

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

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

**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 suggest a latent-class approach to life constraints, assuming individuals have numerous, correlated life constraints. First, 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 that life-constraint classes explain a significant amount of the observed behavioral heterogeneity.

**Keywords:** latent-class models, life constraints, preference heterogeneity, constraint heterogeneity, behavioral heterogeneity, choice, behavior, fitness, BMI, children, skill, exercise, health, disease, recreation, hiking, climbing, mountain biking

Note that the figures are in color.

## 1. Introduction

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

The objective here is to develop a parsimonious method of identifying behavioral heterogeneity caused by constraint heterogeneity and separating it from that caused by preference heterogeneity. 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 constraints such as kids, BMI (body-mass index) fitness, skill, and health. Behavioral heterogeneity, not due to price and income variation, is typically assumed due, in total, to preference heterogeneity. We find this misguided.

We begin by defining behavioral heterogeneity, preferences, preference heterogeneity, constraints, and constraint heterogeneity, doing so in terms of a simple choice model.

Behavioural heterogeneity is simply the variation in behavior across individuals.

An individual's preferences are, simply put, their ranking of states. Preferences can be expressed in terms of what is consumed in each state—e.g. quantity consumed of each good—or in terms of the levels of the exogenous variables in each state (prices, income etc.). The latter typically represented with an indirect-utility function: a numerical representation of the individual's ranking of constraints, where the constraints are the levels of the determinants of choice that are exogenous in the decision period. In addition to prices and income, these include, for example, the amount of attribute  $k$  in good/activity  $j$ .

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 led.

Life-constraints are levels of consumer durables with high disposal costs—there is no free disposal of spouse, kids, or weight. In the shortrun, 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 reduces the pleasure of recreation (negatively complement it and complement sedentary activities). Lack of skill, strength, or endurance removes some activities from the

choice set. Current income is a life constraint, so are, for example, 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 he will do given the levels of the variables in the indirect utility function. The functional form for the indirect is typically assumed the same for all individuals. Relevant variables in the indirect include prices and income, and could include health status and number of kids. Parameters take constant numerical values from the individual's perspective; they might differ across individuals but are exogenous constants for the individual. Such parameters are what we typically want to estimate. Preference heterogeneity is typically *characterized* by allowing 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,  $j = 1, 2, \dots, J$ , 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 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  $\max (U_{i1}, U_{i2}, \dots, U_{iJ})$ .

Choose a functional form such that  $k_i$  influences behavior. Simply, and for example, if there are no income effects,<sup>1</sup> and no preference heterogeneity.

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

The  $\beta$  are the "preference" parameters. In this example specification, kids can influence choice in three ways: by affecting the utility one gets from the numeraire, the  $\beta_{yk} k_i (y_i - p_{ji})$

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<sup>1</sup> The choice probabilities are not a function of income.

term; by directly affecting the utility one gets from alternative  $j$ , the  $\beta_{0j}k_i$  term and via the characteristic level,  $c_j$ , the  $\beta_{ck}k_i c_j$  term. If kids do not matter,  $\beta_{0j} = \beta_{ck} = \beta_{yk} = 0$ .

Eq. (1), in our view, admits no preference heterogeneity: the  $\beta$  are not allowed to vary across individuals. However, we would say that this specification admits life-constraint heterogeneity in terms of the number of kids; that is, number of kids affects choice and number of kids is assumed exogenous in the choice period. There is life-constraint heterogeneity if different people have different numbers of kids. (Note that 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, but not in terms of kids)

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

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

ignoring data on  $k_i$  with, as is common, a random-parameters model, it is incorrect to interpret the variation in the  $\alpha_c$  and variation in the  $\alpha_y$  as a reflection of preference heterogeneity—the  $\alpha$  vary because of variation in the number of kids, not because of variation in the  $\beta$  parameters.

Now generalize Eq. (1) to admit preference heterogeneity. We do so in a latent-class framework by imagining there are  $G$  **preference** classes ( $\beta_g$ ,  $g=1,2,\dots,G$ , where  $\beta_g$  is the  $\beta$  vector for preference class  $g$ ). In which case, the indirect for alternative  $j$ , conditional on being a member of preference class  $g$  is

$$\begin{aligned} & V((y_i - p_{ji}), c_j, k_i | g) \quad (3) \\ & = \beta_{g0j}k_i + \beta_{gc}c_j + \beta_{gck}k_i c_j + \beta_{gy}(y_i - p_{ji}) + \beta_{gyk}k_i(y_i - p_{ji}) \\ & = \beta_{g0j}k_i + (\beta_{gc} + \beta_{gck}k_i)c_j + (\beta_{gy} + \beta_{gyk}k_i)(y_i - p_{ji}) \\ & = \beta_{g0j}k_i + \mu_{ci}c_j + \mu_{yi}(y_i - p_{ji}) \end{aligned}$$

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

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

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

where one assumes  $M$  latent **behavioral** classes, are commingling preference heterogeneity and constraint heterogeneity.<sup>2</sup> 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  $\beta$  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  $\mu_{ci}$  and  $\mu_{yi}$ ) to preference heterogeneity. But that is what is often done. It would also be incorrect to attribute it all to constraint heterogeneity.

