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Analysis

A parsimonious, stacked latent-class methodology for predicting behavioral heterogeneity in terms of life-constraint heterogeneity

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ABSTRACT

Our conjecture is that for many recreational activities a significant amount of the variation in the sites visited can be explained, and predicted, by variation in life constraints such as kids, BMI (body-mass index) fitness, skill, and health. The objective is to develop a parsimonious method for identifying behavioral heterogeneity caused by life-constraint heterogeneity and separating it from that caused by preference heterogeneity. We estimate, for two different recreational activities, with two independent data sets, how much behavioral heterogeneity can be attributed to life-constraint heterogeneity. We develop and estimate a stacked latent-class approach to life constraints, assuming individuals have many correlated life constraints. First, at the bottom of the stack, a latent-class life-constraint model is specified and estimated; then life-constraint class becomes a covariate in a behavioral latent-class model of participation and site selection. We find, with both simple statistics and behavioral models, that life-constraint classes explain a significant amount of the observed behavioral heterogeneity. Prediction is a critical reason to distinguish the influence of current constraints from the influence of current preferences: it is easy to directly observe life-constraint levels. Stacked latent-class models have many potential applications, besides ours.

1. Introduction

Modeling and estimating the observed variation in recreational behavior (behavioral heterogeneity), not caused by price and income variation, are the *raisons d'être* for much research in recreation demand.

One objective is to develop a parsimonious method of identifying behavioral heterogeneity caused by constraint heterogeneity and separating it from that caused by preference heterogeneity. We do this by developing and estimating stacked latent-class models of constraints and behaviors: the output from a latent-class model of constraints becomes a covariate in a latent-class model of behavior.

Our conjecture is that for many recreational activities, a significant amount of the variation in the sites visited can be explained, and predicted, by the simultaneous variation in a large number of correlated explanatory variables, variables such as number of kids, marital status, BMI (body-mass index) fitness, skill, disease, resting heart rate, alcohol consumption, cigarette consumption, and blood pressure.

While a variable that helps explain behavioral variation is often referred to as a "preference shifter," we argue that it is proper and more productive to call explanatory variables of the above sort *life constraints*. Behavioral heterogeneity, not due to price and income variation, is typically assumed due, in total, to preference heterogeneity. We find this misguiding.

We are in good company when we argue that preference heterogeneity should be separated from constraint heterogeneity and that preference heterogeneity should not be relied on to explain most behavioral heterogeneity. Stigler and Becker (1977) conclude that "no significant behavior has been illuminated by assumptions of differences in tastes." Their view is now foreign to many in recreation

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demand. Their argument is that because preference heterogeneity can explain all behavioral heterogeneity, it explains "nothing." They argue that little is gained by attributing behavioral differences to preference variation; more strongly they argue that much unexplained behavioral variation is explained by constraint variation, if one looks hard enough.

We begin by defining behavioral heterogeneity, preferences, preference heterogeneity, constraints, and constraint heterogeneity, doing so in terms of a simple choice model with only one life constraint, a model that we abandon for being intractable when there are a large number of correlated life constraints.

Behavioral heterogeneity is simply the variation in behavior across individuals. [2]

Since we argue that it is important to distinguish between preferences and constraints, it is important that both be carefully defined.

In economics there is not an explicit and generally accepted definition of the word *constraint*. For the purpose of this paper, we define a "constraint" as an exogenous variable or exogenous mapping between variables that influences the behavior of the individual, exogenous in the sense that the individual cannot change it in the choice period. A constraint is a *relevant exogenous variable* or *mapping*.

The price of a Coke is an example of a constraint that can be represented by a level of a variable, so is an individual's weight. The "budget constraint" is an example of a constraining exogenous *mapping*, another example of a constraining mapping is how fast one can hike as a function of one's weight, fitness, and level of effort.

Exogeneity is necessary but not sufficient: by our definition, a constraint must also influence behavior. The temperature on Saturn is exogenous to us all, but has no influence on the behavior of most of us, so is not a constraint; the weather on Earth is a constraint.[3]

Note that many current constraints are determined by past choices and behaviors, sometimes our choices, sometimes those of others. For instance, being married is, in the short run, a constraint. That it is a constraint does not mean that all those married ones would prefer to be un-married; married being a constraint only means that marital status can't be changed in the current choice period and that being married influences one's behavior. Or to take another example, having three children is hopefully—but need not be—a function of one's past preferences, but it is not a "function" of one's current preferences; it is a given. It is noteworthy that economists are comfortable calling "income" a constraint, but some of us are uncomfortable when these other variables are referred to as constraints.

What is, and is not, a constraint is obviously a function of the length of the choice period: the shorter the decision period the fewer the choices. In our two recreation applications we take the view that the decision period is a few days to a week, so the levels of many variables are fixed in the decision period (people typically do not plan short recreation trips months or years in advance). We will, for example, take the average level of overall exercise per week and skill level in the recreation activity as exogenous when each trip choice is made.[4] Alternatively, if one viewed the individual as simultaneous choosing, in early adulthood, how many children to have, whether to become an expert mountain biker, who to marry, and how many hours they would exercise per week in 2012, these would all be, at the beginning of adulthood, choice variables, not constraints.

An individual's preferences are, simply put, the order in which he would choose "states." While preferences can change, the ordering is exogenous in the choice period.[5]

Preferences are typically represented with either a direct or an indirect utility function: a direct utility function associates a number with every conceivable consumption bundle such that higher ranked bundles, states of consumption, are given larger numbers, whereas the indirect utility function associates a number with every conceivable state of the world such that higher ranked states are given larger numbers. A state is defined in terms of the levels of a vector of relevant exogenous variables. In addition to prices and income, these include the exogenous amount of attribute c in good/activity j. The indirect utility function represents the individual's preference ranking of constraints such that preferences are embodied in the functional form and parameter values: preferences being what converts the constraint vector into a number.

In this research, we extend the list of relevant exogenous variables. For example, BMI is a constraint, and BMI affects one's ability to recreate and enjoy recreation. Number of kids is another constraint, so is having a disease. For expositional simplicity we will refer to age, gender, race and other *born-withs* as "constraints" adding the adjective "life" to reflect constraints determined by the life one has experienced.

Life-constraints are levels of consumer durables with high disposal costs—there is no free disposable of spouse, kids, or weight. In the short run, one no longer has choice over these dimensions, and one's demands for other commodities become derived demands. Kids, for example, increase the demand for commodities that complement kids (minivans, trips to Disneyland, easy hiking trails) and decrease the demand for substitutes for children (e.g. high-end restaurant meals, and skill, time, and endurance-intensive recreation). Unfitness and excess weight influence the ability to recreate (negatively complement recreation and complement sedentary activities). Lack of skill, strength, or endurance can remove some activities from the choice set. Current income is a life constraint, so are religious and ethical beliefs, and one's "moral duty."

The distinction between preference heterogeneity and constraint heterogeneity is made concrete by identifying parameters, variables, and functional forms that are the determinants of what one does. One can completely specify an individual's behavior by specifying their indirect utility function: its functional form, its variables, and its parameters. It is a complete determinant of what the individual will do given the levels of the variables in the indirect utility function. The functional form for the indirect utility function is typically assumed the same for all individuals. Parameters take constant numerical values from the individual's perspective; they might differ across individuals but, in the choice period, are exogenous constants for the individual. Such parameters are what we typically want to estimate. Preference heterogeneity is typically *characterized* by allowing some of the parameters in the indirect utility function, the "preference parameters," to vary across individuals.

Making this concrete with a simple discrete-choice example, assume that individual i must choose one of J alternatives, $j=1, 2,\ldots, J$, where income not spent on the alternative is spent on the numeraire. Assume income in the choice period is y_i, and that p_{ji} is the price of alternative j for individual i, such that if the individual chooses alternative j they spend $(y_i - p_{ji})$ on the numeraire. For

[2] We chose the word "behavior" rather than "choice," because it is our conjecture that all behaviors are not chosen/selected.

[3] Some would call the weather on Saturn a "non-binding constraint". In our terminology, a non-binding constraint is simply an exogenous variable with no influence.

[4] Justifying—skill level is acquired gradually, and while one can exercise less, or a bit more, than they did in the previous week, one cannot, without risking injury, rapidly increase exercise time, and since exercise exhibits properties of addiction (Rhodes et al., 2003) large cutbacks are often unpleasant. Being skilled implies one practiced the activity in the past, but does not imply that one, now, participates—we abandon activities when we are bored or because the levels of other life constraints change (e.g., kids arrive).

[5] The reader might correctly note that by our definition of constraint one's "preferences" are a constraint: standard consumer theory assumes preferences are exogenous and influence behavior. So, to keep the two terms separate we will use the word *preferences* to denote the exogenous order in which an individual would choose states, and the word *constraint* to denote all other exogenous influential variables and mappings.

exposition, initially assume each site is described in terms of only one characteristic, c_j, and that there is only one relevant life constraint: number of kids, k_i. The conditional indirect utility function for alternative j is $U_{ij} = V((y_i - p_{ji}), c_j, k_i) + \varepsilon_{ij}$ making the indirect-utility function $max(U_{i1}, U_{i2}, \ldots, U_{iJ})$.

Choose a functional form such that k_i influences behavior. Simply, and for example, if there are no income effects,[6] and no preference heterogeneity,

$$\begin{aligned} &V\left(\left(y_i - p_{ji}\right), c_j, k_i\right) \\ &\quad = \beta_c c_j + \beta_y\left(y_i - p_{ji}\right) + \gamma_{0j} k_i + \gamma_{ck} k_i c_j + \gamma_{yk} k_i\left(y_i - p_{ji}\right) \\ &\quad = \gamma_{0j} k_i + (\beta_c + \gamma_{ck} k_i) c_j + \left(\beta_y + \gamma_{yk} k_i\right)\left(y_i - p_{ji}\right) \\ &\quad = \gamma_{0j} k_i + \alpha_{ci} c_j + \alpha_{yi}\left(y_i - p_{ji}\right). \end{aligned} \tag{1}$$

The $\boldsymbol{\beta}$ are the preference parameters. In this example specification, kids constrain utility in three ways: by changing the utility one gets from the numeraire, the $\gamma_{yk} k_i (y_i - p_{ji})$ term; by directly changing the utility one gets from alternative j, the $\gamma_{0j} k_i$ term, and via the characteristic level, c_j, the $\gamma_{ck} k_i c_j$ term. The parameter γ_{0j} is how much an additional kid *exogenously* changes the utility one can get from site j —one is constrained to experience this shift; $\gamma_{ck} c_j$ is how much an additional kid exogenously changes the utility one can get from the c_j; and γ_{yk} is how much an additional kid exogenously changes the utility one gets from a dollar spent on the numeraire.[7] If at site j, for each kid the individual is constrained to experience the utility effect $\gamma_{0j} + \gamma_{ck} c_j + \gamma_{yk}(y_i - p_{ji})$. If kids do not constrain, $\gamma_{0j} = \gamma_{ck} = \gamma_{yk} = 0$.

