different.

The estimated $\pi_{sq}|c$ are reported in Table 4 along with the average response-levels implied by these estimated probabilities. The mean response levels in Table 4 demonstrate that, relatively speaking, cluster2 are sensation seekers and cluster3 are cautious. In explanation, cluster2 is most likely: i) to agree that "Unpredictability is what makes life enjoyable" (cluster3 least likely); ii) to agree that "I like to do things that are a little frightening"(cluster3 is least likely); iii) to agree that "I like exploring new trails even if I get lost" (cluster3 least likely); iv) to agree that "I rarely spend much time on the details of planning ahead" (cluster3 least likely); v) to choose a "Descent at the limits of your technical ability"(cluster3 a "Fast, smooth descent with little risk of falling"); vi) to agree with "I love to go fast…" (cluster3

Table 4
Latent-class cluster model of sensation-seeking.

Estimated probabilities for each level of each question, by cluster[a]

	Sensation CL1	Sensation CL2 Sensation-seekers	Sensation CL3 Cautious
Cluster size	58%	28%	14%
Sensation			
Sensation1	Unpredictability …life enjoy.		
1[b]	14%	70%	2%
2	63%	29%	33%
3	18%	1%	31%
4	5%	0%	27%
5	0%	0%	6%
Mean	2.14	1.30	3.03
Sensation2	I like…frightening		
1	11%	90%	0%
2	77%	10%	27%
3	10%	0%	28%
4	2%	0%	36%
5	0%	0%	9%
Mean	2.03	1.10	3.26
Sensation3	I like…even if I get lost		
1	38%	88%	11%
2	52%	12%	42%
3	7%	0%	17%
4	3%	0%	22%
5	0%	0%	9%
Mean	1.77	1.12	2.75
Sensation4	I rarely time planning …		
1	8%	15%	4%
2	22%	30%	14%
3	18%	18%	15%
4	37%	28%	42%
5	16%	9%	25%
Mean	3.30	2.87	3.71
Sensation5	smooth descent…or at limits…		
0	49%	23%	76%
1	51%	77%	24%
Mean	0.51	0.77	0.24
Sensation6	I love to go fast…		
1	48%	74%	24%
2	36%	23%	35%
3	11%	3%	21%
4	4%	0%	15%
5	1%	0%	5%
Mean	1.74	1.30	2.43
Sensation7	I worry about crashes or injuries		
1	16%	9%	26%
2	45%	36%	50%
3	20%	22%	15%
4	15%	23%	7%
5	5%	10%	2%
Mean	2.47	2.88	2.08
Sensation8	Riding alone frightens me		
1	3%	1%	4%
2	15%	9%	19%
3	16%	13%	18%
4	24%	24%	24%
5	42%	52%	36%
Mean	3.89	4.17	3.68

[a] For each class, for each question, response categories sum to one.
[b] 1 = Definitely agree, 2 = somewhat agree, 3 = neither agree nor disagree, 4 = somewhat disagree, 5 = definitely disagree.

least likely); and vii) least likely to "Worry about crashes or injuries"(cluster3 most likely): members of cluster2 are riding in a way that makes crashes more likely and they like it that way.

Table 5
Latent-class cluster model of extroversion/introversion.

Estimated probabilities for each level of each question, by cluster[a]

	Extrov CL1	Extrov CL2 Extraverts	Extrov CL3 Introverts
Cluster size	76%	14%	11%
Extroversion			
Extroversion1	"One only needs a few …friends"		
1[b]	14%	0%	58%
2	40%	3%	36%
3	25%	11%	5%
4	16%	35%	1%
5	5%	51%	0%
Mean	2.59	4.33	1.48
Extroversion2	"I have a wide circle of …friends"		
1	15%	78%	1%
2	39%	21%	8%
3	22%	1%	15%
4	20%	0%	48%
5	4%	0%	28%
Mean	2.59	1.24	3.94
Extroversion3	"I try to avoid arguments and …"		
1	22%	25%	30%
2	40%	42%	43%
3	19%	18%	16%
4	15%	13%	10%
5	4%	3%	2%
Mean	2.40	2.28	2.12
Extroversion4	"…rides …opp. enjoy …friends"		
1	49%	73%	26%
2	33%	22%	33%
3	13%	4%	24%
4	3%	0%	11%
5	1%	0%	5%
Mean	1.74	1.32	2.37
Extroversion5	"How often do you socialize off the bike"		
Never	6%	2%	10%
Occasionally	32%	21%	40%
Moderately	31%	32%	28%
Quite often	31%	45%	22%
Mean	1.88	2.20	1.61

[a] For each class, for each question, response categories sum to one.
[b] 1 = Definitely agree, 2 = somewhat agree, 3 = neither agree nor disagree, 4 = somewhat disagree, 5 = definitely disagree.