We estimate, for two different recreational activities, with two independent data sets, how much behavioral heterogeneity can be attributed to constraint heterogeneity. We suggest a latent-class approach to life constraints, assuming individuals have numerous, correlated life constraints.

One might reasonably ask whether it is important to identify constraint heterogeneity separate from preference heterogeneity. The answer is no if one wants only to identify/estimate the distribution of behaviors with no desire to predict how behavior and behavioral variation will change if constraint levels change. The answer is also no if it is not possible to directly observe and measure either constraint heterogeneity or preference heterogeneity.

But researchers often want to predict and often observe constraint heterogeneity.<sup>3</sup> They typically collect price and income data and use it to estimate how choice is influenced by these constraints.<sup>4</sup> Here we want to take advantage of the fact that other relevant life constraints can also be observed, and develop and estimate models to predict how behaviors will change if the levels of multiple life constraints change. Observing that there are life constraints, that they influence behavior, and that they can be observed, brings more explanatory power to the table.

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<sup>2</sup> We chose the word "behavior" rather than, for example, "choice," because it is our conjecture that all behaviors are not chosen/selected.

<sup>3</sup> Note that while it is typically possible to observe and record constraint levels (income, prices, number of kids), direct data on preferences is more difficult to obtain and model. 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, Morey and Thacher (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. They review the literature on the use, and advocacy, of preference-statement data in choice models, and estimate a latent-class model to jointly explain choices and preference statements.

<sup>4</sup> Imagine collapsing  $V_{ij} = \mu_{ci}c_j + \mu_{yi}(y_i - p_{ji})$  to  $V_{ij} = \gamma_{ci}c_j$ , assuming  $\gamma_{ci}$  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 would not do this.

Consider predicting, for a given population, future recreation patterns or predicting patterns in a different population. 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 (H.D. 2009), and family composition is predictably changing (U.S. 2009 and Martin et al., 2009).

Future recreational avidity, site selections, and activities will be different because life-constraints levels will be different, and it is important that we can predict the behavioral shifts, and our model can do this. Saving a wilderness so future generations can visit 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 possibly attributable to changing life-constraint levels.

We are in good company when we argue that preference heterogeneity should not be relied on to explain most behavioral heterogeneity. Stigler and Becker (1977) conclude “no significant behavior has been illuminated by assumptions of differences in tastes.” Their view is now foreign to many in recreation demand. Their argument is that because preference heterogeneity can explain all behavioral heterogeneity, it explains nothing. They make three points: little is gained by attributing behavioral differences to taste variation; more strongly, much unexplained variation is explained by constraint variation, if one looks hard enough; and, most strongly, tastes don’t vary much over time or people. Here, we look to life-constraint heterogeneity to help explain and model behavioral heterogeneity, not to argue there is little preference heterogeneity. Our view is that preference heterogeneity exists and affects behavior.

An empirical question is which variables in the decision period are exogenous/constrained and which are choice variables. This will vary from application to application, and the shorter the decision period the fewer the choices. In our two 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). For example, we will take the average level of overall exercise per week and skill level in the recreation activity studied as exogenous when each trip choice is made. 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 those who exercise a lot exhibit properties of addiction (Rhodes et al, 2003). Being skilled likely means one practiced the activity in the past, but does not imply that one, now, participates a lot—we abandon activities when we are bored or because the levels of other life constraints change (e.g., kids arrive). Alternatively, if one viewed the individual as choosing, in early adulthood, how many children to have, whether to become an expert mountain biker, and how many hours they would exercise per week in 2012, these would all be choice variables, not constraints.

The task of modeling life constraints is complicated if there are more than a few. Consider the expansion of Eq. (1) if there were, for example, four important characteristics, and five relevant life constraints. If the influence of each life constraints was separately modeled, the indirect would have many interaction terms each with a unique  $\beta$  parameter, even if the model admits no preference heterogeneity. Add to this the possibility 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

To account for many correlated life constraints we propose using a latent-class model to identify life-constraint classes, a *latent-class lf model* (Section 3). That is, we suggest that while there can be many combinations of life constraints, operationally, there might be only a small number of latent life-constraint classes. We then ask how much of the behavioral heterogeneity can be explained in terms of 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 don't bind, black-and-white, the way the budget constraint is assumed to bind. The number of lfClasses is estimated. For one data set, 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. Additionally, one estimates the probability a lfClass  $c_{lf}$  individual will have level  $v$  of life-constraint  $q$ .

The prefix and subscript *lf* is required because two different sets of latent classes are specified and estimated: *lf* latent classes and *behavioral* latent classes (hereafter, *bClasses*). Later we will use *b* to denote a behavioral class: a latent class of individuals who exhibit similar **behavior** in terms of the recreational activity being studied. One research question is to what extent lfClasses predict bClasses.