Eq. (1) admits no preference heterogeneity: the $\boldsymbol{\beta}$ are not allowed to vary across individuals, but admits life-constraint heterogeneity in terms of the number of kids; that is, as the number of kids varies, it affects behavior, and it is assumed exogenous in the choice period. (Alternatively, if number of kids was a choice variable and site choice is fixed but different for different individuals, there would be life-constraint heterogeneity in terms of site visited.)

Note that if one directly estimated the last line of Eq. (1)

$$V_{ij} = \alpha_{ci} c_j + \alpha_{yi}\left(y_i - p_{ji}\right) \tag{2}$$

ignoring data on k_i with, as is common, a random-parameters model, it is misleading to interpret the variation in the α_c and variation in the α_y as a reflection of preference heterogeneity—the α vary because of variation in the constraint, number of kids, not because of variation in the $\boldsymbol{\beta}$ parameters.

Now generalize Eq. (1) to admit preference heterogeneity. One can do this in a latent-class framework by imagining there are *G preference* classes ($\boldsymbol{\beta}_{|g}$, $g = 1, 2, \ldots G$, where $\boldsymbol{\beta}_{|g}$ is the $\boldsymbol{\beta}$ vector for preference class g). In which case, the indirect utility function for alternative j, conditional on being a member of preference class g is

$$\begin{aligned} &V\left(\left(y_i - p_{ji}\right), c_j, k_i | g\right) \\ &\quad = \beta_{c|g} c_j + \beta_{y|g}\left(y_i - p_{ji}\right) + \gamma_{0j} k_i + \gamma_{ck} k_i c_j + \gamma_{yk} k_i\left(y_i - p_{ji}\right) \\ &\quad = \gamma_{0j} k_i + \left(\beta_{c|g} + \gamma_{ck} k_i\right) c_j + \left(\beta_{y|g} + \gamma_{yk} k_i\right)\left(y_i - p_{ji}\right) \\ &\quad = \gamma_{0j} k_i + \mu_{ci} c_j + \mu_{yi}\left(y_i - p_{ji}\right). \end{aligned} \tag{3}$$

Note how the μ_c and the μ_y vary across individuals for two reasons (preference class and number of kids), so variation in the estimated μ_{ci} and the μ_{yi} is capturing both constraint heterogeneity (variation in k_i) and preference heterogeneity (variation in $\boldsymbol{\beta}$).

In this example, estimated models that ignore the influence of k_i by starting with either the assumption that $V_{ij} = \mu_{ci} c_j + \mu_{yi}(y_i - p_{ji})$, a random-parameters specification, or

$$V_{j|m} = \mu_{c|m} c_j + \mu_{y|m}\left(y_i - p_{ji}\right) \tag{4}$$

where one assumes M latent *behavioral* classes, are commingling preference heterogeneity and constraint heterogeneity. There are K *life-constraint* classes (one kid, two kids,…), but this is not explicitly recognized. On top of that, behavior is affected because the $\boldsymbol{\beta}$ vary across individuals, either continuously or discretely, and this variation is preference heterogeneity. It is incorrect to attribute all of the variation in the $\mu_{c|m}$ and $\mu_{y|m}$ (or all the variation in the μ_{ci} and μ_{yi}) to preference heterogeneity. But that is what is often done. It would also be incorrect to attribute it all to constraint heterogeneity.

The task of modeling life constraints can overwhelm if there are more than a few. Consider the expansion of Eq. (1) if there were, for example, four important site characteristics, and five relevant life constraints—it is already messy with only one characteristic and one life constraint. If the influence of each life constraints was separately modeled, the indirect utility function would explode with interaction terms, each with a unique γ parameter, even if the model admits no preference heterogeneity. Add to this the complication that the levels of the life constraints are correlated, making it difficult to estimate the separate influence of each. For example, each individual life constraint might have no influence by itself, whereas collectively they do. Generalizing the above will not accommodate such a case.

Our modeling contribution is a stacked latent-class model that allows one to simultaneously and parsimoniously consider many correlated life constraints.

To account for many correlated life constraints we first use a latent-class model to identify life-constraint classes, a *latent-class lf model* (Section 3). That is, we suggest, and test, that while there can be many combinations of life constraints, in effect there is only a small number of latent life-constraint classes.

Specifically, recreators are probabilistically allocated into life-constraint classes (hereafter, *lfClasses*) on the basis of their life-constraints. The method accounts for the fact that life-constraint levels are correlated, accepting that life-constraints limit but don't always bind, black-and-white, the way the budget constraint is assumed to bind. The number of lfClasses is estimated.

We then estimate how much of the behavioral heterogeneity can be explained in terms of life-constraint classes by estimating a latent-class behavioral model of recreation using lfClass as a covariate in a latent-class behavioral model of recreation. A behavioral latent class is a group of individuals who exhibit similar *behavior* in terms of the recreational activity being studied. Put simply, we stack two latent-class models in that estimated output from the latent-class life-constraint model is an input into a latent-class behavioral model.

The prefix and subscript *lf* are used for life-constraint class and the prefix "*b*" will be used for *behavioral* latent classes: One research question is to what extent lfClasses predict bClasses.

For one or our recreation data sets, four lfClasses best explain the life-constraint heterogeneity; in the other data set, seven explain. Class membership is latent/unobserved: one estimates the probability an individual belongs to lfClass c_{lf} as a function of their age and gender. One estimates the probability a lfClass c_{lf} individual will have level v of life-constraint q.

Two different recreation activities are analyzed (mountain biking and hiking/climbing), rather than one, to show that the same life-constraints help explain behavioral heterogeneity in two different recreational activities. Chi-squared tests, ANOVA tests (Sections 4, 5, and 6), and participation and site-selection models (with and without the lfClasses, Section 7) are used to demonstrate that significant behavioral variation is explained by life-constraints.

[6] The choice probabilities are not a function of income.

[7] For example, if kids precluded one from visiting site j, γ_{0j} is a large negative number.

One dataset reports trips taken by hikers and technical climbers to the mountains of the Veneto, Italy (the Veneto includes the Dolomites and the PreAlps), hereafter the *Veneto* sample. All are members of the Veneto chapter of the Italian Alpine Club, so have a preference for alpine activities.[8] For 1397 individuals, there is a trip record for eighteen mountain sites (six PreAlp, twelve Dolomite), along with data on gender, age, height, weight, heart disease, respiratory disease, smoking habits, drinking habits, average weekly overall exercise, and the typical data on travel costs, income level, and family size. The survey also asked typical activity on-site.

The other dataset is from an internet survey completed by 4605 mountain bikers from 49 different countries, hereafter the *MTB* sample. A static version of the survey with summary statistics is at http://www.colorado.edu/economics/morey/static//index.html. The data include gender, age, income, skill level, resting heart rate, overall exercise level, cigarettes per day, presence of a significant other, number of minor children, BMI, presence of a disease that influences ability to strenuously exercise, number of times they mountain biked in the last 30 days, and hours they mountain biked in the last 7 days. In addition, each respondent was presented with 5 pairs of mountain-bike rides, and for each pair asked to select one ride; Fig. 1 is an example choice pair. (Data sets, like ours, with extensive and detailed individual data, once rare, are now common but often all the data is not utilized.)

Before any behavioral models are estimated, we find, using simple statistics, how much one mountain bikes varies significantly and intuitively across the estimated seven lfClasses. One's propensity to choose difficult, or easy rides, also varies predictably across the lfClasses.

For the Veneto sample, we determine that the average number of total trips varies significantly and intuitively across the estimated four lfClasses. How one allocates trips across the Veneto sites also varies significantly by lfClass. The probability one identifies oneself as a regular hiker, occasional hiker, regular climber, occasional climber, climber and hiker, etc. also varies significantly across the lfClasses, and as expected.

Then, for the Veneto data (but not the MTB data set), three behavioral models of participation and site selection—all including the influence of life-constraints—are specified and estimated (Section 7). The preferred model uses lfClass as a covariate in a latent-class behavioral model of participation and site choice.

Prediction is a critical reason to identify the influence of current constraints: it is easy to directly observe life-constraint levels, but it not easy to directly observe preferences, either current or future.[9] Observing that there are many life constraints, that they influence behavior, and that they can be observed, brings more explanatory power to the table.[10]

Consider predicting future recreation patterns or predicting patterns in a different population (e.g. estimating for the U.S. with parameters based on Italian data). Life-constraint levels in a different population can be observed, and, for many populations, there are predictions for future life-constraint levels: BMI is predicted to continue increasing (Rashad et al., 2005; Wang et al., 2008), the U.S. population is aging (Department of Health and Human Services, Division on Aging, 2011), and family composition is predictably changing (Martin et al., 2009; U.S. Government, 2009).

Future recreational avidity, site selections, and activities will be different because life-constraint levels will be different, and it is important that one can predict the behavioral shifts. Saving a wilderness so future generations can visit it is futile if they have the desire but lack the fitness and ability to enjoyably visit. If the experience is miserable, people will have low use values, even if the "desire" to experience the site is great. Well publicized recent literature finds that after rising for fifty years, per-capita visits to U.S. State and National Parks, and elsewhere, have been declining since 1987 (Pergams and Zaradic, 2008). Some of this decline is probably attributable to changing life-constraint levels.

2. Literature on Life-constraints

Few life-constraints are included in economists' recreation-demand models, and those models that do, include only one or two. We searched the environmental economics journals using the following terms: children, weight, BMI, household, marriage, fitness, skill(s), time, age, gender and race. These terms appear, but mostly not in recreation demand. The major exception is the life-constraint current income.

Time constrains; life-constraints influence both time available for recreation, and how recreation time is spent. Feather and Shaw (1999) estimate the value of leisure time as a function of age, gender, and family composition, ignoring that these constraints affect behavior in numerous ways, not only through their influence on the value of time. Our approach, rather than specifying an explicit time constraint, assumes that life-constraints determine available time, how it can be used, and how one chooses to use it.

Economists' recreation-demand models do not consider health status or fitness. Skill is a minor exception (Hynes et al., 2007; Morey, 1981; Morey et al., 2002; Oh and Ditton, 2006; Scarpa and Thiene, 2005).

With respect to other constraints and recreation, Dosman and Adamowicz (2006) find that a beach vacation is "selected" more often if one is vacationing with children. Beharry-Borg et al. (2009) find women on vacation select different beaches than men. Dellaert et al. (1998) find that children were the most important determinant of vacation type. Huhtala and Pouta (2009) find recreation participation higher for males, older people, and the more educated.

There are thousands of health-literature articles on how recreation influences BMI and weight, but we have found little on how BMI and fitness affects recreation—an exception is a New York Times article on how recreation is often limited for those overweight. There is, of course, much sports literature on how training affects sports performance.

The field of leisure research has investigated the role of age, gender, children, race, culture etc. on recreation (Culp, 1998), and, while sometimes only descriptive, this research finds these variables affect recreational behavior, and describes them as "constraints." For example, Miller and Brown (2005) find women with young children less likely to participate in active leisure, attributing this to constraining "gender-based time negotiation and an ethic of care." Depression and limits to physical functioning decrease leisure activities (Janke et al., 2006), and body image and beliefs about appearance constrain women's leisure (Liechty et al., 2006). Floyd et al. (2006), with a

[8] Both of our example samples are samples of populations that have a preference for the activity considered. While no inferences can be drawn from these samples to people in general, they are attractive for investigating the influence of constraint heterogeneity in that preference for the activity is likely more homogenous in these populations than among people in general. Since everyone in the sample participates, at least occasionally, one cannot use our data to study how life constraints completely preclude an individual from an activity (e.g. too unfit to visit any site).