4.3. The Estimated Mixed-Mode LC Cluster Model of Extroversion/Introversion

There are five questions about extroversion: four Likert-scale questions, plus "How often do you socialize off the bike." Seven of the $\gamma_{qq'}$ parameters are significantly different from zero: γ_{14}, γ_{15}, γ_{23}, γ_{34}, $\gamma_{35} > 0$ and γ_{25}, $\gamma_{45} < 0$; so, like in the competition model, all of the indicators are jointly dependent (there is one h and all five indicators are in this set). The estimated $\pi_{sq}|c$ are reported in Table 5, along with the average response-levels implied by these estimated probabilities.

Starting with mean response levels for cluster and indicator (Table 5), relatively speaking, cluster2 are extroverted and cluster3 are introverted. In explanation, cluster2 is: i) least likely to agree with "One only needs a few dependable friends" (cluster3 most likely); ii) most likely to agree with "I have a wide circle of good friends" (cluster3 least likely); iii) more likely to disagree with "I try to avoid arguments and confrontations" than is cluster3; iv) most likely to agree that "Rides are an opportunity to enjoy friends" (cluster3 least likely); v) most likely to socialize off the bike (cluster3 least likely). Most riders are assigned with high certainty to an extroversion/introversion cluster.

4.4. The Ride Choice-Model Estimates

Parameter estimates for the final estimated choice model are reported in Table 6. The coefficient for the covariate $Extrov_i$ was not

Table 6
Parameter estimates for the behavioral ride-choice model.

Variables	Behavioral classes				
	$Class_b1$	$Class_b2$	$Class_b3$	*p*-Value	p-diff
Attributes					
low expenditure	−0.38	−0.08	−0.11	0.000	0.000
medium expenditure	−0.30	−0.06	−0.12	0.000	0.000
high expenditure	−0.29	−0.04	−0.20	0.000	0.000
single	0.02	0.01	0.03	0.000	0.002
trail	0.14	0.00	0.01	0.000	0.000
climbs	0.36	0.19	0.01	0.000	0.001
grade	16.28	−1.45	286.26	0.000	0.000
solo	−1.32	−1.32	−0.85	0.000	0.037
back10	−1.30	−0.77	−0.07	0.000	0.001
back5	−0.61	−0.53	−0.09	0.000	0.270
back2	−0.33	−0.55	0.95	0.000	0.000
front2	−1.37	−0.45	0.93	0.000	0.000
front5	−0.11	−0.66	0.01	0.000	0.003
front10	−1.32	−0.94	0.20	0.000	0.000
Intercept	0.00	0.83	−0.68	0.000	
Covariates					
Most competitive	0.00	−0.23	0.20	0.068	
Not competitive	0.00	0.12	−0.85	0.028	
Introverted	0.00	−1.28	−0.06	0.001	
Sensation-seekers	0.00	−0.31	0.30	0.000	
Cautious	0.00	0.59	0.01	0.030	
Class membership probabilities	27%	58%	15%		
Log-likelihood	−13,527.1				

significant, so $\lambda_{E|c_b}$ was set to zero–this separates us from the studies that found extroversion to be a significant determinant of exercise and recreational activity. The β parameters on *solo* for behavioral classes 1 and 2 were constrained to be equal, as the null hypothesis of equality could not be rejected.

Based on a likelihood-ratio test, the choice model with the five significant personality covariates statistically dominates the choice model without these covariates. Based on the estimated *p-values*, all the specified explanatory variables are significant determinants of the choice pairs and their influence varies significantly by class. Overall $R^2$is 0.37(.51 for $Class_b1$, 0.12 for $Class_b2$ and 0.67 for $Class_b3$).