Contrast our approach with attempting to model life-constraints the way the budget constraint is modeled: given prices and income, an activity bundle is either financially affordable or not. The influence of individual constraints is less distinct; age, gender, and life-constraint levels influence collectively, and, typically, do not entirely eliminate activities.<sup>5</sup> Running a 10K is still possible, but different from when one was young and fast. The latent-class If model embraces these interdependencies and ambiguities.

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 IfClasses, Section 7) are used to demonstrate that significant behavioral variation is explained by life-constraints.

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.<sup>6</sup> 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;

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<sup>5</sup> If having a skill level below some point, or a high BMI, eliminates an activity or site from the choice set (e.g. a climbing route, ski run, or white-water), that alternative should be eliminated from the choice set of individuals with these life-constraint levels.

<sup>6</sup> 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. But, everyone in the sample participates, at least occasionally in the activity, so one cannot use our data to study how life constraints completely preclude an individual from an activity (e.g. too unfit to hike).

Figure 1 is an example choice pair. (Data sets, like ours, with extensive and detailed individual data, once rare, are now common but underutilized.)

We find 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.

In addition, for the Veneto data, three behavioral models of participation and site selection—all including the influence of life-constraints—are specified and estimated (Section 7)

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Insert figure 1 about here

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## **2. Literature on Life-constraints**

Few life-constraints are included in economists' recreation-demand models. 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. A 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 life 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 (Morey (1981), Morey et al. (2002), Scarpa and Thiene (2005), Oh and Ditton (2006) and Hynes et al. (2007)).

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 uncomfortable 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 they affect recreational behavior, and describes these characteristics 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 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.

Many 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 removing alternatives from the choice set, but also influencing utility directly.

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 increase recreational opportunities, speculating that men are “less time constrained than women.” (See also Teal and Loomis (2000), Brown and Taylor (2000), and 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, Mariel, and Fernández-Macho (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) also identify the significant influence of children on 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.

### **3. A Latent-Class If Model**

Each individual is assumed to be in one IfClass, 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 IfClasses 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 IfClass, 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 unconditional class-membership probabilities as a function of age, gender, and life-constraints. The  $\ln$  likelihood function for a  $C_{lf}$  lfCclass latent-class model is

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

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,

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

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,

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

Note 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 If 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. The following are assumed life-constraints: skill, resting heart rate, cigarettes per day, significant other, number of minor children, BMI, diseases, and average amount of overall exercise per week.<sup>7</sup> The data on age, gender and the seven life-constraints was used to estimate latent-class If models with one through nine IfClasses; estimation was with the software Latent Gold (Vermunt and Magidson, 2005).

Using fit criteria (the LL, BIC, AIC, AIC3, and CAIC), seven IfClasses best characterize the population. For details on fit criteria see Thacher et al. (2005).

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% (IfClass1), 20.3% (IfClass2), 18.8% (IfClass3), 13.5% (IfClass4), 8.6% (IfClass5), 8.0% (IfClass6), and 6.9% (IfClass7).<sup>8</sup>

IfClass1 members are unconstrained by significant other and kids, unfit, and mostly male. IfClass2 are highly-constrained, middle-age, heavy males. Contrasting, IfClass3 members are constrained, middle-age, highly-skilled, fit males. IfClass4 are the expert fitness junkies, men and women. IfClass5 is characterized by thin women with one or no children. IfClass6 are old low-skilled males. The thin, unmarried, under 30, belong to IfClass7 - the *20-somethings*.

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Insert table 1 about here

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<sup>7</sup> 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.

<sup>8</sup> 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.

#### 4.1 Justifying our Characterizations of the Seven Ifclasses: the Details

Those in IfClass5 are most certainly female (98.7% probability), the opposite is true for IfClass3. Ninety-four percent of IfClass7 members are estimated to be under 30, while those in IfClass6 are likely over 60.

Table 1 reports the estimated probabilities for each level of each life-constraint, for each estimated IfClass. Those in IfClasses 3 and 4 are estimated highly skilled. Contrasting, 72.1% of IfClass5 are predicted to be skill 1 or 2: low skilled. Figure 2 confirms, showing average estimated skill levels by IfClass. For example, the estimated average skill level is 3.7 (out of 4) for IfClass3, 3.8 for IfClass4, and 2.5 for IfClass5.

All seven IfClasses exercise, but the predicted amounts vary substantially: IfClass2 moderately, IfClass4 intensely—more than 10 hours a week for over forty-percent. IfClass2 has the highest probability of not exercising (7.2%); this probability is less than one percent for members of IfClass4. Almost fifty percent of IfClass4 members are predicted to have a resting heart rate of 50 or less, so very fit. IfClass3 is close with 41.2%; for the other five IfClasses the predicted percentage below 50 bpm ranges from 0.1% to 10.7%. If one is in IfClass2 or 6, there is a 4% probability that one has a resting rate over 100, unhealthy; this probability is zero for those in IfClasses 3 and 4.