[9] Direct data on preferences is difficult to obtain. Consider the requirements for data to be direct data on preferences. Two necessary conditions are that it is a reflection of underlying preferences, and it is not influenced by constraints. Observed behavior is not direct preference data. One candidate is what Breffle et al. (2011) call "preference-statement data": questions on the importance of different attributes of a good or a question that describes a strong preference in first-person terms and asks the extent to which the respondent agrees or disagrees.

[10] Imagine collapsing $V_{ij}=\mu_{ci}c_j+\mu_{yi}(y_i-p_{ji})$ to $V_{ij}=\gamma_{ci}c_j$, assuming $\boldsymbol{\gamma}_{ci}$ is a random draw from a suitably chosen density, $f_\gamma()$. One would model all of the variation in behavior without income or prices playing an explanatory role, and could attribute all of the variation, if one so desires, to preference heterogeneity. Most economists would be highly uncomfortable attributing behavioral heterogeneity due to price and income variation to "preference" heterogeneity. They would argue that price and income variations reflect constraint heterogeneity, and argue that explicitly modeling this constraint heterogeneity brings explanatory power to the table.

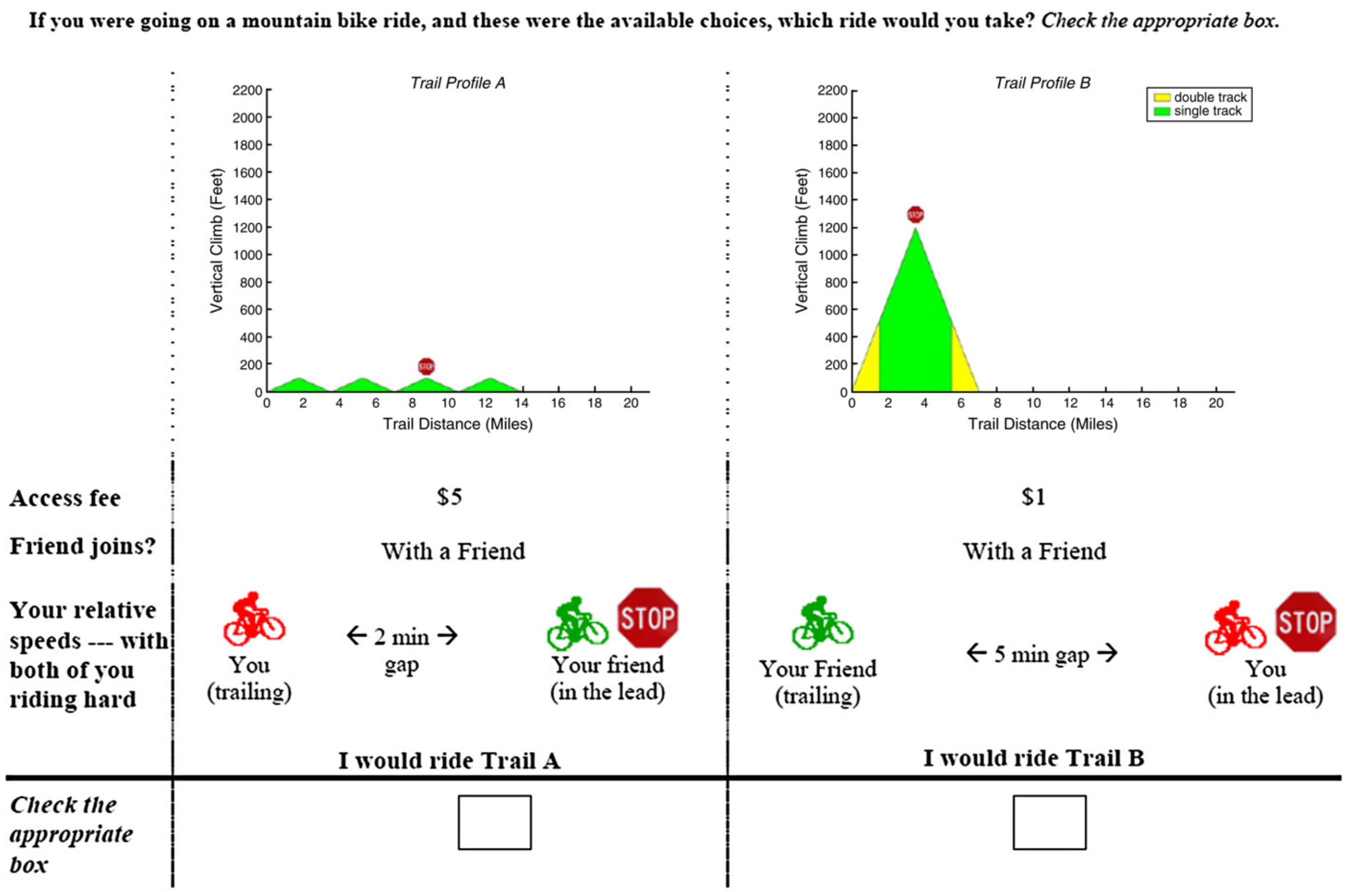

Fig. 1. MTB: example of choice pairs.

simple logistic regression, study the effects of age, race and ethnicity, gender, and socioeconomic status on recreational fishing.

Crawford and Godbey (1987) divide "constraints" into three categories: intrapersonal, interpersonal, and structural barriers. Intrapersonal constraints include psychological states such as stress and anxiety that cause the individual to avoid activities that would maximize their anxiety-free utility. Interpersonal constraints include the need to include others (family, children, etc.). Structural barriers include not enough money, not enough time, and not enough skill.

Multiple constraints on recreation are jointly considered by Shores et al. (2007), also by Stemerding et al. (1999) who suggest and implement a strategy for integrating constraints into a behavioral model. Amusement parks are blocked from the choice set when they violate, for example, a time constraint. Repeating our view, there are multiple ways life-constraints influence behavior, sometimes completely removing alternatives from the choice set, but also limiting utility from an alternative.

There is a literature on how willingness-to-pay, WTP, for an improved environment is influenced by gender and parental status, but these studies, with a few exceptions, are not recreation-demand models. Dupont (2004) finds that WTP for environmental improvements is higher for mothers than fathers if the improvement reduces a health risk, but higher for fathers if the improvement increases recreational opportunities, speculating that men are "less time constrained than women." (See also Teal and Loomis, 2000; Brown and Taylor, 2000; Torgler and García-Valiñas, 2007.)

A number of studies find that "ethical beliefs" and "moral duty"—life constraints—can influence WTP for environmental improvements; See, for example, Gelso and Peterson (2005), Spash (2000), and Spash and Hanley (1995). Hoyos et al. (2009) consider how "cultural identity" can influence environmental values.

We know of no studies where WTP for environmental improvements varies with fitness level, health status, or bad habits.

There is evidence that the life constraints we employ influence *other types of behaviors*. Tepper et al. (1997), Duerksen et al. (2007) and Duffey et al. (2007) find that BMI and other life-constraints affect food choices, while Fu and Goldman (1996) find that obesity, heavy drinking, and higher educational attainment decrease the probability of marriage, so does being short, at least for men (Herpin, 2005). Overweight individuals, especially men, report fewer sex partners (Nagelkerke et al., 2006). Studies that investigate how health status and BMI affect wages, income and employment include Brunello and D'Hombres (2007), Morris (2006, 2007), and Thomas and Strauss (1977).

People without children eat out more often and often at different places than those with young children (Auty, 1992). Dauphin et al. (2008), Lundberg et al. (2007) and Arora and Allenby (1999) identify the significant influence of children on other purchases.

Cameron et al. (2007) estimate adults' WTP for reducing own health risks as a function of number of children and their age categories. Related, Dickie and Messman (2004) find that parents value their children's health more than their own. Alberini et al. (2004) asks whether the value of a statistical life varies with age and health status.

Botti et al. (2008) present a conceptual framework for how restrictions (social norms, laws, budget, health, self-imposed "rules") affect the individual behaviorally, noting that restrictions can be "soft." Their intent, like ours, is to emphasize that restrictions are important behavioral determinants, different from preferences. They stress that restrictions affect utility directly, not simply through their influence on current choices: one must live with one's life-constraints.

Table 1
MTB—estimated probabilities for each level of each constraint, by lfClass.[a]

	Total	lfClass1	lfClass2	lfClass3	lfClass4	lfClass5	lfClass6	lfClass7
Skill level								
Skill1	4.6	4.0	6.2	0.4	0.7	7.7	13.1	8.0
Skill2	31.5	25.7	31.1	22.6	21.3	64.5	54.6	28.5
Skill3	5.1	7.5	8.3	1.4	1.6	3.1	7.0	3.9
Skill4	46.6	48.5	46.9	59.6	55.5	23.5	25.2	40.3
Skill5	12.2	14.3	7.5	15.9	20.9	1.2	0.0	19.3
Exercise/week (hours)								
Did not know	0.1	0.2	0.1	0.0	0.2	0.0	0.3	0.0
None	3.9	5.3	7.2	1.6	0.9	1.8	4.3	4.0
Less than 2	8.6	12.9	13.8	2.5	2.2	5.7	9.1	10.7
2–5	26.7	25.0	37.7	21.3	15.1	23.3	32.7	34.9
5–10	41.2	45.3	35.1	47.6	39.4	50.0	36.9	24.4
10 or more	19.5	11.3	6.1	27.1	42.2	19.2	16.8	26.0
Heart rate (bpm)								
Did not know	40.2	65.3	48.9	13.7	12.3	41.7	28.0	66.7
Less than 50	17.3	2.6	2.8	41.2	48.8	10.6	10.7	0.1
50–60	27.0	14.3	23.1	37.3	34.8	31.7	40.6	17.9
60–70	12.5	13.6	19.8	7.6	3.6	13.1	16.3	12.6
70–80	0.6	1.0	0.8	0.0	0.5	1.1	0.0	0.0
80–90	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.0
90–100	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0
Over 100	2.3	3.0	4.6	0.0	0.0	1.8	4.4	2.7
Body mass index								
Did not know	6.4	5.5	5.7	7.1	9.0	2.9	0.7	15.3
Less than 20	4.4	1.0	1.3	0.6	5.5	19.5	2.0	18.0
20–24	48.0	40.4	24.9	59.1	67.1	65.3	37.7	65.4
25–26	20.2	25.0	26.9	23.0	12.1	6.1	28.3	0.8
27 or more	21.0	28.2	41.3	10.2	6.3	6.3	31.5	0.5
Cigarettes/day								
Did not know	0.4	0.3	0.6	0.3	0.2	1.0	0.9	0.0
0	95.5	90.4	95.7	98.6	98.9	97.4	98.7	92.0
1–6	2.3	5.1	1.4	1.1	0.9	1.6	0.0	5.0
7–20	1.7	4.1	2.3	0.0	0.0	0.0	0.5	3.1
20 or more	0.0	0.1	0.1	0.0	0.0	0.0	0.0	0.0
Disease								
Yes	8.0	5.9	8.5	7.7	5.9	7.7	20.0	4.8
Live with significant other								
Missing	0.7	0.0	0.9	1.1	0.2	0.7	0.5	1.9
No	33.7	62.8	2.1	4.3	60.3	30.8	13.2	81.9
Yes	65.6	37.2	97.0	94.6	39.5	68.6	86.3	16.2
Minors/family (n)								
Did not know	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0
0	65.0	90.4	22.8	38.0	95.7	80.2	80.9	78.1
1	14.9	6.1	28.1	24.4	3.3	8.7	11.6	14.5
2	15.2	2.8	34.3	30.6	0.7	8.4	7.1	6.3
3	4.0	0.8	11.6	6.4	0.4	2.3	0.1	0.5
4	0.7	0.0	2.6	0.4	0.0	0.4	0.0	0.3
5 or more	0.2	0.0	0.7	0.3	0.0	0.1	0.0	0.3

[a] Rows, by life constraint and class, sum to 100.