Instead of discussing specific β parameters, which are difficult to interpret independently of the other β parameters, we describe the results in terms of summary statistics: estimated probabilities, odd-ratios, and per-ride WTP estimates. The unconditional behavioral class-membership probabilities are 27%, 58% and 15%, respectively. WTP for another unit of each site characteristic varies by behavioral-class and by the individual's weekly level of expenditures on entertainment (low, medium and high). For example, for those with low expenditures, estimated WTP for an additional climb is 97 cents ($Class_b1$), $2.32 ($Class_b2$) and 6 cents ($Class_b3$). For the high expenditure group the comparable estimates are $1.26. $4.96 and 3 cents, indicating substantial income and class effects.[14] The contrasting estimates for an additional mile of trail are, by class, 38 cents, 4 cents and 12 cents for low-expenditure individuals; for those with high expenditures they are 49, 8 and 6 cents. Everyone prefers an additional climb to an additional mile, but how much in dollars varies greatly. One sees similar differences in terms of the choice probabilities.

Table 7 reports the probability of choosing, *ceteris paribus*, each level of each ride attribute; for example the probability of choosing a 35 mile trail is 83% for $Class_b1$, 26% for $Class_b2$, and 30% for $Class_b3$ (each column sums to one). Fig. 2 shows how utility shifts depending on your companion's relative ability. Negative bars indicate the alternative is inferior to the same ability; positive bars indicate preferred. For all three classes, riding with someone of your own ability is preferred to riding alone ($solo = 1$).

Summarizing summarizing the effect on ride choice of trail attributes and companion's ability (Tables 6 and 7), one sees that members of $Class_b3$ want rides that are anaerobically challenging, technically exciting, and where they are challenged by a rider whose ability is close to theirs, but, ideally, not equal—they want to be challenged. You see the same thing if preferences are expressed in terms of money. Table 8 reports per-ride WTP for riding with a companion of your own ability rather than a companion who is 2 min. faster; of note is that they are much larger, in absolute value, than the WTP estimates for marginal changes in site characteristics. Members of the first two classes would pay would pay between $3.62 and $13.81 for a companion of their own ability rather than 2 min. faster, but members of $Class_b3$ would have to be compensated between $4.69 and $8.62 to accept this switch. And, more of $Class_b3$ would prefer to ride alone (challenging themselves) than to ride with someone who is substantially faster or slower (they don't want to ride with the doped Lance, or with grandma). Members of $Class_b1$ want to ride with someone of their own ability on a long and endurance-challenging ride. Members of $Class_b2$, the largest class, have more uniform preferences over trail characters, want a companion and the closer their companion is to their ability, the better.

4.4.1. The Influence of Each Personality Trait on Class Membership

Table 9 reports the class-memberships probabilities as a function of each personality type (set of three personality traits). Recollect that the class-membership probabilities with no personality information are 27%, 58% and 15%, respectively. Knowing a rider's personality type allows the researcher to more accurately identify the rider's most-likely behavioral class. For example, whereas 15% of respondents are in $Class_b3$, mountain bikers who are non-competitive, cautious and not introverted have only a 4% probability of being in $Class_b3$. Whereas mountain bikers who are highly competitive, sensation seekers and introverts have a 36% probability of

[14] Marginal utility of expenditures decreases for $Class_b1$ and 2, but increases for $Class_b3$ which is why for $Class_b3$ WTP per-trip declines in absolute terms as weekly expenditures on entertainment increases.

Table 7
Estimated probability of choosing each level of each attribute, by behavioral class.[a]

	Behavioral classes		
	$\text{Class}_b 1$	$\text{Class}_b 2$	$\text{Class}_b 3$
Class size	27%	58%	15%
single (%)			
0–17	13%	19%	7%
20–40	26%	32%	17%
50	10%	10%	8%
60–66	25%	23%	26%
100	26%	17%	42%
Mean	55.80	47.63	68.65
trail (miles)			
7	2%	24%	21%
14	4%	25%	23%
21	11%	25%	25%
35	83%	26%	30%
Mean	32.07	19.56	20.61
climbs (n)			
0	11%	17%	25%
1	16%	21%	25%
2	24%	25%	25%
4	49%	37%	25%
Mean	2.59	2.18	1.76
grade (%)			
0	8%	17%	0%
0.9–1.3	13%	26%	0%
1.8–3.6	22%	34%	0%
5.4	9%	8%	0%
9.0–13.0	48%	15%	100%
Mean	0.07	0.03	0.14
solo			
No	79%	79%	70%
Yes	21%	21%	30%
back10			
No	79%	68%	52%
Yes	21%	32%	48%
back5			
No	65%	63%	52%
Yes	35%	37%	48%
back2			
No	58%	63%	28%
Yes	42%	37%	72%
front2			
No	80%	61%	28%
Yes	20%	39%	72%
front5			
No	53%	66%	50%
Yes	47%	34%	50%
front10			
No	79%	72%	45%
Yes	21%	28%	55%