No IfClass smokes much, but 9.3% of IfClass1 and 8.0% of IfClass7 are predicted to smoke. IfClass2 members have a high probability of being overweight (BMI of at least 27 for 41.3%). IfClasses 1 and 6 are also relatively heavy. Contrasting, only 0.5% of those in IfClass7 are predicted to have a BMI over 27. Almost nineteen percent of IfClass7 is predicted to be thin (BMI 20 or less). Twenty percent of IfClass6 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 one-hundred percent (IfClass2) to less than twenty percent (IfClass 7). Few have more than two kids: those in IfClass3 have a 55% chance of having one or two kids, for IfClass2 is it 62.4%. The probability of having no children at home varies from 95.7% (IfClass4) to 22.8% (IfClass2).

We now consider, using simple statistics, the relationship between IfClasses, 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.

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Insert figure 2 about here

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## 5. IfClasses 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 hours. 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  $\Pr(c_{if} : z_i | x_i)$ , precisely places most individuals in a IfClass.

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

Table 2 reports average days and hours mountain biking, by IfClass. Statistically, one rejects the null hypothesis that average biking days do not vary by IfClass. The mean number is highest for IfClasses 3 and 4, and lowest for overweight males and thin mothers with one or no kids (IfClasses 2 and 5). The most variant is IfClass7 (the 20- somethings). Consider the probability one does not ride for 30 days, by IfClass. IfClass7 (thin, unmarried, under 30) and IfClass5 (overweight males) are least likely to ride, IfClass3 (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 IfClass is rejected. The averages vary, significantly, from 2.7 (IfClass5: thin females with one or no kids) to 4.5 hours for IfClass3. In seven days, almost half of IfClass5 are estimated to have no mountain-bike hours; it is only a quarter for IfClass3. Also of interest is the average hours by IfClass for those who had positive hours; IfClass7 has the highest.

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Insert table 2 about here

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### 5.2. There Are also Significant and Intuitive Differences, by IfClass, 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. IfClass 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 (IfClasses 3 and 4) significantly more likely to choose the difficult trail, details on request.

## 6. Members of The Veneto Alpine Club: Simple Statistics and a Latent-class If 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. Figure 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. Figure 4 shows it for preAlp trips.

This data was used to estimate *latent-class lf models* with 1 - 6 lfClasses. 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, averaged over covariate levels, 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.<sup>9</sup>

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Insert figure 3-4 about here

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Justifying our characterizations, Table 3 reports the estimated probabilities for each level of each life-constraint, by lfClass. Figure 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 eighty percent 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 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% 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.

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<sup>9</sup> Forcing more classes would likely split lfClass1, making it less catch-all, but not substantially improve fit or explanatory power.

## **7. The Veneto Ifclasses ‘Explain’ Significant Variation in Participation, Site Selection and Activity on-Site**

For the Veneto, we investigate, in two steps, the relationship between the IfClasses 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 IfClasses.

### **7.1. There are Significant Differences in Behaviors Across the Four Veneto IfClasses: Simple Statistical Tests**

The estimated If latent-class model places 87% of the Club members in a IfClass with at least 90% precision, and 98% with at least 70% precision. The average number of actual trips, by IfClasses 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. IfClass3 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 IfClasses 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 1,500 m. in elevation; the Dolomite sites range from a 1000 to 3,000 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 IfClass. Table 4 reports the observed trip proportions by estimated IfClass. Not surprisingly, IfClass3 (retired, less fit and bad habits) and IfClass4 (kid-constrained and less fit) take significantly more of their trips to the preAlps than IfClasses 1 and 2. IfClass3, the least fit, are more likely to hike than to climb or mountaineer, making the preAlps attractive.

Consider next how the different IfClasses allocated their trips across the 14 specific Veneto sites (Table 4). One rejects the null hypothesis that the allocations do not differ by IfClass. IfClass2, 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. IfClass4 (mothers and older females) are under-represented at the extreme Dolomite sites. Those retired and with bad habits (IfClass3) are the most represented class at Piccole, Asiago and Grappa, which are easy-hiking preAlp sites. IfClass3 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 IfClass. For example, IfClass3 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 IfClass2 members, the young and fit. IfClass4 (kid constrained and older women) are overrepresented in type 4 (occasional hikers who do not climb) and under-represented in regular climbers. IfClass2, the young and fit, are over-represented in the ranks of those who both hike and climb.

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Insert table 4-5 about here

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## 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.

### 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

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

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  $\alpha$  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, 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.