3. A Latent-class lf Model

Each individual is assumed to be in one lfClass, but which class is latent/unobserved from the researcher's perspective, so probabilistic. The classes segment individuals by their life-constraint levels. The number of lfClasses is estimated and the estimated class-membership probabilities depend on age and gender (covariates). The model appropriately assumes that life-constraint levels are correlated, but assumes that once one conditions on lfClass, constraint levels are independent.

Consider two probabilities: (1), the probability that a lfClass c_{lf} individual has level v of constraint q, and (2), the unconditional class-membership probability (the probability that individual i belongs to lfClass c_{lf} given his or her covariates). The probability that a lfClass3 individual has a high BMI is of the first type. Of the second type is the probability an individual belongs to lfClass3 given their age and gender.

The goal is to estimate the most likely life-constraint-level probabilities and the unconditional class-membership probabilities as a function of age, gender, and the observed life-constraint levels. The *ln* likelihood function for a C_{lf} lfClass latent-class model is

$$\ln L = \sum_{i}^{N} \ln\left[\sum_{c_{lf}=1}^{C_{lf}} \Pr\left(c_{lf} : z_i\right) \prod_{q=1}^{Q} \prod_{v=1}^{V} \left(\pi_{qv|c_{lf}}\right)^{x_{iqv}}\right] \tag{5}$$

where $\pi_{qv|c_{lf}}$ is the probability that an individual has level v of life-constraint q, conditional on being a member of c_{lf}. $\Pr(c_{lf} : z_i)$ is the unconditional probability that individual i belongs to c_{lf} as a function of gender and age, z_i. And $x_{iqv} = 1$ if individual i's level of constraint q is v, and 0 otherwise. And,

$$\Pr\left(c_{lf} : z_i\right) = \frac{\exp\left(\omega_{lf} + \omega_{lff}(f_i) + \sum_{a=1}^{7} \omega_{lfa}(age_{ai})\right)}{\sum_{n=1}^{4} \exp\left(\omega_n + \omega_{nf}(f_i) + \sum_{a=1}^{7} \omega_{na}(age_{ai})\right)} \tag{6}$$

where $f_i = 1$ if individual i is a female, and zero otherwise; $age_{ai} = 1$ if individual i is in age category a (there are 7 categories).

After estimation of the $\Pr(c_{lf} : z_i)$ and $\pi_{qv|c_{lf}}$, one can calculate $\Pr(c_{lf} : z_i|x_i)$ and $\Pr(x_i : z_i)$: the former is the probability that individual i belongs to c_{lf} given their age and gender, and conditioned on their life-constraint levels—these conditional class membership probabilities can be used to assign individuals to a specific lfClass with high certainty. The latter, the $\Pr(x_i : z_i)$, is the probability of observing an individual's life-constraint levels given their age and gender, for example, the probability that you are overweight, unfit, and have small children, given that you are a 35 year-old male.

Specifically,

$$\Pr = \left(c_{lf} : z_i|x_i\right) = \frac{\Pr\left(c_{lf} : z_i\right)\prod_{q=1}^{Q}\prod_{v=1}^{V_q}\left(\pi_{qv|c_{lf}}\right)^{x_{ivs}}}{\sum_{c_{lf}=1}^{C_{lf}}\Pr\left(c_{lf} : z_i\right)\prod_{q=1}^{Q}\prod_{v=1}^{V_q}\left(\pi_{qv|c_{lf}}\right)^{x_{iqv}}}. \tag{7}$$

Note that this *latent-class lf model* is not a choice model. Three site-choice models are developed and estimated in Section 7. Our preferred behavioral model will use lfClass as an explanatory variable.

4. Life-constraints and a Latent-class lf Model for 4605 Mountain Bikers

Sample proportions for the different life-constraint levels are in Table 1, column two. (The legend for tables and figures for the mountain-bike data start with "MTB". Those for the Veneto data start with "Veneto.") Most respondents are experienced mountain bikers. There are 634 women; 20% have children; in contrast, 37.4% of the males have children. Each respondent was shown four sets of four photographs, each photo a photo of a short stretch of a mountain-bike trail (http://www.colorado.edu/economics/morey/static/bikefinal011.html) and asked if they had the skill to ride those sections of trail. Based on their responses, each respondent was assigned a skill level: skill 1, the lowest, and skill 5, the highest. It is important to distinguish between skill and fitness; one can be fit and unskilled, or skilled and unfit (out of shape but able to descend very technical trails). It is also important to distinguish between skill and preference. There are eight life-constraints in the data set: skill, resting heart rate, cigarettes per day, significant other, number of minor children, BMI, diseases, and average amount of overall exercise per week.[11] The data on age, gender and the eight life-constraints was used to estimate latent-class lf models with one through nine lfClasses; estimation was with the software Latent Gold (Vermunt and Magidson, 2005).

Using fit criteria (the LL, BIC, AIC, AIC3, and CAIC), seven lfClasses best characterize the population. All eight life constraints are significant class determinates.[12]

Gender and age are significant determinants of the life-constraint class-membership probabilities. The details are below. The estimated class sizes (class-membership probabilities after averaging over the covariates) are 24.0% (lfClass1), 20.3% (lfClass2), 18.8% (lfClass3), 13.5% (lfClass4), 8.6% (lfClass5), 8.0% (lfClass6), and 6.9% (lfClass7).[13]

LfClass1 members are unconstrained by significant other and kids, unfit, and mostly male. LfClass2 are highly-constrained, middle-age, heavy males. Contrasting, lfClass3 members are constrained, middle-age, highly-skilled, fit males. LfClass4 are the expert fitness junkies, men and women. LfClass5 is characterized by thin women with one or no children. LfClass6 are old low-skilled males. The thin, unmarried, under 30, belong to lfClass7—the "20-somethings."

4.1. Justifying Our Characterizations of the Seven lfClasses: The Details

Those in lfClass5 are most certainly female (98.7% probability), the opposite is true for lfClass3. Ninety-four percent of lfClass7 members are estimated to be under 30, while those in lfClass6 are likely over 60.

Table 1 reports the estimated probabilities for each level of each life-constraint, for each estimated lfClass. Those in lfClasses 3 and 4 are estimated highly skilled. Contrasting, 72.1% of lfClass5 are predicted to be skill 1 or 2: low skilled. Fig. 2 confirms, showing average estimated skill levels by lfClass. For example, the estimated average skill level is 3.7 (out of 4) for lfClass3, 3.8 for lfClass4, and 2.5 for lfClass5.

All seven lfClasses exercise, but the predicted amounts vary substantially: lfClass2 moderately, lfClass4 intensely—more than 10 h a week for over 40%. lfClass2 has the highest probability of not exercising (7.2%); this probability is less than 1% for members of lfClass4. Almost 50% of lfClass4 members are predicted to have a resting heart rate of 50 or less, so very fit. lfClass3 is close with 41.2%; for the other five lfClasses the predicted percentage below 50 bpm ranges from 0.1% to 10.7%. If one is in lfClass2 or 6, there is a 4% probability that one has a resting rate over 100, unhealthy; this probability is zero for those in lfClasses 3 and 4.

No lfClass smokes much, but 9.3% of lfClass1 and 8.0% of lfClass7 are predicted to smoke. lfClass2 members have a high probability of being overweight (BMI of at least 27 for 41.3%). lfClasses 1 and 6 are also relatively heavy. Contrasting, only 0.5% of those in lfClass7 are predicted to have a BMI over 27. Almost 19% of lfClass7 is predicted to be thin (BMI 20 or less). Twenty percent of lfClass6 are predicted to have a disease that limits their ability to do strenuous exercise, for the other classes the range is 4.8% to 8.5%.

The estimated probability of having a significant other varies from almost 100% (lfClass2) to less than 20% (lfClass 7). Few have more than two kids: those in lfClass3 have a 55% chance of having one or two kids, for lfClass2 is it 62.4%. The probability of having no children at home varies from 95.7% (lfClass4) to 22.8% (lfClass2).

We now consider, using simple statistics, the relationship between lfClasses, how much one mountain bikes, and which rides one chooses. Then we analyze the Veneto hiker climber data using both simple statistics and behavioral models.

5. lfClasses Explain Significant Variation in Mountain-bike Participation and Site Selection

The 4605 sampled mountain bikers collectively mountain biked 28,910 days in "the last 30 days," and in "the last seven days," biked 16,085 h. The day range is 0 to 30; the hour range in the last seven days is 0 to 40. Calculating the individual's conditional class-membership probabilities, the $\Pr(c_{lf}{:}z_i|x_i)$, precisely places most individuals in a lfClass.

5.1. There Are Significant, and Intuitive, Differences by lfClass in How Much One Bikes

Table 2 reports average days and hours mountain biking, by lfClass. Statistically, one rejects the null hypothesis that average biking days do not vary by lfClass. The mean number is highest for lfClasses 3 and 4, and lowest for overweight males and thin mothers

[11] Note that for most of the even most avid mountain bikers in our sample, mountain biking only accounts for a fraction of average exercise time: mountain biking is a seasonal activity, typically requiring dry conditions; most mountain bikers get much of their exercise in other ways.

[12] Note that fit criteria for determining the number of classes are *criteria* not statistical tests—there are no classical statistical tests for determining the number of latent classes—so it is reasonable to ask if our basic findings would differ if there were slightly more or fewer classes. The answer is our basic points remain: (1), for our two data sets, each with lots of life constraints, life-constraint latent-class models separate recreators into classes that make sense; and (2), life-constraint class is an important determinant of how often one recreates, where one recreates and how one recreates. With fewer latent classes, some of the smaller classes merge and some life constraints become insignificant. For example, in the reported seven lfClass model, disease is a significant determinant of class, but it would not be a significant determinant if one assumed only three classes: only 8% of the sample has a disease that affects their ability to exercise. For an introduction to fit criteria, see Thacher et al. (2005).

[13] Number of estimated classes is typically weakly monotonic with respect to the sample size and we have a very large sample, so seven distinct life-constraint classes.