[a] For each class, for each attribute, attribute levels sum to one.

being in $\text{Class}_b 3$. We expected that being competitive and sensation-seeking would make it more likely a rider is in $\text{Class}_b 3$, but did not anticipate being an introvert would do the same, the opposite of what some of the earlier research found.

Table 10 shows how personality traits change the odds of being in each class. For example, the first box reports the odds of you being in each class if you are highly competitive as compared to non-competitive. For example, if you are highly competitive, cautious and not introverted, you are over three times more likely (odds are 3.42) to be in $\text{Class}_b 3$ than a rider who is non-competitive, cautious and not introverted. In general, having extreme personality traits pushes one out of $\text{Class}_b 2$, toward both $\text{Class}_b 1$ and 3. Being highly competitive rather than non-competitive pushes mountain bikers more toward $\text{Class}_b 3$ than toward $\text{Class}_b 1$. Being a sensation seeker rather than being cautious does the same, but the relative push toward $\text{Class}_b 3$ is not as strong. Being an introvert pushes a little more toward $\text{Class}_b 1$ than $\text{Class}_b 3$.

Table 11 reports the WTP per-ride by personality type for having a companion of your own ability rather than a companion two minutes faster. These are the WTP per-ride by class (Table 8) weighted by the probabilities a personality type is in each class. Only one of the WTP estimates by personality type is negative (a highly competitive, sensation-seeking, introvert with low weekly expenditure on entertainment). This is because only $\text{Class}_b 3$ has a negative per-ride WTP (see Table 8) and only 15% of the mountain bikers are in $\text{Class}_b 3$. Within each weekly expenditure category, WTP per ride varies between four-fold and ten-fold as a function of personality type, a remarkable result.

5. Relevance, Conclusions and a Few Thoughts

5.1. Modeling Issues

Our position is that in LC models one should consider and account for the possibility of post-conditioning dependencies between indicators–all indicators, not only personality indicators. While our three cluster models of personality traits allowed for and estimated such dependences, our LC choice model did not—this is a deficiency. The indicators of class in our LC model of site choice are the answers to the choice questions and the choice model we estimated, as is standard, assumes an individual's site choices are independent, conditional on class. That is, class is assumed the only determinant of why your answer to choice-pair 2 might be correlated with your answer to pair 3. This is restrictive and while correlations across choice occasions (due to fatigue or other factors) have been incorporated into repeated logit models of site choice, we have not yet tried to tackle the dependency issue in the context of a LC choice model. Our LC choice model assumed that each $\varepsilon_{ij|c_b}$ in $U_{ij|c_b} = V_{ij|c_b} + \varepsilon_{ij|c_b}$ is an independent draw from an Extreme-value distribution. More generally, in theory, one could, for example, assume an individual's sequence of choices was a draw from a joint distribution that allowed the choices to be correlated even after one conditions on class. It might be possible to to do this by modifying the specified LC mixed-mode cluster model. Conjecturing: the relevance $R_{sq|c}$ (Eq. (3)) would be the deterministic component of utility conditional on choosing alternative s in pair q conditional on belonging to class c, where the indicators (answers to the choice pairs) are nominal/discrete. One would factor conditional utility into two components as in $R_{sq|c} = \mu_{sq} + \alpha_{sq|c}$ (Eq. (4)): a part independent of class plus a part dependent on class. The parameters $\mu_{sq} + \alpha_{sq|c}$ are replaced with functions of ride attributes and the parameters on those ride attributes. One would then incorporate dependence parameters (the γ) in the manner of Eq. (7).