### 7.2.2 Three Behavioral Models Where Life-constraints Have Influence

i) 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*:  $\Pr(c_b : lf1_i, lf2_i, lf3_i, lf4_i)$  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

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

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  $lfw_i$ . The  $\alpha_{j|c_b}$  and  $\beta_{|c_b}$  in  $\Pr(j|c_b)$ , Eq. (8), and the  $\varphi_m$  and  $\lambda_{m w}$  are all simultaneously estimated, conditional on the  $lfw_i$ . Behavioral heterogeneity is best explained with four behavioral classes.<sup>10</sup> 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 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 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)—only 4% of *lfClass4* is estimated to be in *bClass3*. And, those in *lfClass1* (most working, most

<sup>10</sup> The estimated number of *bClasses* need not equal the estimated number of *lfClasses*; they just happen to in this application.

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 1.2 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 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 were 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 small-font 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 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.

Figure 3 compares, for the *behavioral model with lf Class 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.

Figure 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.

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Insert table 6-7-8-9 about here

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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, loses 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).<sup>11</sup> 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.

ii) *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:  $\Pr(c_b : z_i, \mathbf{x}_i)$  where  $\mathbf{x}_i$  is individual  $i$ 's vector of life-constraints. Age, gender and the life-constraint

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<sup>11</sup> For example, the probability of being in bClass2 increases from 26% to 39% when one switches from lfClass2 to lfClass4, Table 7.

variables are directly entered as covariates influencing the individual's bClass membership probabilities—there are no lfClasses. Specifically,

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

$V_q$  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  $\chi_{c_b}$ ,  $\rho_{c_b,k}$ ,  $k_{c_b}$  and the  $\tau_{c_b,k}$  in  $\Pr(c_b : z_i, \mathbf{x}_i)$  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 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*.

iii) *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*.

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 Figure 5.

Figure 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. Figure 3 shows how much of the estimated variation in the number of trips is due to lfClass alone (dark blue compared to light blue). Figure 4 makes the same comparisons for the proportion taking  $t$  preAlp trips. Put simply, this behavioral model with lfClass imposed 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 contribution has six components: (1) family, skill, body-mass index, smoking and drinking, health, fitness and other life-constraints help ‘explain’ and predict where, how often, and how one recreates. (2) Behavioral heterogeneity caused by constraint heterogeneity is identified and separated from that caused by preference heterogeneity (3) This is accomplished, parsimoniously, by first 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 accounts for many life-constraints with many levels and complex correlation patterns. (4) Null hypotheses that behavior does not vary across lfClasses are all rejected. (5) We develop and estimate three behavioral models of participation and site selection with life-constraints: two model life-constraints in terms of lfClasses, one models life-constraints in terms of the life-constraints themselves. The number of behavioral classes is estimated. And (6), our recommended model, a latent-class behavioral model with lfClass as a covariate can be estimated for most discrete-choice problems, given data on life-constraint levels.

We feel 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* 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 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.

Summarizing, life-constraints are significant determinants of participation and site selection, but, not surprisingly, preference heterogeneity, or other factors, still has a role to play in explaining behavioral heterogeneity.

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Table 1  
*MTB - Estimated probabilities for each level of each constraint, by lfClass*

	Total	lfclass 1	lfclass 2	lfclass 3	lfclass 4	lfclass 5	lfclass 6	lfclass 7
<i>Skill level</i>								
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
<i>Exercise/week (hours)</i>								
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
<i>Heart rate (bpm)</i>								
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
<i>Body mass index</i>								
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
<i>Cigarettes/day</i>								
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
<i>Disease</i>								
yes	8.0	5.9	8.5	7.7	5.9	7.7	20.0	4.8
<i>Live with significant other</i>								
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
<i>Minors/family (n)</i>								
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

(rows, by life constraint and class, sum to 100)

Table 2

*MTB - Average days biked in the last 30 days and average hours biked in the last week*

	IfClass1	IfClass2	IfClass3	IfClass4	IfClass5	IfClass6	IfClass7
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

Table 3  
*Veneto - Estimated probabilities for each level of each life-constraint, by lfclass*

	Total	lfClass1	lfClass 2	lfClass 3	lfClass 4
<i>Retired</i>					
Yes	16.8	0.2	0.1	80.9	50.7
<i>Education</i>					
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
<i>Body Mass Index</i>					
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
<i>Exercise/week (hours)</i>					
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
<i>Cigarettes/day</i>					
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
<i>Alcohol/day (drinks)</i>					
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
<i>Kid constrain* (scale 0-3)</i>					
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
<i>Heart disease</i>					
Yes	3.1	2.2	1.2	8.2	5.1
<i>High Blood Pressure</i>					
Yes	4.9	3.4	0.3	17.2	4.3

(\* 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)

Table 4  
*Veneto - Percentage of trips to each site, by estimated lfClass*

	lfClass1	lfClass2	lfClass3	lfClass4
<i>Pre-Alps (total)</i>	55.7	55.6	68.9	65.9
<i>Dolomites (total)</i>	44.3	44.4	31.1	34.1
<i>PreAlps</i>				
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
<i>Dolomites</i>				
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

Table 5  
*Veneto - Respondents by recreator type, by estimated lfClass*

	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

(columns sum to 100%)