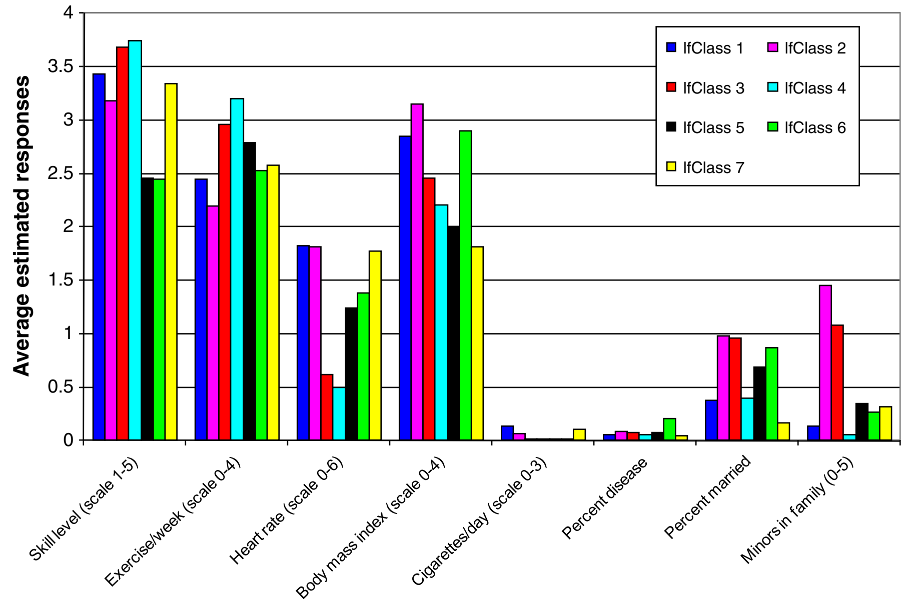

Fig. 2. MTB: average estimated constraint levels, by lfClass.

with one or no kids (lfClasses 2 and 5). The most variant is lfClass7 (the 20-somethings). Consider the probability one does not ride for 30 days, by lfClass. lfClass7 (thin, unmarried, under 30) and lfClass5 (overweight males) are least likely to ride, lfClass3 (constrained, middle-age, highly skilled, fit males) most likely. Note that the old guys bike, in days, as often as the expert, fitness junkies—the old guys have free time.

The null hypothesis that the average number of hours of biking does not vary by lfClass is also rejected. The averages vary, significantly, from 2.7 per week (lfClass5: thin females with one or no kids) to 4.5 h for lfClass3. In seven days, almost half of lfClass5 are estimated to have no mountain-bike hours; it is only a quarter for lfClass3. Also of interest is the average hours by lfClass for those who had positive hours; lfClass7 has the highest.

5.2. There Are Also Significant and Intuitive Differences, by lfClass, in the Selection of Mountain-bike Rides

Recollect, each respondent was presented with 5 pairs of mountain-bike rides. Across the fifteen survey versions, 75 choice pairs appeared. The ride attributes were trail length, percentage single track, number of climbs, total vertical feet of climbing, fee to ride the trail, whether one had a companion, and, if so, the companion's relative speed. lfClass 2 (the overweight males), 5 (thin females) and 6 (old guys) are significantly more likely to choose the easier alternative in each pair, and the highly skilled and fit (lfClasses 3 and 4) significantly more likely to choose the difficult trail, details on request.

Table 2
MTB—average days biked in the last 30 days and average hours biked in the last week.

	lfClass1	lfClass2	lfClass3	lfClass4	lfClass5	lfClass6	lfClass7
Average days	5.9	5.5	7.5	7.5	5.2	6.3	6.5
Percent with zero days	16.7	14.9	9.7	11.9	21.9	12.0	22.5
Average hours	3.2	2.7	4.5	4.4	2.7	3.1	4.1
Percent with zero hours	39.8	39.0	26.2	31.6	45.8	33.8	41.8

6. Members of the Veneto Alpine Club: Simple Statistics and a Latent-class lf Model

The six PreAlp sites are Feltrine, Piccole, Alpago, Asiago, Grappa, and Baldo; the twelve Dolomite sites are Antelao, Pelmo, Cortina, Duranno, Sorapis, Agner, Tamer, Marmarole, Lavaredo, Civetta, Martino, and Marmolada. Hiking and technical climbing are the primary activities. Fig. 3 shows, in yellow (ignore for now the blue and green bars), the proportion of individuals taking *t* trips; starting with 1–5 trips, the proportions monotonically decline. Fig. 4 shows it for PreAlp trips.

There is data on the levels of eight life constraints (listed in Table 3); this data was used to estimate *latent-class lf models* with 1–6 lfClasses. All eight of these life constraints are significant determinants of the classes. This sample is best characterized with four lf latent-classes. Age category and gender are significant determinants of the class-membership probabilities: female are most likely in lfClass2 or 4, and old people in lfClass3 or 4. The estimated class sizes are 56.7% (lfClass1), 20.5% (lfClass2), 15.3% (lfClass3), and 8.4% (lfClass4).

Summarizing, lfClass4 members exercise little and are thin. lfClass4 is effectively the only kid-constrained class. lfClass3 members are most inclined to smoke and drink, and most are retired. lfClass2 are highly educated, thin, and fit, few smoke or drink; lfClass1 is everyone else; it is common in latent-class model to have such a catch-everyone-else class.[14]

Justifying our characterizations, Table 3 reports the estimated probabilities for each level of each life-constraint, by lfClass. Fig. 5 graphs the average estimated constraint levels. For example, lfClass2 is estimated most educated, likely to drink the least, thinnest, and estimated to spend the most time, on average, exercising. None in lfClass2 are predicted to be retired, but over 80% of lfClass3 are. lfClass3 members are predicted to exercise little and not be constrained by children. And, relative to the other classes, are predicted to drink more, smoke more, have more heart disease, and have more high blood pressure. lfClass4 is the only kid-constrained class, but members also have a high predicted probability of being retired (50.7%) and old (49% are predicted to be 50 or over). lfClass1 is

[14] Forcing more classes would likely split lfClass1, making it less catch-all, but not substantially improve fit or explanatory power.

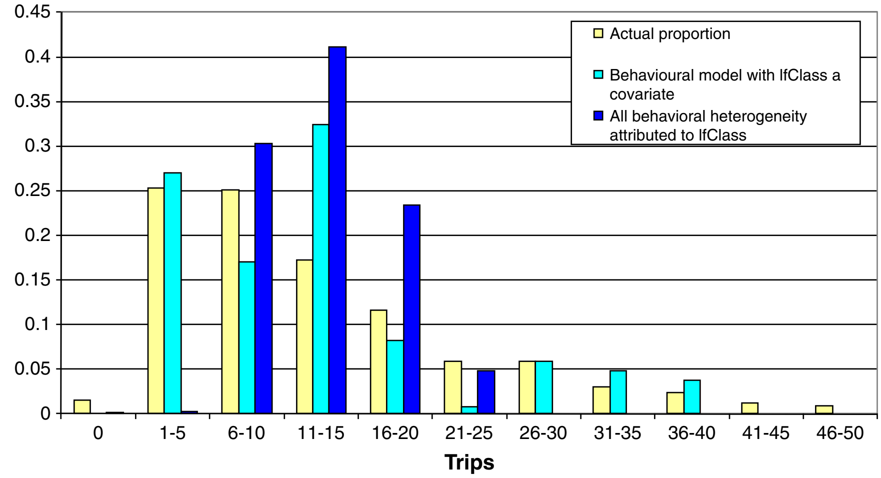

Fig. 3. Veneto—proportion of individuals taking *t* trips.

everyone else; none are predicted to be retired, and 58% are predicted to be less than 50. Relatively speaking, they are predicted to be highly educated and exercise prone, but not at the levels of lfClass2. They are predicted to drink more than all but those in lfClass3.

Those in lfClass1 have a high probability of being male, those in lfClass2 of being young (66% are female), those in lfClass3 a high probability of being old and male, and those in lfClass4 a high probability of being female and over thirty.

7. The Veneto lfClasses 'Explain' Significant Variation in Participation, Site Selection and Activity On-site

For the Veneto, we investigate, in two steps, the relationship between the lfClasses and behavior: first with simple statistical tests and analysis, then by proposing and estimating three behavioral models of participation and site selection as a function of either life constraints themselves or lfClasses.

7.1. There Are Significant Differences in Behaviors Across the Four Veneto lfClasses: Simple Statistical Tests

The estimated lf latent-class model places 87% of the Club members in a lfClass with at least 90% precision, and 98% with at least 70% precision. The average number of actual trips, by lfClasses 1, 2, 3 and 4 are 13.49, 11.37, 14.52, and 13.41. Based on an ANOVA, the null hypothesis that they are equal is rejected. lfClass3 take, on average, the most trips, probably because they have the most time (76% are predicted to be retired and none are predicted to be kid constrained). Interestingly, those predicted to be young and fit, take the fewest trips. Our suspicion, which we confirm below, is that their trips are farther from home and more challenging.

Consider next how the different lfClasses allocate their actual trips between the PreAlp and Dolomite sites. Almost sixty percent of all trips are to the PreAlps: for most Veneto residents, the PreAlps are closer to home (closer to Venice, Padua, Verona). The PreAlp sites range from 800 to 1500 m in elevation; the Dolomite sites range from a 1000 to 3000 m and are wilder: rock faces and spires projecting hundreds of meters skyward, most hiking is above tree line, and weather is always a factor. For a representative picture of the PreAlps, see http://www.colorado.edu/economics/morey/asiago.pdf, for the Dolomites, http://www.colorado.edu/economics/morey/3cime.pdf. While there are many pleasant walks, the Dolomites are famous for high-alpine mountaineering and technical climbing.

One rejects, with a Chi-squared test, the null hypothesis that the allocation of trips between the two regions does not differ by lfClass. Table 4 reports the observed trip proportions by estimated lfClass. Not surprisingly, lfClass3 (retired, less fit and bad habits) and lfClass4 (kid-constrained and less fit) take significantly more of their trips to the

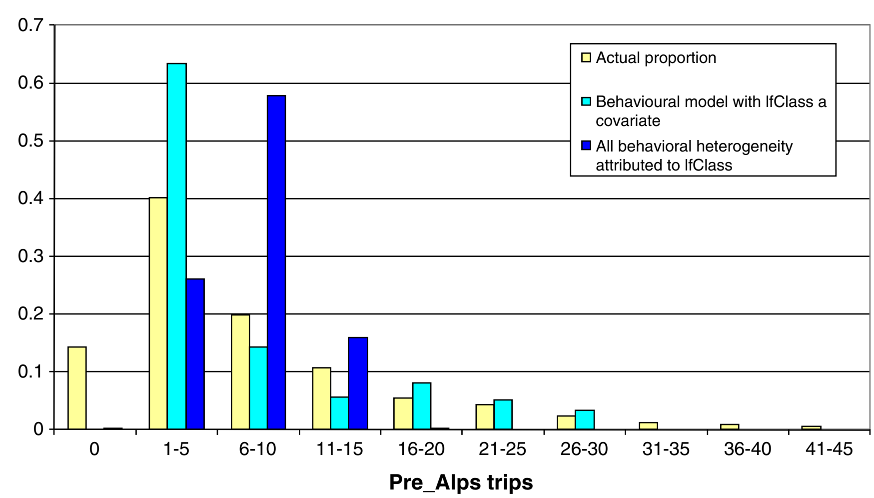

Fig. 4. Veneto—proportion of individuals taking *t* trips to Prealps.