The second LC modeling issue we tackled is that indicators differ on two dimensions: whether the answers are discrete (A, B or C) or continuous (how much did you spend on beer last week) and whether an answer has only nominal meaning, only ordinal meaning, or cardinal meaning. One wants a model that correctly specifies the distribution for each separate indicator and that does not attribute too much, or too little, informational content to the indicator. Our estimated LC mixed-mode cluster models allowed for all these different types of indicators, but, in our application, we only have indicators that are ordinal discrete (the Likert-scale personality questions). In future applications it would be of interest to include additional continuous indicators and indicators that are either cardinal or only nominal. But, even if our limited application, we accounted for the ordinal nature of Likert-scale answers,

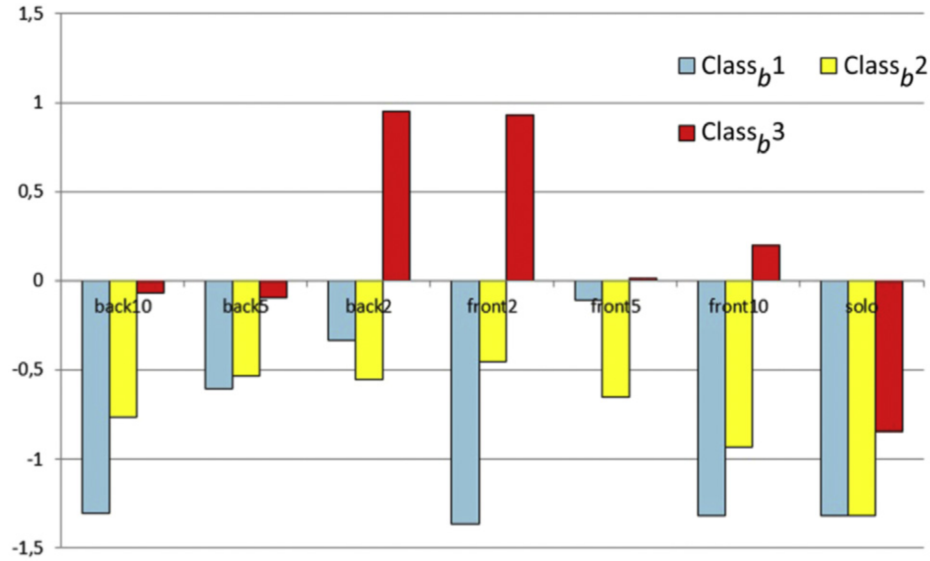

Fig. 2. Utility as a function of the gap, by behavioral class. The first, second, and third bars in each triplet represent Class$_b$1, Class$_b$2, and Class$_b$3. (color version online: each triplet is ordered class1, 2, and 3)

whereas most LC cluster models assume Likert-scale answers only have nominal meaning.

In our LC choice model, all of the indicators are discrete (answers to discrete-choice questions) and the choice model takes account that if an individual chooses ride B over ride A, that individual ordinally ranks B over A—so an appropriate specification in terms of the indicators–except for the independence assumption. But one could imagine a larger data set where in addition to making discrete choices over alternatives the individual reports how many times they would visit each site in different sets of sites. In such cases one would have indicators that are both discrete/ordinal and continuous/cardinal.

5.2. Personality Traits

Our estimated LC choice-model clearly indicates that personality traits interact with site characteristics and companion's ability to explain where and with whom you mountain bike. Preferences for mountain-bike rides are based, at least in part, on whether you seek thrills or caution, whether you prefer to compete against others or yourself, and whether you are introverted. It is likely personality traits would also be explanatory for many types of recreational activities.

It is our position that personality traits be further investigated as determinants of preference heterogeneity over recreational alternatives and environmental policies–but care is needed and many questions remain, particularly in terms of how primitive/basic personality traits are in terms of describing an individual. While personality traits can change over time, they are fairly stable over time, situations and task, arguing for their consideration. But how exactly? We implicitly assumed that competitiveness, extroversion and sensation-seeking are independently varying aspects of one's personality and estimated a separate LC cluster model for each. Alternatively, we could have estimated one LC cluster model that included, as indicators, all of the personality questions (our data set is available to attempt this). This approach would have identified personality types rather than personality traits and would have likely been difficult to estimate. A second issue is whether personality traits (or personality type) should be the only covariates in the LC choice model–what we did in this application. We, and most other recreational modelers have, over the years, not included personality traits, but have included many other covariates: age, gender, ability,

Table 8
WTP per-trip for a companion of the same ability rather than two minutes faster.