Table 6  
*Veneto - Proportion of lfClassW estimated to be in bClassY*

	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

(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

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
<i>PreAlp sites</i>				
Feltrine	5.0	6.3	6.7	4.9
Piccole	<b>20.4</b>	8.2	6.0	<b>19.5</b>
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	<b>12.3</b>	4.8
<i>Dolomite sites</i>				
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	<b>15.5</b>	<b>11.8</b>	<b>17.7</b>	10.9
Civetta	8.4	<b>14.9</b>	6.2	<b>12.8</b>
Martino	5.2	10.4	4.1	8.0
Marmolada	4.1	8.8	8.6	8.5

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

If you were going on a mountain bike ride, and these were the available choices, which ride would you take? *Check the appropriate box.*

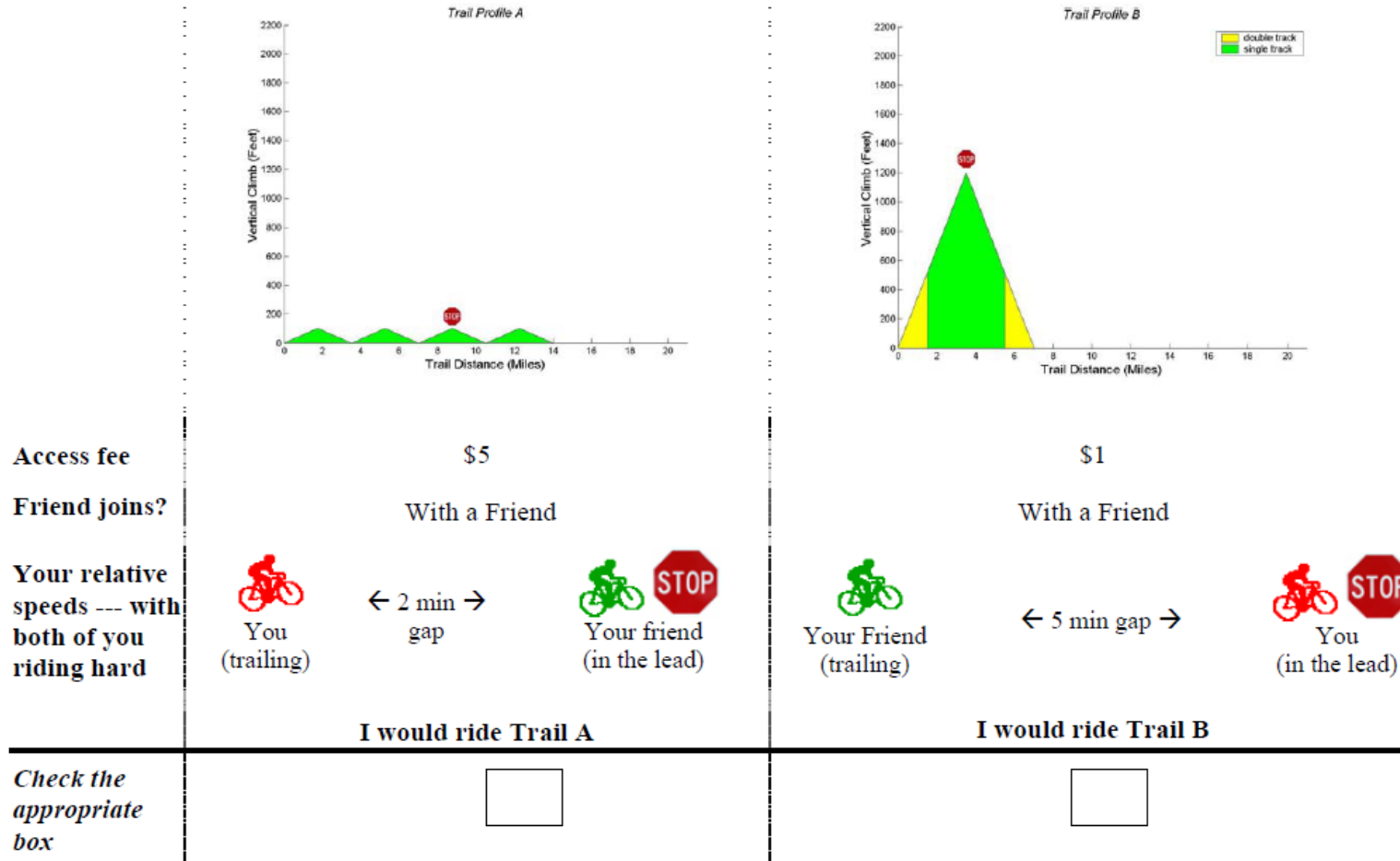


Figure 1. MTB: Example of Choice Pairs