Table 3
Veneto—estimated probabilities for each level of each life-constraint, by lfclass.

	Total	lfClass1	lfClass 2	lfClass 3	lfClass 4
Retired					
Yes	16.8	0.2	0.1	80.9	50.7
Education					
Not reported	0.4	0.1	0.6	1.9	0.0
Primary school	4.0	0.3	0.0	19.8	9.3
Secondary school	24.0	23.5	9.8	38.0	36.2
High school	55.8	60.3	67.0	31.4	42.7
Degree	15.8	15.8	22.6	8.9	11.7
Body mass index					
Less than 20	11.1	2.3	40.4	2.4	13.6
20–24	64.4	68.6	57.1	52.8	74.9
25–27	16.3	19.6	1.0	28.7	9.6
28 or more	8.2	9.5	1.5	16.1	2.0
Exercise/week (hours)					
0	53.6	51.3	39.7	72.9	67.5
1–2	10.5	10.0	15.0	4.6	13.3
3–5	21.5	23.5	27.0	11.6	12.7
6–8	7.8	8.8	8.2	5.6	4.2
9–14	5.6	5.9	7.7	3.8	1.6
14 or more	1.1	0.5	2.3	1.6	0.7
Cigarettes/day					
0	84.0	80.5	90.3	84.8	90.6
1–6	6.0	6.4	6.7	5.4	2.7
7–20	9.5	12.4	3.0	9.3	6.7
20 or more	0.4	0.6	0.0	0.5	0.0
Alcohol/day (drinks)					
0	48.7	38.9	82.7	27.8	68.3
1–2	30.4	39.1	15.4	21.7	24.5
3–4	14.7	15.2	1.9	34.7	6.3
5–6	4.9	5.5	0.0	12.1	0.0
6 or more	1.4	1.3	0.0	3.7	0.9
Kid constrain[a] (scale 0–3)					
0	91.4	100.0	94.6	100.0	11.0
1	4.6	0.0	0.0	0.0	54.5
2	2.7	0.0	2.1	0.0	27.3
3	1.3	0.0	3.3	0.0	7.2
Heart disease					
Yes	3.1	2.2	1.2	8.2	5.1
High blood pressure					
Yes	4.9	3.4	0.3	17.2	4.3

[a] 0 = males and females with no kids; 1 = females who are at least age 46 and have one kid, or at least 50 with two or more kids; 2 = females 45 or less with one kid, or 46 to 49 with two or more kids; 3 = pregnant females, or 46 or less with two or more kids. Rows, by covariate and class, sum to 100.

PreAlps than do lfClasses 1 and 2. lfClass3, the least fit, are more likely to hike than to climb or mountaineer, making the PreAlps attractive.

Consider next how the different lfClasses allocated their trips across the 14 specific Veneto sites (Table 4). One rejects the null hypothesis that the allocations do not differ by lfClass. lfClass2, those predicted to be young, fit, and highly educated, are the most represented at the most extreme Dolomite sites: Lavaredo, Civetta and Pale S. Martino (famous for challenging climbs), Marmolada (with a glacier) and Pelmo, where access to hiking is technically challenging. lfClass4 (mothers and older females) are under-represented at the extreme Dolomite sites. Those retired and with bad habits (lfClass3) are the most represented class at Piccole, Asiago and Grappa, which are easy-hiking PreAlp sites. lfClass3 are under-represented at all 12 Dolomite sites.

We identified ten types of recreators, listed in Table 5, along with the proportion of the sample of each type. Overall, respondents are most likely to be hikers who do not climb. One rejects the null hypothesis that what one does on-site does not vary by lfClass. For example, lfClass3 members (old males) are overrepresented in occasional climbers who do not hike and regular hikers who do not climb, and are three times more likely to be occasional climbers who do not hike than are lfClass2 members, the young and fit. lfClass4 (kid constrained and older women) are overrepresented in type 4 (occasional hikers who do not climb) and under-represented in regular climbers. lfClass2, the young and fit, are over-represented in the ranks of those who both hike and climb.

7.2. Class Models of Participation and Site Selection that Consider Life-constraints

To further investigate the extent to which life-constraints predict participation and site selection, we develop and estimate, using the Veneto data, four behavioral models of participation and site-selection heterogeneity. Like the simple statistical tests, they demonstrate the explanatory significance of life-constraints. Unlike the simple statistical tests, these models can predict how recreation selections will change if life-constraints change. Our preferred model out of these four can be used to estimate and model behavior for most discrete-choices where there are relevant life constraints.

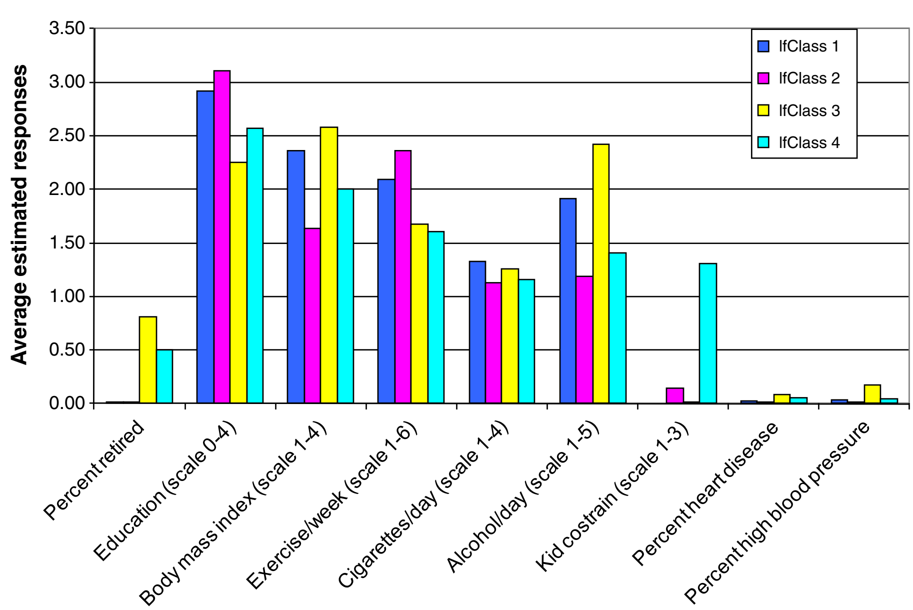

Fig. 5. Veneto—average estimated constraint levels, by lfClass.

Table 4
Veneto—percentage of trips to each site, by estimated lfClass.

	lfClass1	lfClass2	lfClass3	lfClass4
Pre-Alps (total)	55.7	55.6	68.9	65.9
Dolomites (total)	44.3	44.4	31.1	34.1
PreAlps				
Feltrine	8.4	7.7	7.4	7.2
Piccole	18.9	16.8	23.4	17.1
Alpago	4.3	6.1	3.7	3.7
Asiago	9.1	9.1	14.3	13.4
Grappa	6.1	7.0	9.3	9.1
Baldo	8.9	8.9	10.9	15.4
Dolomites				
Antelao	2.2	2.1	1.6	2.8
Pelmo	2.4	3.9	1.7	2.7
Cortina	3.2	2.9	2.2	2.4
Duranno	0.8	0.5	0.4	0.4
Sorapis	1.5	1.4	0.8	0.9
Agner	1.6	1.1	1.4	1.0
Tamer	2.9	2.1	1.8	2.4
Marmarole	2.4	1.9	1.7	1.5
Lavaredo	6.6	7.8	5.2	6.7
Civetta	8.8	9.0	5.5	5.1
Martino	8.4	8.0	6.5	5.7
Marmolada	3.6	3.7	2.4	2.5

7.2.1. A Commingled Behavioral Model: Preference and Life-constraint Heterogeneity Commingled, a Standard Latent-class "Choice" Model

Observed behavioral heterogeneity results from price variation, income variation, preference heterogeneity, and life-constraint heterogeneity. If one simply wanted to model participation and site-selection heterogeneity, without explaining the heterogeneity, except that caused by price and income variation, one might reasonably choose to estimate a latent-class *commingled behavioral model*: number of behavioral-classes estimated; behavioral-class-membership probabilities estimated, and the probability of being in behavioral-class b estimated, ignoring life-constraints. We use the adjective "commingled" to indicate, as with Eq. (4), that the estimated parameters are capturing preference and life-constraint heterogeneity with no separation; this model is Eq. (4), and is the "standard" latent-class model. We start with this model in order to show that when life-constraint levels are explicitly added, fit and explanatory power significantly improves, demonstrating that life-constraint do indeed matter, and showing how much of the heterogeneity is explained by the life constraints.

Assume that conditional on belonging to behavioral-class b, c_b, the probability an individual i selects alternative j on a choice occasion is

$$\Pr\left(j|c_b\right) = \frac{\exp\left(\alpha_{j|c_b} + \beta_{|c_b} Cost_{ij}\right)}{\sum_{k=0}^{18} \exp\left(\alpha_{k|c_b} + \beta_{|c_b} Cost_{ik}\right)} \quad c_b = 1, 2, \ldots C_b \tag{8}$$

where $Cost_{ij}$ is trip cost to site j by individual i. There are 18 sites and $k = 0$ represents the alternative staying home where $Cost_{i0} = 0$. The $\boldsymbol{\alpha}$ reflect the relative qualities of the 19 alternatives. For statistical identification, the $\alpha_{0|c_b}$ are set to zero. We assume 50 choice occasions: few respondents took more than 50 trips. Let y_{ki} be the number of times individual i chose alternative k and $\Pr(c_b)$ the unconditional probability an individual belongs to behavioral-class c_b.

Four behavioral classes best describe the population, and the maximum likelihood estimates of the $\alpha_{|c_b}$, $\beta_{|c_b}$and $\Pr(c_b)$ constants are all significant selection determinants. The estimated model has 79 parameters (18 site qualities for each bClass, 4 estimated cost parameters, one for each bClass, and 3 estimated bClass-membership probabilities). While this is an attractive, and common, model, it is dominated, in our view, by models that explicitly incorporate life constraints. (On the basis of a likelihood-ratio test, it is statistically dominated by our next model, a *behavioral model with lfClass as a covariate*.) The sizes of the bClasses and the quality estimates for the alternatives for the *commingled behavioral model* are visually similar to those for the *behavioral model with lfClass as a covariate*, so not reported. Note that this *commingled behavioral model* explains none of the behavioral heterogeneity.

Table 5
Veneto—respondents by recreator type, by estimated lfClass.[a]

	lfClass1	lfClass2	lfClass3	lfClass4
Occasional climbers who do not hike	6.6	4.4	13.6	11.2
Regular climbers who do not hike	15.9	6.9	6.0	6.9
Climbing instructor who do not hike	4.3	0.8	0.0	0.0
Occasional hikers who do no climb	21.0	31.0	25.1	33.6
Regular hikers who do no climb	30.3	35.1	42.7	37.9
Ski mountaineering	0.7	0.0	0.0	0.0
Regular hikers and occasional climbers	9.5	8.5	3.0	3.4
Occasional hikers and regular climbers	2.0	2.4	2.0	0.9
Occasional climbers and occasional hikers	1.2	2.0	0.5	1.7
Regular climbers and regular hikers	8.4	8.9	7.0	4.3

[a] Columns sum to 100%.