	Class$_b$1	Class$_b$2	Class$_b$3
Low entert. expend.	$3.62	$5.52	−$8.62
Med. entert. expend.	$4.58	$7.30	−$7.67
High enter. expend.	$4.70	$13.81	−$4.69

Table 9
Prob. of class membership as a function of the 10 personality types.

Personality type			Classes		
Comp trait	Sensation trait	Introv trait	Class$_b$1	Class$_b$2	Class$_b$3
Hcomp	SensSeek	Introv	47%	17%	36%
Hcomp	SensSeek	Not Introv	32%	42%	26%
Hcomp	Cautious	Introv	40%	37%	23%
Hcomp	cautious	Not Introv	20%	67%	13%
Ncomp	SensSeek	Introv	56%	29%	15%
Ncomp	SensSeek	Not Introv	31%	60%	9%
Ncomp	cautious	Introv	40%	52%	8%
Ncomp	cautious	Not Intov	17%	79%	4%
Not extreme	Not extreme	Not Introv	26%	60%	13%

Table 10
Odds ratios of being in each behavioral class.

	ODDS ratios		
	Class$_b$1	Class$_b$2	Class$_b$3
Only change Hcomp vs. Ncomp			
Thrill/Introv	0.84	0.59	2.39
Thrill/NotIntrov	1.01	0.71	2.88
Cautious/Introv	1.00	0.70	2.86
Cautious/NonIntrov	1.20	0.84	3.42
Only change SenSeek vs. Caut			
Hcomp/Introv	1.16	0.47	1.55
Hcomp/NotIntrov	1.55	0.63	2.07
Ncomp/Introv	1.39	0.57	1.85
Ncomp/NotIntrov	1.85	0.75	2.46
Only change Introv vs. NonIntrov			
Hcomp/Thrill	1.47	0.41	1.39
Hcomp/Cautious	1.96	0.55	1.86
Ncomp/Thrill	1.77	0.49	1.67
Ncomp/Cautious	2.35	0.65	2.22

Table 11
WTP per-trip by personality type for having a companion of one's ability rather than two minutes faster.

Personality type			Weekly expend on entert		
Comp trait	Sensation trait	Introv trait	Low	Medium	High
Hcomp	SensSeek	Introv	−$0.49	$0.61	$2.53
Hcomp	SensSeek	Not Introv	$1.23	$2.53	$5.26
Hcomp	Cautious	Introv	$1.45	$2.70	$5.10
Hcomp	Cautious	Not Introv	$3.35	$4.85	$5.64
Ncomp	SensSeek	Introv	$2.32	$3.51	$5.36
Ncomp	SensSeek	Not Introv	$3.64	$5.09	$8.08
Ncomp	Cautious	Introv	$3.60	$4.98	$7.62
Ncomp	Cautious	Not Intov	$4.67	$6.28	$9.99
Not extreme	Not extreme	Not Introv	$3.14	$4.59	$7.75
No information about personality	$2.86	$4.32	$8.58		

education level, etc. Including a lot of covariates in a choice model that are correlated with one another will likely lead to biased estimates of their separate influence. For example, imagine that one includes both personality traits and education level as covariates in a choice model, and, as some research suggests, education is largely determined by personality traits. Note that independence of covariates is a different issue than independence of indicators, and an issue we do not consider in this paper. Important questions are whether personality traits are primitive aspects of the self, and, if so, what are the other primitive aspects of the self.

Another important theoretical question, and one we do not deal with, is whether personality traits are co-determined with your preferences (a type of preference such as a preference for risk) or whether they are constraints on which your preferences are constructed. Here, we are in the latter camp. If one is in the former camp, one would want a model that jointly estimates personality traits and an individual's preferences over recreation alternatives. In this case personality traits are indicators, not covariates in the class-membership probabilities, and it would be a misspecification to model preference heterogeneity as function of personality traits. In such a specification they are jointly determined–which is maybe why economists are remiss to include personality traits as covariates. If one estimates a model that includes, as indicators, both discrete choices and Likert-scale answers to personality questions, one would want to use a LC model that allowed the indicators to be dependent, even after one conditions on class/cluster.