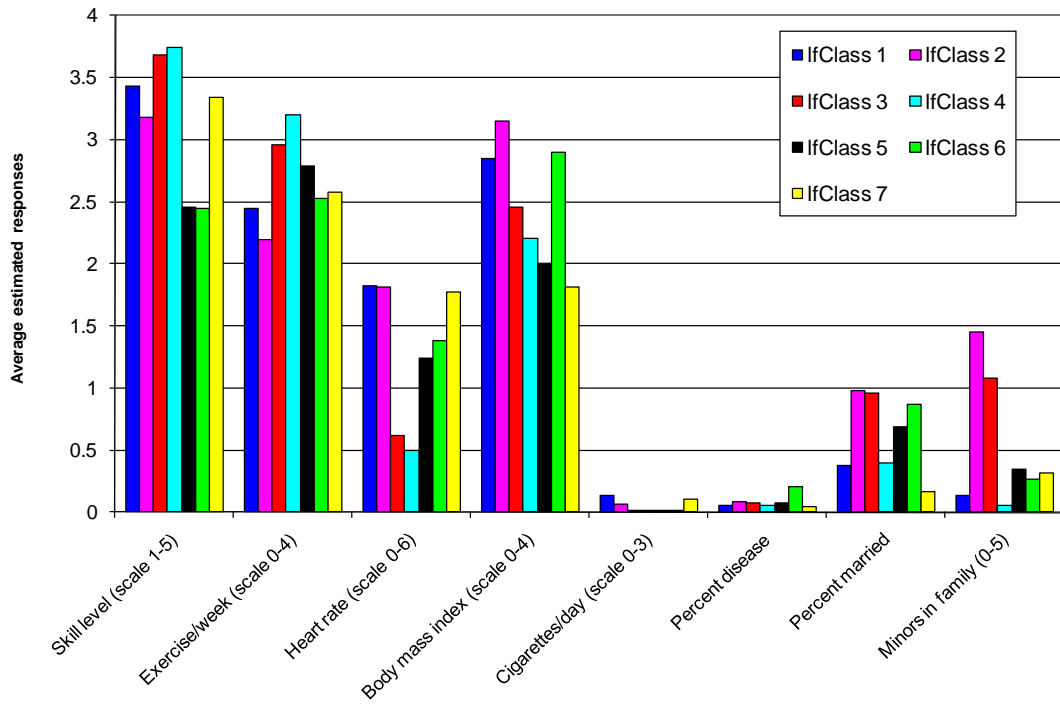


Figure 2. MTB: Average Estimated Constraint Levels, by IfClass

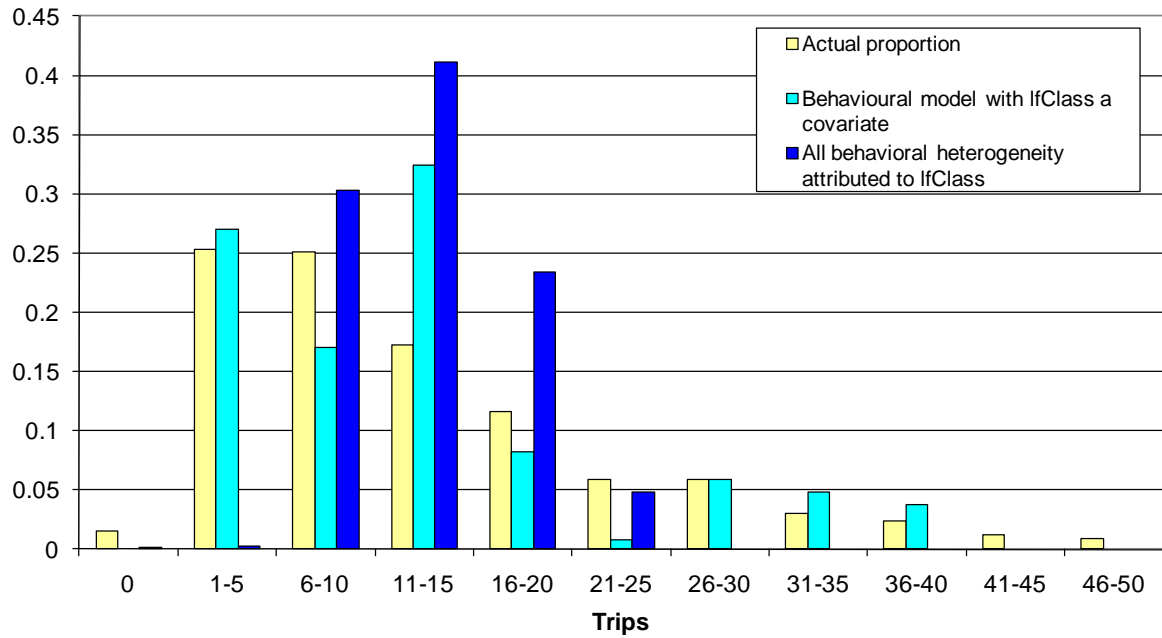


Figure 3. Veneto - Proportion of Individuals Taking  $t$  Trips

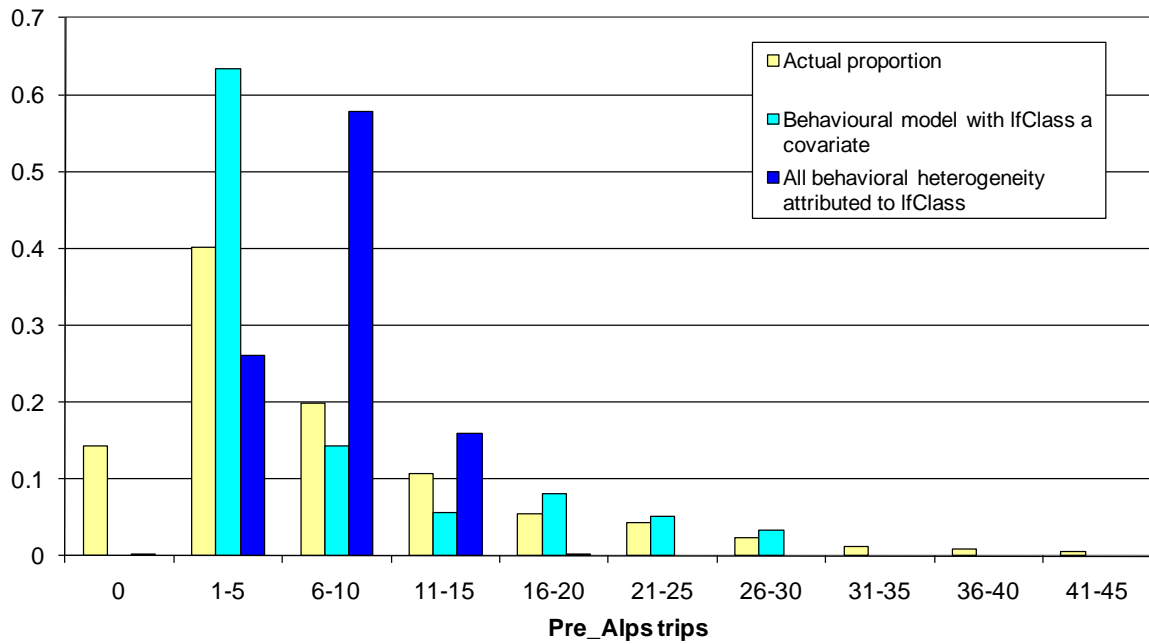


Figure 4. Veneto - Proportion of Individuals Taking  $t$  Trips to Prealps

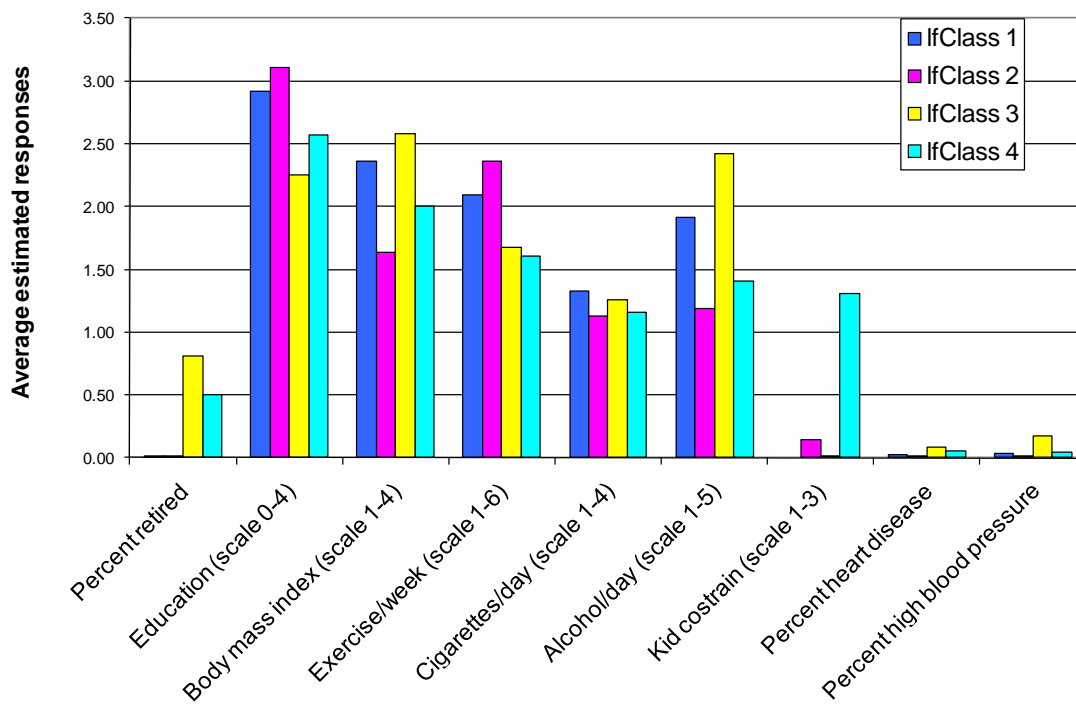


Figure 5. Veneto - Average Estimated Constraint Levels, by IfClass