7.2.2. Three Behavioral Models Where Life-constraints Have Influence

7.2.2.1. A Behavioral Model with lfClass as a Covariate. This, our preferred model, explicitly incorporates the constraint heterogeneity. This model is Eq. (8) with the behavioral-class membership probabilities, the $\Pr(c_b)$, not constants, but functions of the individual's most likely lfClass: $\Pr(c_b\text{: } lf1_i, lf2_i, lf3_i, lf4_i)$ where $lfw_i = 1$ if individual i most likely belongs to lfClass$w$, and zero otherwise. One determines the lfw_i by first estimating the *latent-class lf model*, Eq. (5), and then allocating each individual to their most likely lfClass based on their age, gender and life-constraints. Recollect that there are four estimated lfClasses. Assume

$$\Pr(c_b : lf1_i, lf2_i, lf3_i, lf4_i) = \frac{\exp\left(\phi_{c_b} + \sum_{w=1}^{4} \lambda_{c_b w} lfw_i\right)}{\sum_{m=1}^{B}\left[\exp(\phi_m + \sum_{w=1}^{4} \lambda_{mw} lfw_i)\right]} \tag{9}$$

where m indexes the B bClasses and w indexes the four lfClasses. The individual's most likely lfClass enters the behavioral model as a covariate that directly influences the individual's bClass membership probabilities; age and gender enter only through their influence on the lfw_i.[15] The $\alpha_{j|c_b}$ and $\beta_{|c_b}$ in $\Pr(j|c_b)$, Eq. (8), and the ϕ_m and λ_{mw} are all simultaneously estimated, conditional on the lfw_i. Behavioral heterogeneity is best explained with four behavioral classes.[16] There are 88 identified parameters, only 9 more than in the *commingled behavioral model*. The hit rate, the percentage of times the model correctly predicts the alternative chosen, is 73.89%. An estimated R^2 is 57.47%. The estimated behavioral class sizes are 47% (bClass1), 27% (bClass2), 16% (bClass3) and 10% (bClass4).

Based on a likelihood ratio test, one rejects the null hypothesis that the lfClass covariates, the lfw_i, have no influence on participation and site selection. Put simply, an individual's life-constraints are significant determinants of behavior, and their influence is incorporated with only 9 additional parameters since lfClasses are estimated and used as covariates.

The influence of the covariates is summarized in Table 6. Remember that bClass1 (ave. approx. 6 trips, 4 to PreAlps—see Table 9) is the

[15] Contrast this probabilistic approach to modeling life-constraints with the deterministic way the budget constraint is typically modeled; lfClass affects the probability that one is in each bClass. Imagining an extreme example, if there are configurations of life-constraint levels that make it very difficult to participate in the activities at a particular site or sites (e.g. life-constraint levels make it impossible to climb), and if significant numbers have these constraint levels, we would expect this model to generate an "incapable" lfClass, to generate a bClass where the probability of visiting this site(s) is very low, and a high probability that those in this incapable lfClass are in that bClass.

[16] The estimated number of bClasses need not equal the estimated number of lfClasses; they just happen to in this application.

largest bClass and bClass4 (ave. 33 trips, 20 to PreAlps) the smallest. Note that, on average, one is more likely to be in a larger than a smaller bClass. Some highlights from Table 6: those in lfClass3 (retired, some bad habits, and mostly male) are approx. 6 times more likely to be in bClass3 (ave. 21 trips, 16 to PreAlps) than are those in lfClass4 (thin, exercise little, and the only kid constrained class), And, those in lfClass1 (most working, most males, fit, but not the fittest) are 1.7 times more likely to be in bClass2 (ave. 12 trips, 4 to PreAlps) than are those in lfClass3, but only l.2 times more likely to be in bClass2 than are those in lfClass2 (highly educated, thin, and fit, males and females).

Rather than report the estimated $\alpha_{j|c_b}$ parameters themselves, Tables 7 and 8 report the more intuitive estimated probabilities of choosing each alternative, conditional on bClass, restrictively assuming all alternatives cost zero, including staying home. They indicate, by bClass, the relative cardinal qualities of the 19 alternatives. Table 7 collapses the alternatives into three alternatives: staying home, the PreAlp sites, and the Dolomite sites, while Table 8 reports the estimated probabilities for the individual sites. Table 8 columns sum to 100%. There is significant variation in the relative quality of staying home; if visiting sites were costless, the model predicts that individuals in bClass3 would take 46.5 (50–.07(50)) trips, and individuals in bClass2, 22.1 trips. The ratio, the last row in Table 7, would be 1.0 if the respondent was predicted, with zero trip costs, to allocate half of his trips to the PreAlps. For all four bClasses, the Dolomite sites, as a group, have higher quality: 50% higher for bClasses 3 and 4, and almost 300% higher for bClass2.

In Table 8, the bolded numbers identify the two highest quality sites, by bClass; the two small-font numbers are the least attractive. bClass2 is the Dolomite class. bClass3 find Baldo very attractive and twice as attractive as Feltrine, whereas bClass2 find Feltrine much more attractive than Baldo—Baldo is kid friendly, Feltrine is not. Lavaredo is in the top three for all four bClasses: while this site has incredible climbs it also has, a breathtaking, but kid-friendly, short walk, ending at an alpine hut (see the earlier photo link).

However, behavior depends on cost as well as quality. The estimated cost parameters for the four bClasses are all significantly different from zero, and all significantly different from one another, varying from minus .1 (bClass2) to minus .39 (bClass3). bClass2 is the only class for which site qualities explain more selection variation than do site costs. The first column of Table 9 reports the average number of trips in the sample. The other columns report, based on this *behavioral model with lf Class as a covariate*, the predicted average number of trips to the PreAlps and Dolomites by bClass. Individuals in bClass4 are predicted to take the most trips, 32.67, those in bClass1 the least, 6.35. Those in bClass2, by prediction, take two-thirds of their trips to Dolomite sites, unlike those in the three other bClasses, which are predicted to take less than half to Dolomite sites.

Fig. 3 compares, for the *behavioral model with lfClass as a covariate* (in light blue), the estimated proportion that will take t trips with the actual proportions (in yellow). Not surprisingly, this model misses those few taking either zero trips or more than forty trips, but nicely captures the right tail up to forty trips.

Fig. 4 makes the same comparison for the proportion taking t PreAlp trips: the *behavioral model with lfClass as a covariate* comes close to predicting the sample proportion that will take 0 to 5 PreAlp trips, but wrongly predicts they will all take at least one trip.

Table 6
Veneto—proportion of lfClassW estimated to be in bClassY.[a]

	bClass1	bClass2	bClass3	bClass4
lfClass1	0.44	0.31	0.14	0.11
lfClass2	0.56	0.26	0.11	0.08
lfClass3	0.48	0.18	0.23	0.10
lfClass4	0.43	0.39	0.04	0.14

[a] Rows sum to 1.

Table 7
Veneto—behavioral model with lfClass as covariate: estimated proportion of occasions each aggregate will be selected, assuming zero costs.

	bClass1	bClass2	bClass3	bClass4
Stay at home (%)	46.4	55.8	7.0	9.5
A PreAlp site (%)	24.1	12.1	37.1	35.4
A Dolomite site (%)	29.5	32.2	55.9	55.1
Dolomite/PreAlps	1.22	2.66	1.51	1.56

The *behavioral model with lfClass as a covariate* can be used to predict how each individual's number of trips and site selections will change if their life-constraint levels change. If life-constraint levels don't change enough to change the individual's predicted lfClass, behavior is predicted to remain the same. For example, if the individual simply gains a little weight, predicted behavior does not change, a reasonable prediction. However if his or her life-constraint levels change sufficiently to cause a change in lfClass, predicted behavior will change. For example, as predicted by the *latent-class lf model*, many young, fit, childless, exercise-active females are likely in lfClass2 (highly educated, thin, and fit, males and females). If she then has a child, losses fitness, exercising less, she is likely to move to lfClass4 (thin, exercise little, and the only kid constrained class). And, many males initially in lfClass2 can, by acquiring bad habits (more cigarettes and alcohol, and less exercise) and weight, shift to one of the other lfClasses, lfClass1 the most likely. A change in likely lfClass is a change in the covariates in the *behavioral model with lfClass as a covariate*. For example, the female who shifts from lfClass2 to lfClass4 becomes much more likely to be in bClass2 (ave.12 trips, 4 to PreAlps) or bClass4 (ave. 33 trips, 20 to PreAlps) and less likely to be in bClasses 1 (ave. 6 trips, 4 to PreAlps) or bClass3 (ave. 21 trips, 16 to PreAlps).[17] The specific site predictions for an individual depend on the individual's specific trip costs, but for many individuals shifting from lfClass2 to lfClass4 will result in more trips but with a smaller proportion to the Dolomites.

7.2.2.2. A Behavioral Model with the Life-constraints Themselves as Covariates. This model is Eq. (8) with the behavioral-class membership probabilities, the $\Pr(c_b)$, not constants, but a function of the individual's levels of each life constraint: $\Pr(c_b{:}z_i, \boldsymbol{x}_i)$ where $\boldsymbol{x}_i$ is individual i's vector of life-constraints. Age, gender and the life-constraint variables are directly entered as covariates influencing the individual's bClass membership probabilities—there are no lfClasses. Specifically,

$$\Pr(c_b : z_i, x_i) = \frac{\exp\left(\chi_{c_b} + \kappa_{c_b}(f_i) + \sum_{a=1}^{7}\rho_{c_b a}(age_{ai}) + \sum_{q=1}^{Q}\sum_{v=1}^{V_q}\tau_{c_b vq}\left(x_{ivq}\right)\right)}{\sum_{m=1}^{4}\left[\exp\left(\chi_m + \kappa_m(f_i) + \sum_{a=1}^{7}\rho_{ma}(age_{ai}) + \sum_{q=1}^{Q}\sum_{v=1}^{V_q}\tau_{mvq}\left(x_{ivq}\right)\right)\right]}. \tag{10}$$

V_q is the number of levels of life-constraint q. The $\alpha_{j|c_b}$ and $\beta_{|c_b}$in $\Pr(j|c_b)$, Eq. (8), and the χ_{c_b}, ρ_{c_b}, κ_{c_b} and the $\tau_{c_b k}$ in $\Pr(c_c{:}z_i, \boldsymbol{x}_i)$ are all simultaneously estimated.

With four estimated bClasses, there are 175 identified parameters, 87 more than in the *behavioral model with lfClass as a covariate*. Based on a likelihood ratio test, one rejects the null hypothesis that the life-constraints themselves have no influence on selections. Like the previous one, this model demonstrates that life-constraints help to explain behavioral heterogeneity.

We prefer the *behavioral model with lfClass as a covariate* over this *behavioral model with the life-constraints themselves as covariates*. First, the former model is more parsimonious: it incorporated the influence of life-constraints with 9 additional parameters, the latter required 96 additional parameters. Second, life-constraints are correlated for an individual, so attempting to identify their separate

[17] For example, the probability of being in bClass2 increases from 26% to 39% when one switches from lfClass2 to lfClass4, Table 7.