References

Agresti, A., 2002. Categorical Data Analysis. second edition, Wiley, New York.
Agresti, A., Booth, J.G., Hobert, J.P., Caffo, B., 2000. Random-effects modeling of categorical response data. Sociol. Methodol. 30, 27–80.
Almlund, M., Duckworth, A., Heckman, J., Kautz, T., 2011. Personality Psychology and Economics. In: Hanushek, E., Machin, S., Woessman, L. (Eds.), Handbook of the Economics of Education. Elsevier, Amsterdam, pp. 1–181.
Bereczkei, T., Vörös, A., Gál, A., Bernáth, L., 1997. Resources, attractiveness, family commitment. Reproductive decision in mate choice. Ethology 103, 681–699.
Blanton, H., Buunk, B.P., Gibbons, F.X., Kuyper, H., 1999. When better-than-others compares upward: the independent effects of comparison choice and comparative evaluation on academic performance. J. Pers. Soc. Psychol. 76, 420–430.
Brickman, P., Bulman, R.J., 1977. Pleasure and pain in social comparison. In: Suls, J., Miller, R.L. (Eds.), Social Comparison Processes: Theoretical and Empirical Perspectives. Hemisphere, Washington DC..
Buunk, A.P., Gibbons, F.X., 2007. Social comparison: the end of a theory and the emergence of a field. Organ. Behav. Hum. Decis. Process. 102, 3–21.
Corulla, W.J., Coghill, K.R., 1991. Can education streaming be linked to personality? A possible link between extraversion, neuroticism, psychoticism and choice of subject. Personal. Individ. Differ. 12 (5), 367–374.
Davis, C., Fox, J., Brewer, H., Ratusny, D., 1995. Motivation to exercise as a function personality characteristics, age and gender. Personal. Individ. Differ. 19 (2), 65–174.
De Moor, M.H., Beem, A.L., Stubbe, J.H., Boomsma, D.I., De Geus, E.J., 2006. Regular exercise, anxiety, depression and personality: a population-based study. Prev. Med. 42 (4), 273–279.
Doeven-Eggens, L., De Fruyt, F., Hendriks, A.A.J., Bosker, R. l. J., Van der Werf, M.P.C., 2008. Personality and personal network type. Personal. Individ. Differ. 45, 689–693.
Egloff, B., Gruhn, A.J., 1996. Personality and endurance sports. Personal. Individ. Differ. 21 (2), 223–229.
Everitt, B.S., 1988. A finite mixture model for the clustering of mixed-mode data. Stat. Probab. Lett. 6, 305–309.
Farizio, B.A., Oglethorpe, D., Solinõ, M., 2016. Personality traits and environmental choices: on the search for understanding. Sci. Total. Environ. 566-567, 157–167.
Festinger, L., 1954. A theory of social comparison processes. Hum. Relat. 7 (5), 117–140.
Fleeson, W., Noftle, E., 2008. The end of the person-situation debate: an emerging synthesis in the answer to the consistency question. Soc. Personal. Psychol. Compass 2 (4), 1667–1684.
Funder, D.C., 2009. Persons, behaviors and situations: an agenda for personality psychology in the postwar era. J. Res. Pers. 43 (2), 120–126.
Gilbert, P., Price, J., Allan, S., 1995. Social comparison, social attractiveness and evolution: how might they be related? New Ideas Psychol. 13, 149–165.
Goodman, L.A., 1979. Simple models for the analysis of association in cross classifications having ordered categories. J. Am. Stat. Assoc. 74, 537–552.
Grebitus, C., Lusk, J.L., Nayga, R.M., Jr., 2013. Effect of distance of transportation on willingness to pay for food. Ecol. Econ. 88, 67–75.
Hagenaars, J.A., 1988. Latent structure models with direct effects between indicators: local dependence models. Sociol. Methods Res. 16, 379–405.
Haidt, J., 2012. The Righteous Mind: Why Good People are Divided by Politics and Religion. Pantheon Books, a Division of Random House, New York.
Hirsh, J.B., 2010. Personality and environmental concern. J. Environ. Psychol. 30, 245–248.
Hirsh, J.B., Dolderman, D., 2007. Personality predictors of consumerism and environmentalism: environmentalism: a preliminary study. Personal. Individ. Differ. 43, 1583–1593.
Hopwood, C.J., Baker, K.L., Morey, L.C., 2008. Personality and drugs of choice. Personal. Individ. Differ. 44, 1413–1421.
Jack, S.J., Ronan, K.R., 1998. Sensation seeking among high and low-risk sports participants. Personal. Individ. Differ. 25 (6), 1063–1083.
Jonason, P.K., Luevano, V.X., Adams, H.M., 2012. How the Dark Triad traits predict relationship choices. Personal. Individ. Differ. 53, 180–184.
Jones, E.E., Berglas, S., 1978. Control of attributions about the self through self-handicapping strategies: the appeal of alcohol and the role of underachievement. Pers. Soc. Psychol. Bull. 4 (2), 200–206.
Kerr, J.H., 1987. Differences in the motivational characteristics of "professional," "serious amateur" and "recreational" sports performers. Percept. Mot. Skills 64, 379–382.
Kerr, J.H., van Lienden, H.J., 1987. Telic dominance in masters swimmers. Scand. J. Sport Sci. 9, 85–88.
Kirkcaldy, B., Furnham, A., 1991. Extraversion, neuroticisms, psychoticism, and recreational choice. Personal. Individ. Differ. 12 (7), 737–745.
Mascie-Taylor, C.G.N., 1988. Assortative mating for psychometric characters. In: Mascie-Taylor, C., Boyce, A.J. (Eds.), Human Mating Patterns. Cambridge University Press, Cambridge, pp. 61–82.
MacNicol, S.A.M., Murray, S.M., Austin, E.J., 2003. Relationships between personality, attitudes and dietary behaviour in a group of Scottish adolescents. Personal. Individ. Differ. 35, 1753–1764.
Merz, E.L., Roesch, S.C., 2011. A latent profile analysis of the Five Factor Model of personality: modeling trait interactions. Personal. Individ. Differ. 51, 915–919.
Milfont, T., Sibley, C., 2012. The big five personality traits and environmental engagement: associations at the individual and societal level. J. Environ. Psychol. 32, 187–195.
Morey, E.R., Buchanan, T., Waldman, D., 2002. Estimating the benefits and costs to mountain bikers of changes in trail characteristics, access fees, and site closures: choice experiments and benefits transfers. J. Environ. Manage. 64 (4), 411–422.
Moustaki, I., 1996. A latent trait and a latent class model for mixed observed variables. Br. J. Math. Stat. Psychol. 49, 313–334.
Moustaki, I., Papageorgiou, I., 2004. Latent class models for mixed outcomes with applications in archaeometry. Comput. Stat. Data Anal. 48 (3), 659–675.
Qu, Y., Tan, M., Kutner, M.H., 1996. Random effects models in latent class analysis for evaluating accuracy of diagnostic tests. Biometrics 52, 797–810.
Scarpa, R., Rose, J.M., 2008. Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why. Aust.J.Agric.Resour.Econ. 52, 253–282.