Table 8
Veneto—behavioral model with lfClass as covariate: estimated proportion of trips to each site assuming zero trip costs (%).

Sites	bClass1	bClass2	bClass3	bClass4
PreAlp sites				
Feltrine	5.0	6.3	6.7	4.9
Piccole	**20.4**	8.2	6.0	**19.5**
Alpago	3.1	3.1	5.3	2.7
Asiago	8.8	3.5	6.7	5.2
Grappa	2.9	2.8	2.7	2.3
Baldo	4.9	2.4	**12.3**	4.8
Dolomite sites				
Antelao	3.7	2.9	2.1	1.5
Pelmo	3.1	4.0	2.4	3.1
Cortina	6.7	6.3	6.2	6.2
Duranno	0.4	0.8	1.0	0.88
Sorapis	2.4	2.8	1.9	2.0
Agner	0.9	1.8	2.2	2.5
Tamer	1.4	3.3	1.3	2.9
Marmarole	3.4	2.6	6.3	2.2
Lavaredo	**15.5**	**11.8**	**17.7**	10.9
Civetta	8.4	**14.9**	6.2	**12.8**
Martino	5.2	10.4	4.1	8.0
Marmolada	4.1	8.8	8.6	8.5

influences is optimistic. We report the *behavioral model with the life-constraints themselves as covariates* only to demonstrate that one can directly model the life-constraints themselves and show them important without assuming a *latent-class lf model*.

7.2.2.3. A Model with All Behavioral Heterogeneity Attributed to lfClass. The two previous models allow behavior to vary with both life-constraints and preferences, explicitly modeling the life-constraint variation. In contrast, this model forces all behavioral heterogeneity to be the result of life-constraint heterogeneity—preference heterogeneity is not admitted. So, this model, by construction, explains less behavioral heterogeneity than the three previous models unless, of course, all behavioral heterogeneity is due to life-constraint heterogeneity. We report this model to demonstrate that life-constraint heterogeneity does not explain all behavioral heterogeneity, but definitely explains a significant chunk of it. This model is estimated by first estimating the *latent-class lf model*, Eq. (5), then deterministically assigning each individual to their most likely lfClasses, then estimating Eq. (8) assuming each lfClass is a bClasses. Here, bClass is *not latent*, it is assigned, so there are no bClass membership probabilities to estimate. The difference between the *behavioral model with lfClass as a covariate* and this model is in the former one's lfClass probabilistically determines one's bClass and the number of bClasses is estimated; in this model, each bClass is constrained to be a different lfClass. Note this model does not nest, or is not nested in, any of the three other behavioral models. The model has 76 identified parameters (18 site qualities for each of the four estimated lfClasses, and 4 estimated cost parameters), three less than the *commingled behavioral model*.

For this model, the *model with all behavioral heterogeneity attributed to lfClass*, the estimated cost parameters vary significantly across the four lfClasses, but they vary less than the cost parameters in the *behavioral model with lfClass as a covariate*.

Table 9
Veneto—behavioral model with lfClass as covariate: estimated average number of trips to each aggregate, including the effect of trip costs, after assigning each individual to their most likely bClass.

Average observed trips sample	Aggregate	bClass1	bClass2	bClass3	bClass4
13.06	Total trips	6.35	12.23	21.40	32.67
7.66	A PreAlp site	4.03	4.22	16.24	20.34
5.4	A Dolomite site	2.33	8.01	5.15	12.33
0.705	Dolomite/PreAlp	0.58	1.90	0.32	0.61

The null hypothesis that the quality estimates do not significantly differ across the four lfClasses is rejected—some of the behavioral heterogeneity is caused by life-constraint heterogeneity. The quality parameters are, as expected, quite different from those for the *behavioral model with lfClass as a covariate*; they vary less across regions and sites. Briefly, lfClass3 (retired, mostly male, bad habits) value the sites the highest, and lfClass2 (educated, thin and fit) the lowest—this is consistent with those in lfClass3 taking the most trips and those in lfClass2 the fewest trips. While the probability of staying home on a choice occasion varies across bClasses between 7.0% and 55.8% in the *behavioral model with lfClass as a covariate*, in this model, they vary only between 29.6% and 44.5%.

For this model, lfClass imposed as the bClass, individuals in lfClass3 are predicted to take, on average, the most trips, 14.5; those in lfClass2 take the least, but those in lfClass2 are predicted to take twice as many of their trips to the Dolomites. This is consistent with the estimates from the *latent-class lf model* reported in Table 4 and Fig. 5.

Fig. 3 compares, for the behavioral model with lfClass imposed (in dark blue), the estimated proportion of the sample that will take t total trips with the actual proportions (in yellow) and the predicted proportions for the *behavioral model with lfClass as a covariate* (in light green). Since it allows no preference heterogeneity, the behavioral model with lfClass imposed generates less estimated variation in total trips, six to twenty-five, and misses the right tail starting at twenty-six trips. Fig. 3 shows how much of the estimated variation in the number of trips is due to lfClass alone (dark blue compared to light blue). Fig. 4 makes the same comparisons for the proportion taking t PreAlp trips. Put simply, this behavioral model with lfClass imposed as bClass squeezes the predicted trip distribution towards the median, but does exhibit and explain significant behavioral heterogeneity, confirming our initial conjecture.

8. Summary, Thoughts and Relevance

Our product has seven overlapping components: (1) Explanatory variables such as marital status, number of children, skill, body-mass index, smoking and drinking habits, health status, and fitness are important determinants, and predictors, of where, how often, and how one recreates. This is demonstrated both with simple statistics and behavioral models. (To date, few recreation-demand models have considered such explanatory variables, and those models each only include only one or two.) (2) Our argument that such explanatory variables are properly and productively viewed as *life constraints* rather than some sort of “preference shifters.” As part of this discussion, *constraint* is formally defined. Constraint levels can be observed and predicted, so productively used to predict future behavior and behavior in other populations. (3) Behavioral heterogeneity caused by constraint heterogeneity is identified and separated from that caused by preference heterogeneity, demonstrating that observed constraint variation can explain at lot, but not all, behavioral heterogeneity, and that all behavioral heterogeneity, not attributed to price and income variation, need not, and should not, be attributed to variation in current preferences. (4) Life constraints are handled parsimoniously by developing and estimating a latent-class lf (life-constraint) model: recreators are segmented into lfClasses using life-constraints; the number of classes is estimated. The latent-class lf model allows for many life-constraints with many levels and complex correlation patterns. (5) Null hypotheses that behavior does not vary across lfClasses are all rejected. (6) We develop and estimate three behavioral models of participation and site selection. Our preferred behavioral model is a latent-class model of participation and site choice with life-constraint class as covariate. The number of behavioral classes is estimated. One of the other two behavioral models ignores life-constraints; the other includes all life constraint as separate covariates. Both are predictably inferior. (7) Our empirical analysis of life constraints was limited to the life-constraint variables in our two data sets, but there are other relevant constraints that one might consider in addition to the ones we include, constraints such as cultural identity, body image, psychological state, and language, all of which have been shown, individually, and in other studies, to influence recreation.

We feel that using lfClasses as explanatory variables to explain behavioral heterogeneity is more parsimonious than using the individual life-constraints themselves. That said, one might accept our conjecture that life-constraints matter, and reject our conjecture that our *latent-class lf model*, stacked with a behavioral model, is the preferred way to model a multitude of life-constraints.

Two independent data sets, for two different recreational activities, were utilized to test the conjecture that life-constraints are important determinants of participation, site selection, and activities on site. In our Veneto hiker and climber data set, life-constraints are best explained with four lfClasses, seven for our mountain-bike data.

The lfClasses are easily and intuitively characterized. For the mountain-bike sample, lfClass1 members are unconstrained by significant other and kids, unfit, and mostly male. lfClass2 are highly-constrained, middle-age, heavy males. Contrasting, lfClass3 members are constrained, middle-age, highly-skilled, fit males. lfClass4 are the expert fitness junkies, men and women. lfClass5 is characterized by thin women with one or no children. lfClass6 are old low-skilled males. The thin, unmarried, under 30, belong to lfClass7—the 20-somethings.

For the Veneto sample, lfClass4 members exercise little and are thin. lfClass4 is effectively the only kid-constrained class. lfClass3 members are most inclined to smoke and drink, and most are retired. lfClass2 are highly educated, thin, and fit, few smoke or drink; lfClass1 is everyone else.

For the Veneto data, the four estimated behavioral latent-classes vary in terms of total number of trips, and how those trips are distributed across the sites, in particular the allocation between pre-Alp sites and Dolomite sites. Being in lfClass2, for example, makes it more likely you in bClass2 (ave. 12 trips, 8 to Dolomites), and being in lfClass3 makes it more likely you are in bClass3 (ave. 21 trips, 16 to PreAlps).

In terms of prediction, a small change in the level of a single life-constraint such as BMI generates no estimated behavioral change—what one would intuitively predict—but an individual's behavior will change when their life constraint levels change enough to change lfClass. For instance, the model predicts having children or becoming obese will change behavior. Consider average weight in the U.S. population increasing by five pounds. If this average increase results from everyone's weight increasing by the same percentage amount, the model predicts little effect on recreational behavior. But, if the average increases by five pounds because 20% of the population has gained twenty-five pounds, the model predicts a much higher proportion of trips to the "easier" pre-Alp sites.

Describing our modeling approach more generally, we develop and implement a technique to "stack" latent-class models. At the bottom of the stack a large set of potential explanatory variables, likely correlated, are used to estimate a finite number of "explanatory" latent classes. From the latent-class model at the bottom of the stack one estimates the probability that each individual belongs to each of the *explanatory* classes as a function of the levels of the explanatory variables of interest; then one uses these as covariates in the latent-class model next up the stack. In our application, the stack has only two levels and the application is recreation demand, but neither need be the case. Imagine conjecturing that one's WTP to value an environmental improvement is a function of how the environment will be improved and one's political beliefs, and that one's political beliefs are a function of one's personality and psychological state of mind. Everyone in your sample answers a set of standard psychological questions to assess their personality and psychological state; they also answer a set of standard questions about their politics. At the bottom of the stack, one could estimate a latent-class model of personality and psychological state, probabilistically allocating individuals among a finite number of personality/psychological latent classes. Class-membership probabilities from this exercise then can be used as covariates in a latent-class model of political attitudes using the answers to the politics questions. The class-membership probabilities from this latent-class model could then be used as covariates in the model at the top of the stack: for example, a latent-class choice model based on the answers to hypothetical questions such as choice pairs over different states of the environment at different costs. Or, alternatively, imagine using the answers to psychological questions on extroversion/introversion, risk-taking, and competitiveness, to probabilistically allocate individuals into latent personality classes and then using the class-membership probabilities as covariates in a behavioral model, not of site choice but of recreational activity and who one recreates with.

In closing, food for thought: "Products" (1)–(3), listed above, highlight the distinction between behavioral heterogeneity and choice heterogeneity: the adjective "choice" suggests that people behave differently because they are choosing to behave differently; which is incorrect if people behave differently because they are constrained to behave differently. Our finding, for recreation, that many variables both constrain and matter, makes us wonder whether economists overuse the word "choice" in that often behavior is determined more by constraints than the "freedom to choose."

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