Shepperd, J.A., Taylor, K.M., 1999. Ascribing advantages to social comparison targets. Basic Appl. Soc. Psychol. 21, 103–117.
Sit, C.H.P., Lindner, K.J., 2005. Motivational orientations in youth sport participation: using achievement goal theory and reversal theory. Personal. Individ. Differ. 38, 605–618.
Solinõ, M., Farizo, B.A., 2014. Personality traits underlying environmental preference: a discrete choice experiment. PLoS ONE 9 (2), e89603. http://dx.doi.org/10.1371/journal.pone.0089603.
Suls, J., Martin, R., Wheeler, L., 2002. Social comparison: why, with whom and with what effect? Curr. Dir. Psychol. Sci. 11 (5), 159–163.
Thomson, C.J., Carlson, S.R., Rupert, J.L., 2013. Association of a common d3 dopamine receptor gene variant with sensation seeking in skiers and snowboarders. J. Res. Pers. 47, 153–158.
Tolea, M.I., Terracciano, A., Simonsick, E.M., Metter, E.J., Costa, P. l. T., Jr., Ferrucci, L., 2012. Associations between personality traits, physical activity level, and muscle strength. J. Res. Pers. 46, 264–270.
Vermunt, J.K., Magidson, J., Hagenaars, J.A., McCutcheon, A.L., 2002. Latent Class Cluster Analysis. Applied Latent Class Analysis, Cambridge University Press, Cambridge., pp. 89–106.
Vermunt, J., Magidson, J., 2005. Latent GOLD 4.0 Users Guide. . Statistical Innovations Inc, Belmont, Massachusetts.
Wills, T.A., 1981. Downward comparison principles in social psychology. Psychol. Bull. 90, 245–271.